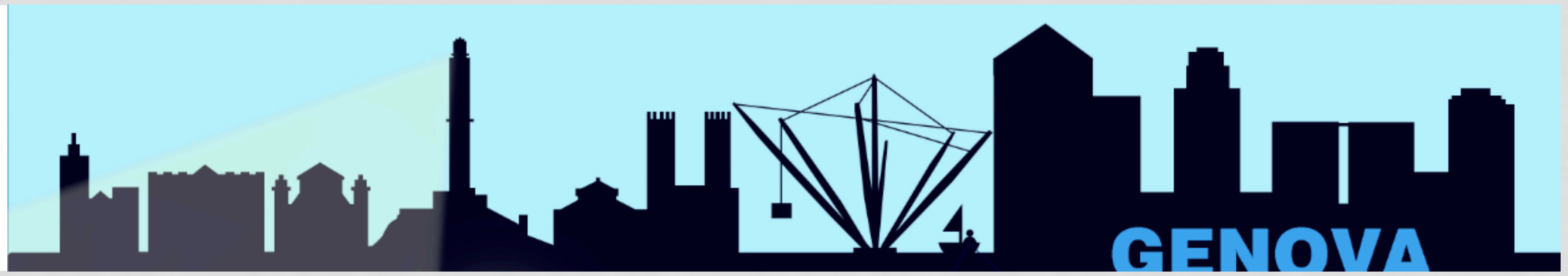

# EXPERIMENTAL INTRODUCTION

DILIA MARÍA PORTILLO QUINTERO

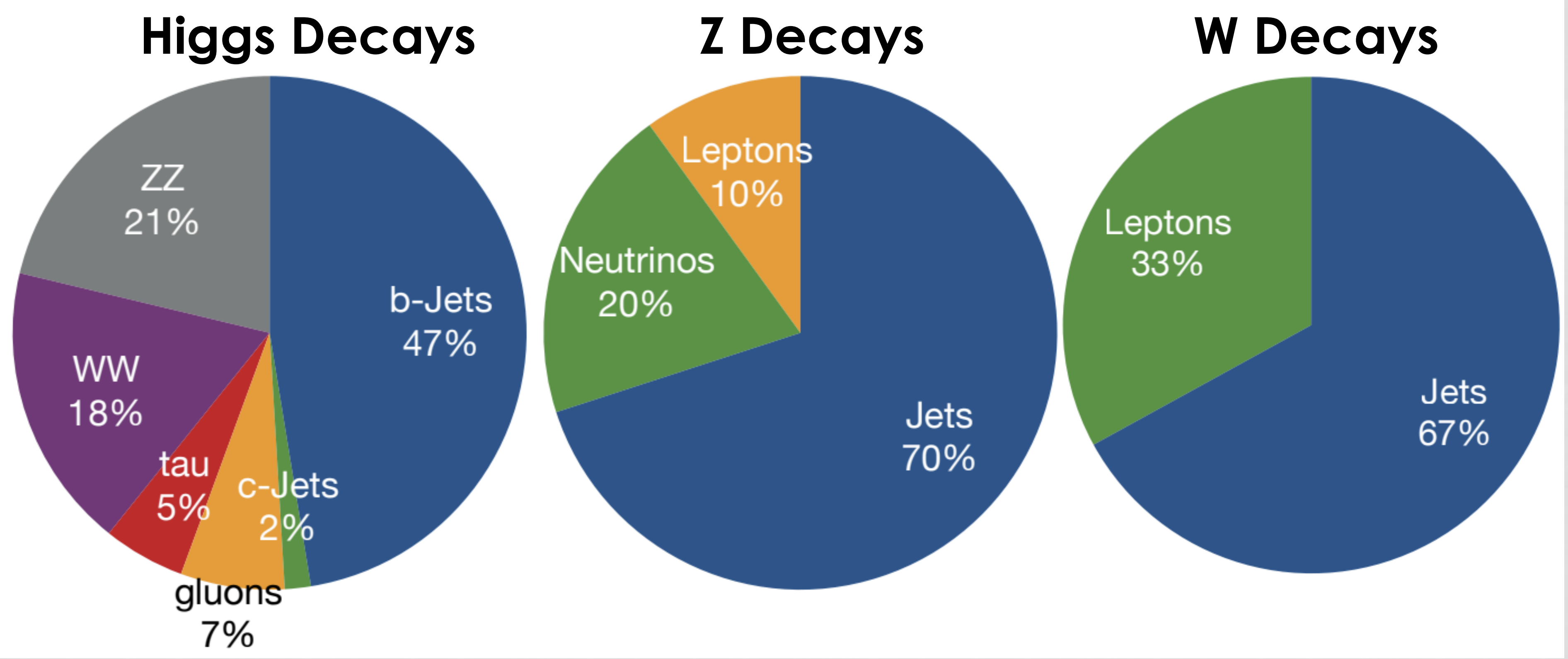
BOOST 2024
29 July - 2 August, Genova - Italy

TRIUMF



# Jets!

- Jets plays a critical role on the LHC physics program
- The majority of Higgs bosons, W's, and Z's decay to jets!
- Jets are present in almost any kind of measurement or search you can do




## Searches

- We have not found beyond the SM physics (yet)!
- Most remaining scenarios involve heavy new particles
  - Reconstructed objects are necessarily boosted
- Jet taggers are a great tool to suppress background and increase signal efficiency
  - Machine learning techniques are currently leading the developments

## Measurements

- Precise QCD calculations opens the opportunity to do precision measurements
- New tools available in the past years
  - Lund jet plane, energy correlators, event shapes…
- Jets are useful for studying
  - QCD processes
  - MC generators and shower models

# Outline

- In this talk I will briefly cover how to build a jet and some use-cases
  - Define Inputs/constituents (and calibrate them)
  - Use Pile-Up (PU) mitigation techniques to make them as much resilient as possible
  - Reconstruction algorithm (preferably infrared and collinear safe)
  - Grooming techniques to mitigate PU and soft radiation
  - Calibrate it
  - Tag it (if needed)
  - Do Physics analysis with jets or study them
- And highlight (some) of the greatest and latests

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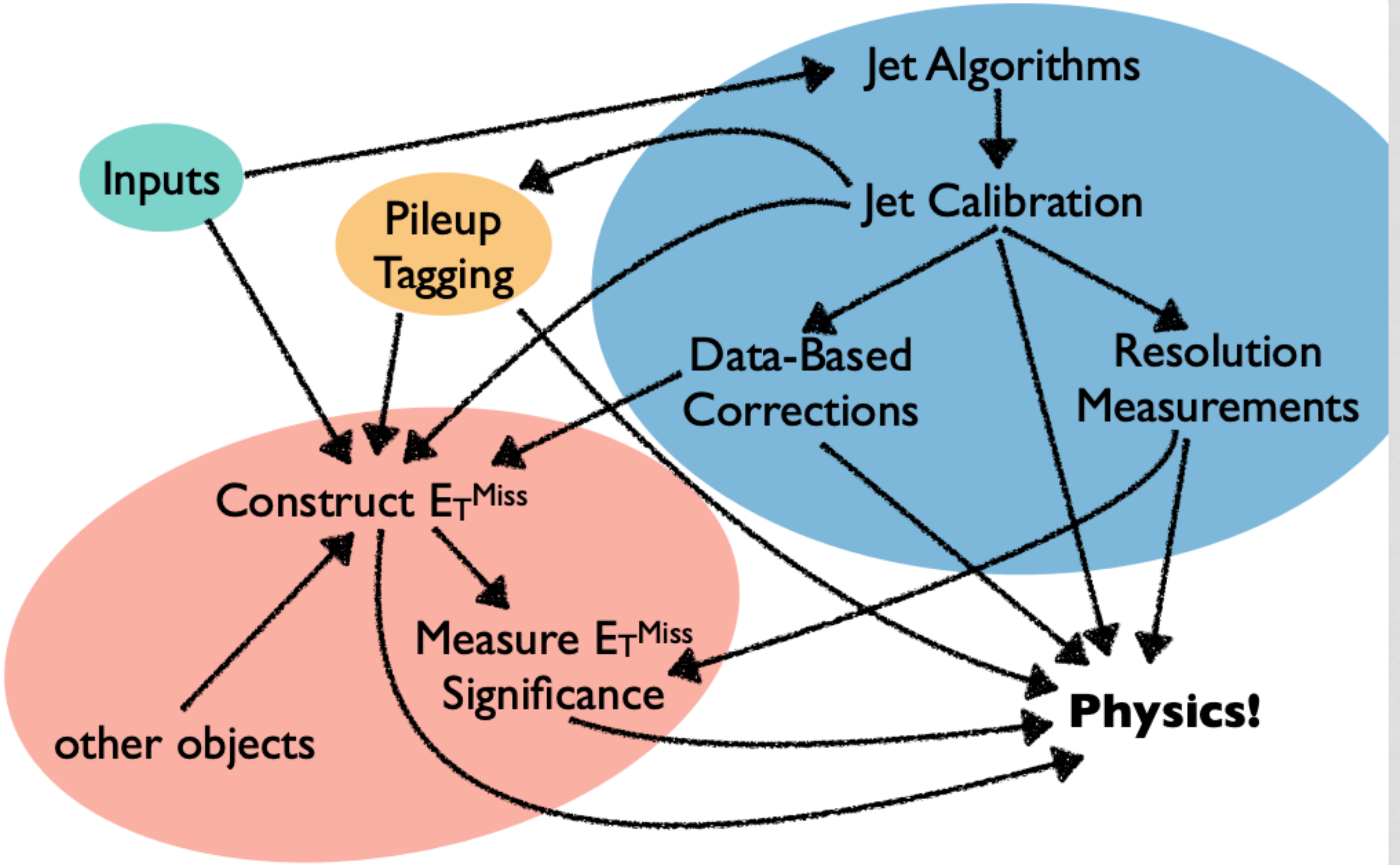

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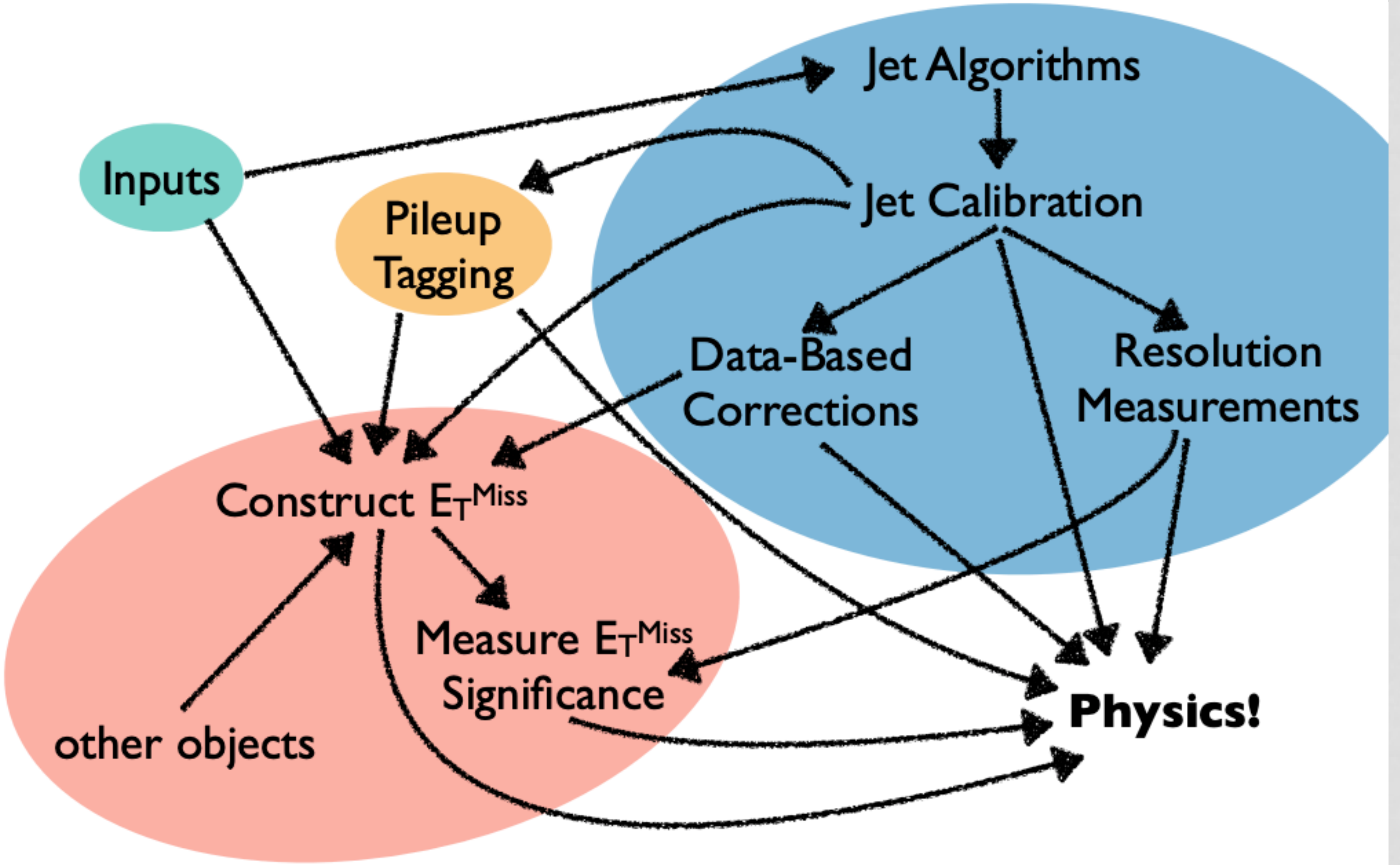

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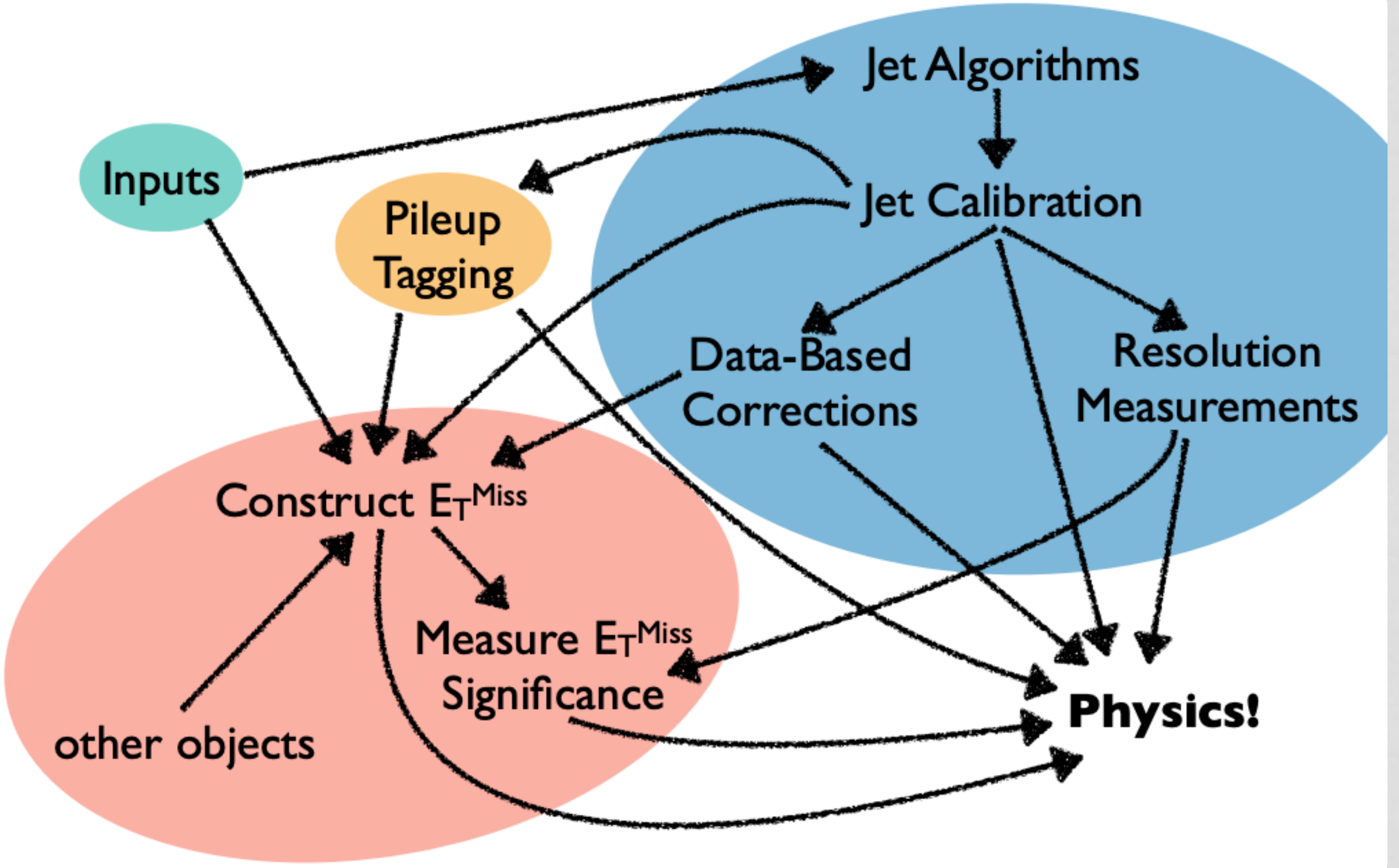
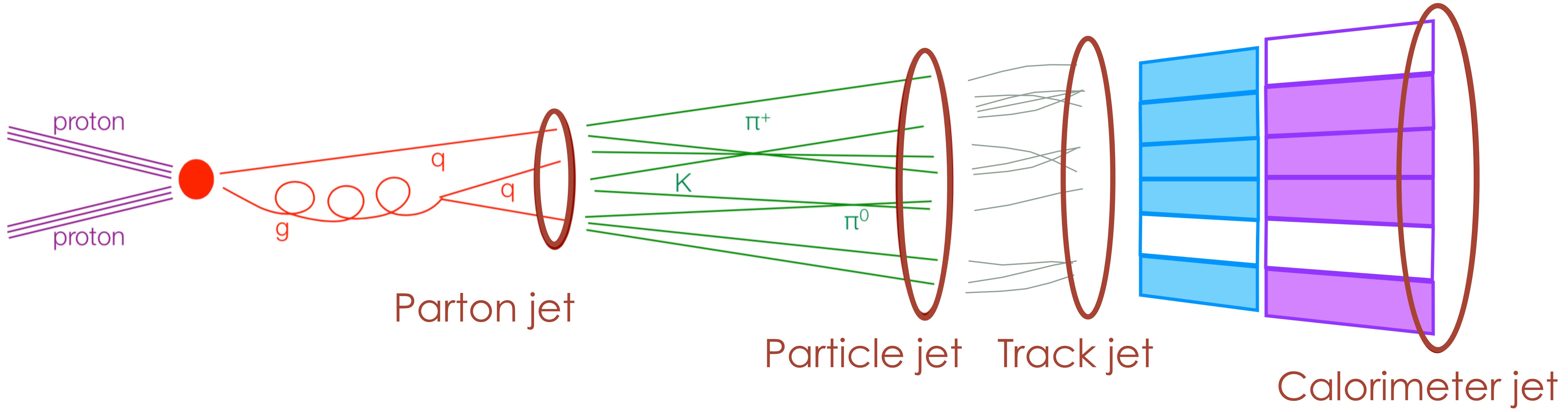


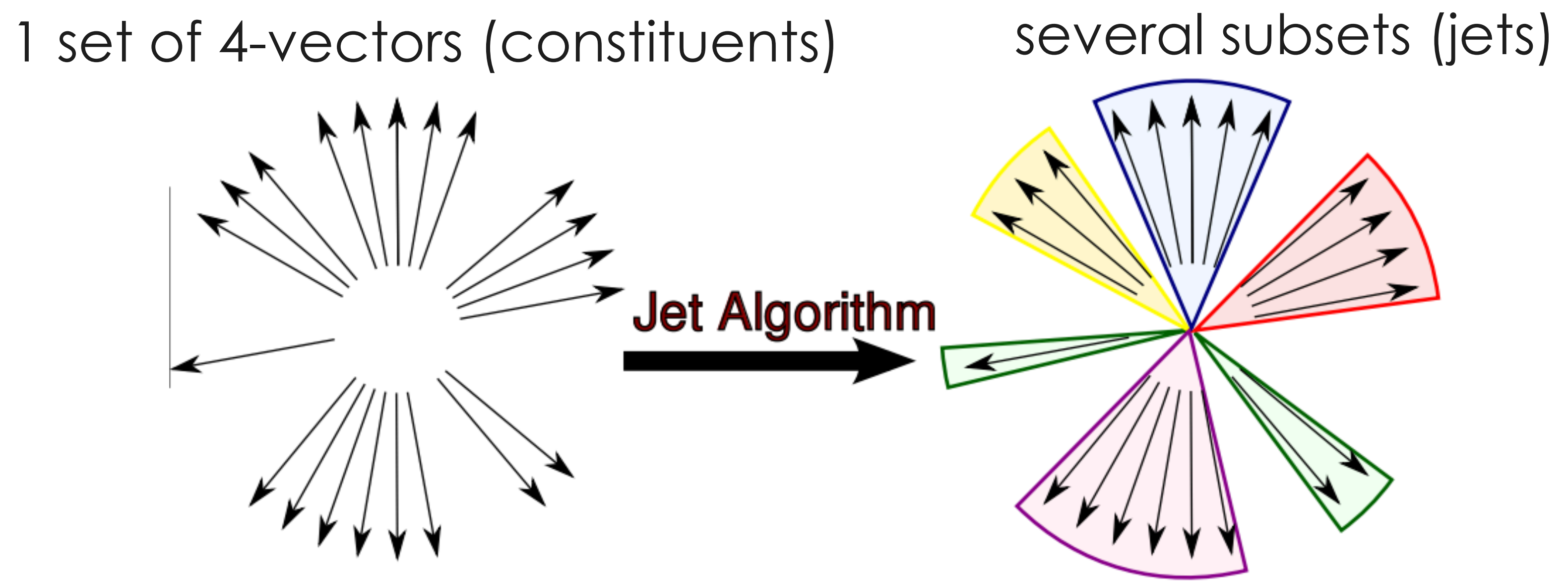

The goals of this talk:
- ✳An introduction of some concepts for the non-experts
- ✳An "appetizer" of new highlights (to follow-up during the week) for the experts

# Forming a Jet

- Jets represent the a collimated shower of energetic hadrons




- Jets can be formed of any 4-vector (simulated particles: truth jets, ID tracks: Track jets)
- Use a jet algorithm to cluster objects into a jet: It maps final state particle momenta to jet momenta.
  - The Anti-Kt is the most widely used jet algorithm
  - Defined by their radius parameter: this sets the stopping criteria

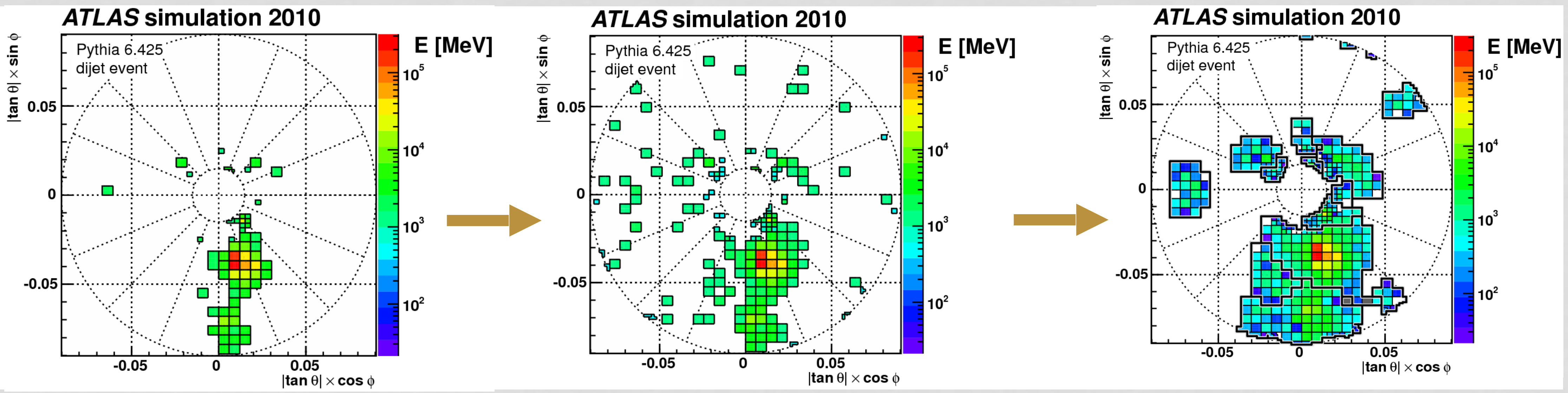



Depending on physics intent, different size of jets radii are useful

- CMS: 0.4, 0.8
- ATLAS: 0.4, 1.0

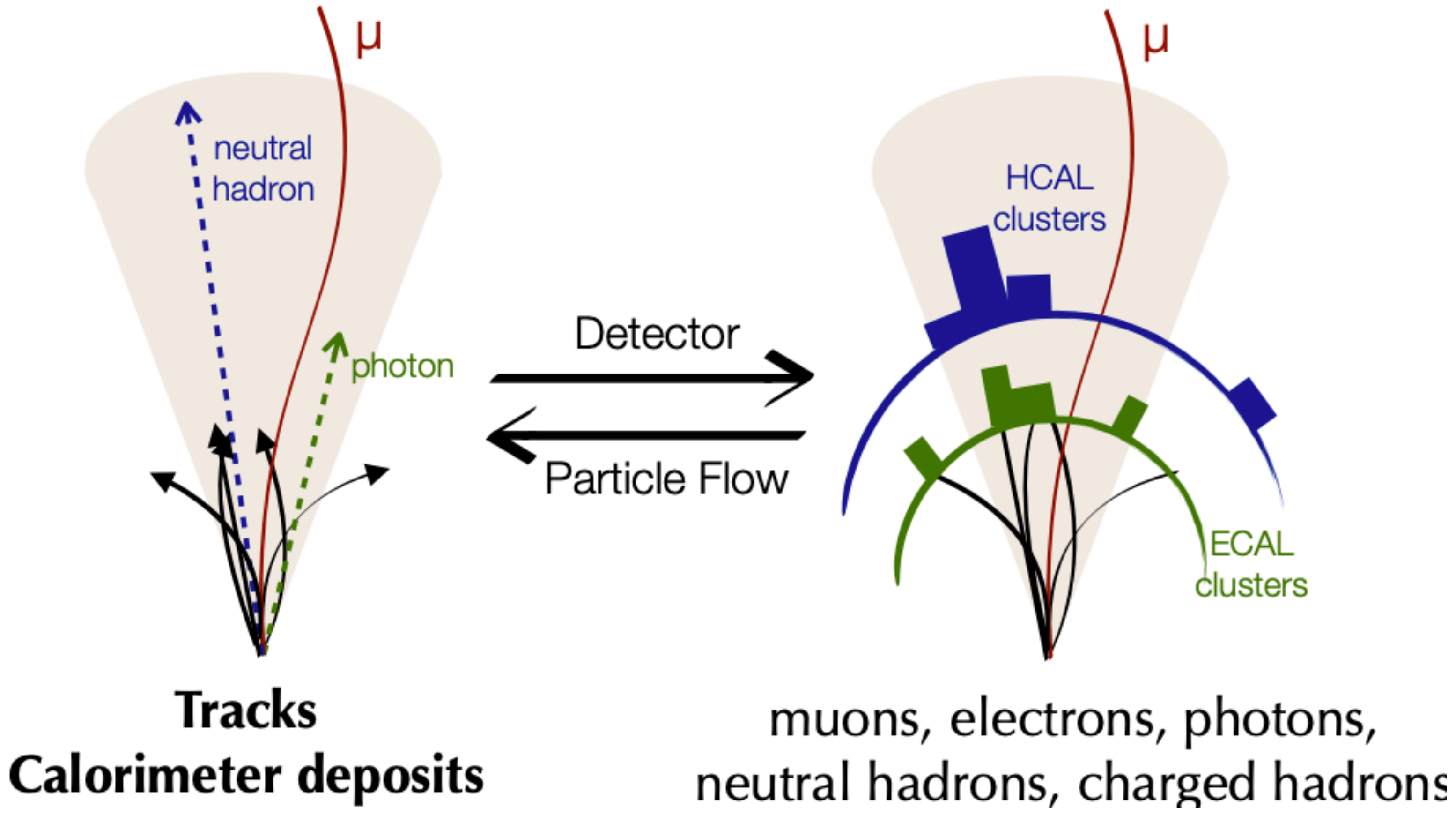
# What are the inputs to jet reconstruction?

- **ATLAS's** work-horse jets for ~10 years used calorimeter inputs
- **Topo-clusters:** 3D clusters of noise-suppressed calorimeter cells based on cell-energy significance

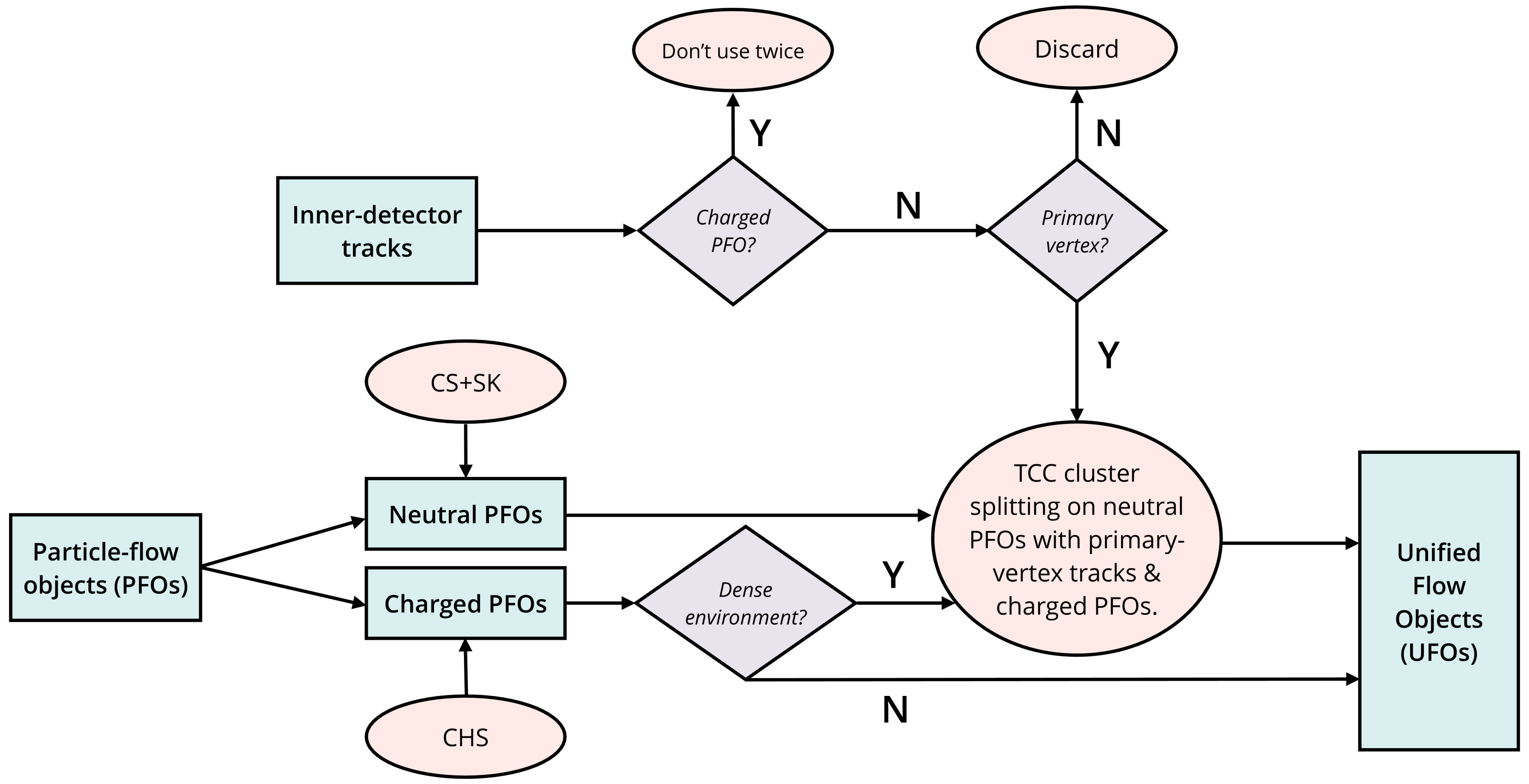



## Combining information form sub detectors

- **CMS**
  - **Particle Flow** (PF) algorithm used since the start of data-taking.
  - Combines information from all subdetectors (single combination technique) and provides a mutually exclusive list of particles




- **ATLAS**
  - **PFlow**: subtract (cell-by-cell) expected energy from the calorimeter defined by the matched track. For **Small-R** in Run2
  - **TCC**: Split cluster if more than one track is pointing at it, use η, φ from tracks. For **Large-R** jets in some Run2 analysis
  - **UFO**: Combine PFO and TCC depending on environment to make best of both. For **Large-R** jets (**Small-R** underway) from Run-3 on



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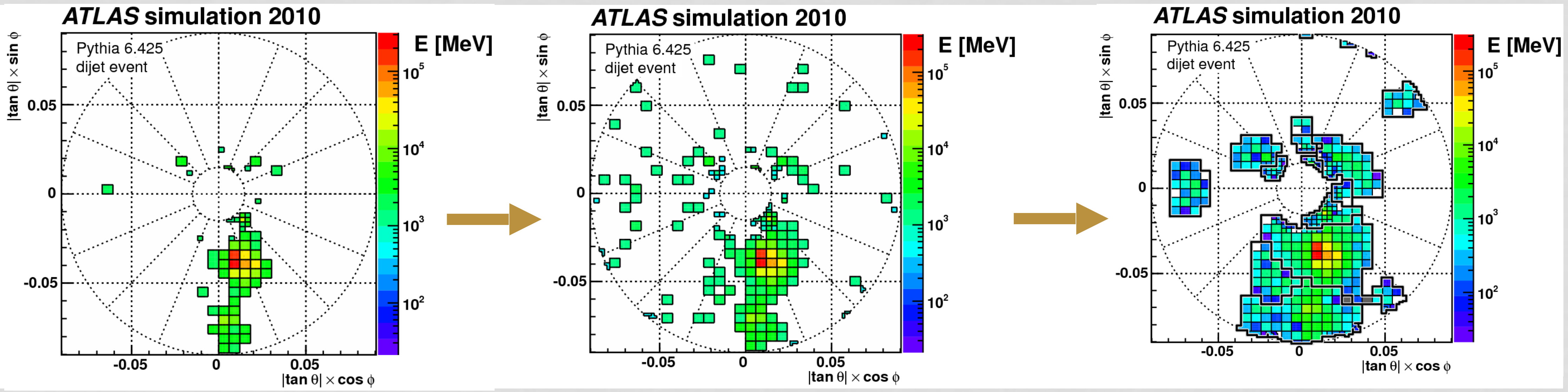


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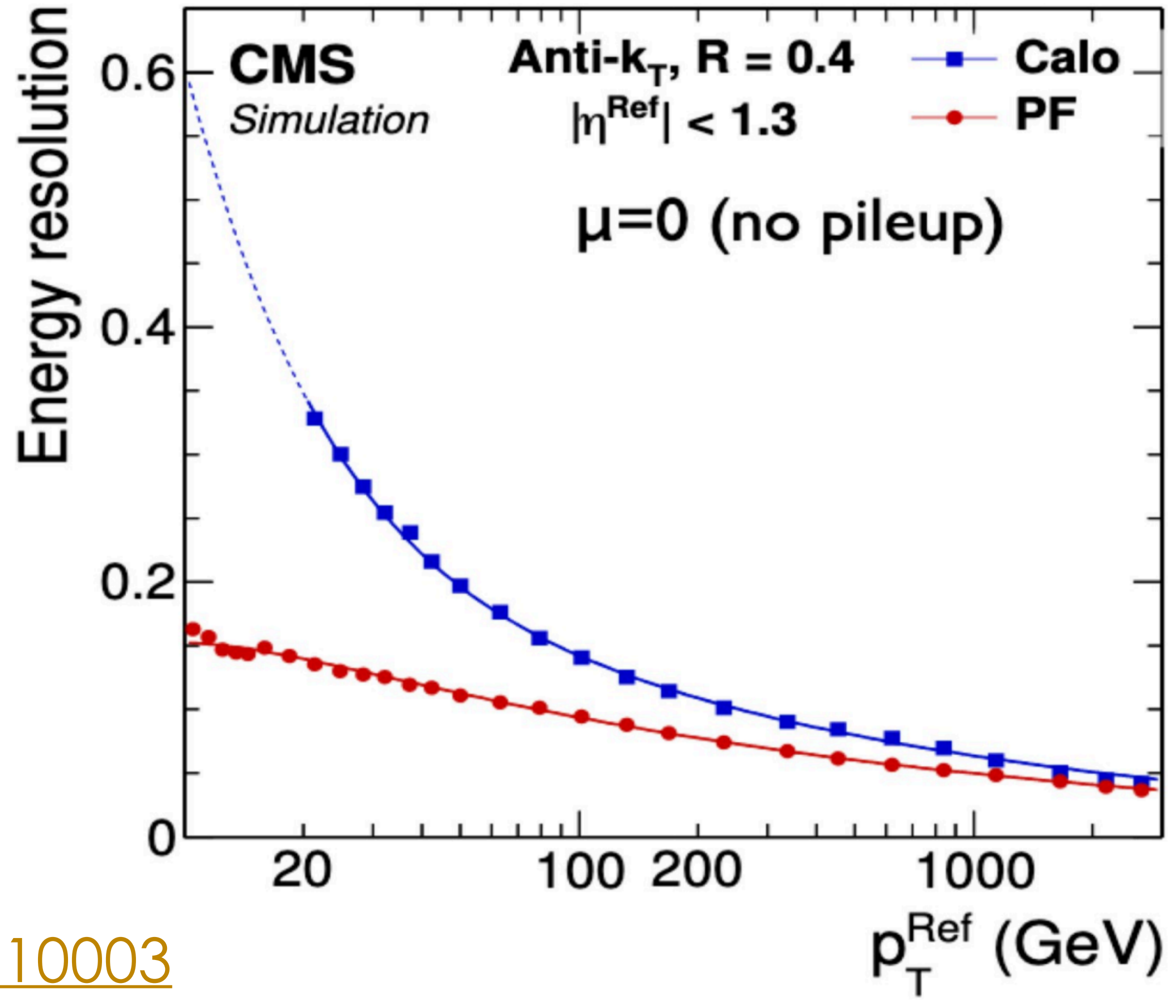


JINST 12 (2017) P10003

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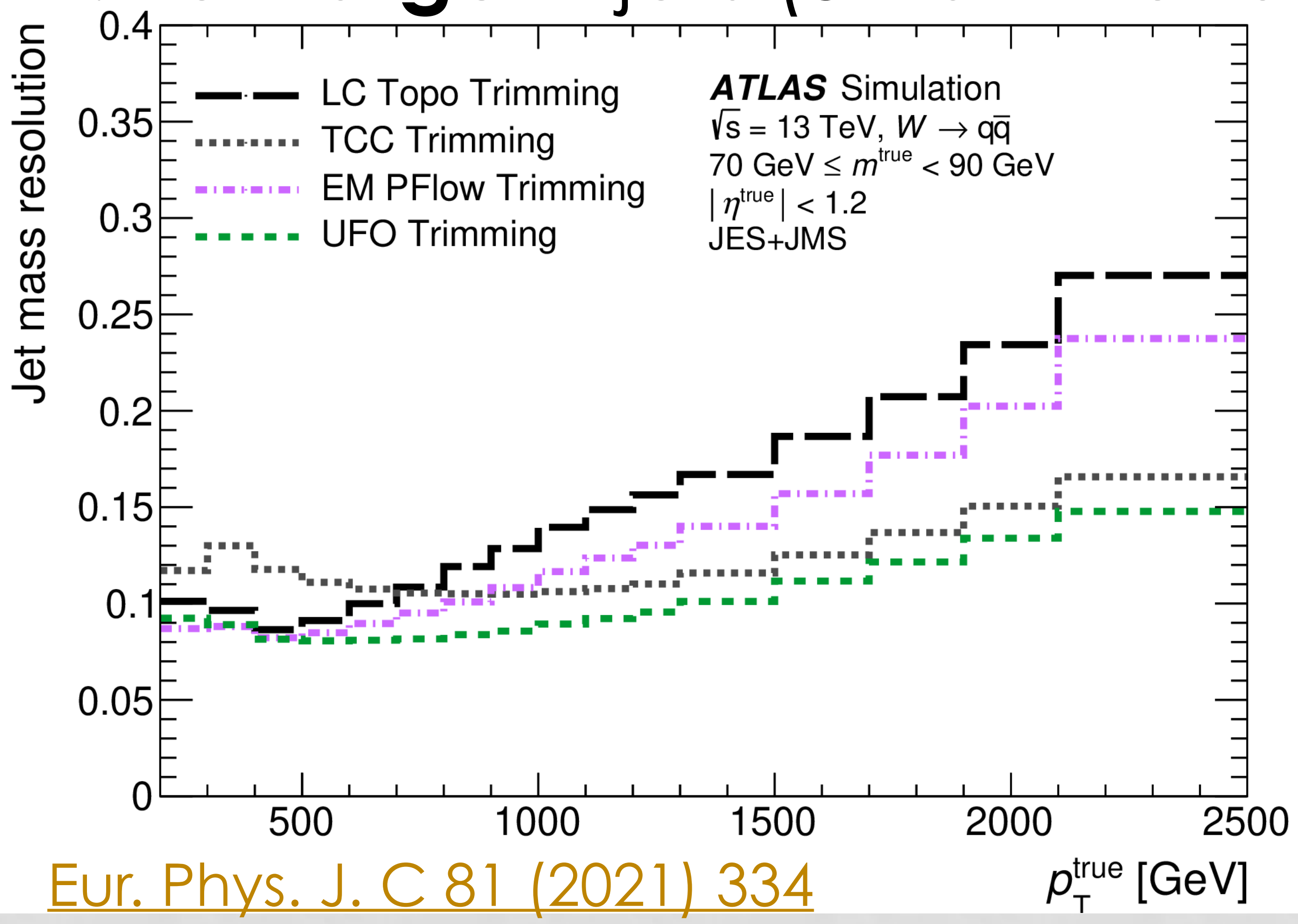


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# Combating Pile-Up effects

### How we can mitigate PU?

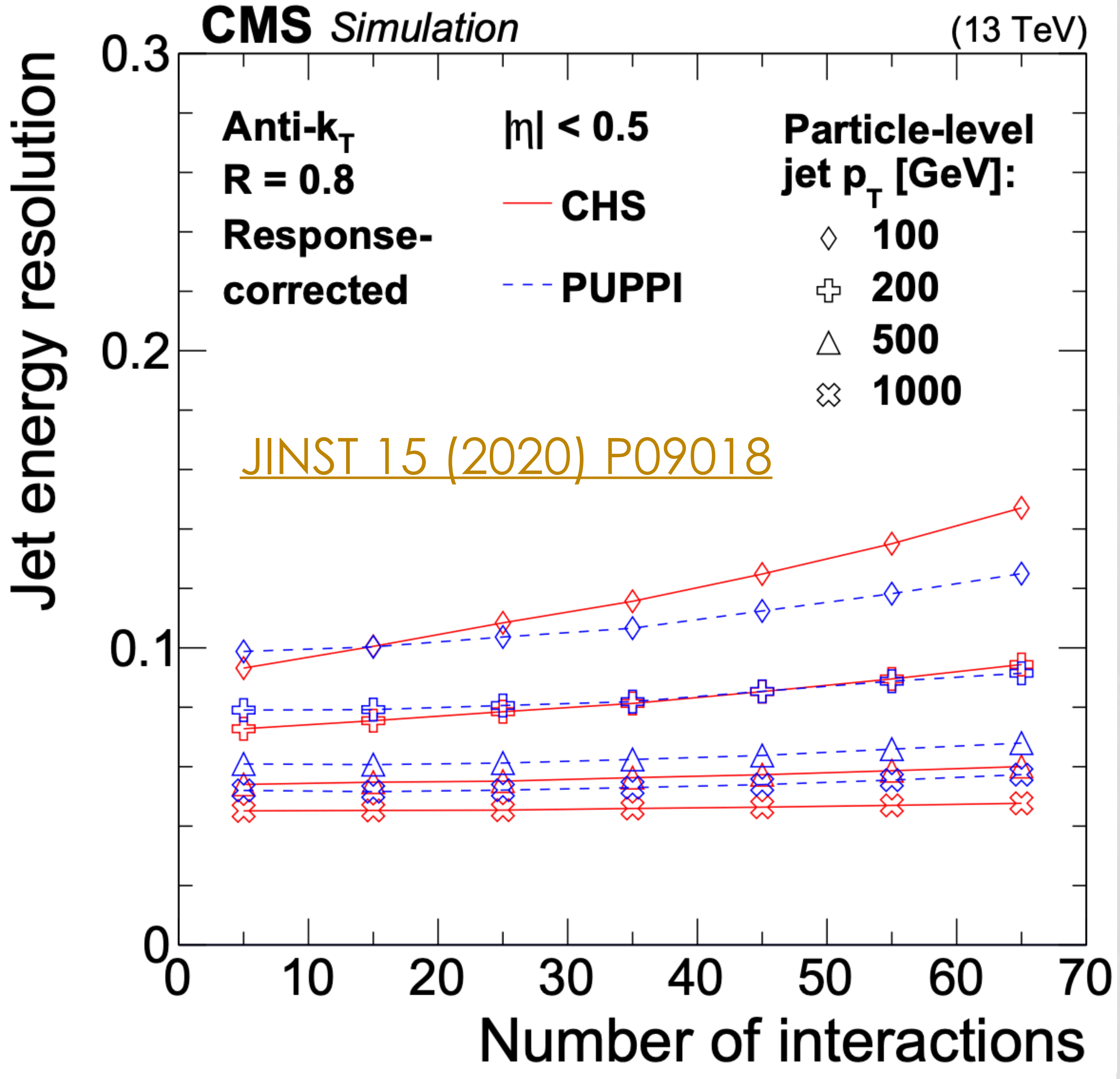
- Estimate and subtract PU contribution to object energy
- Filter out objects originating from PU

### At different levels

- **From the constituent reconstruction**
  - Topo-Clusters (noise suppression)
  - No PV0 charged objects can be rejected in UFOs
- **Constituent-level**
  - Charge Hadron subtraction (CHS)
  - Constituent Subtraction (CS)
  - SoftKiller (SK)
  - PU per particle identification (PUPPI)
- **Jet-level**
  - Jet-Area Subtraction + PU correction in calibration
  - Jet Vertex Tagger ( JVT), Forward Jet Vertex Tagger (fJVT) in ATLAS
  - PU Jet ID in CMS
  - Large-R jets: Grooming (trimming, soft drop)

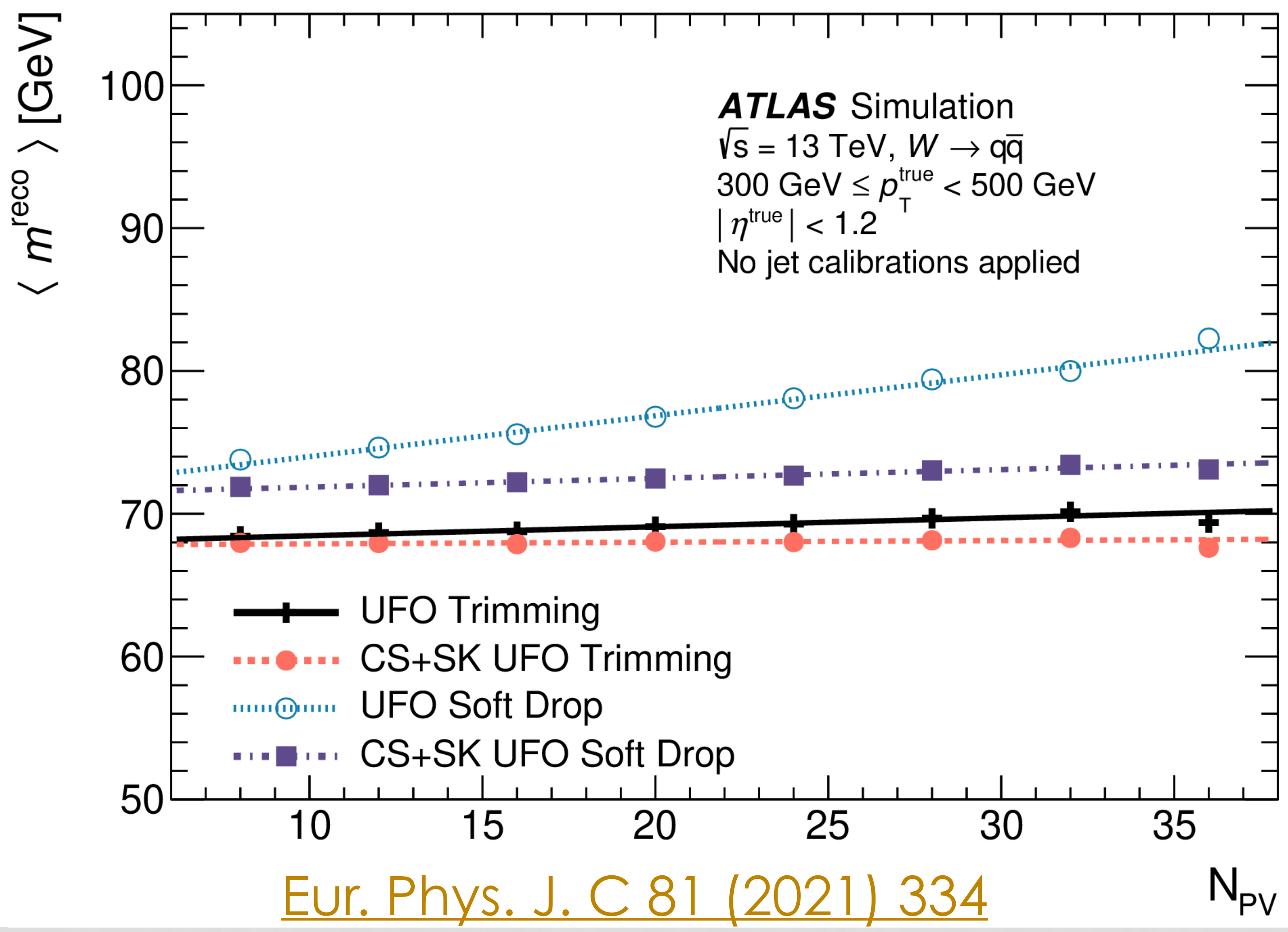
### CMS

- Before: PF+CHS for Small-R
- **PUPPI for all jets** in Run3
  - Assign a weight to every particle depending on its probability to originate from a leading or PU vertex.
- **Large-R**: uses PUPPI & Soft-Drop grooming




### ATLAS

- **Large-R:**
  - Before: LC-Topo with Trimming
  - Now: UFO jets with CS+Sk and Soft Drop
- **Small-R:** PFlow with CHS

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# Jet inputs and PU mitigation highlights

## Time as a new discriminant

- Reduces residual out-of-time PU that was not suppressed by clustering
- New default in Run-3

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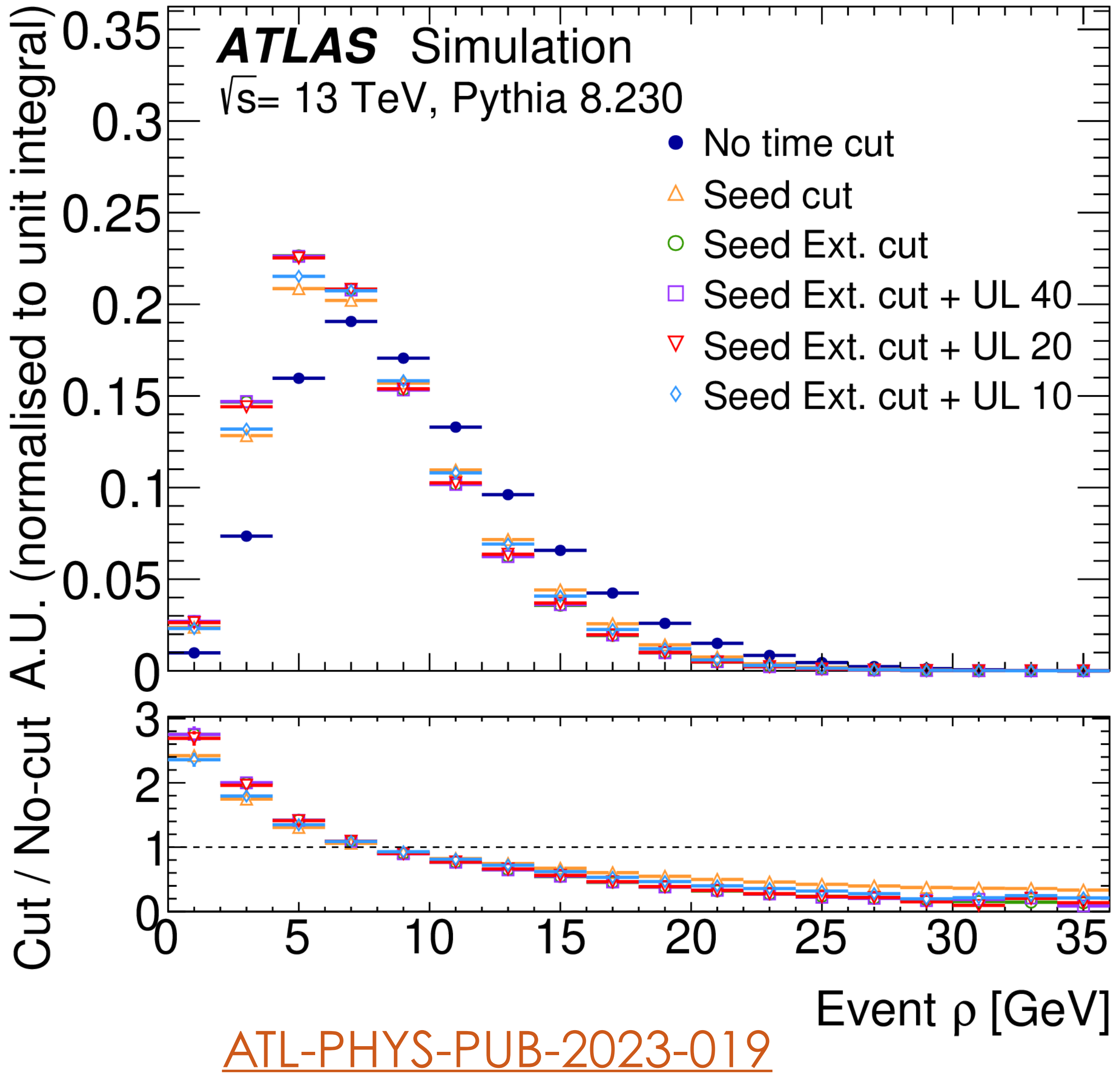


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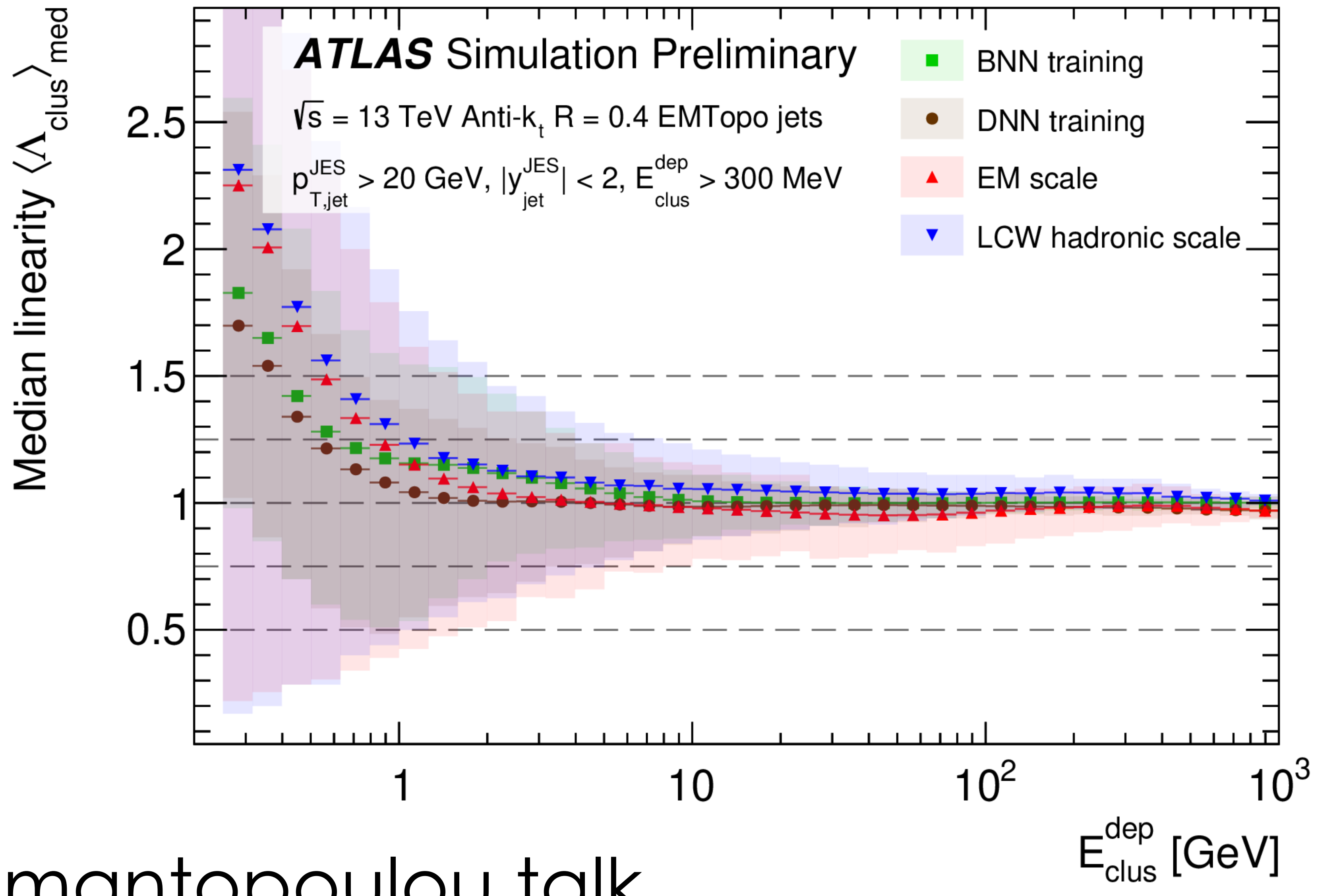
## Cluster Calibration with ML

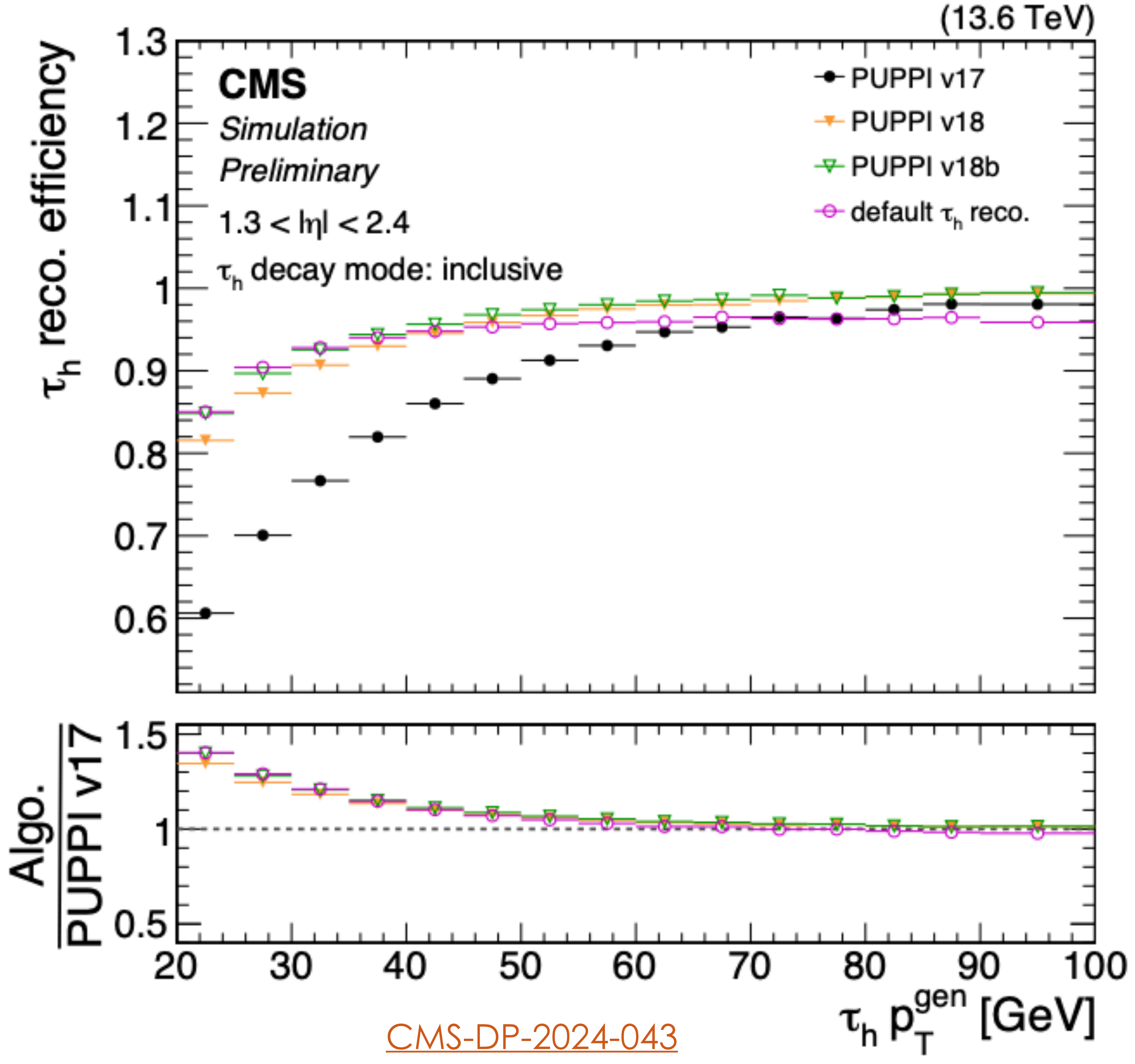
- Neural Network for topo-cluster calibration
- Mainly corrects differences in detector response (calorimeter non-compensation)




More details on Magda Diamantopoulou talk

## Optimisation of PU mitigation technique for $\tau_h$ identification

- Unified flavor identification for small-cone jets extended to hadronic taus



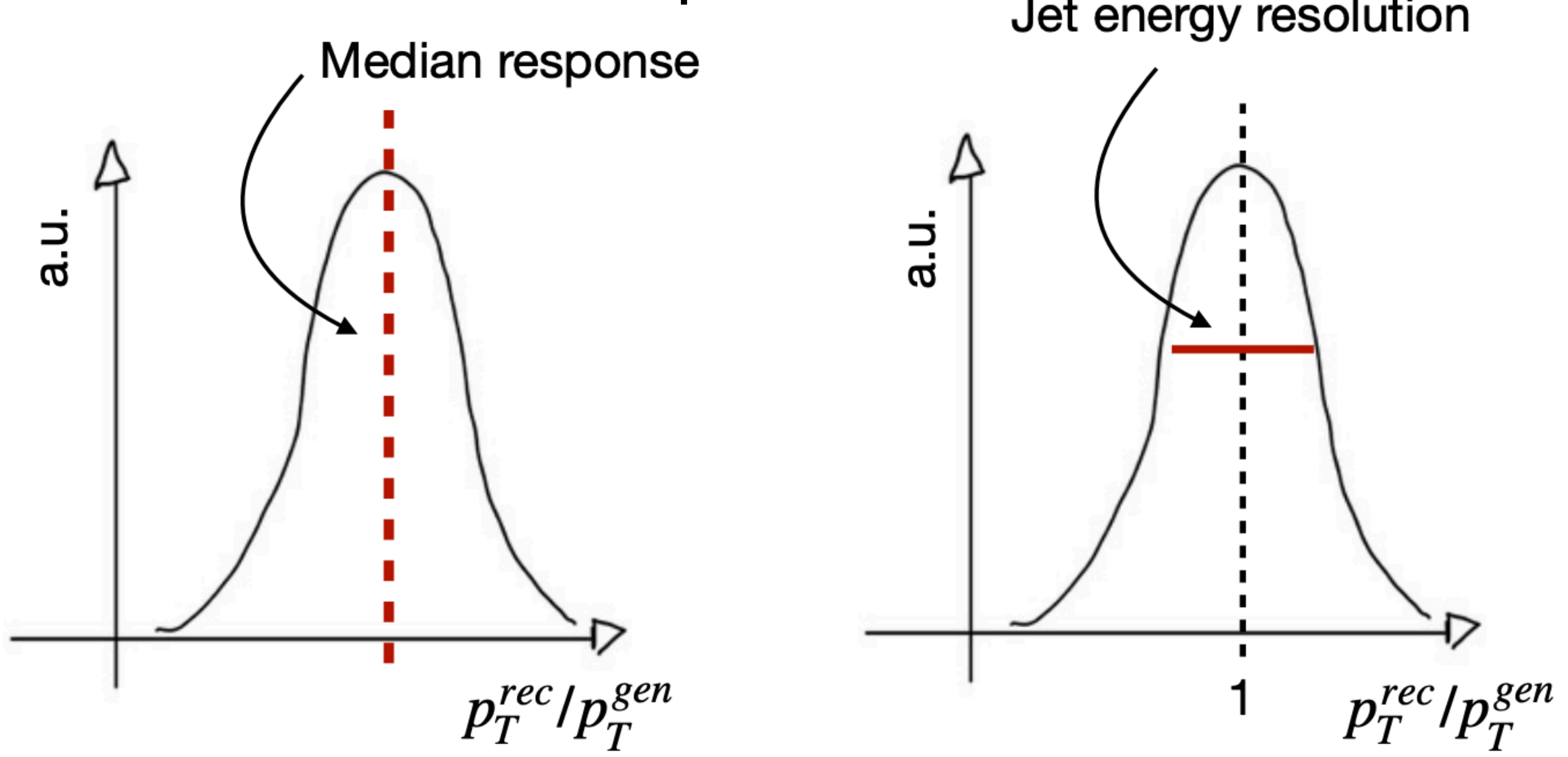

CMS-DP-2024-043

More details on Nurfikri talk

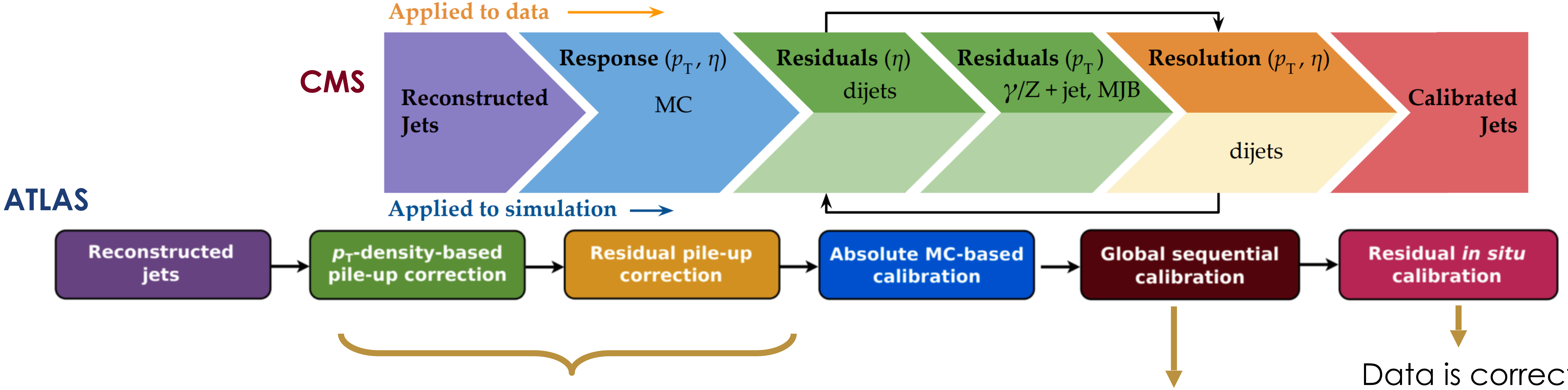
# Calibrate it!

- The "Jet Energy Scale" correction calibrates reco-jets to true-jets (from the generator): larger corrections at low energy, forward regions
  - Multiply the original jet energy by this factor: bring jets to "truth" scale

- The important metrics




- Both ATLAS and CMS have in place a calibration chain
  - Factorised approach:
    pileup → simulation → residuals in data




PU correction is not needed in CMS after PUPPI implementation
Likely will not be needed in ATLAS when CS+SK UFO small-R jets commissioned

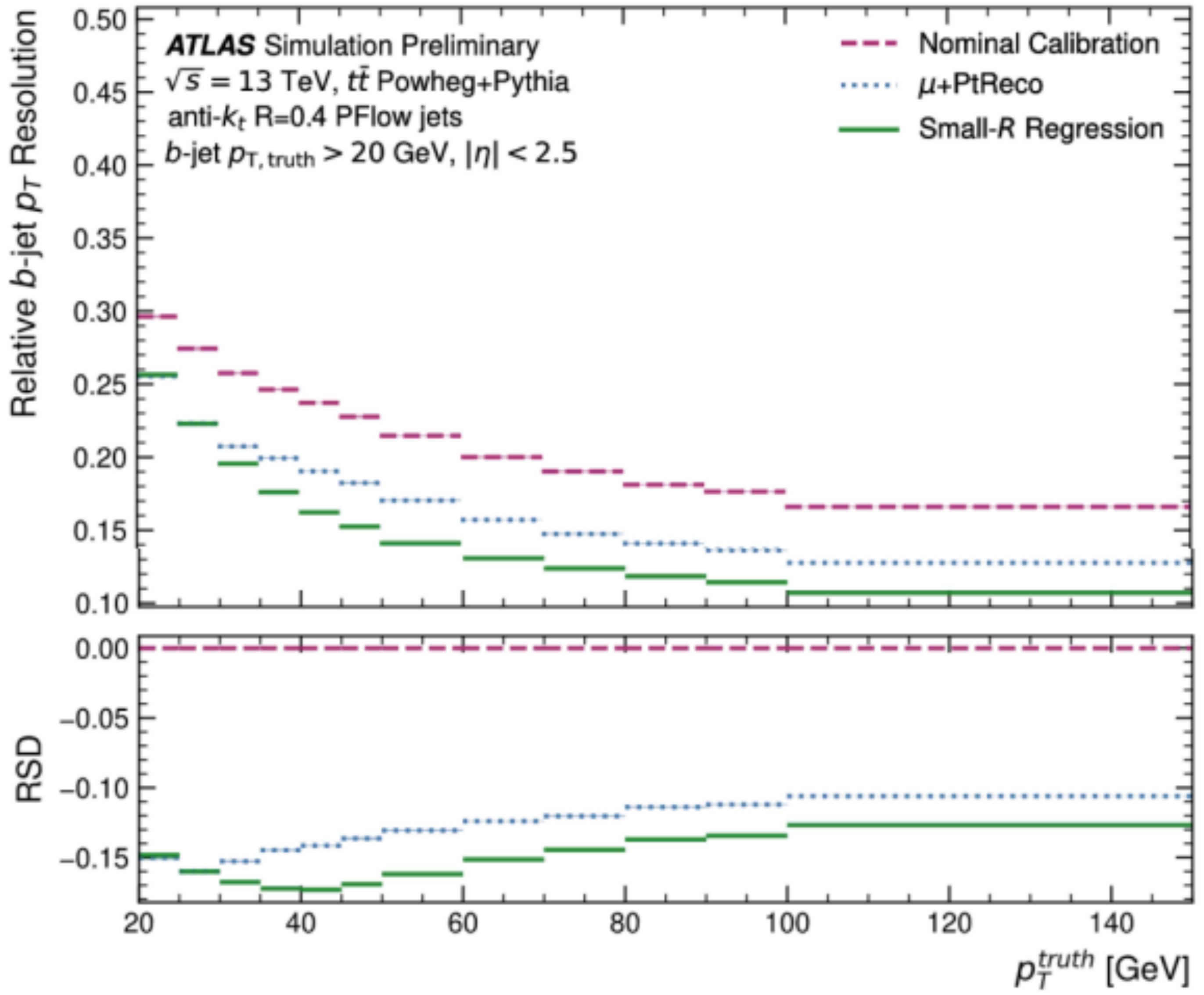
Reduces jet-by-jet response variations
Only in ATLAS

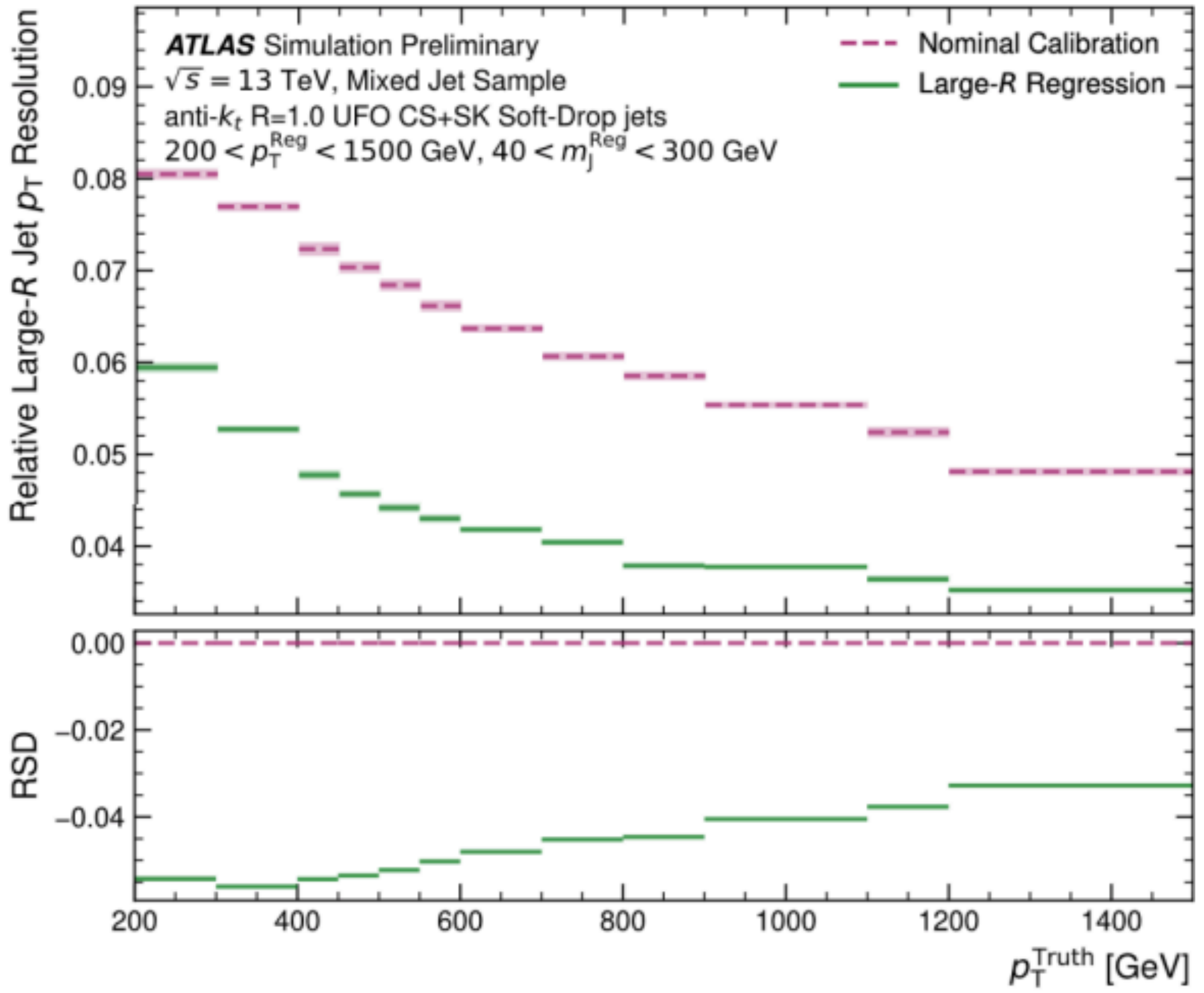
Data is corrected in-situ from measured pT balance of jets in multi-jet and Z/γ + jet events to match MC

# Jet Calibration Highlights

- New developments on simulation-based calibration using machine learning
- Both collaborations focusing on getting a good JES for b-jets

- **New dedicated b-JES calibration**
  - Using transformer networks



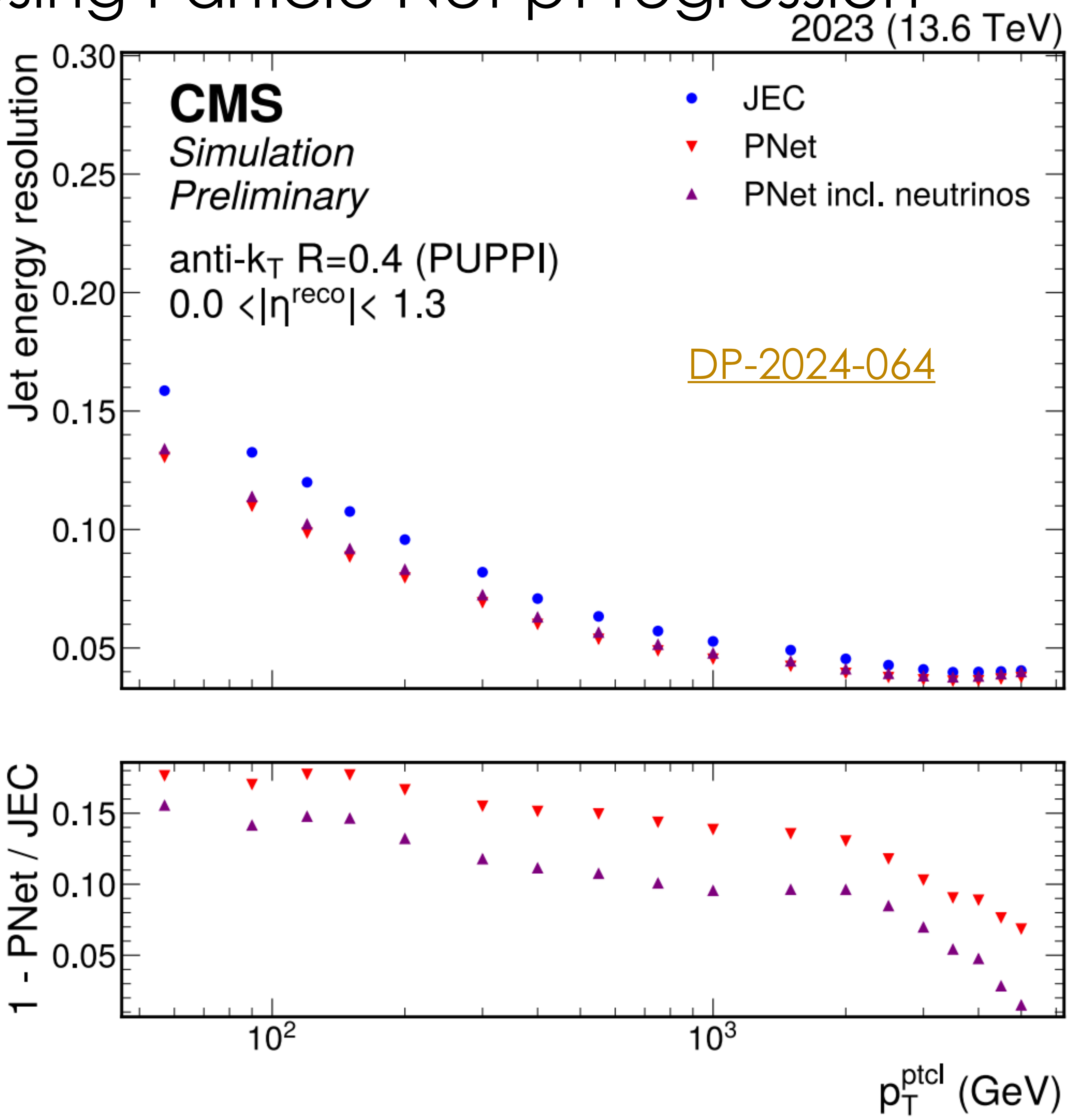




- Small-R:
  - 18-31% better resolution
- Large-R:
  - 25-35% better resolution

ATL-PHYS-PUB-2024-015

More details on Magda Diamantopoulou talk
and poster from Andrius Vaitkus

- **First flavor-aware regression for small-R jets**
  - Using Particle Net pT regression



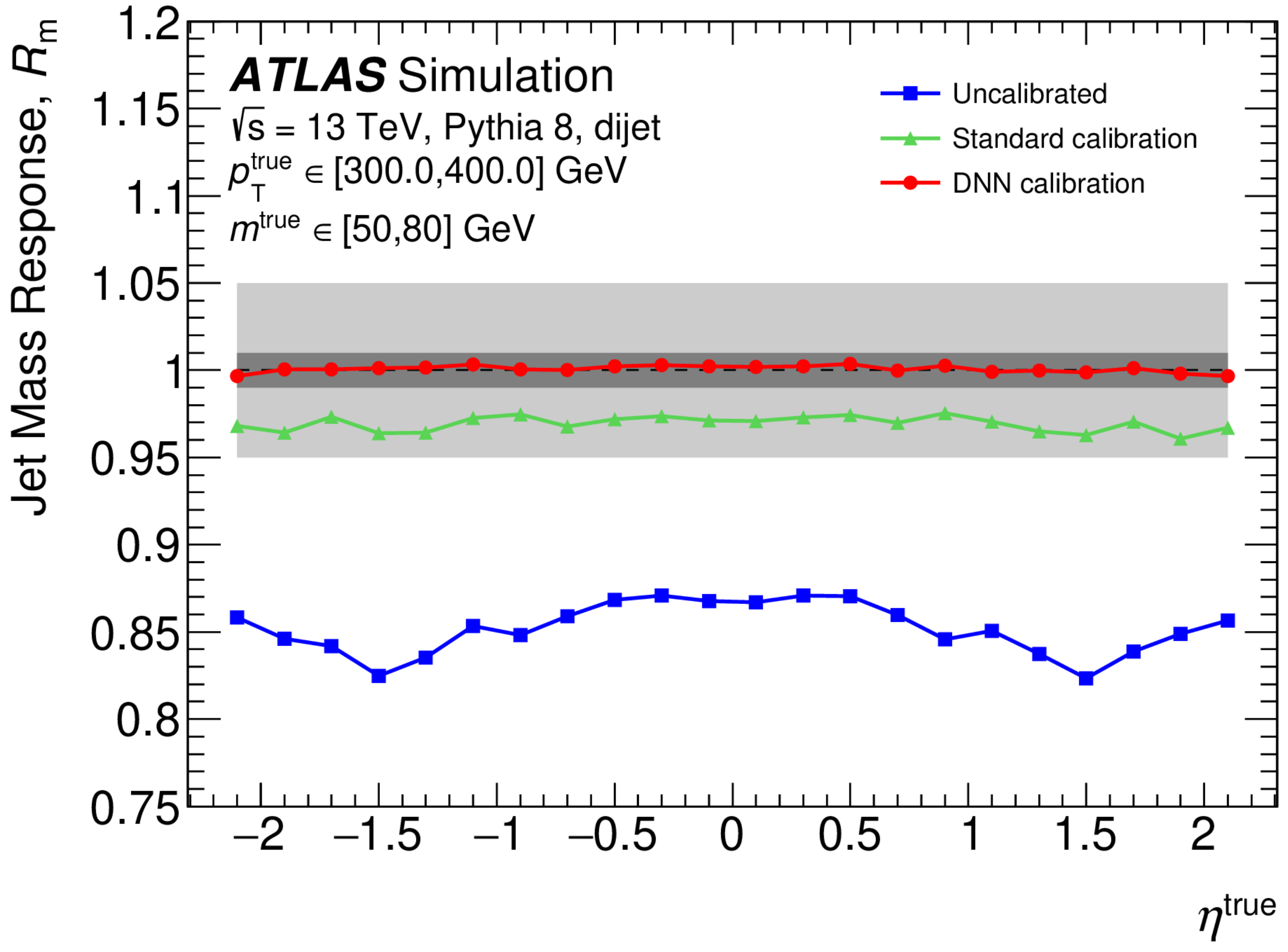

- Significant resolution improvement of up to 17%

More details on Nurfikri talk

# Jet Calibration Highlights in ATLAS

## MC-based calibration for Large-R jets

Simultaneous JES+JMS using DNN




submitted to MLST

## Small-R jets

Reconstructed jets → $p_T$-density-based pile-up correction → Residual pile-up correction → Absolute MC-based calibration → Global sequential calibration → Residual *in situ* calibration

**Global Neural Network Calibration (GNNC)**

- NEW DNN-based calibration to replace the multiple steps of GSC
- Reduce difference between q/g-jets

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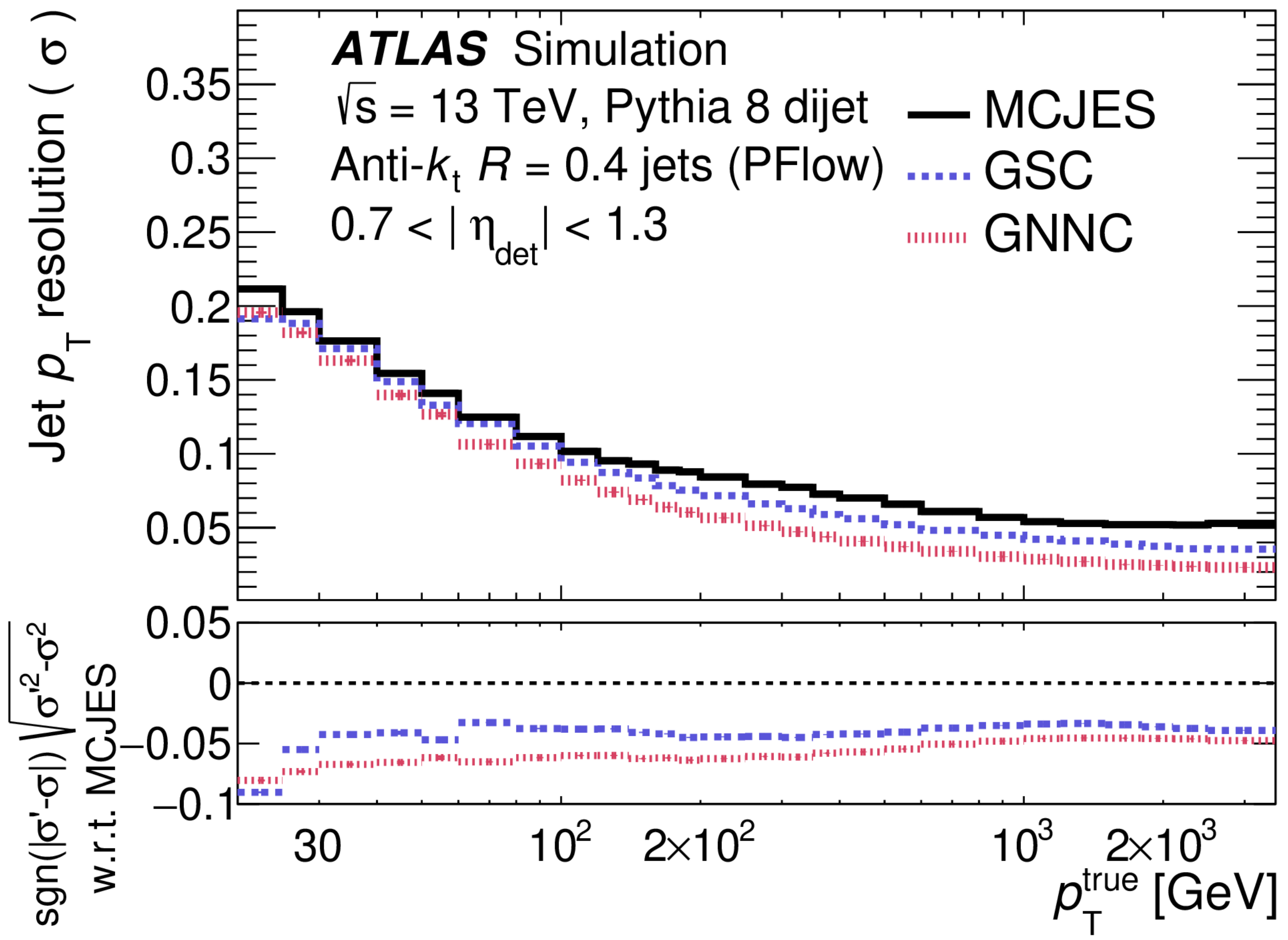
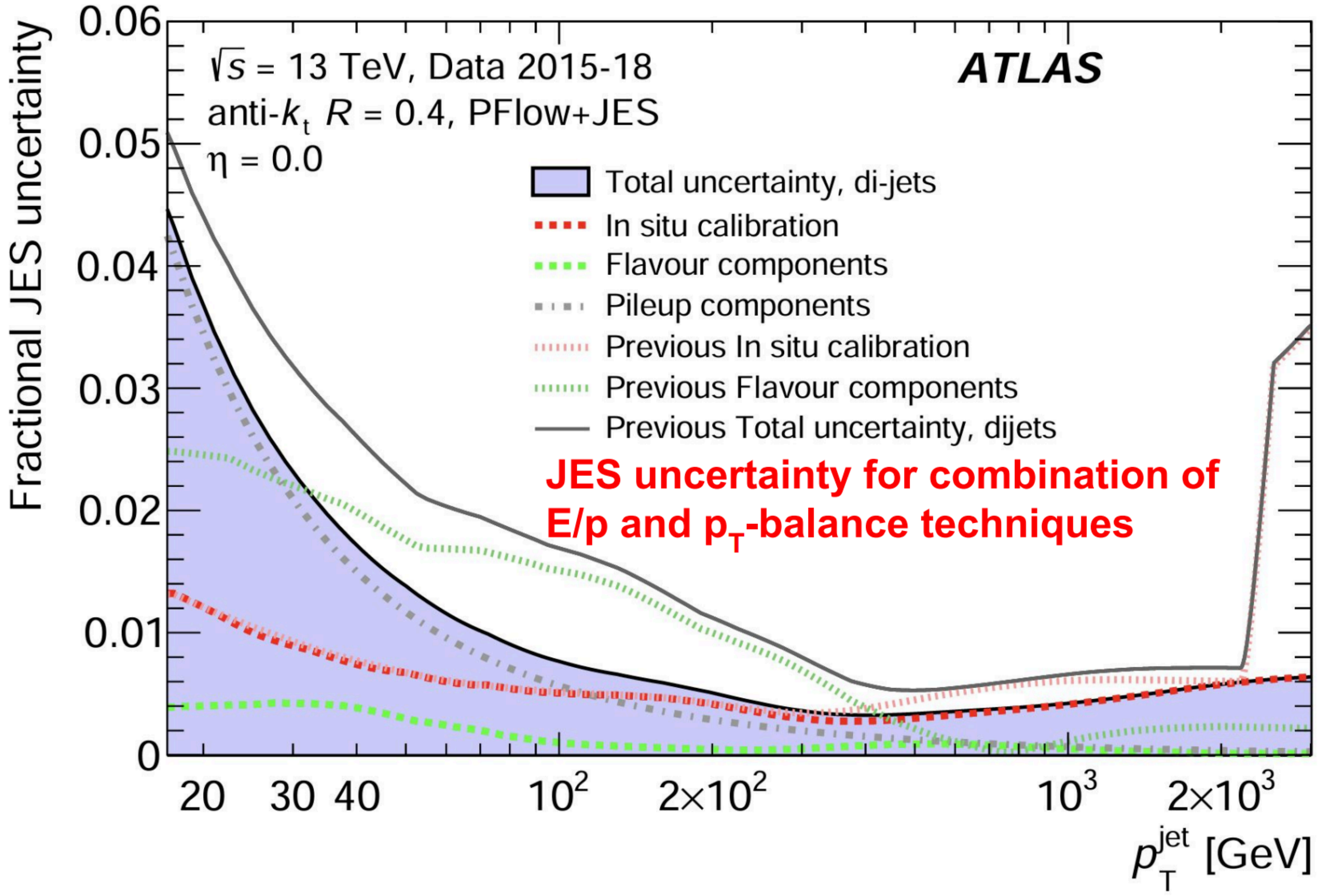



New single particle measurement with W→ $\tau\nu$ events

submitted to EPJC




JES Uncertainty goes down to < 1% for jet pT > 100 GeV

See poster from L.Panwar!

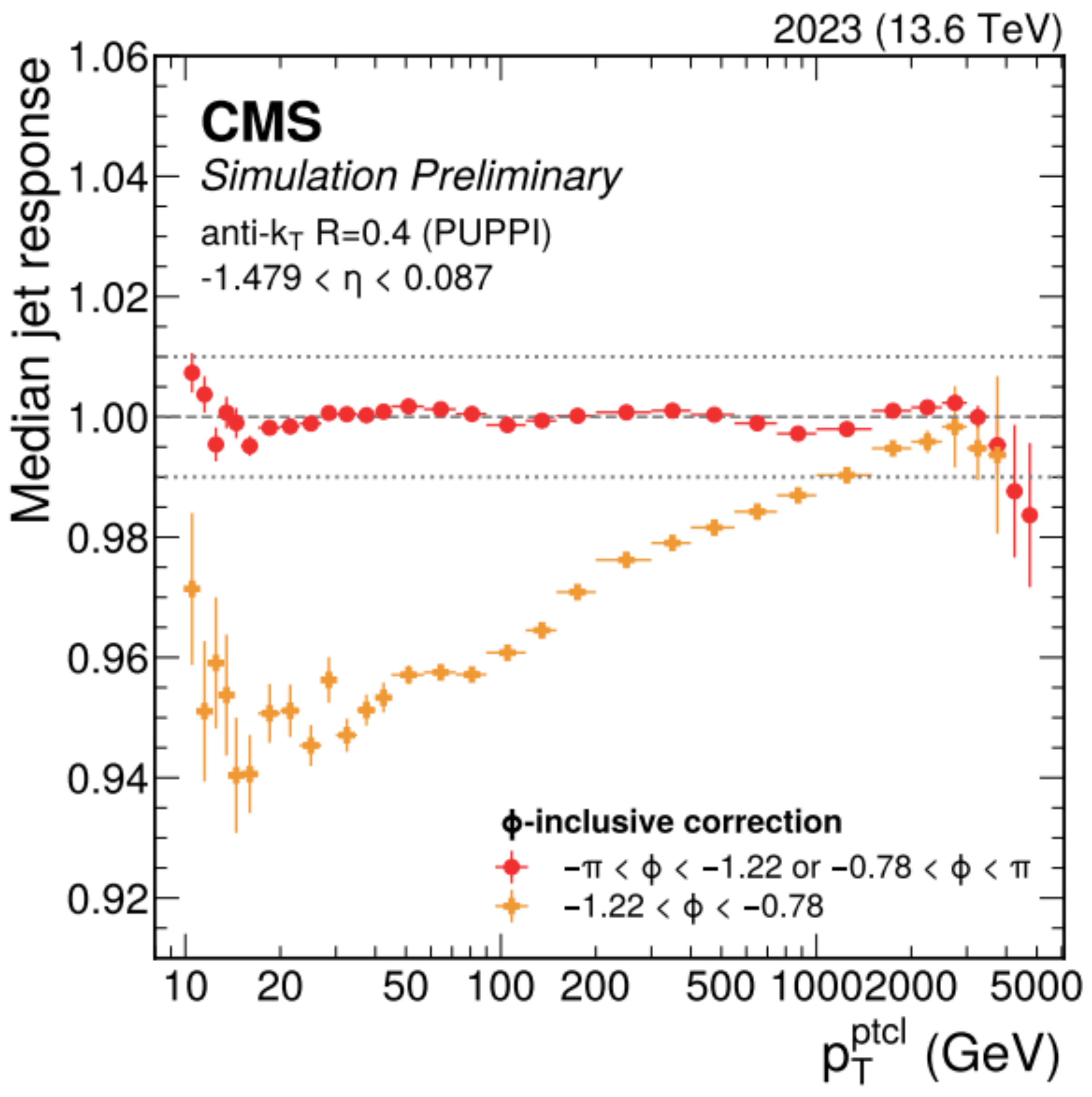
More details on Magda Diamantopoulou talk

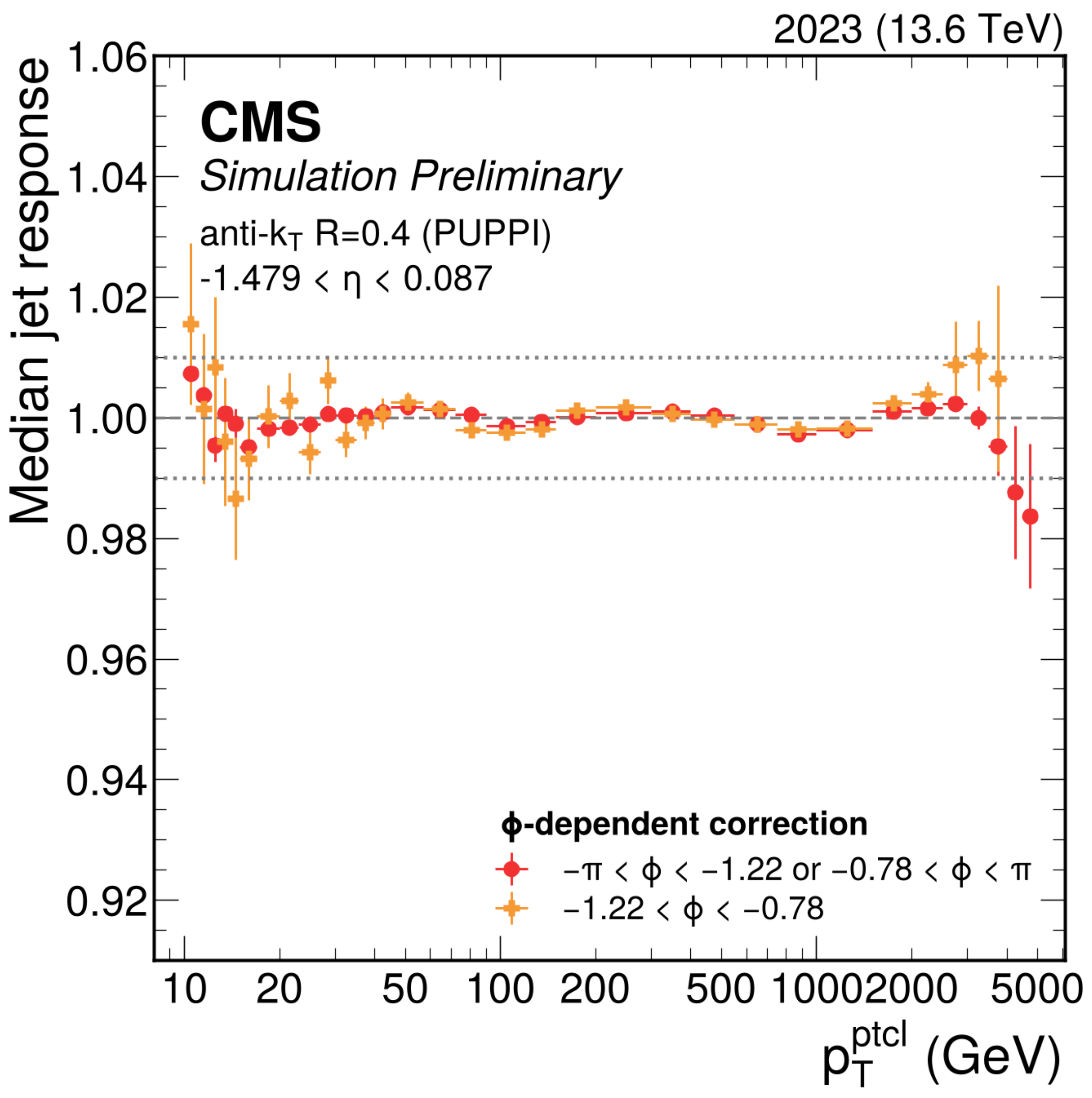
# Jet Calibration Highlights in CMS

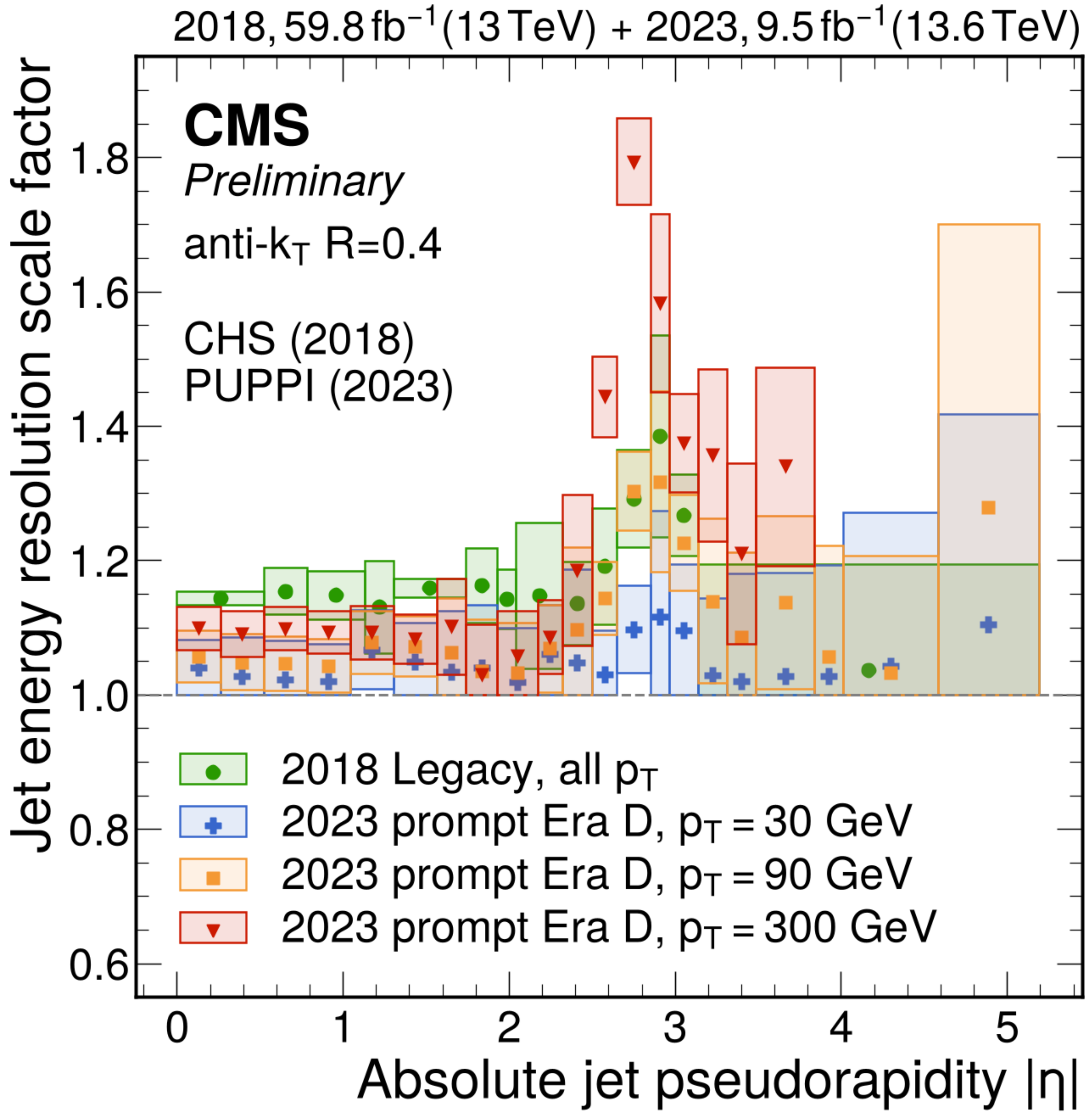
- NEW Jet Energy Correction (JEC) and resolution (JER) results using Run 3 data

## Phi-dependent Jet Energy Correction

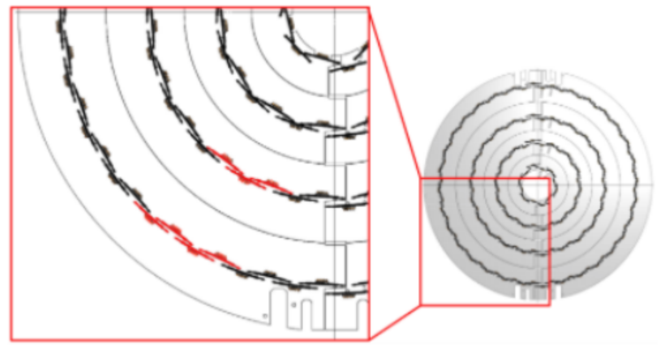
DP2024_039




Due to reduced efficiency in tracking



- Outperforming legacy Run2 reconstruction in barrel region with promptly reconstructed data!

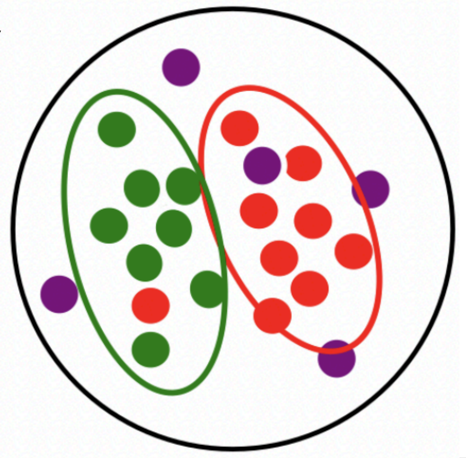
More details on Nurfikri talk

# Tag it!

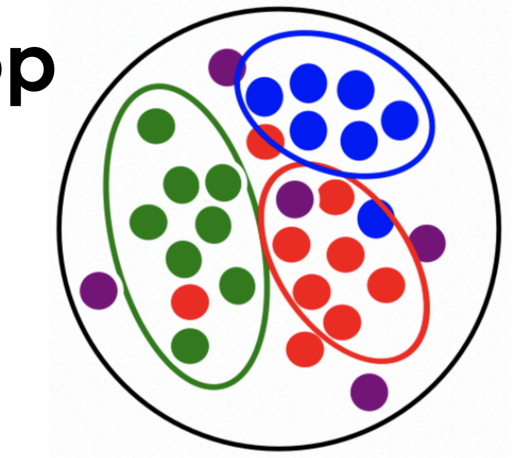
### Jet Substructure:

- Study the inner structure / energy flow to distinguish signal large-R jets (W, Z, top) from background jets (q/g-initiated)

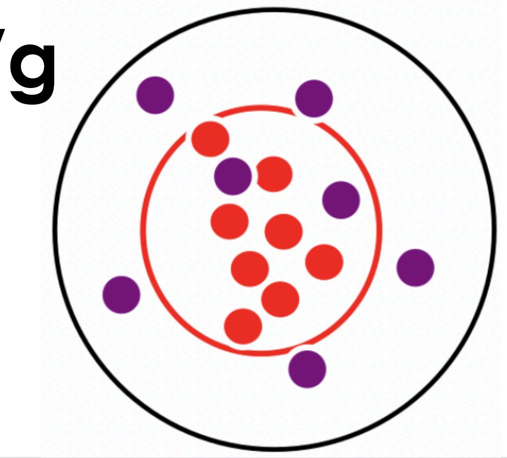
W/Z



Top



q/g



### Types of taggers

- Simple **cut-based** taggers often referred to as smooth taggers
  - 3-variable tagger for W/Z tagging using jet mass, D2 and ntrk
- **Multivariate** taggers using **high-level** information
  - Inputs are various substructure variables
- **Multivariate** taggers using **low-level** information
  - Inputs are the constituents of the jets (+ potentially additional information)
- **Declustering** taggers: attempt to reconstruct the jet's shower history
  - e.g. shower deconstruction, Lund jet plane based taggers

### Important Metrics

- $\epsilon_S$: fraction of signal jets that are correctly identified (tagged)
- The background rejection ($1/\epsilon_{Bkg}$) tells us how much of the QCD jets we reject
- Working Points (WP) are defined usually with $\epsilon_S = 50\,\%\,,\,80\,\%$

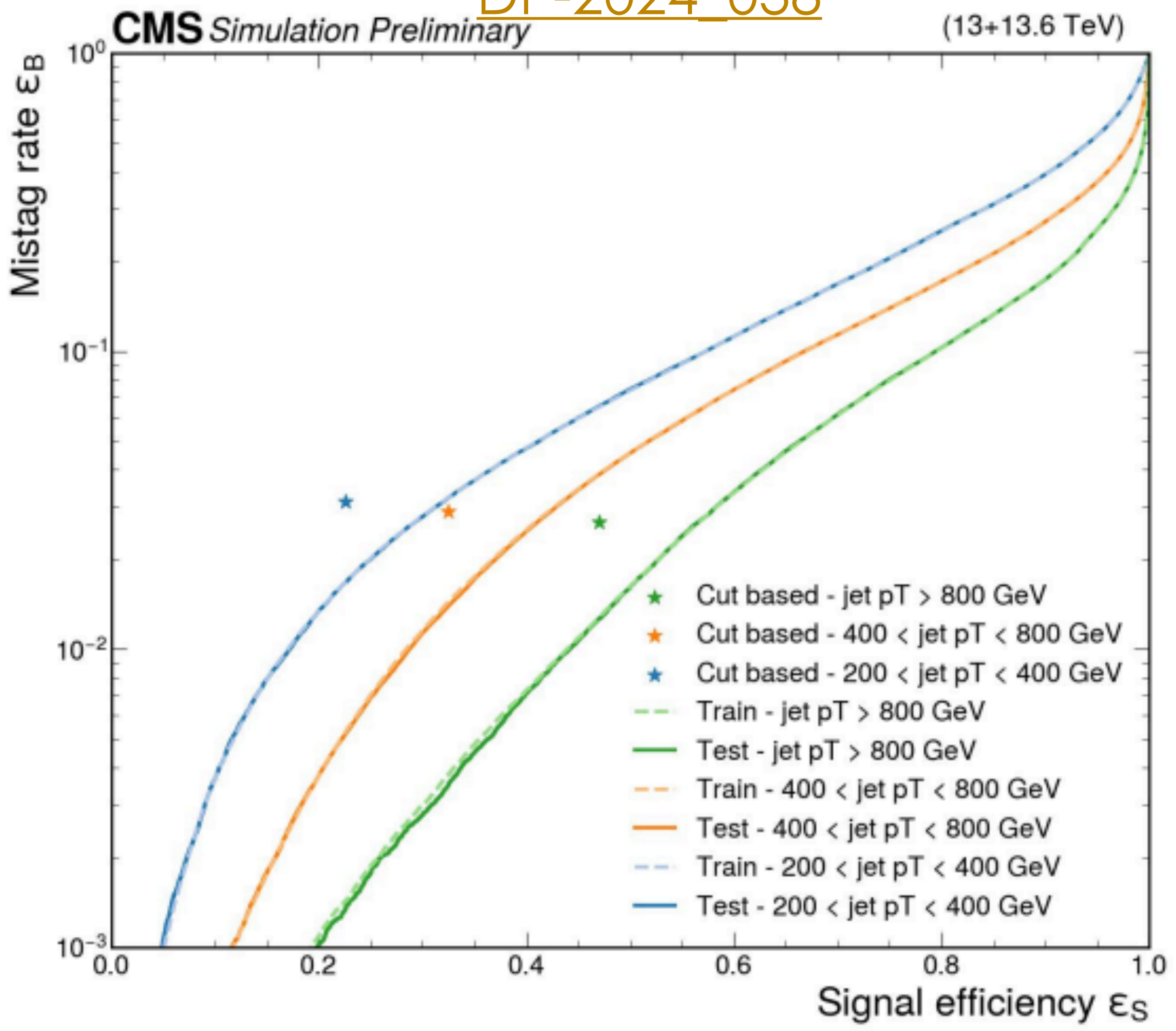
### Bonus points

- If the tagger is mass-decorrelated
  - Does not sculpt the mass shape

# Jet Tagging highlights

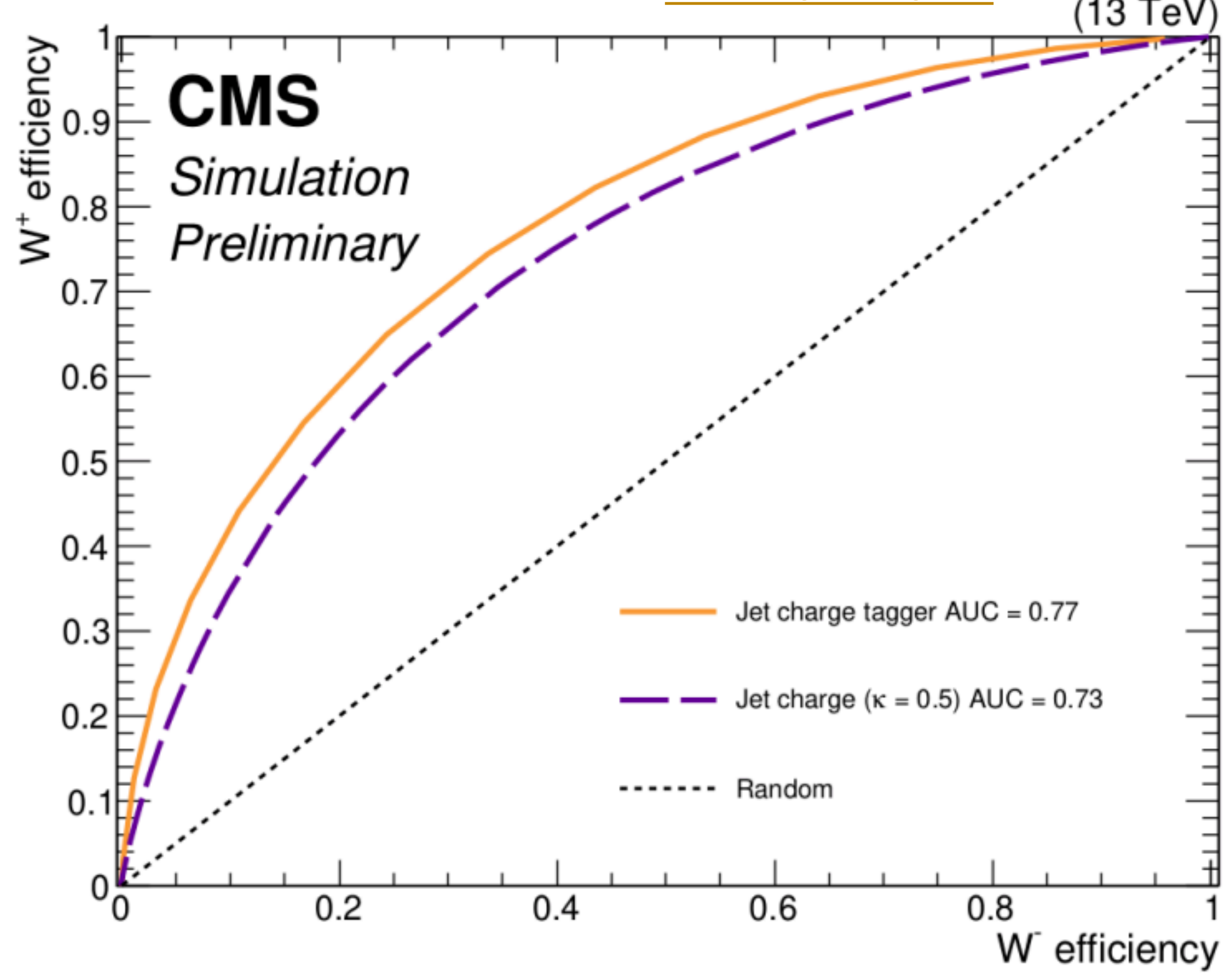
- New developments for top tagging with variable-sized jets

[DP-2024_038]



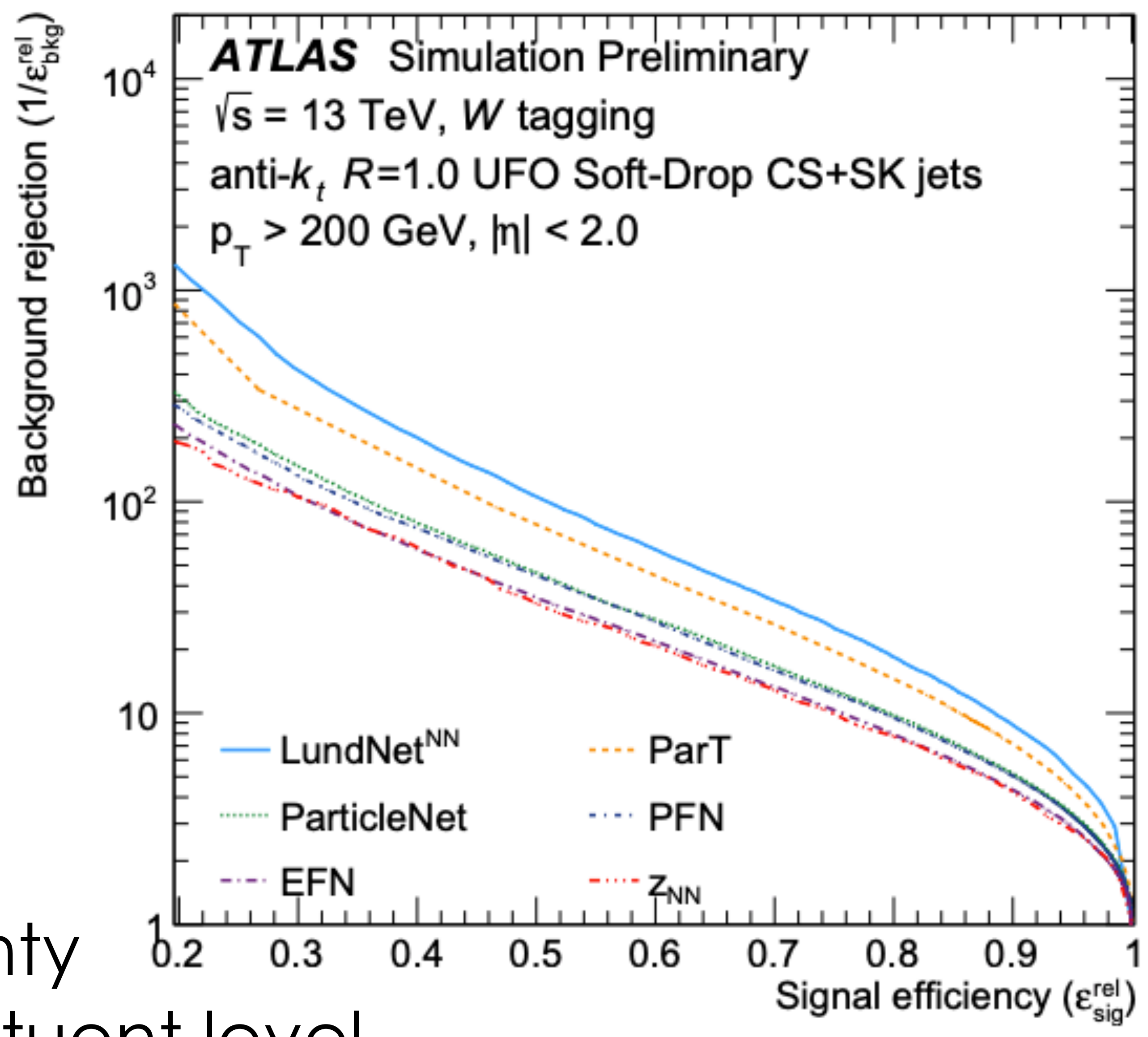

- New charge tagger to differentiate W+, W-

[DP-2024-044]

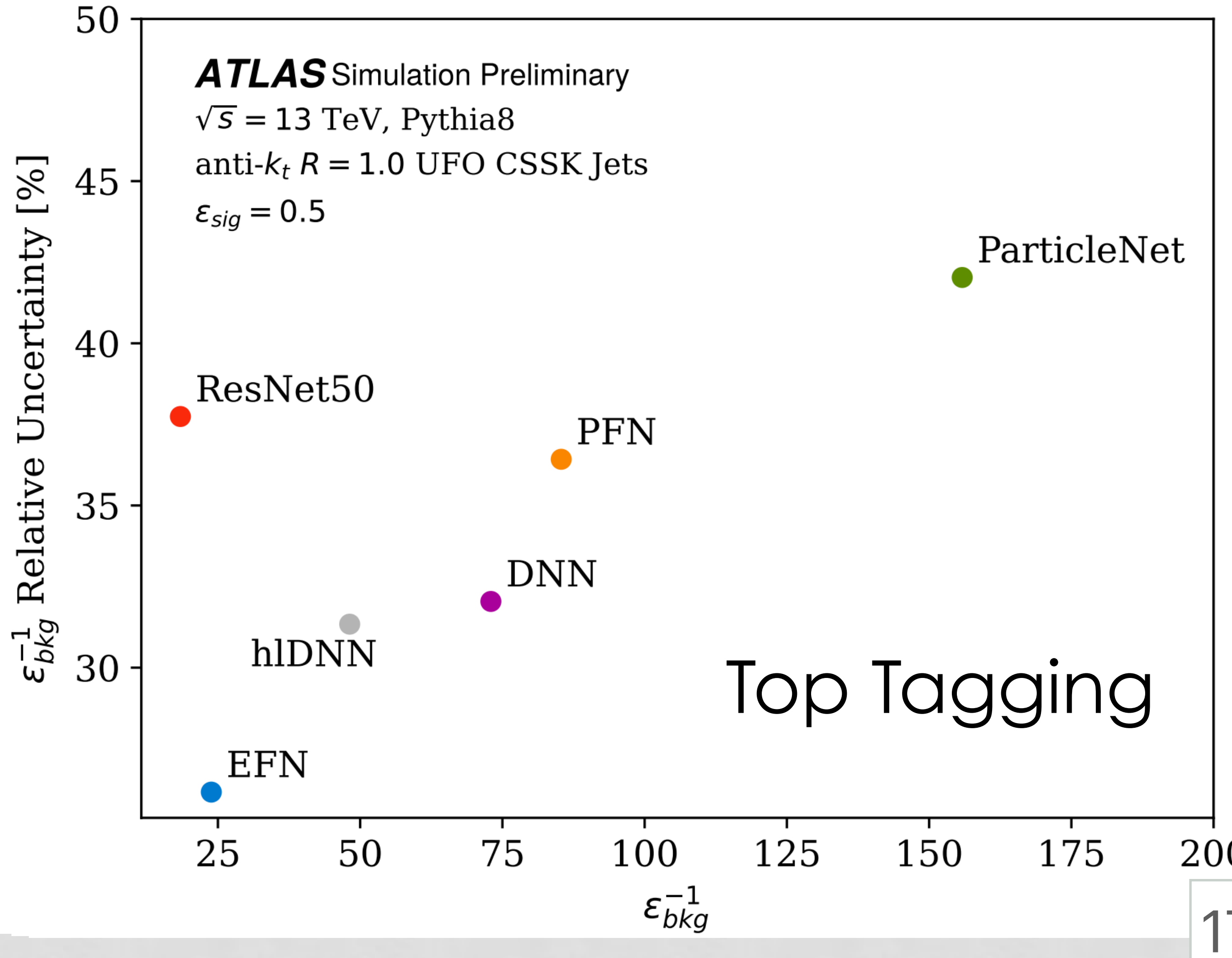



- New Lund-net tagger and is performing the best so far

[JETM-2023-003]



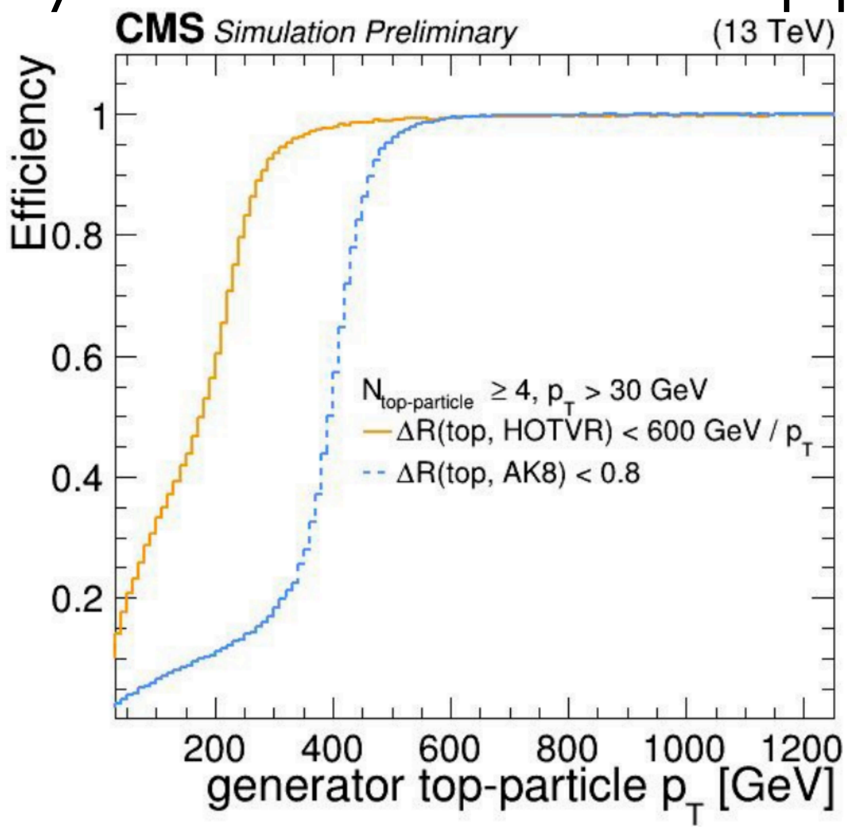

However, uncertainty increases for constituent level taggers with ML




- BDT for top quarks on HOTVR and Jet charge tagger improves performance significantly over cut-based approaches

HOTVR top quark reconstruction efficiency

[DP-2024-038]

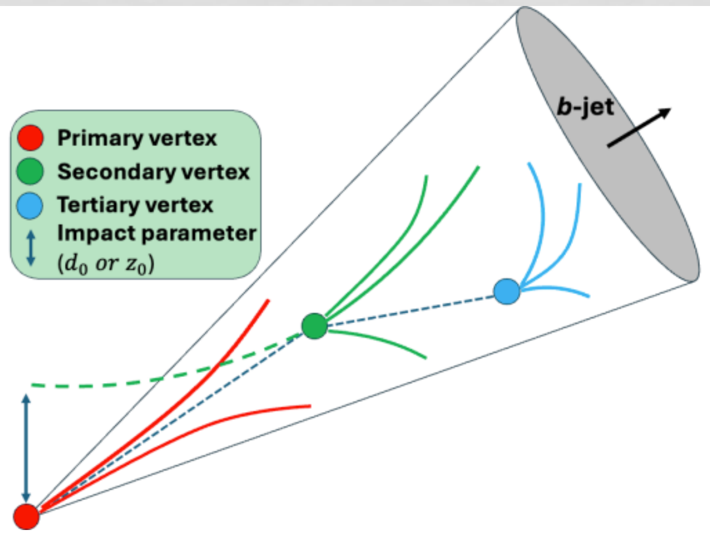


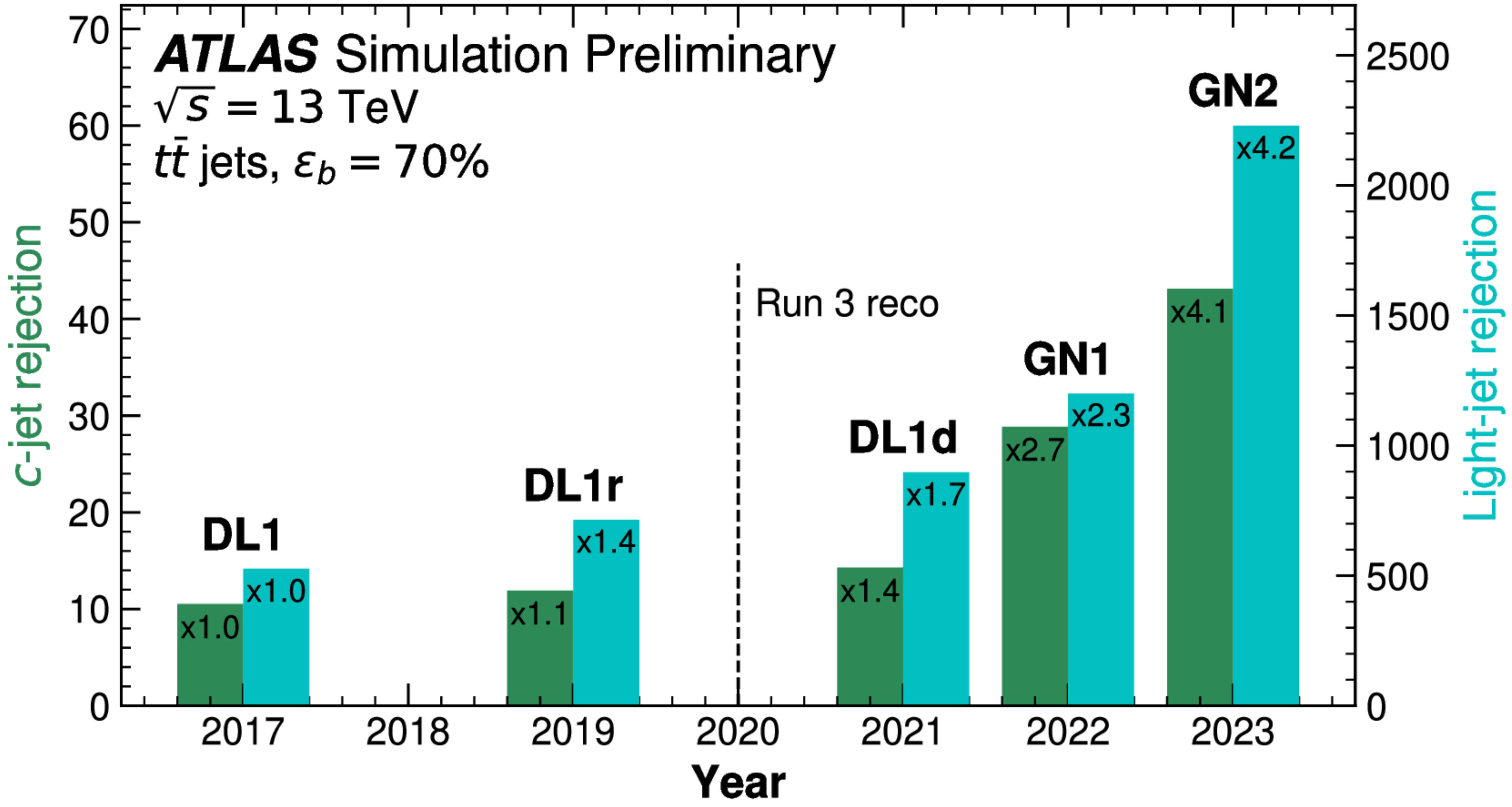

More details on [Donato Troiano] talk

More details on [Robert Les] talk

# Flavour Tagging highlights

- Flavour tagging using jets & track properties for B/C hadron identification
- Today in Flavour tagging is all about transformers!

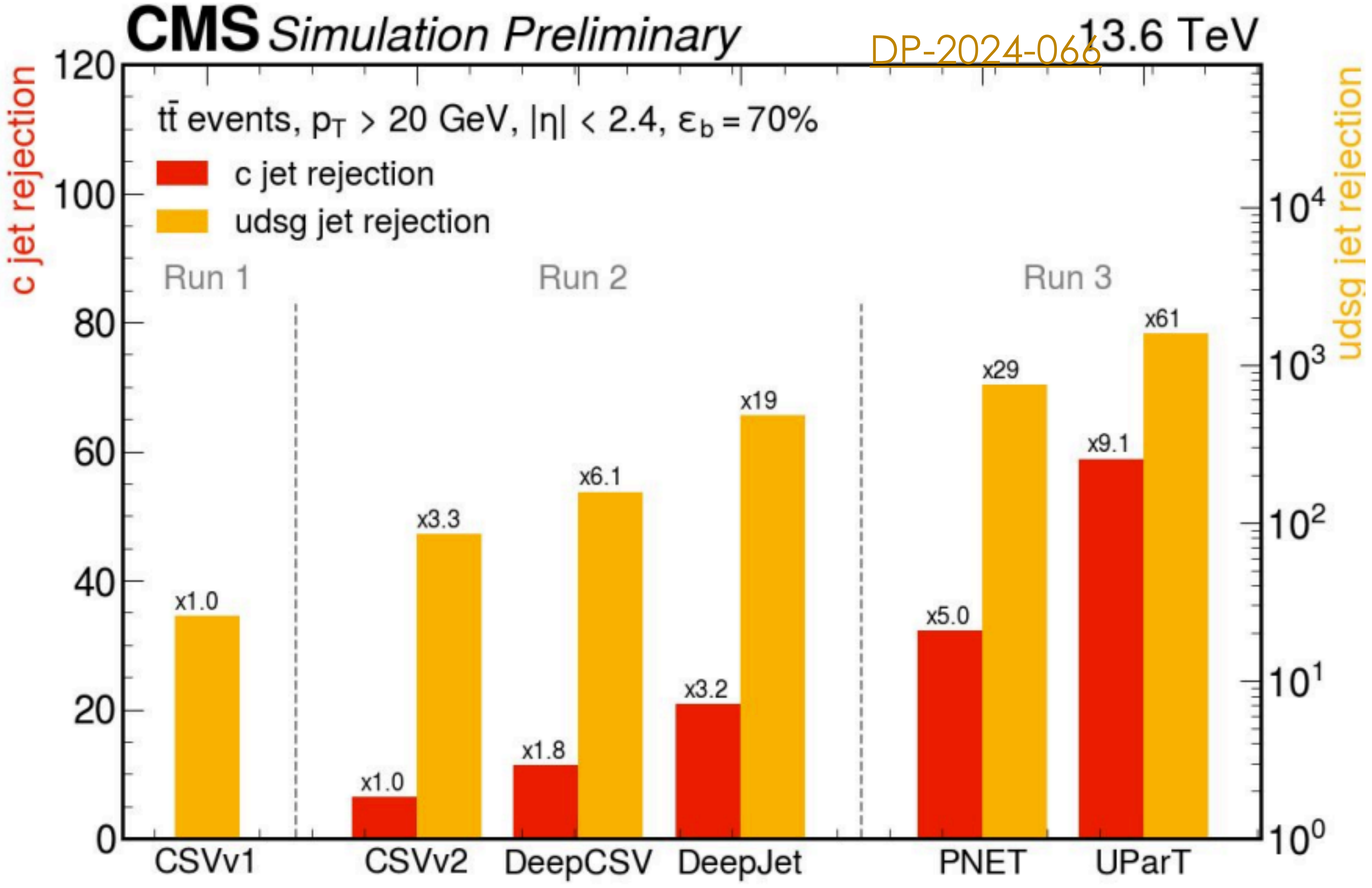



- 4x background rejection improvement with GN2 compared to Run-2

More details on Neelam talk

- **UParT**: New algorithm based on the ParticleTransformer architecture for Run 3
  - Extending from b/c identification to s and $\tau_{\text{had}}$ jets




Background discrimination for 70% efficient b tagging

# Jet Tagging highlights

- On The X→bb taggers!

**GN2X – H(bb/cc) tagger**

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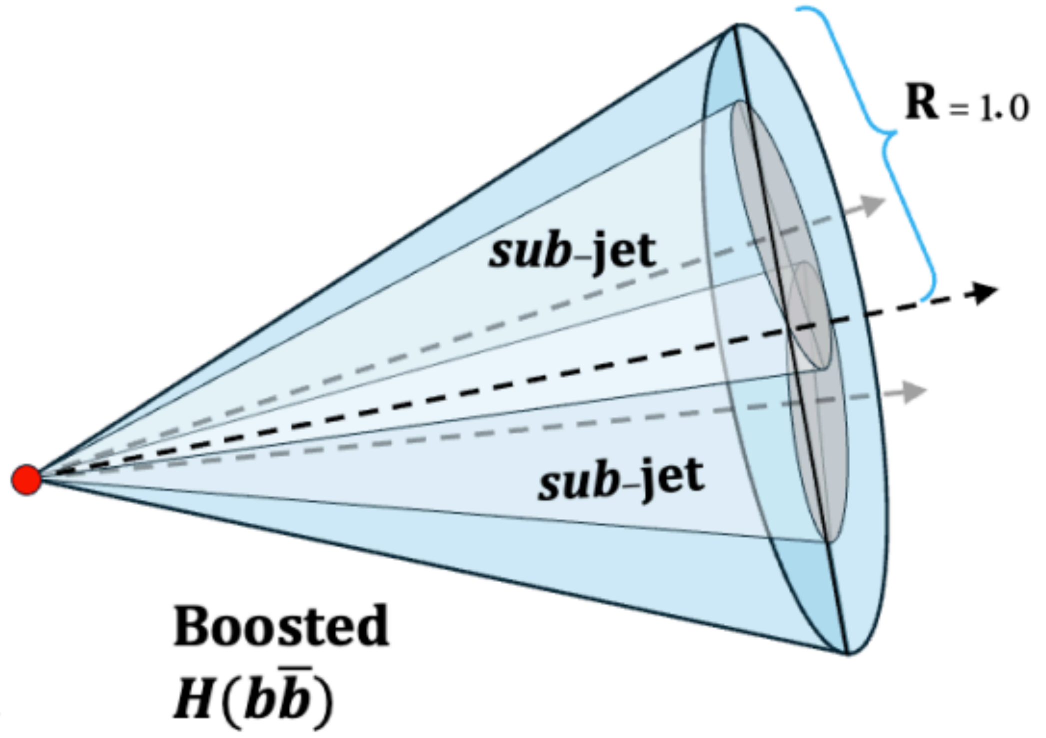
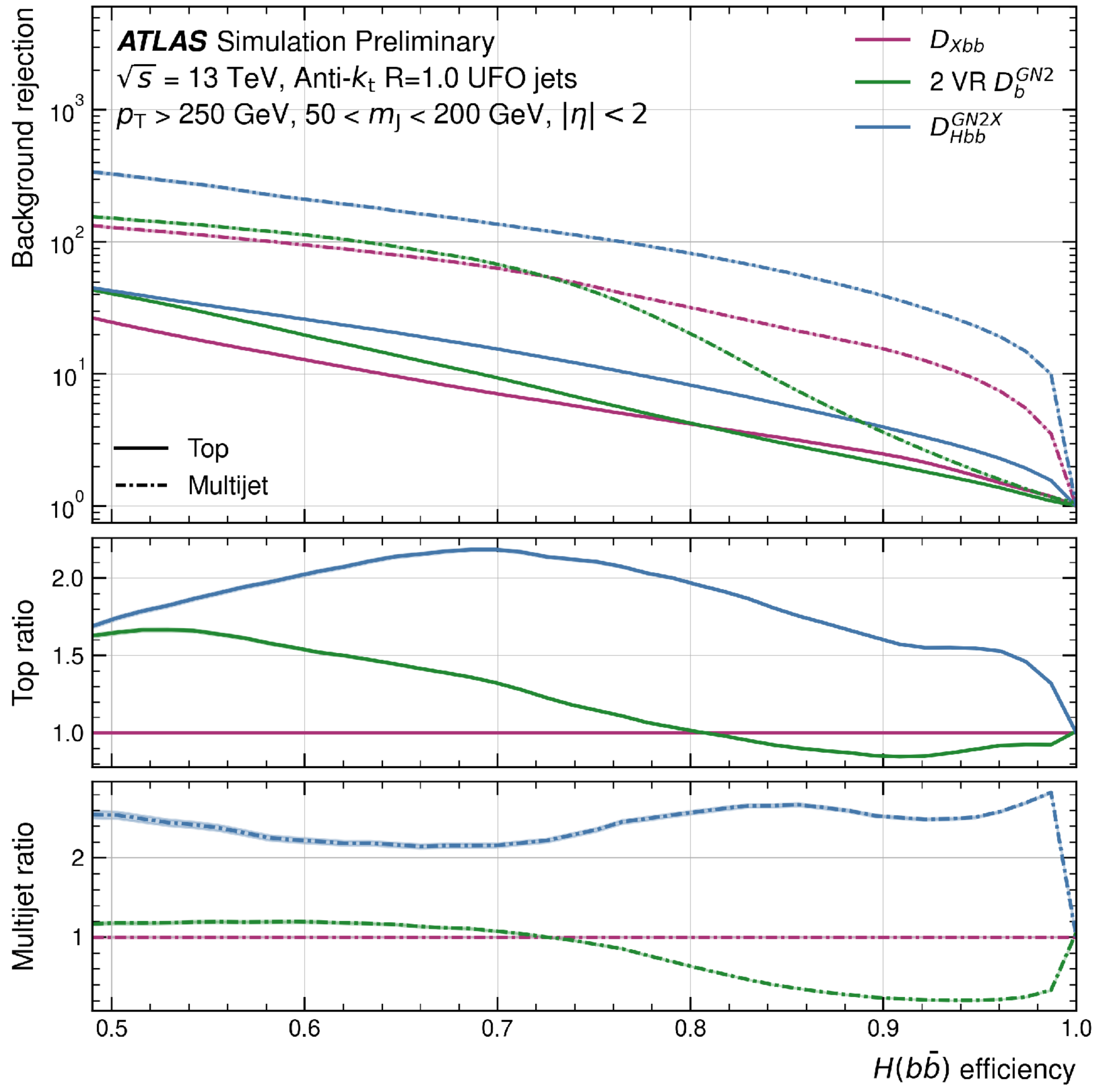
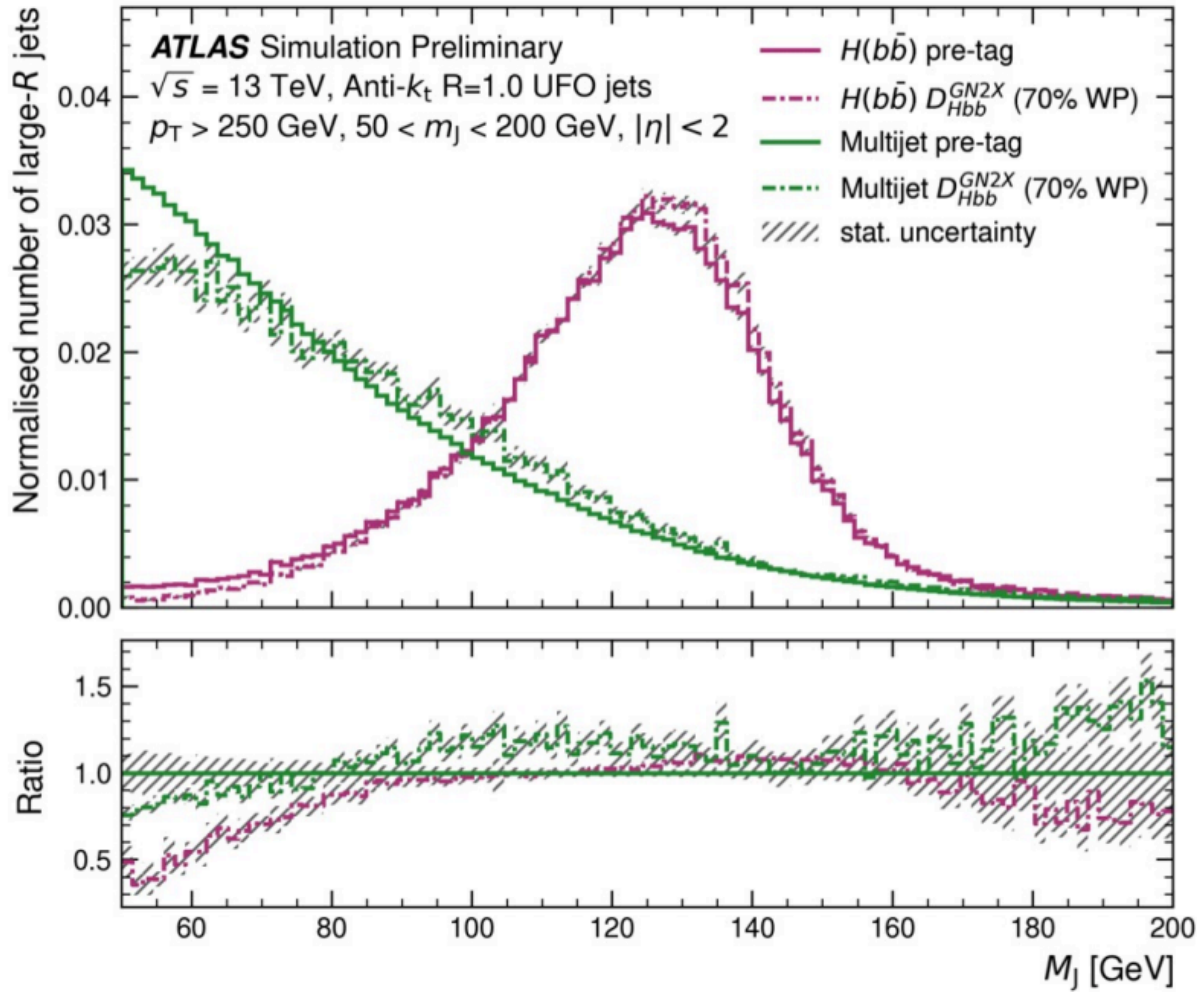


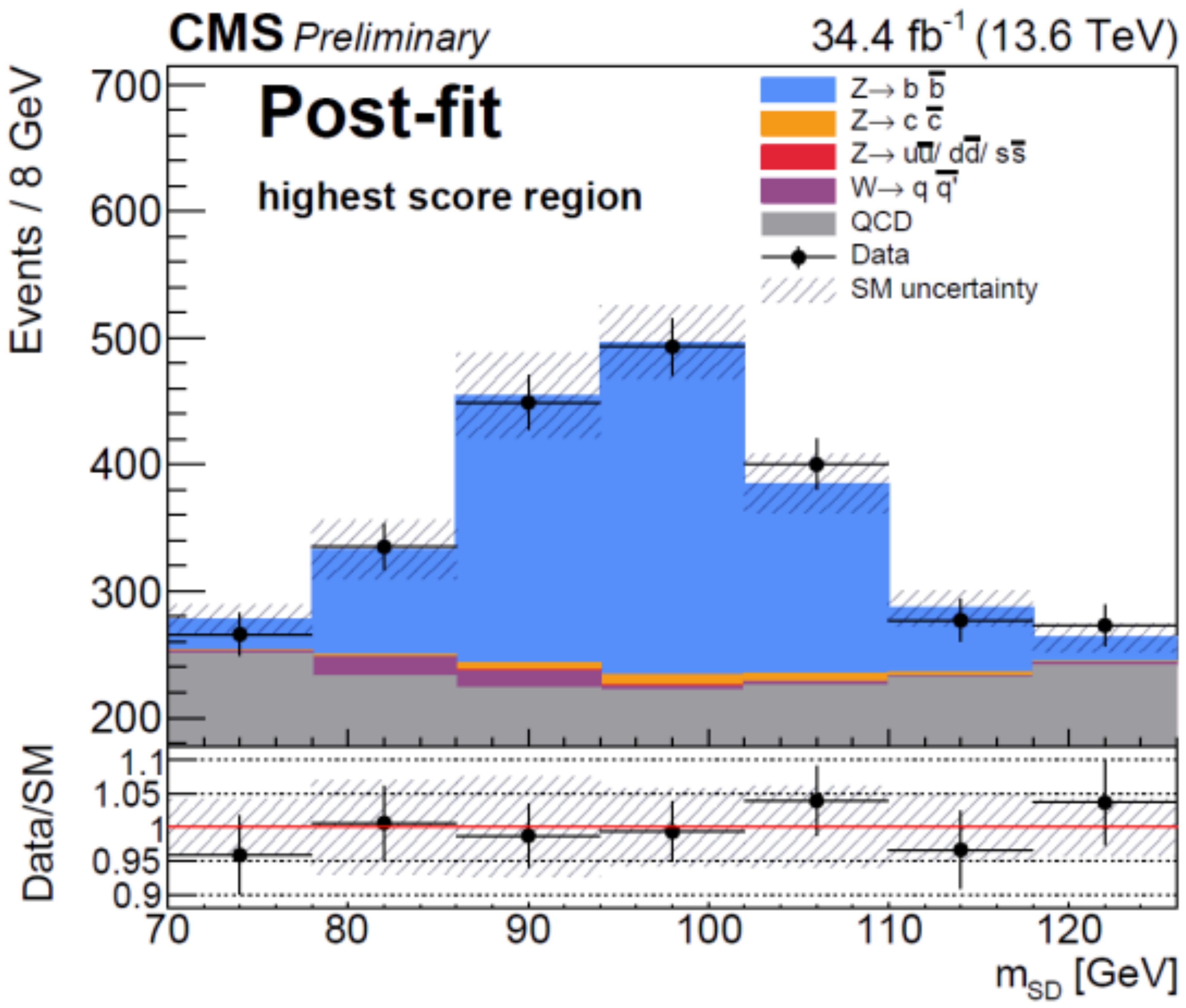

**ParticleNet-MD (Mass Decorrelated)**

DP2024_055

- Transformer based Xbb tagger




@60% signal efficiency: More than double the top and QCD rejection

More details on Neelam talk

- New training with Run 3 data
- Validated on Z→bb like events

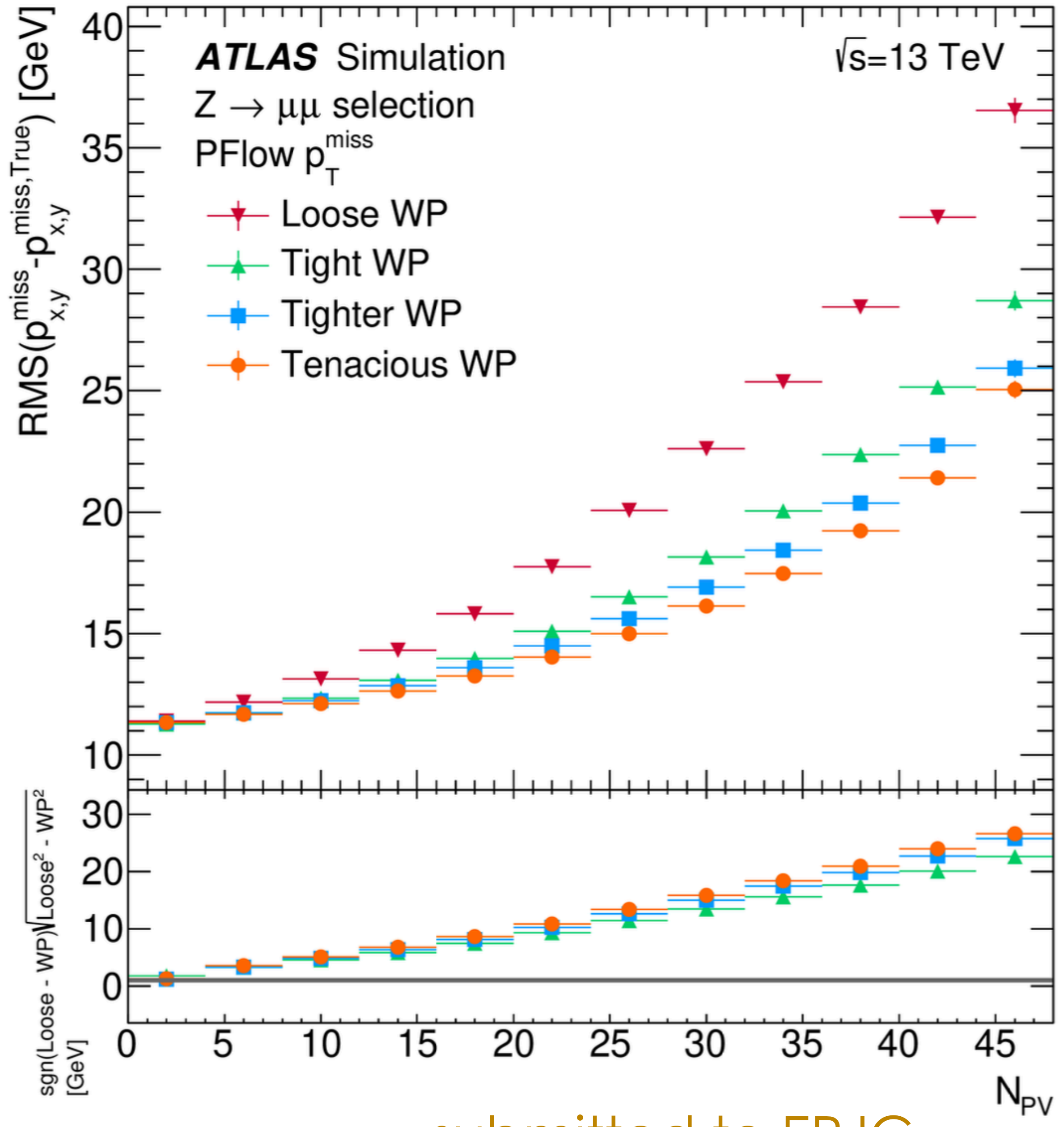
More details on Donato talk

# Missing Transverse Momentum

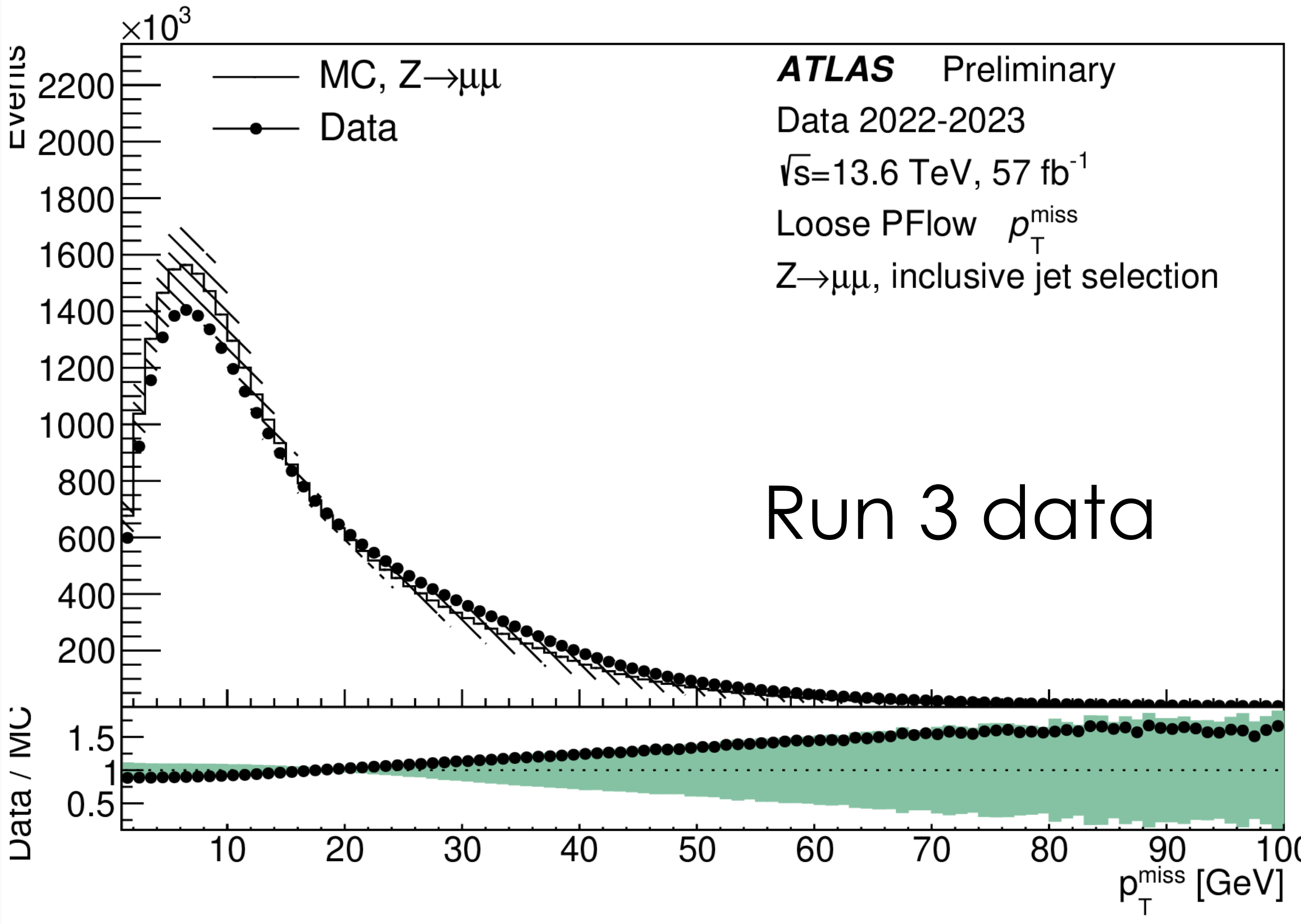
$$\overrightarrow{P_{\mathrm{T}}^{\mathrm{miss}}} = -\left(\vec{p}_{\mathrm{T}}^{\,\mathrm{muons}} + \vec{p}_{\mathrm{T}}^{\,\mathrm{electrons}} + \vec{p}_{\mathrm{T}}^{\,\mathrm{photons}} + \vec{p}_{\mathrm{T}}^{\,\mathrm{taus}} + \vec{p}_{\mathrm{T}}^{\,\mathrm{jets}} + \vec{p}_{\mathrm{T}}^{\,\mathrm{soft\ term}}\right)$$

- Jets plays a crucial role on $\overrightarrow{P_{\mathrm{T}}^{\mathrm{miss}}}$

- ATLAS defines different WPs for different jet criteria




submitted to EPJC

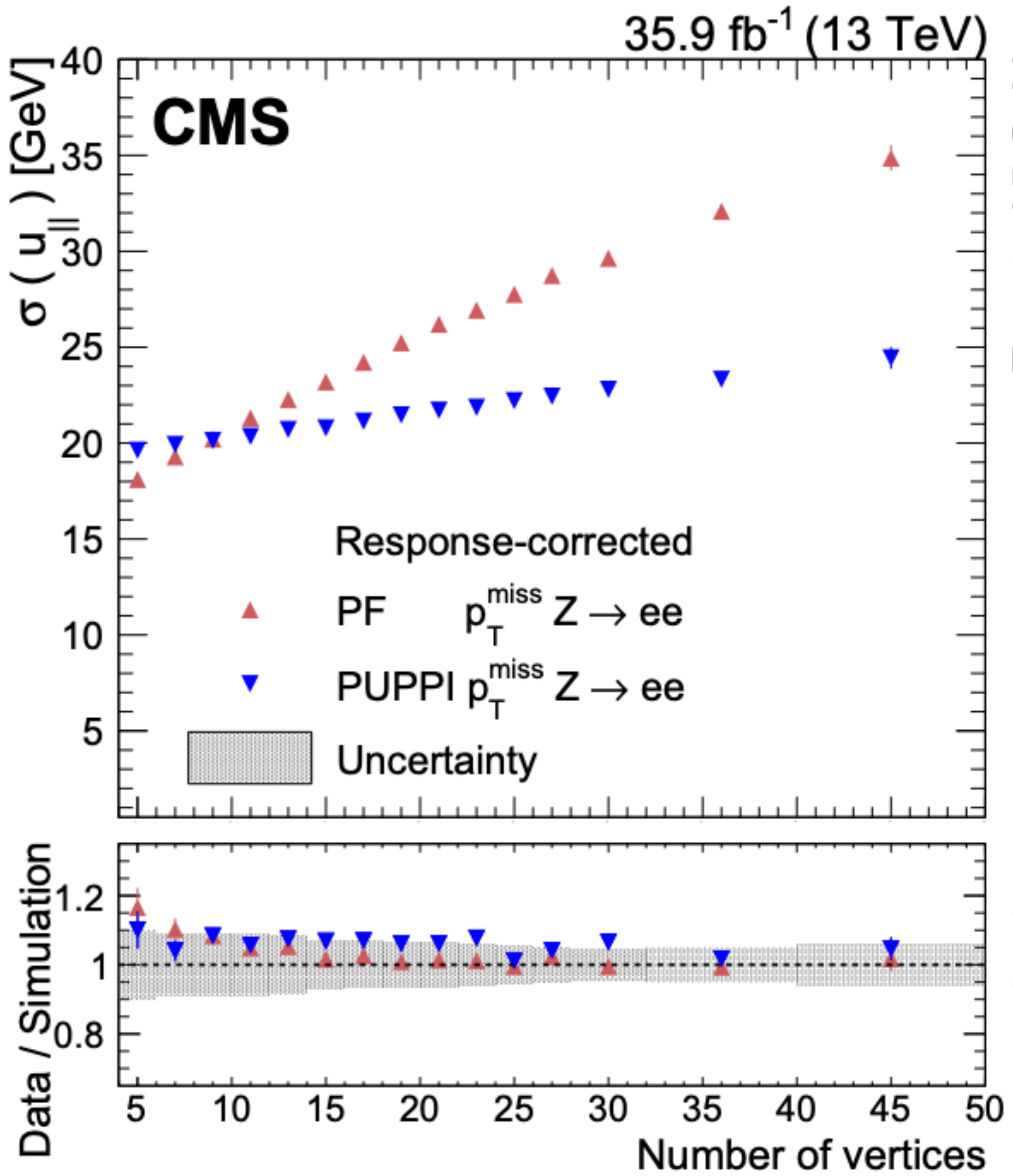



JETM-2024-03

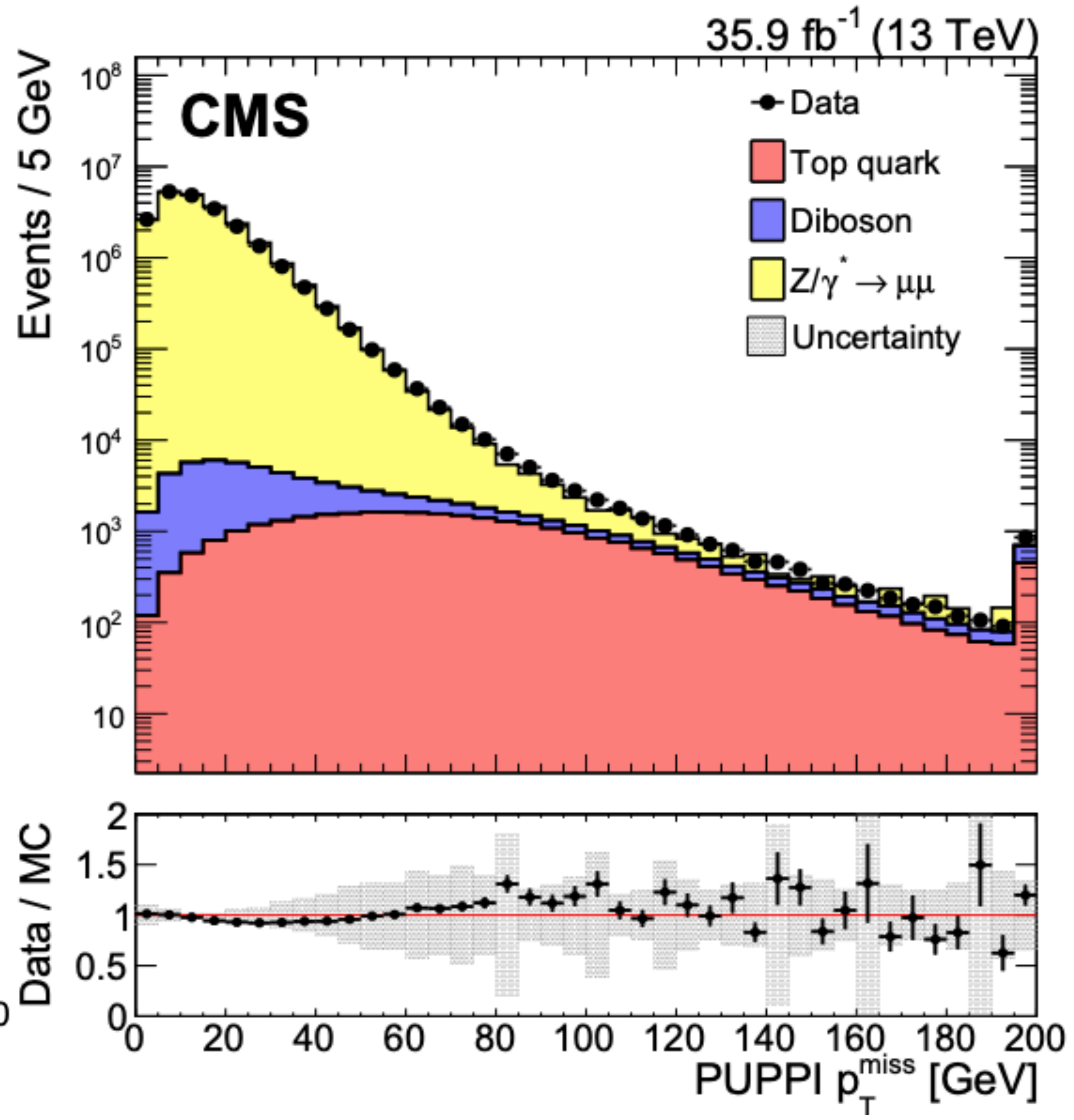
First $\overrightarrow{P_{\mathrm{T}}^{\mathrm{miss}}}$ performance result focusing on Particle Flow jets!

More details on Sebastian Rutherford Poster

- PUPPI $\overrightarrow{P_{\mathrm{T}}^{\mathrm{miss}}}$ is now the default in CMS




JINST 15 (2020) P09018

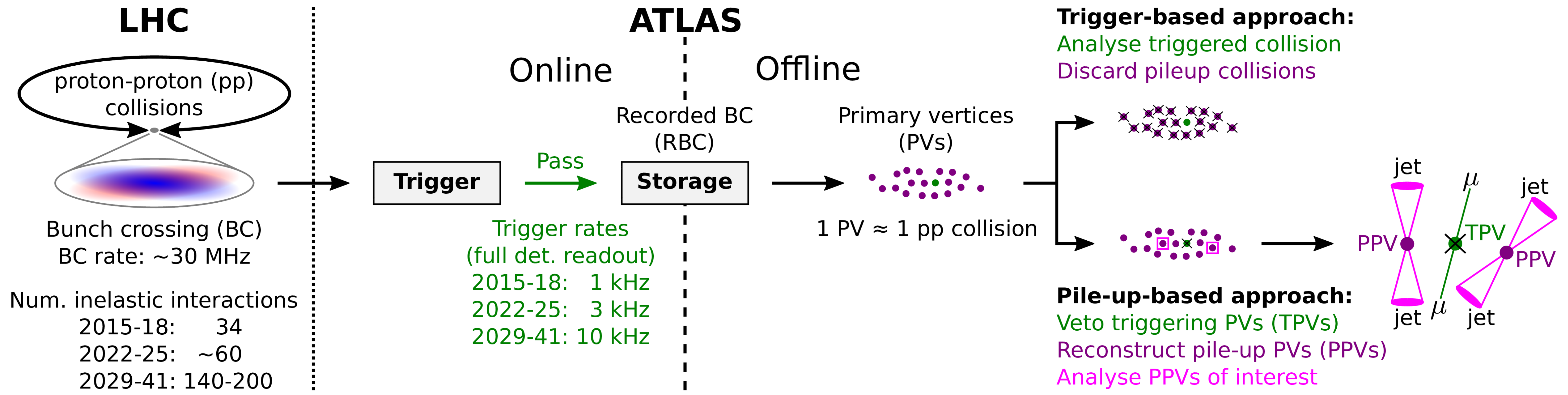


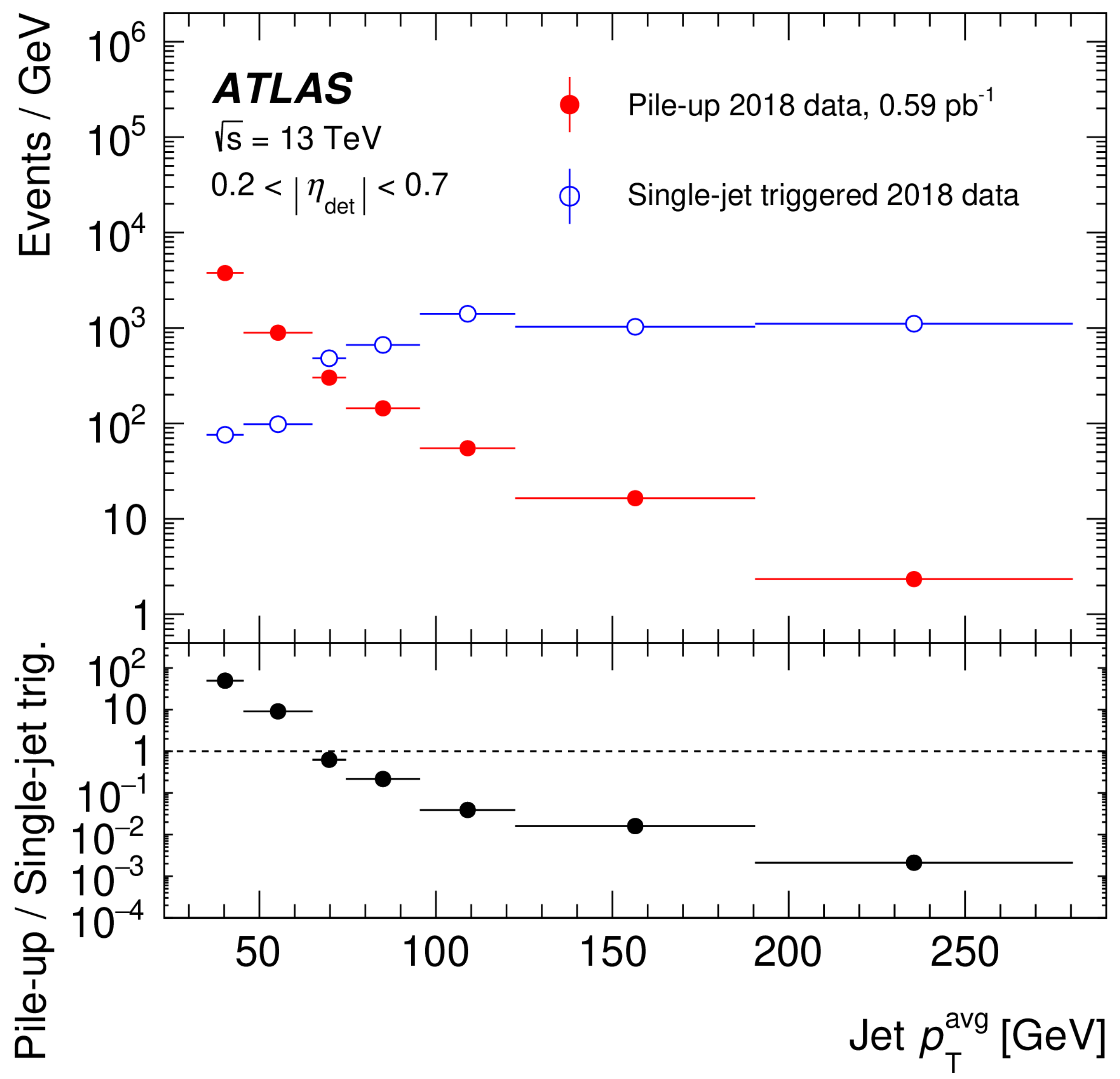

JINST 14 (2019) P07004

# Using pile-up for physics

[submitted to JHEP](#)

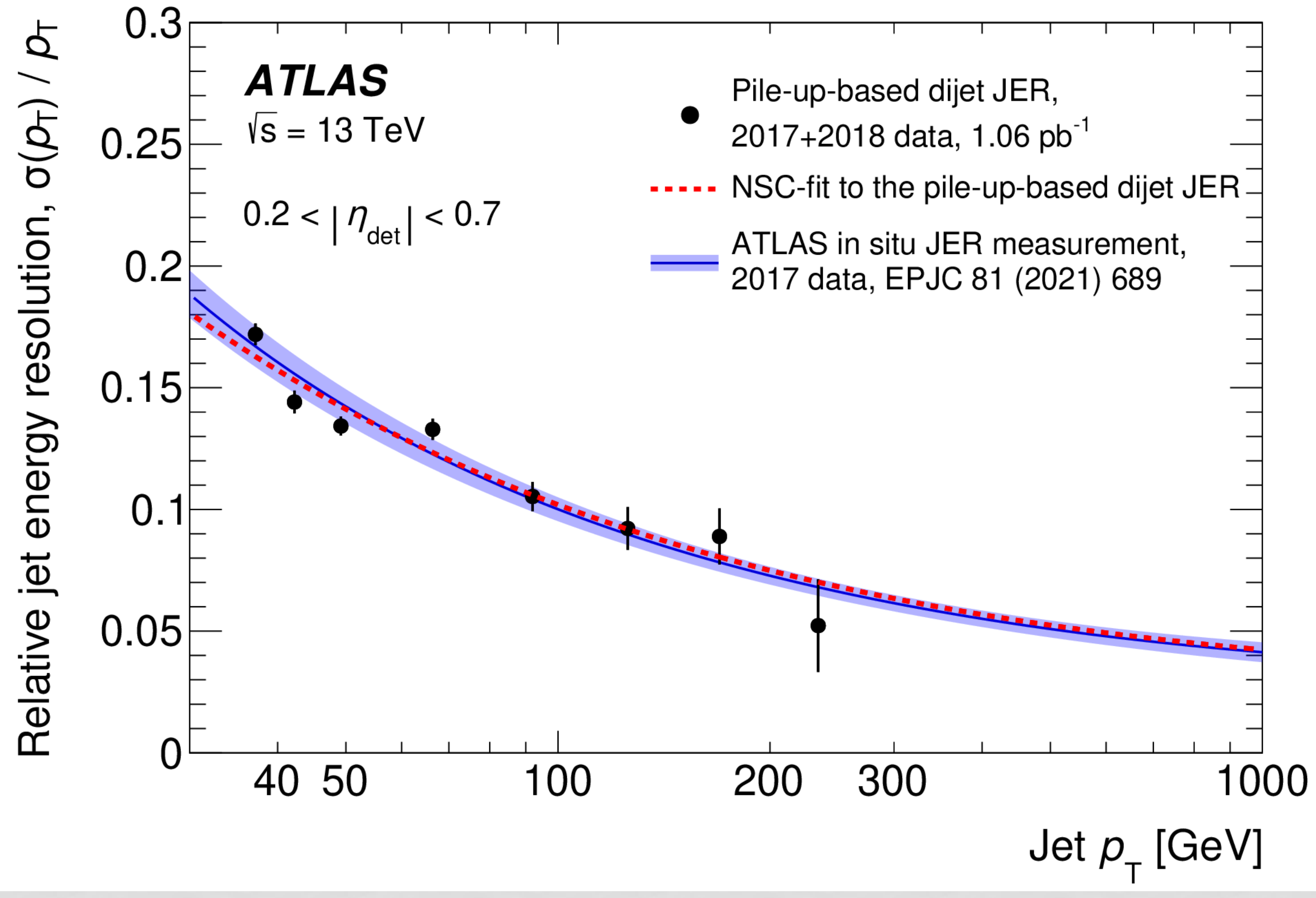
- Novel approach of exploiting already recorded data
- Useful wherever standard triggers are inefficient or prescaled
  - New strategy to increase the statistics for hadronic processes at low energy: Reconstruct jets from pile-up



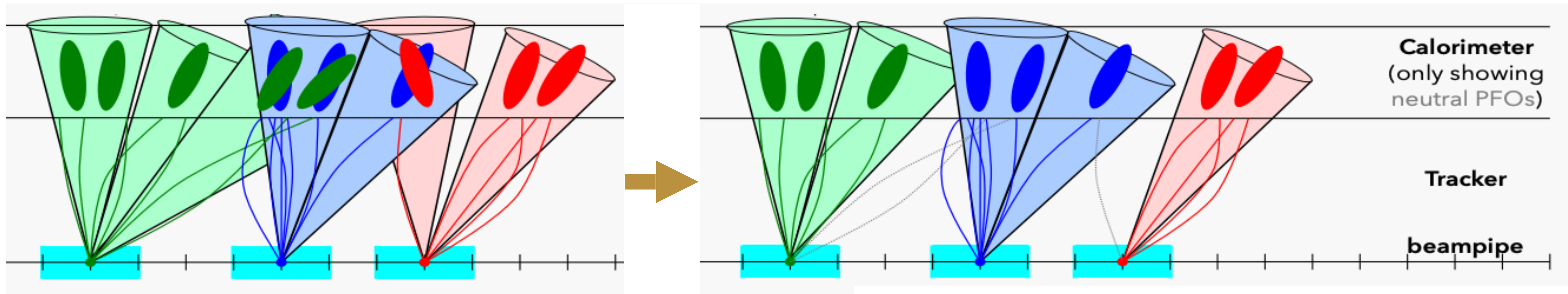




Up to 50**x** dijet collisions from pile-up!

- Extracting the JER using pileup!



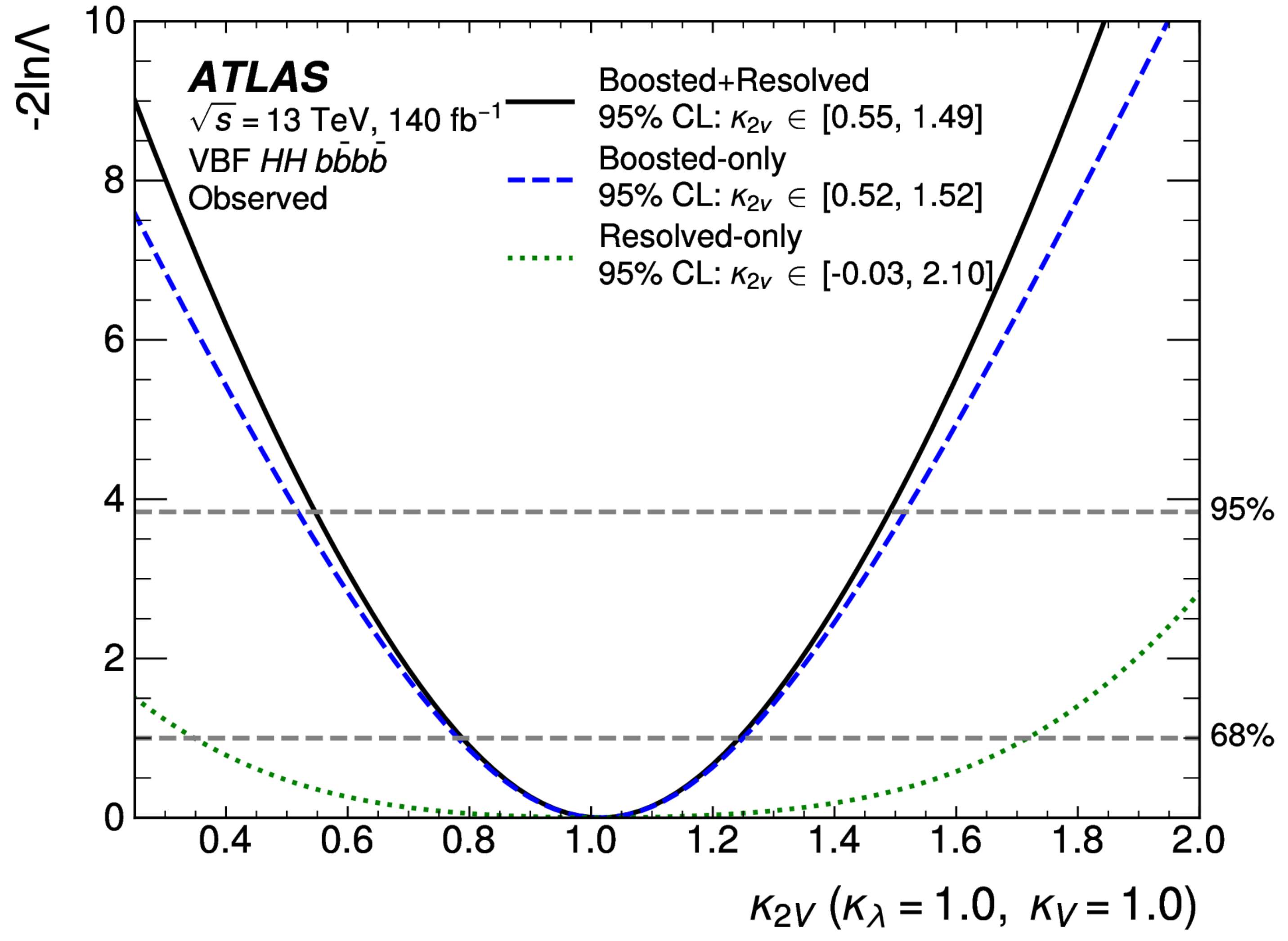

- Build particle flow objects from each PU vertex
  - Removing overlaps

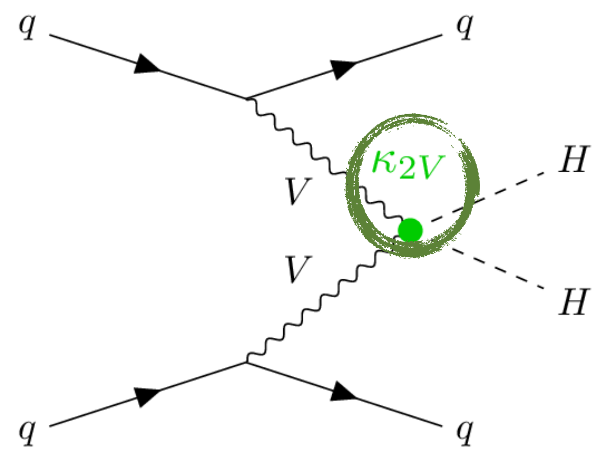



More details on [Magda Diamantopoulou](#) talk and Vilius Čepaitis Poster

# Boosting Searches

- New Boosted VBF di-Higgs search
- Using $H \to b\bar{b}$ tagger in boosted topologies
- Boosted topology dominating the sensitivity in $\kappa_{2V}$!

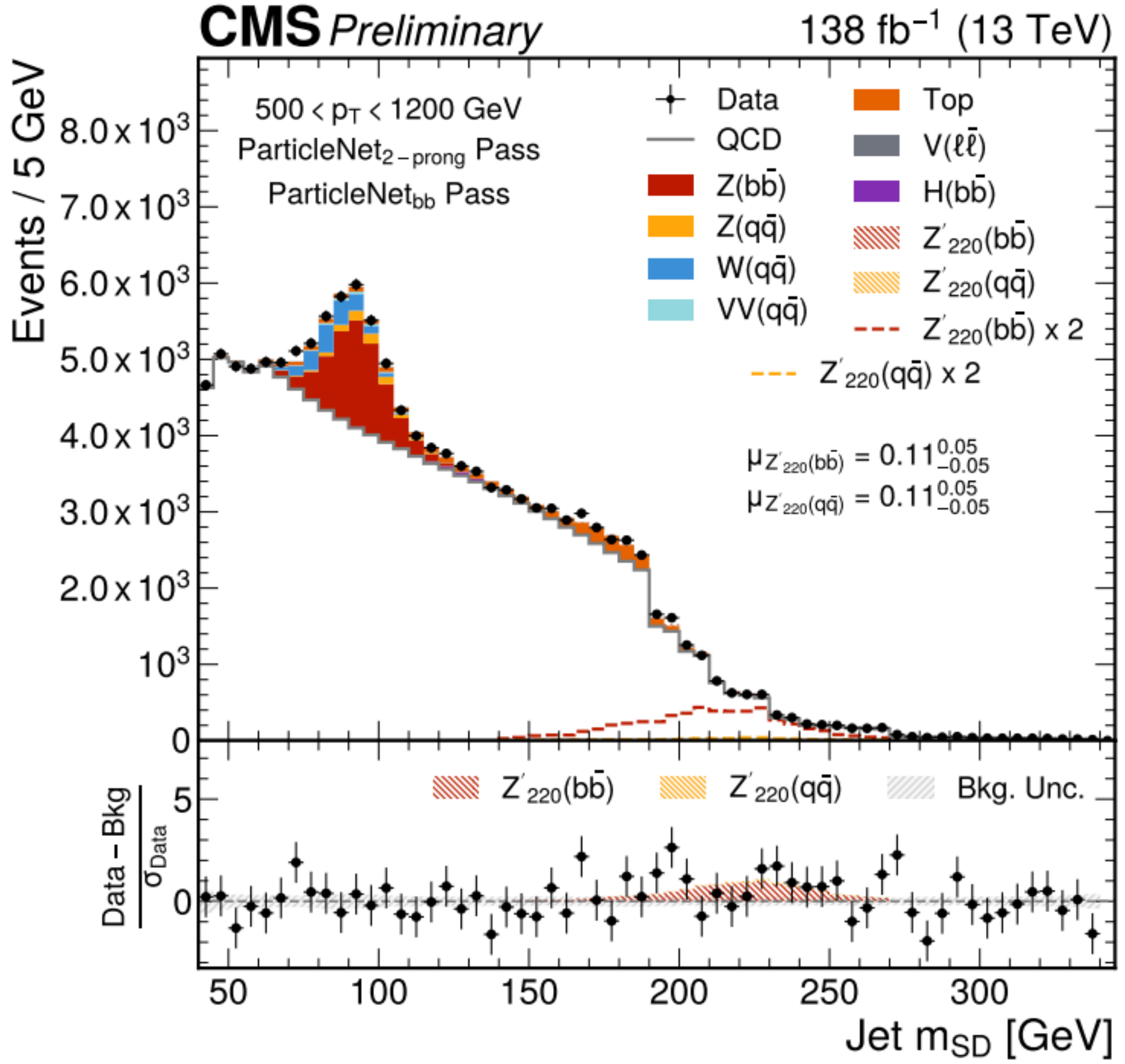



Submitted to Phys. Lett. B.

More details on Fabrizio talk

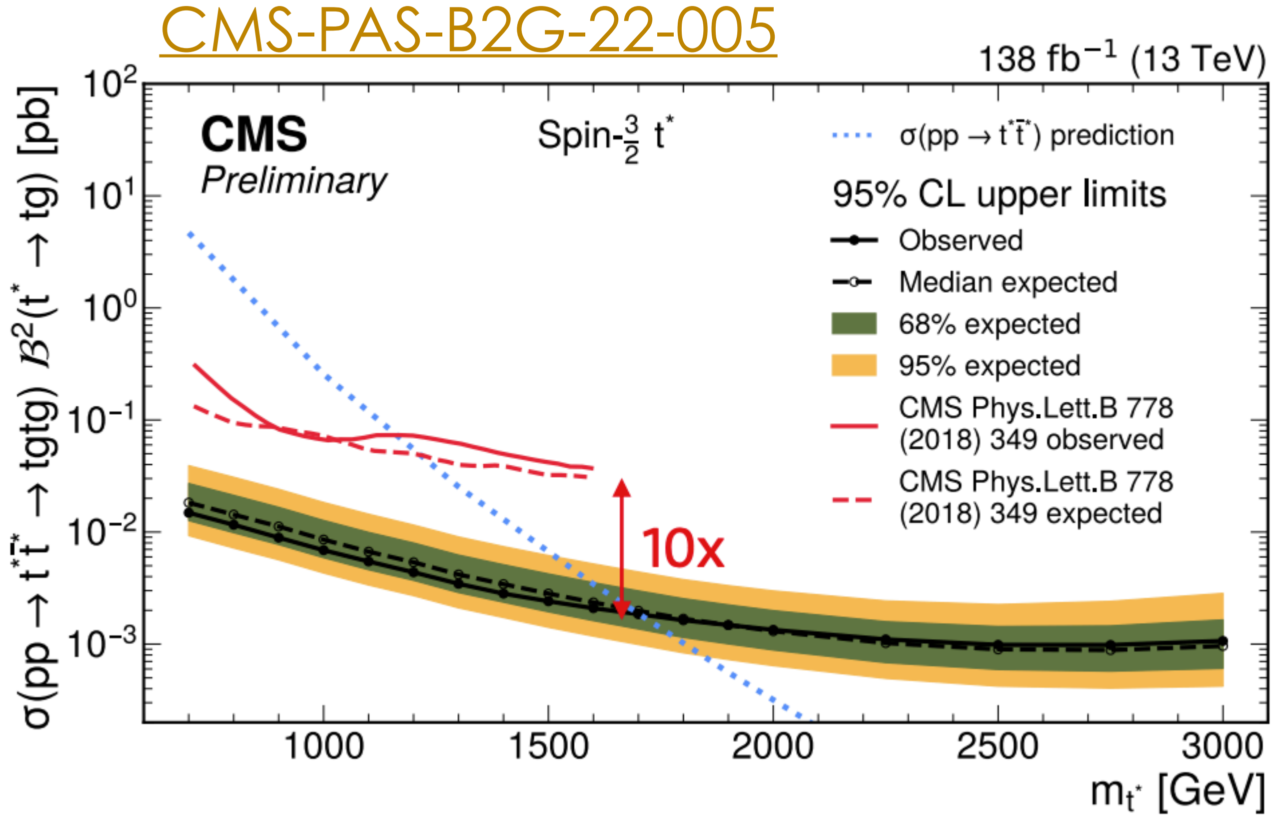
- Search for boosted low-mass resonances decaying to a merged dijet system
- ParticleNet to identify these two-prong jets




More details on Simon talk

- Search for pair production $t^*\bar{t}^* \to tg\bar{t}g$
- HOTVR jets: allow access to wide range of jet momenta, due to variable radius

CMS-PAS-B2G-22-005

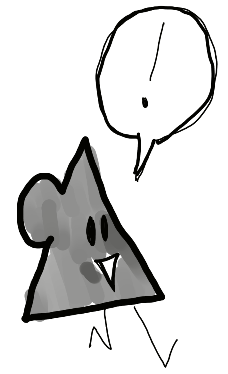


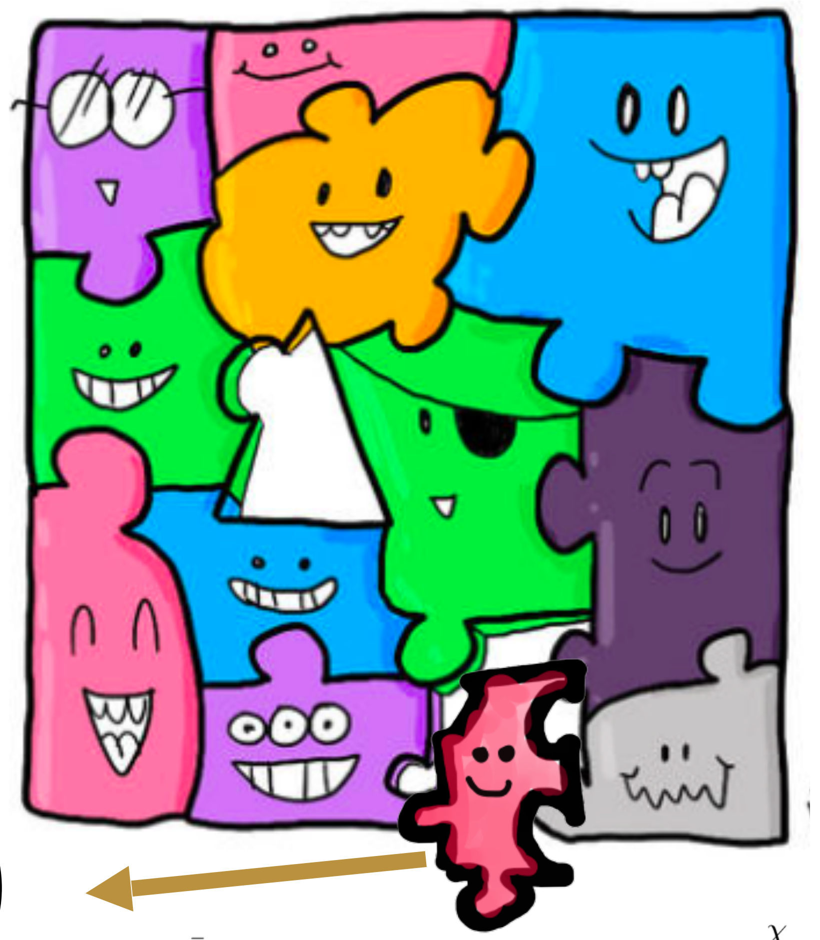

More details on Suman talk

Also checkout Chen Zhou talk on Searches with ML-based event classification

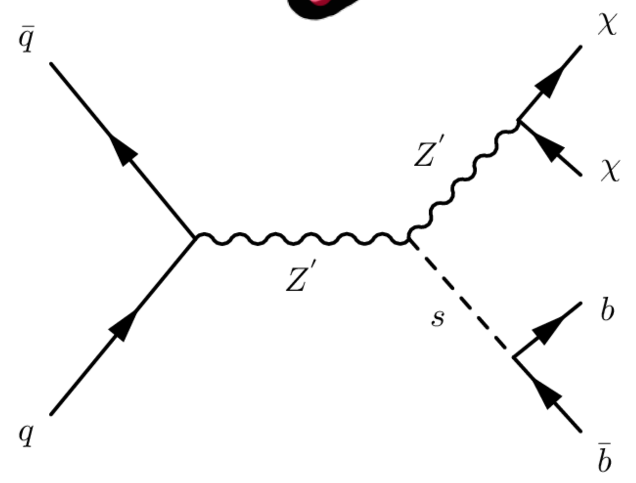
# The Dark Sector

- Growing interest on Dark Sectors



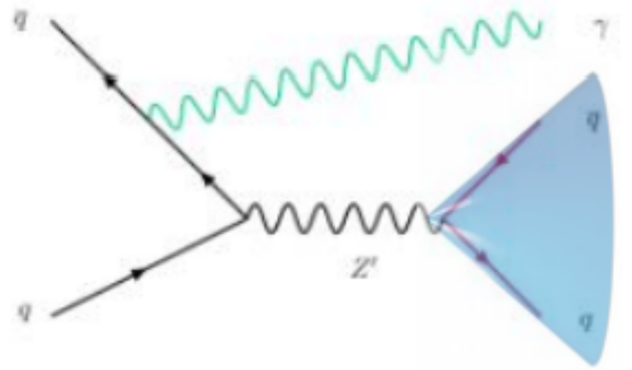




- New Bosons! (containing a portal)
- Highly boosted dark Higgs
  - Reclustered jet with double b-tag from tracks or Xbb tagger on calorimeter jet

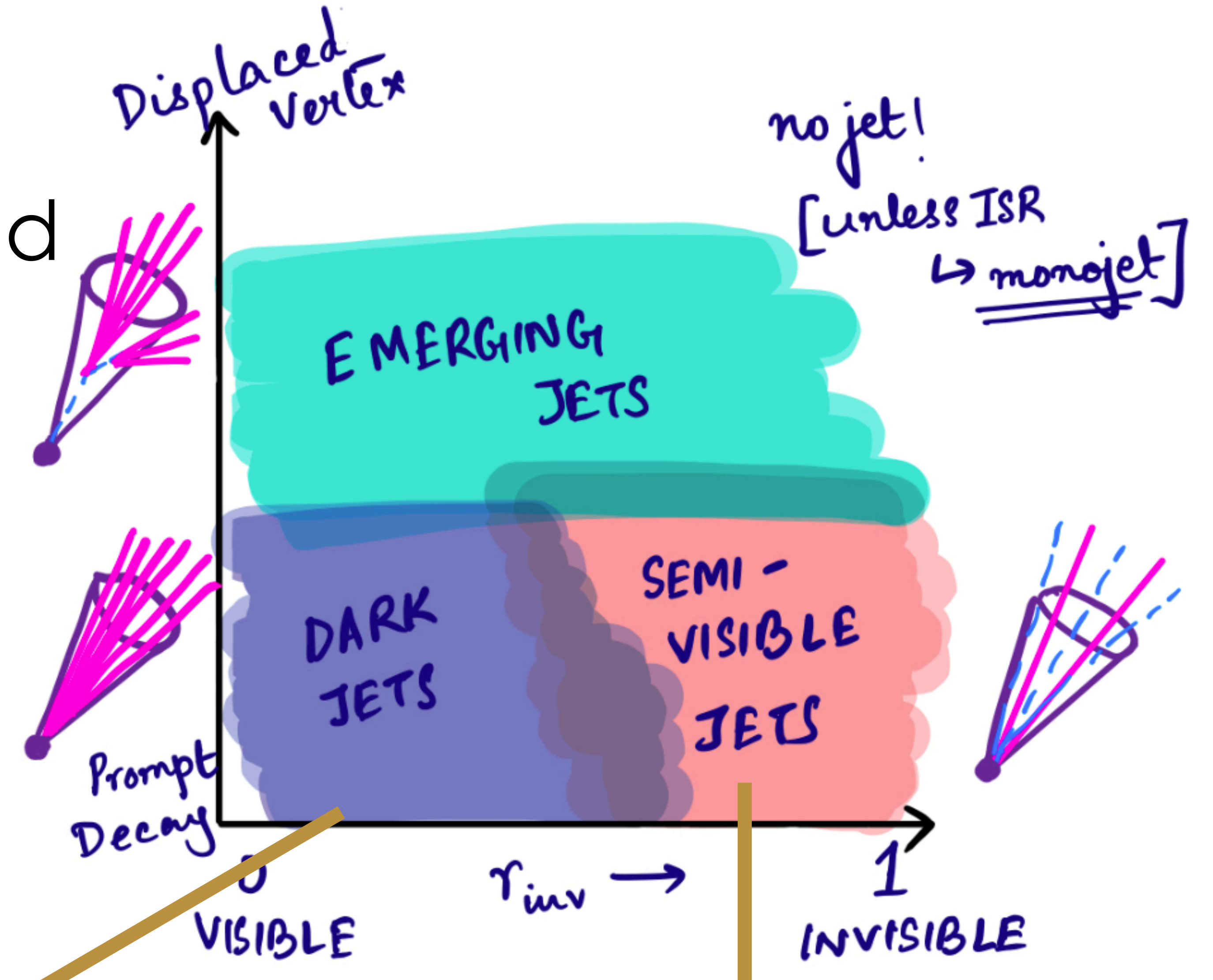


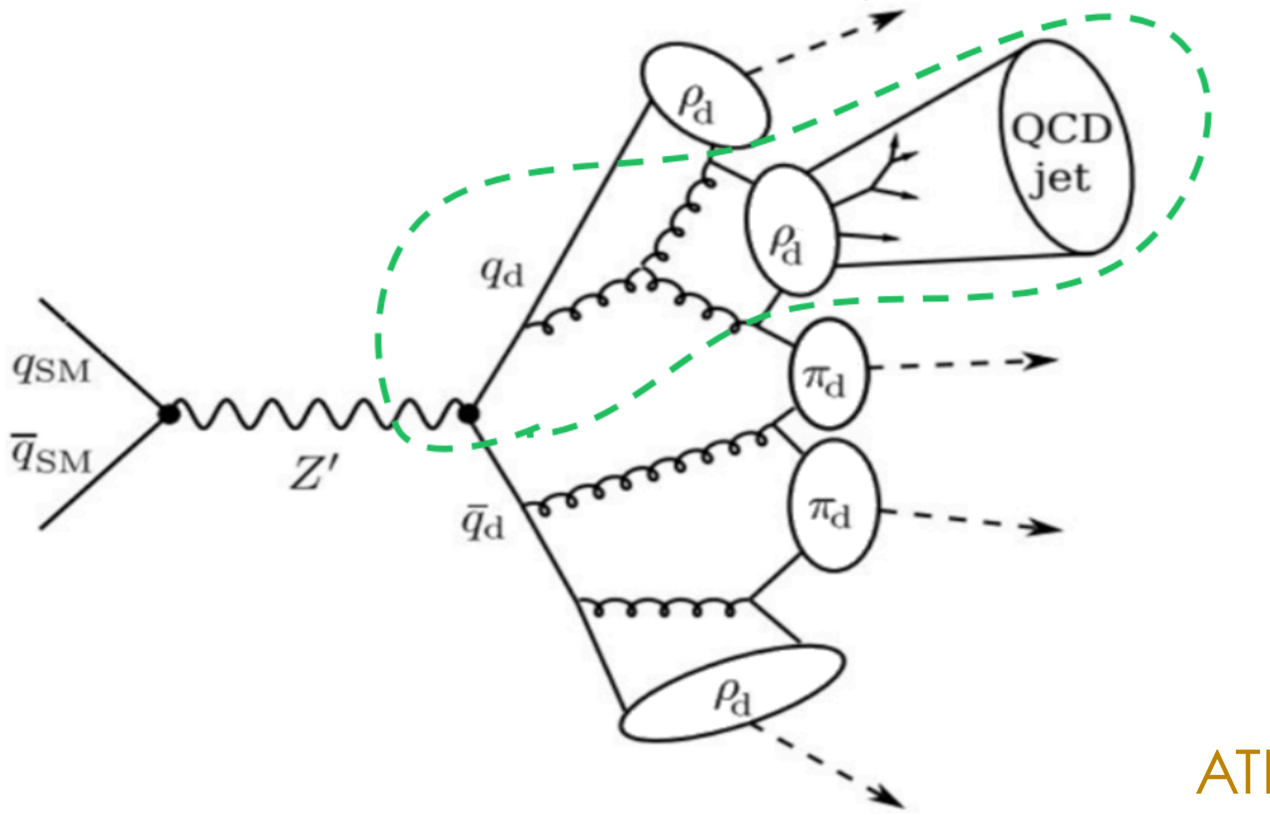

submitted to Physics Review Letters

- Explore low mass range of Z' mediator decaying hadronically
- Use TrackAssisteReclustered (TAR) jets [ATL-PHYS-PUB-2018-012]
- Use D2 substructure variable

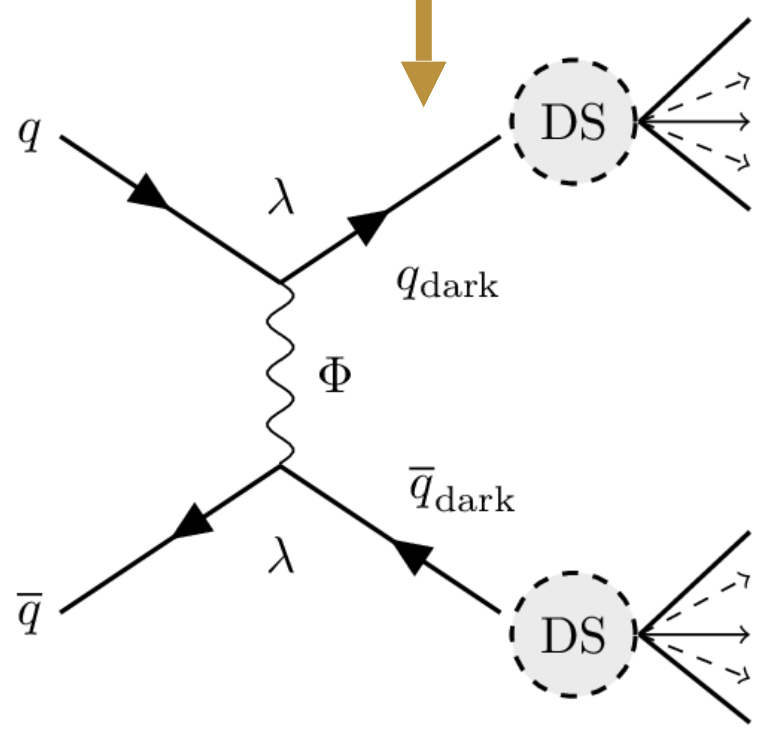


- Strongly interacting Dark Sector
- Awesome playground for new tools




Dark quarks: *JHEP 2402 (2024) 128*
Dark Mesons: submitted to JHEP

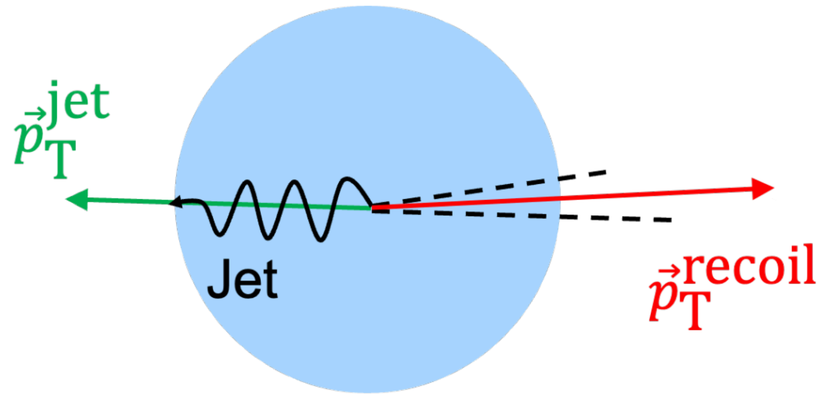


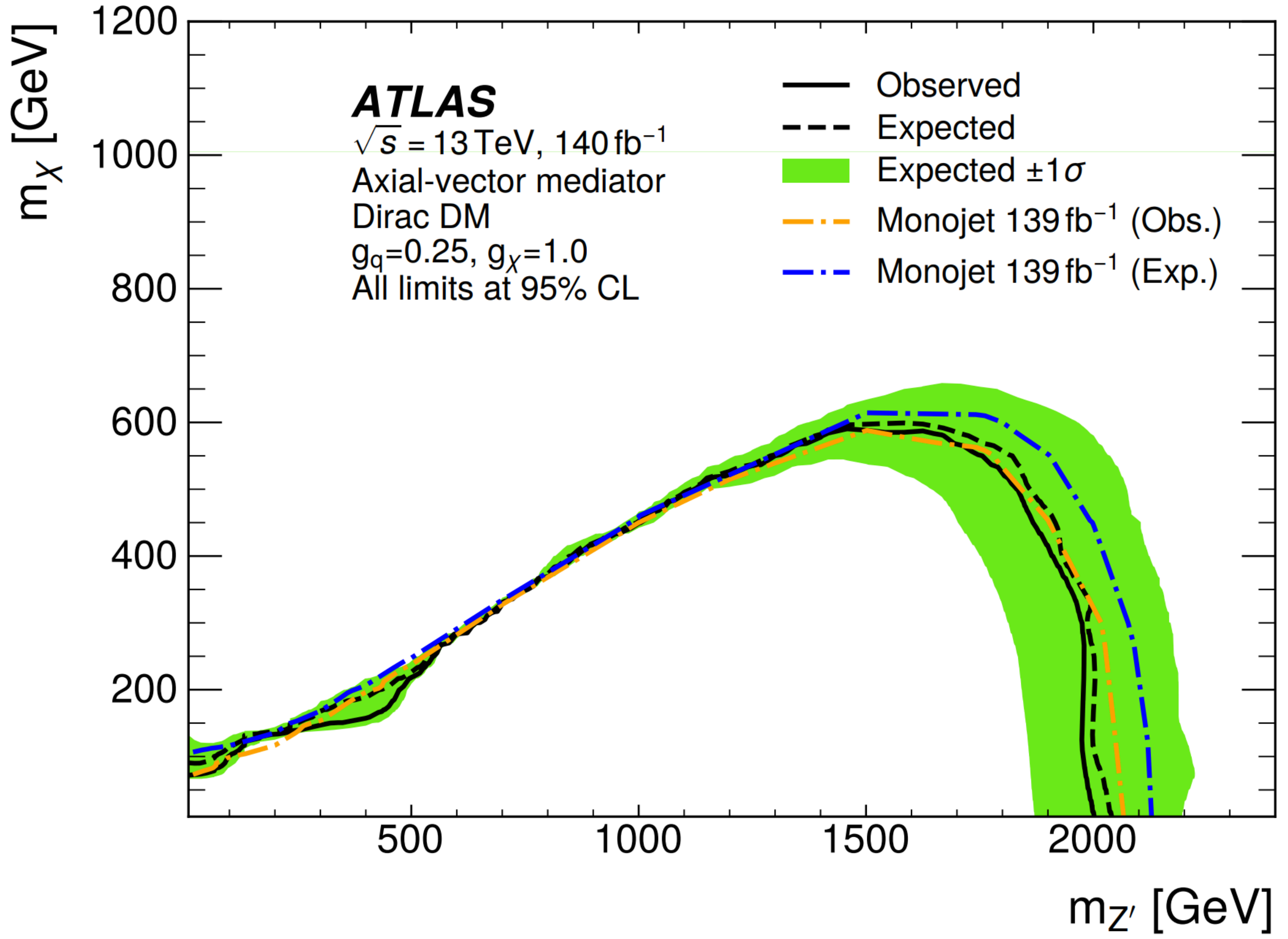

ATLAS: Phys. Lett. B 848 (2024) 138324
CMS: (JHEP 06 (2021) 156)

More details on Davide talk    Dark Sectors @ CMS

# Measurements

- First inclusive **particle-level measurement of** $p_T^{miss}$, using full ATLAS Run-2 dataset

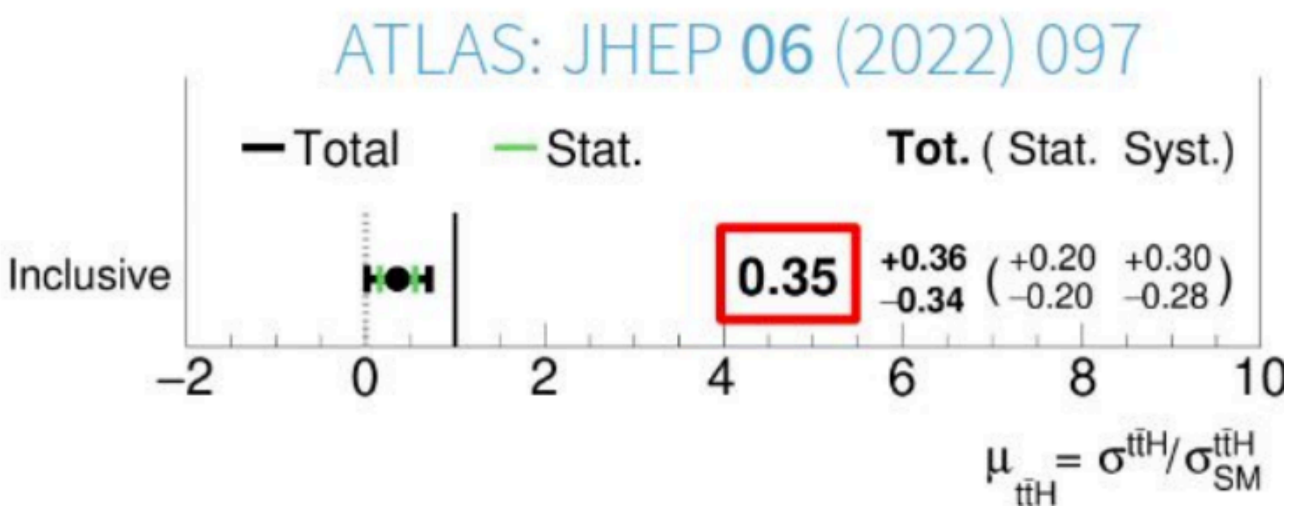



particle-level measurements can be as powerful as dedicated BSM searches in terms on constraining power!

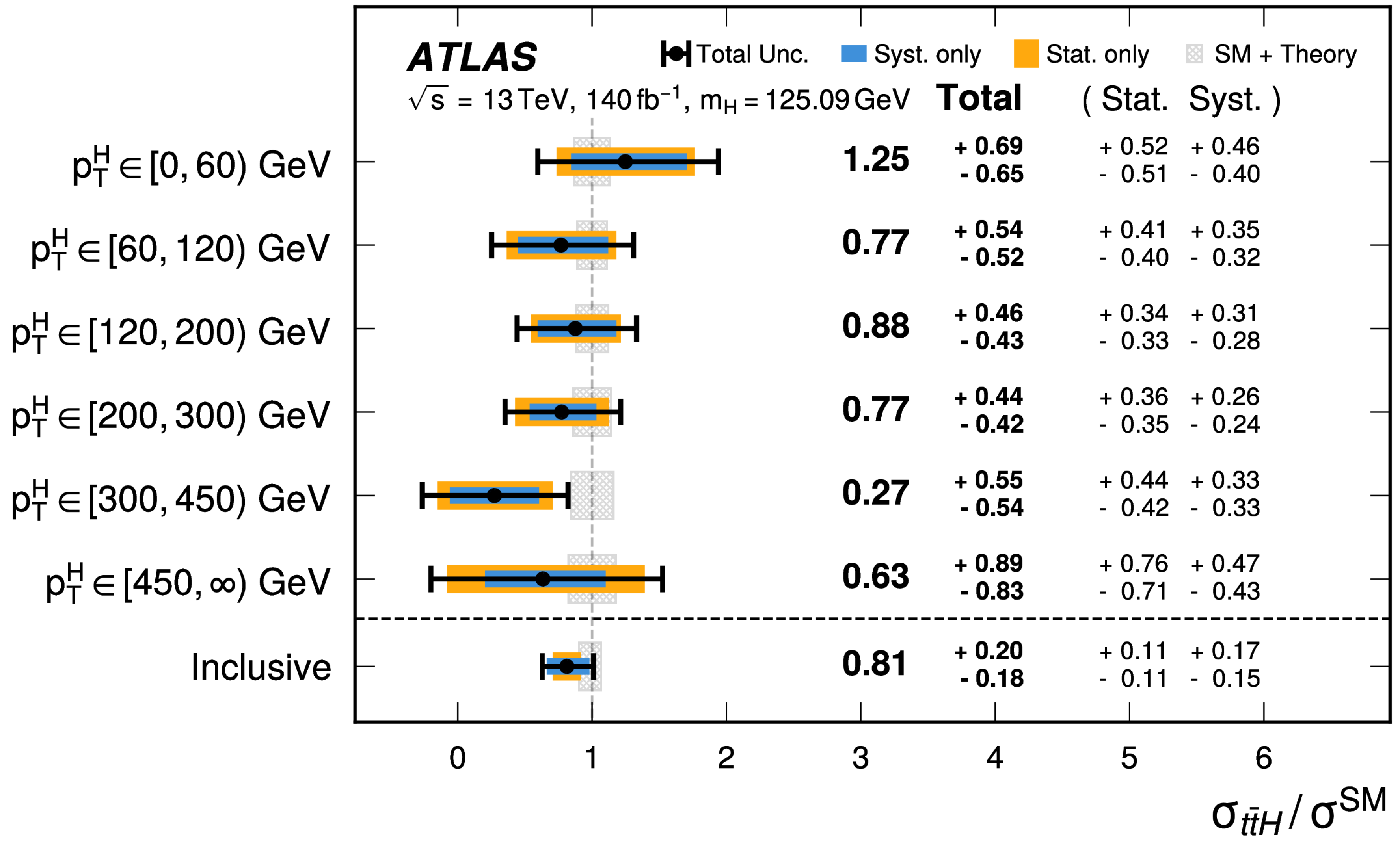
More details on Yoran talk

- **Precision Higgs -** $ttH(bb)$




- Particle-flow jets for Small-R
- Reclustered for Large-R
- Improved tagging of b-jet

submitted to EPJC

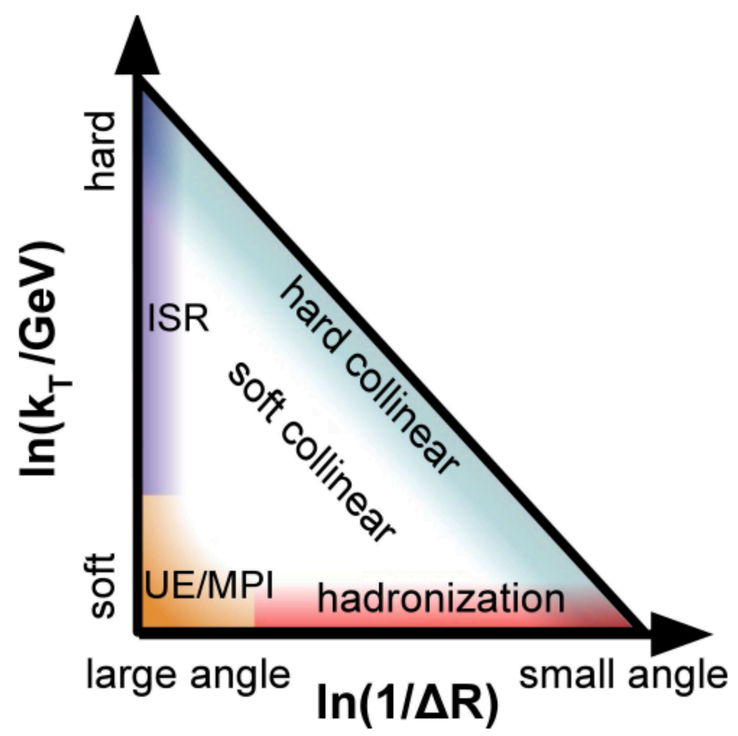



Improve precision and 4.6σ observed significance in ttH(bb) alone!

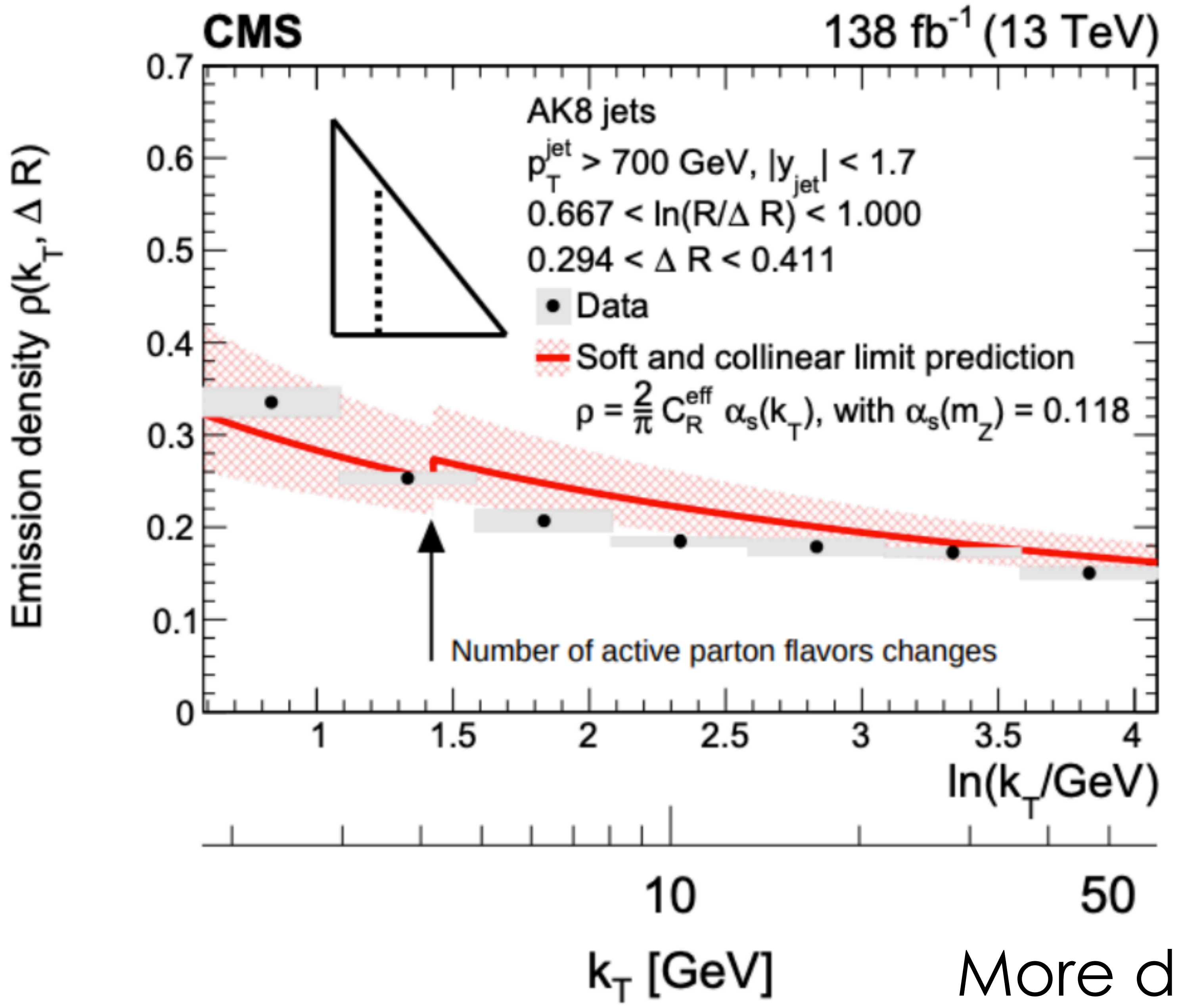
More details on Kulin talk

# Substructure Measurements: Lund Jet Plane

- **Lund Jet Plane**
  - Recluster jet with C/A algorithm and each split represented on lund jet plane based on:
    - transverse momentum kT , angle Δ, and momentum fraction z




- First measurement by CMS of the (average) density of emissions in the primary LJP (for both small- Large-R jets)
- The first measurement of the LJP in large-R jets

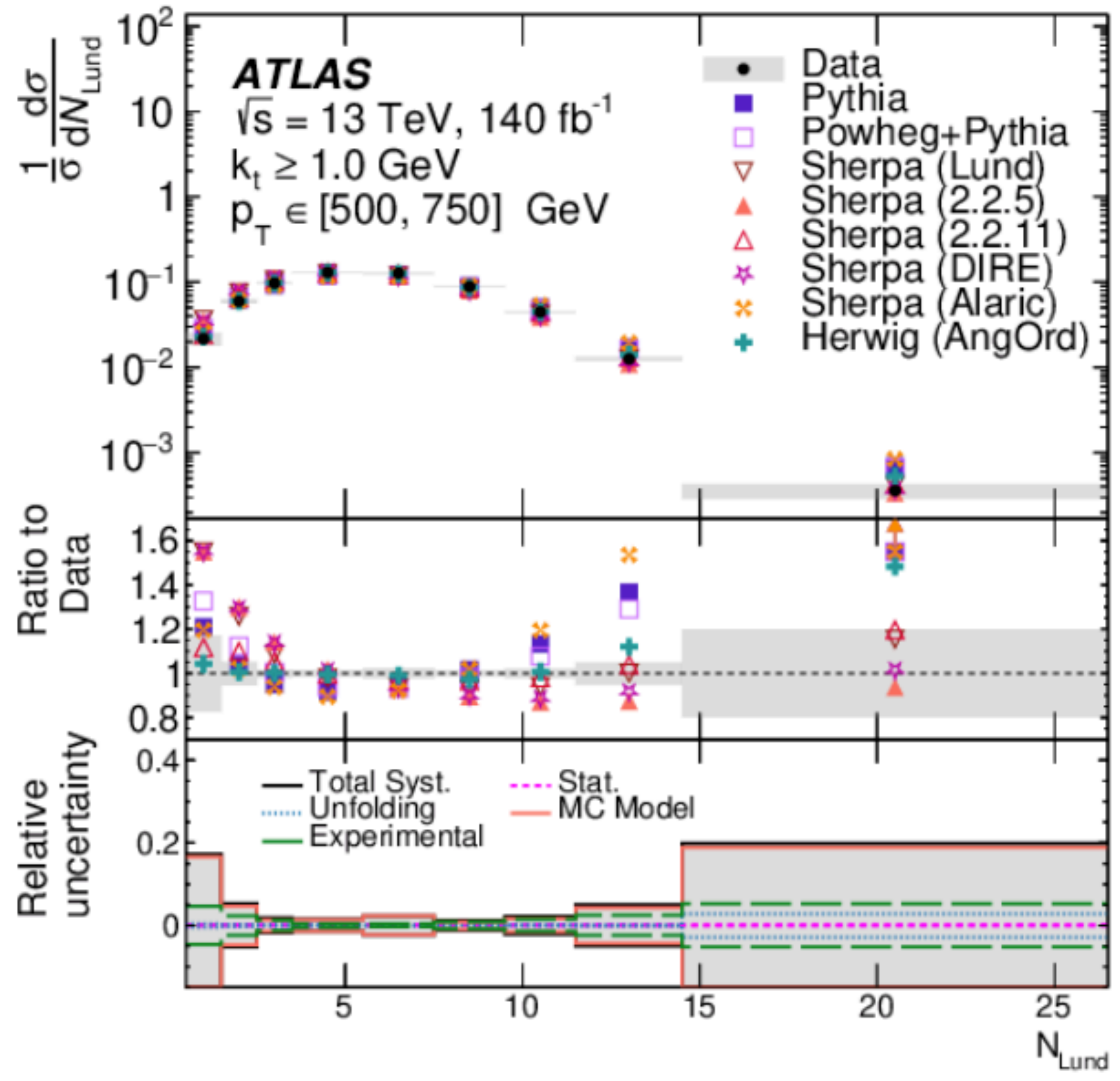


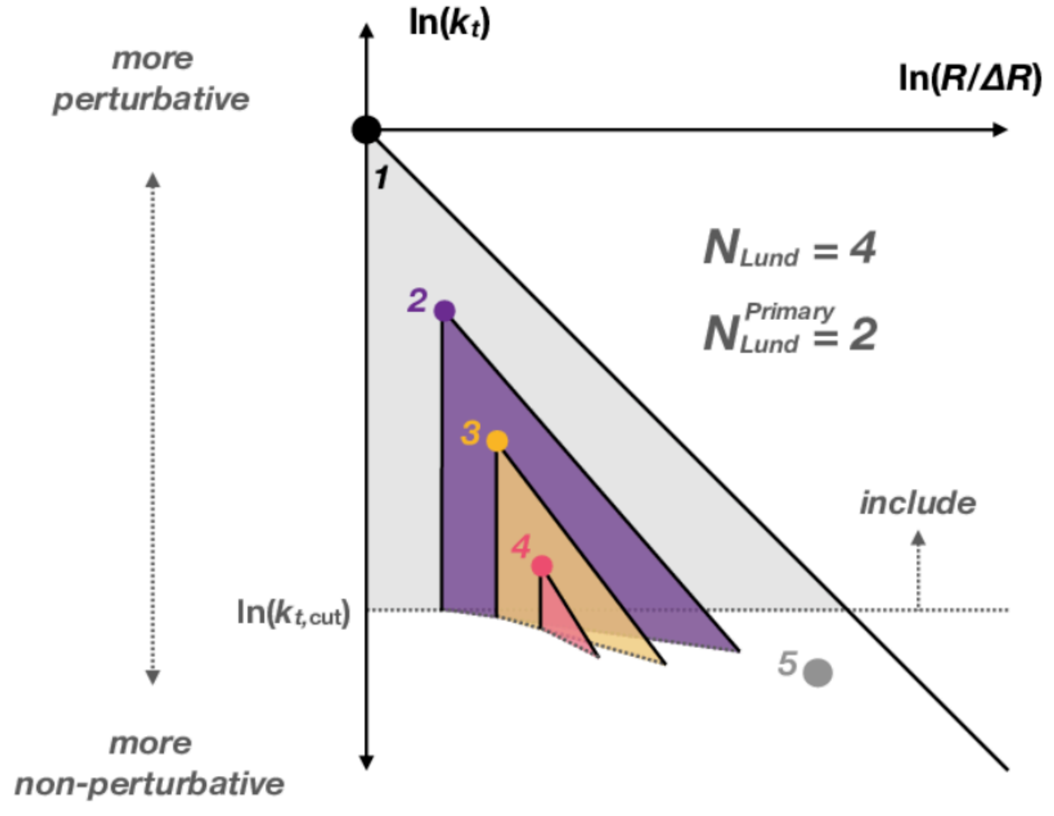

JHEP 05 (2024) 116

- Qualitative agreement between the data and the softcollinear prediction

More details on Kaustuv talk

- Lund Subjet Multiplicities




- The Lund subjet multiplicity measurement provides key inputs for validating the higher accuracy parton shower development

More details on Jingjing talk

# To finalise…

- I just presented my very biased review of the status and the latest and greatest developments. But there are other recent results I missed due to lack of time :(
- The experimental community has been very active in the last year!
- This meant to be an “amuse bouche” to get exited and stay tune for the rest of the week

# BONUS

# TOPO-CLUSTERS

Topo-clusters: 3D clusters of noise-suppressed calorimeter cells

Eur. Phys. J. C 77 (2017) 490

- Calorimeter jet **constituents**
- Baseline and most common **inputs to jet algorithm.**

**To form a topo-cluster**: Use a recursive algorithm to combine cells with related energy deposits

- Define for each cell: **significance**

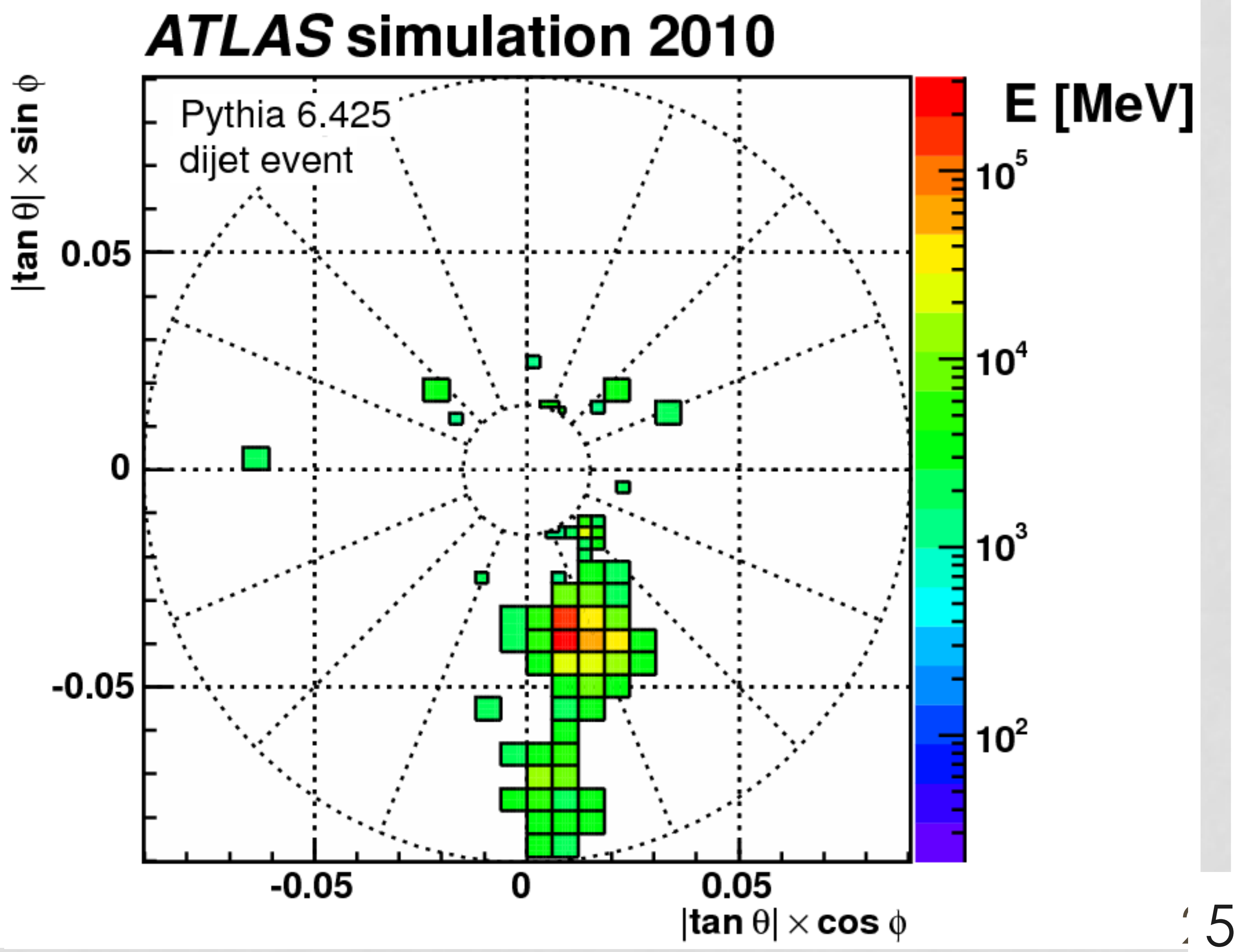
  Ratio of energy measured to expected average energy due to noise in that cell

$$\zeta^{EM}_{cell} = \frac{E^{EM}_{cell}}{\sigma^{EM}_{noise,cell}}$$

## Clustering algorithm

- Clusters are **seeded** by cells with large energy over noise ratio
  - $|\zeta|>4$

Seed cells



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Eur. Phys. J. C 77 (2017) 490

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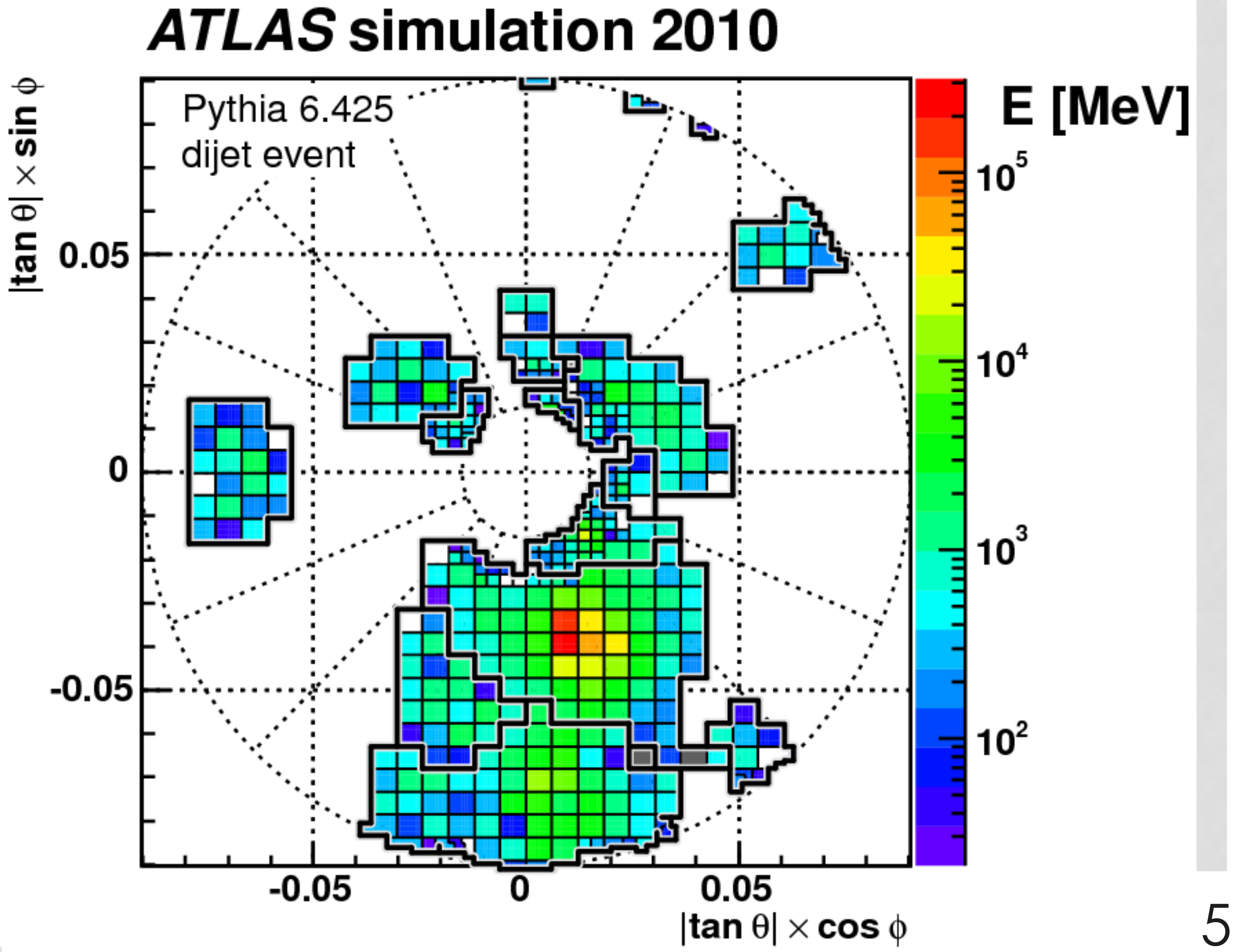
  Ratio of energy measured to expected average energy due to noise in that cell

$$\zeta_{cell}^{EM} = \frac{E_{cell}^{EM}}{\sigma_{noise,cell}^{EM}}$$

## Clustering algorithm

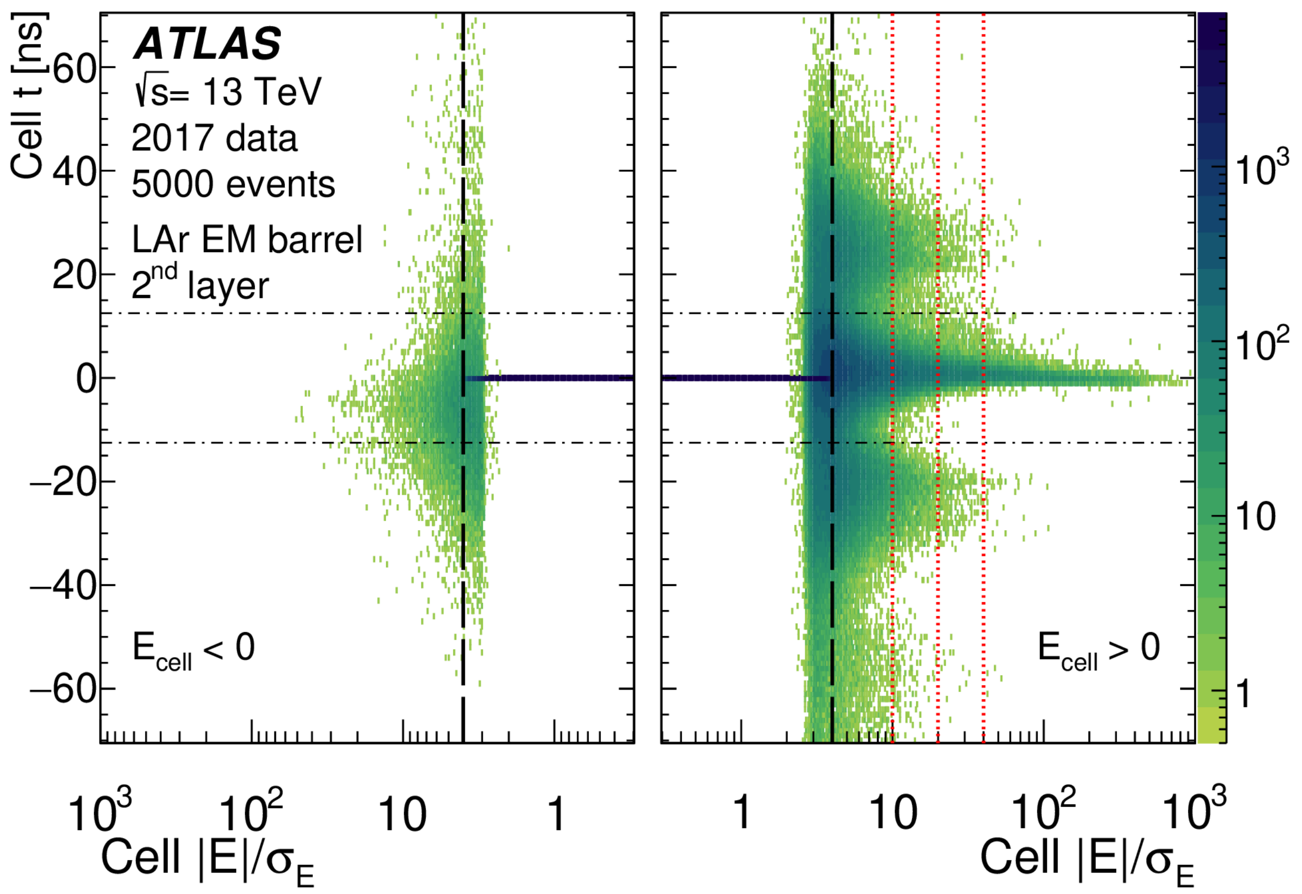
- Clusters are **seeded** by cells with large energy over noise ratio
  - $|\zeta|>4$
- Expanded on neighbouring cells
  - All **Neighbors** with $|\zeta|>2$ are added
- **All neighbouring** cells are added regardless of the significance
  - $|\zeta|>0$
- Final cluster splitting step breaks up large topo-clusters with multiple local maxima

Boundary cells

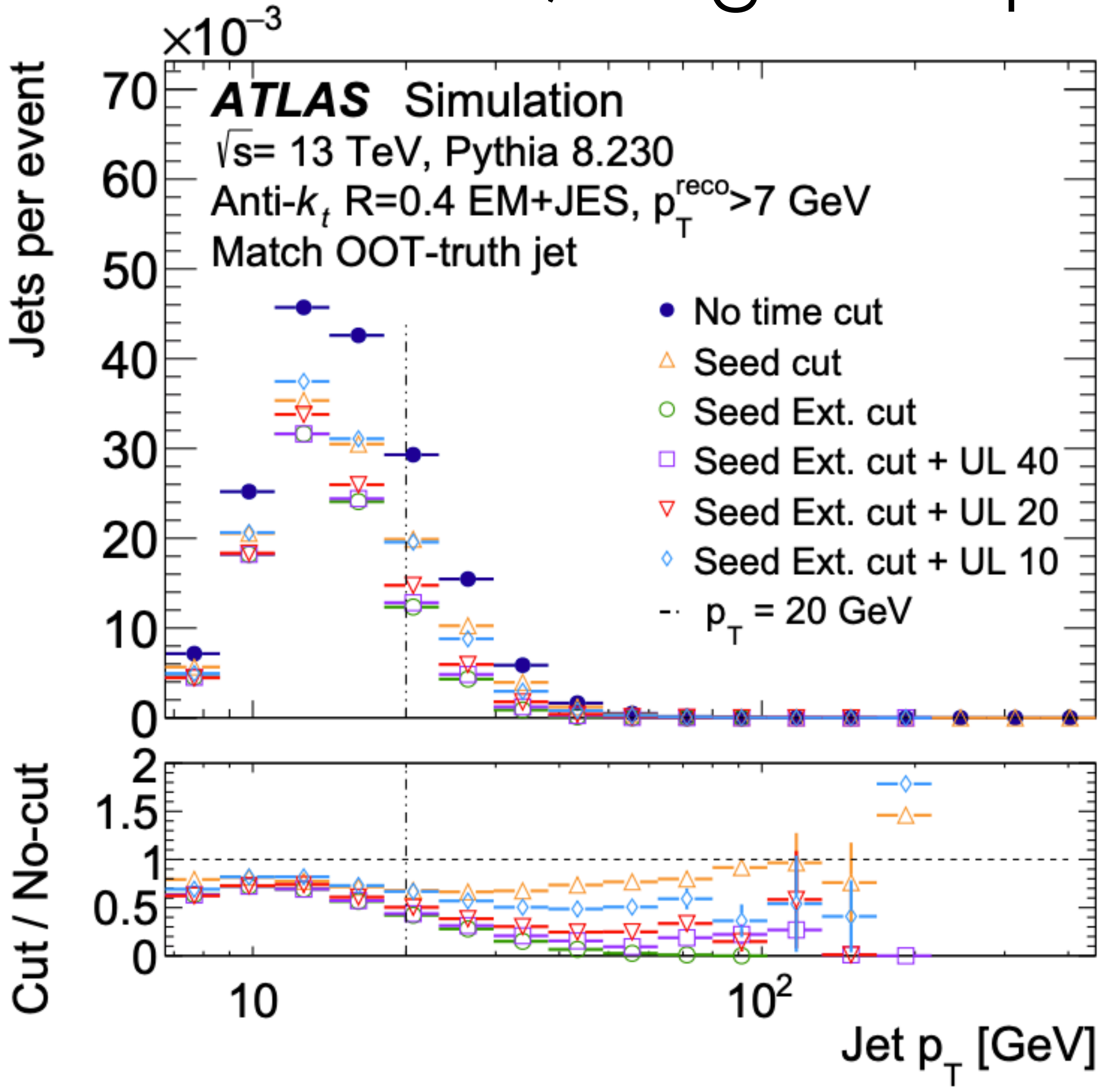


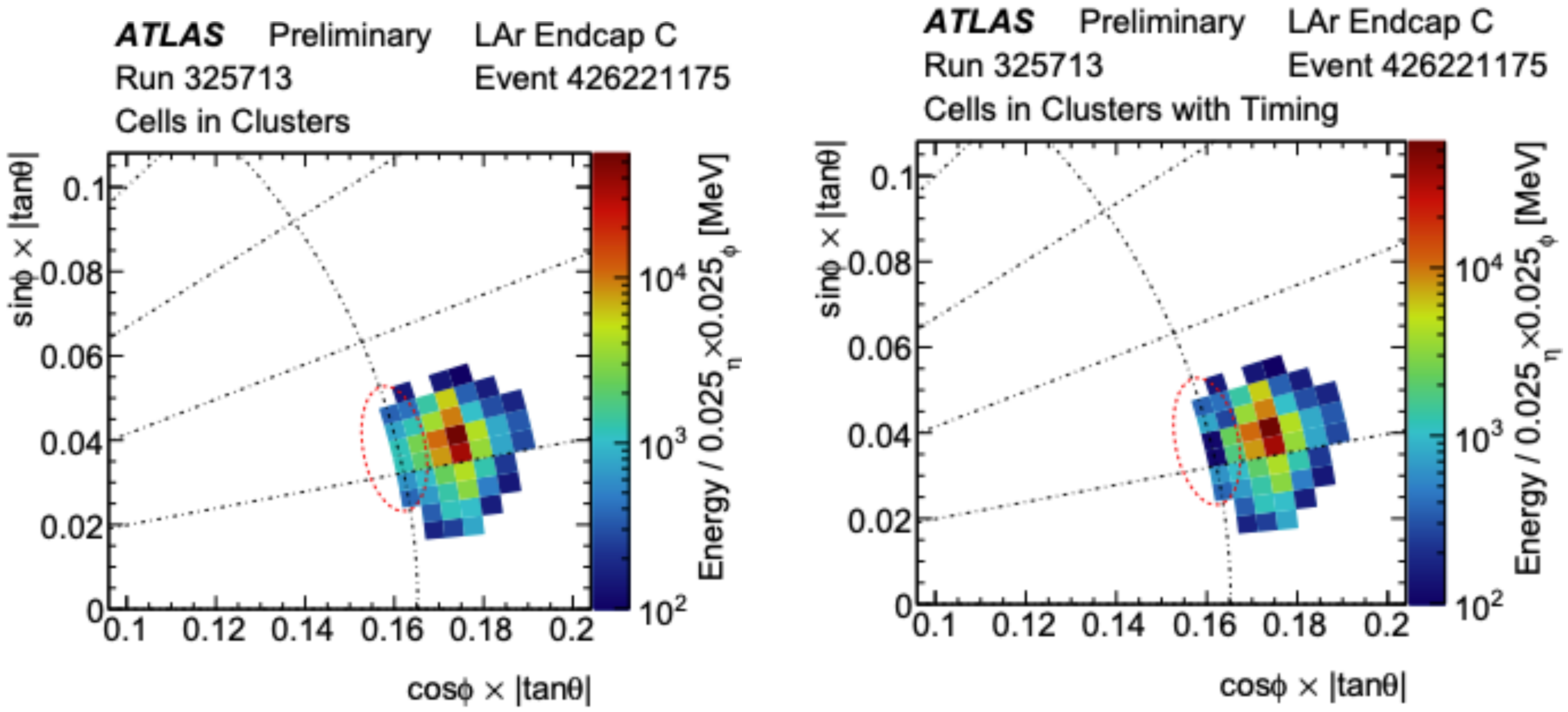
# Time as a new discriminant

- Calorimeter topo clustering is based on the cell energy significance $\zeta_{cell}^{EM} = \frac{E_{cell}^{EM}}{\sigma_{noise,cell}^{EM}}$




- Cell-time information as additional discriminator:
  - Cut at |t| < 12.5 ns for any cell that has | E| > 4σ
  - But restrict the time cut to those cells with E < 20σ
    - to keep significant, positive energy deposits that are out-of-time (searches for exotic, long-lived particles)



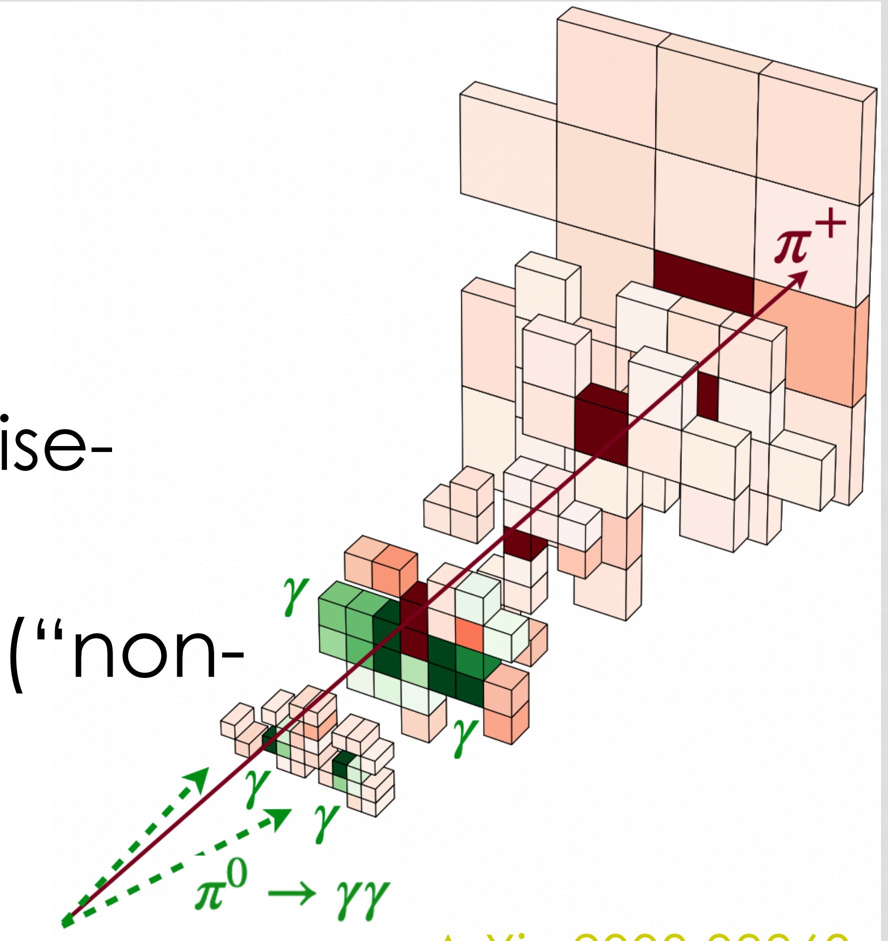




- suppresses out-of-time jets while retaining in-time signals: about -50% at pT =20 GeV and -80% for pT>50 GeV

# Jet Inputs: Local Hadronic calibration in ATLAS

**Reconstruct jets**

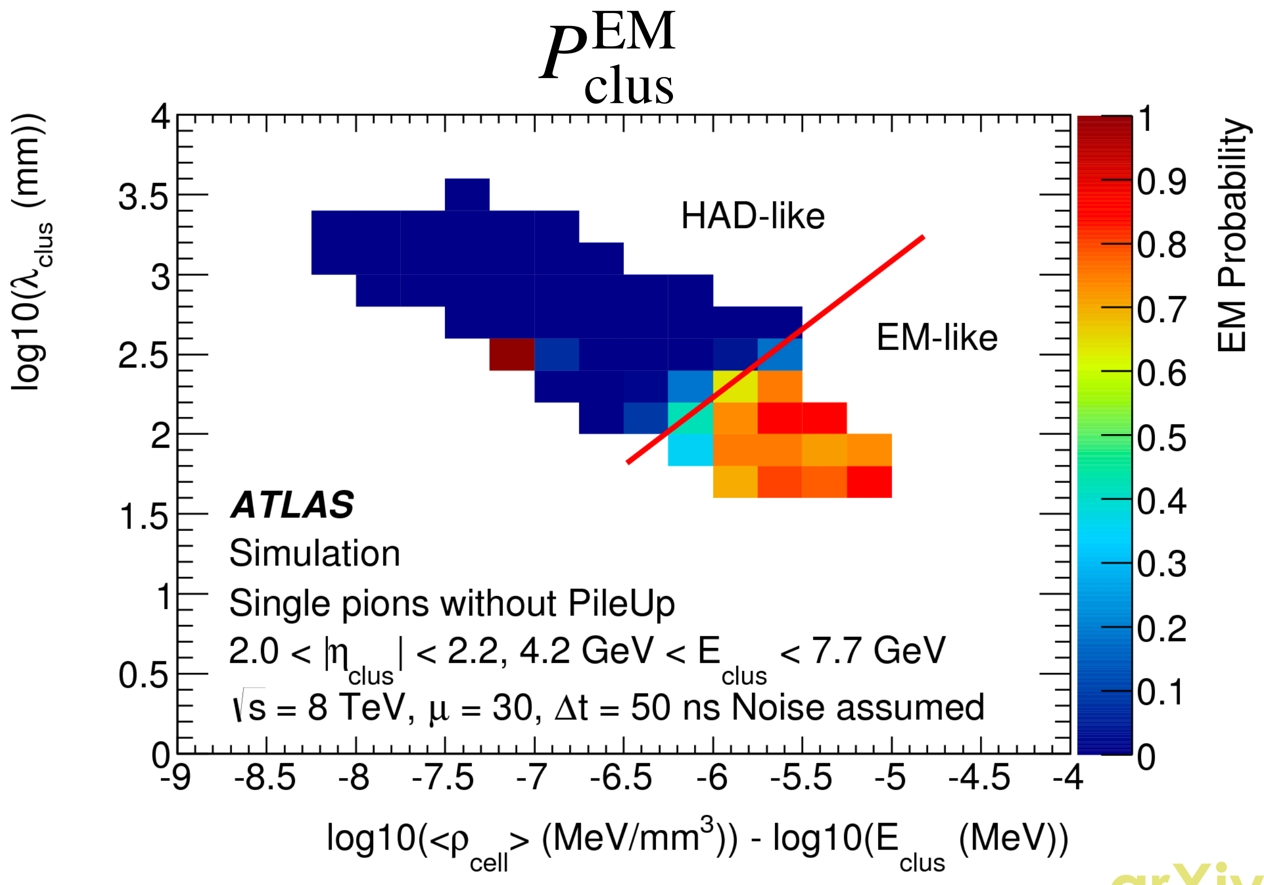
- Hadronic showers are mostly composed of pions
  - $\pi^0$: Captured by the **electromagnetic** calorimeter
  - $\pi^{\pm}$: Require the dense material in the **hadronic** calorimeter to be stopped
- **Topo-clusters**: Baseline inputs for hadronic reconstruction, uses clusters of noise-suppressed calorimeter cells.
  - Different detector response and measurement for $\pi^0$ vs. $\pi^{\pm}$ showers ("non-compensating calorimetry")

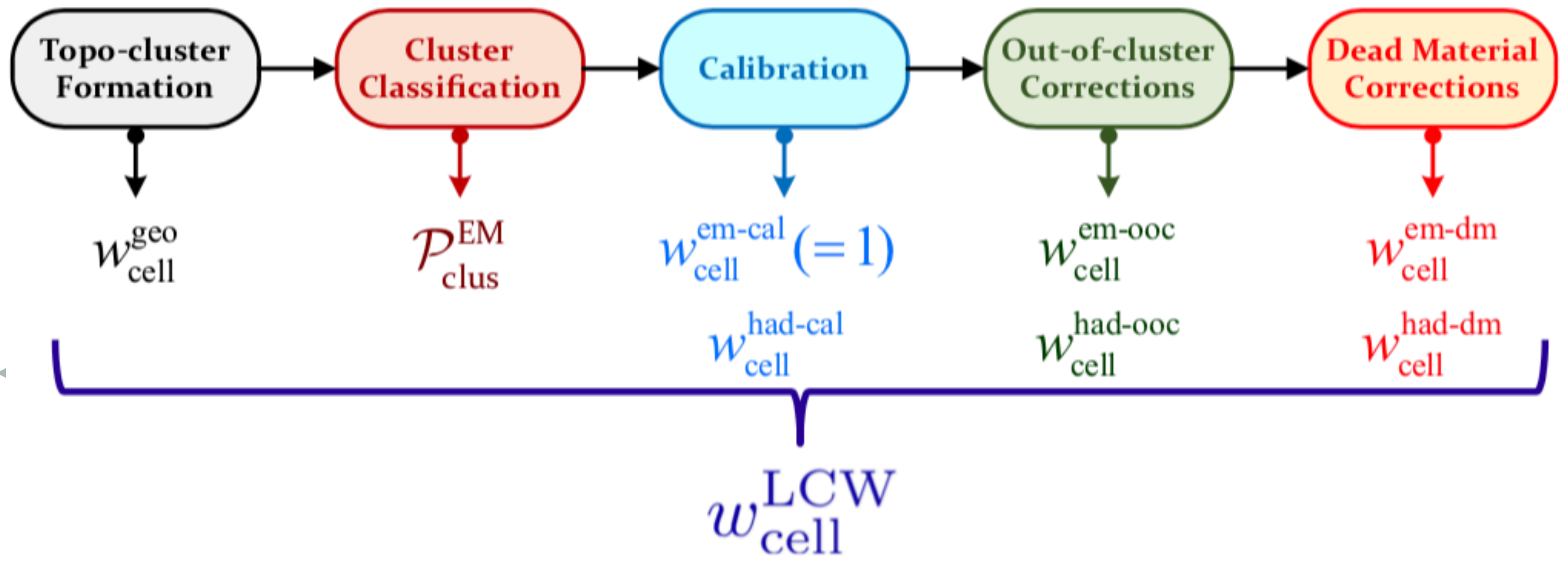



ArXiv:2003.08863

- **Topo-cluster calibration: Local Cell Weighting (LCW)**

1. **Classify** as **electromagnetic** or **hadronic** calculating the EM probability $\mathcal{P}^{\mathrm{EM}}_{\mathrm{clus}}$
2. **Calibrate** its energy to account for differences in response.




$$E^{\mathrm{LCW}}_{\mathrm{clus}} = \sum_{i \in \mathrm{cluster}} w^{\mathrm{LCW}}_{\mathrm{cell},i} \, E^{\mathrm{EM}}_{\mathrm{cell},i}$$

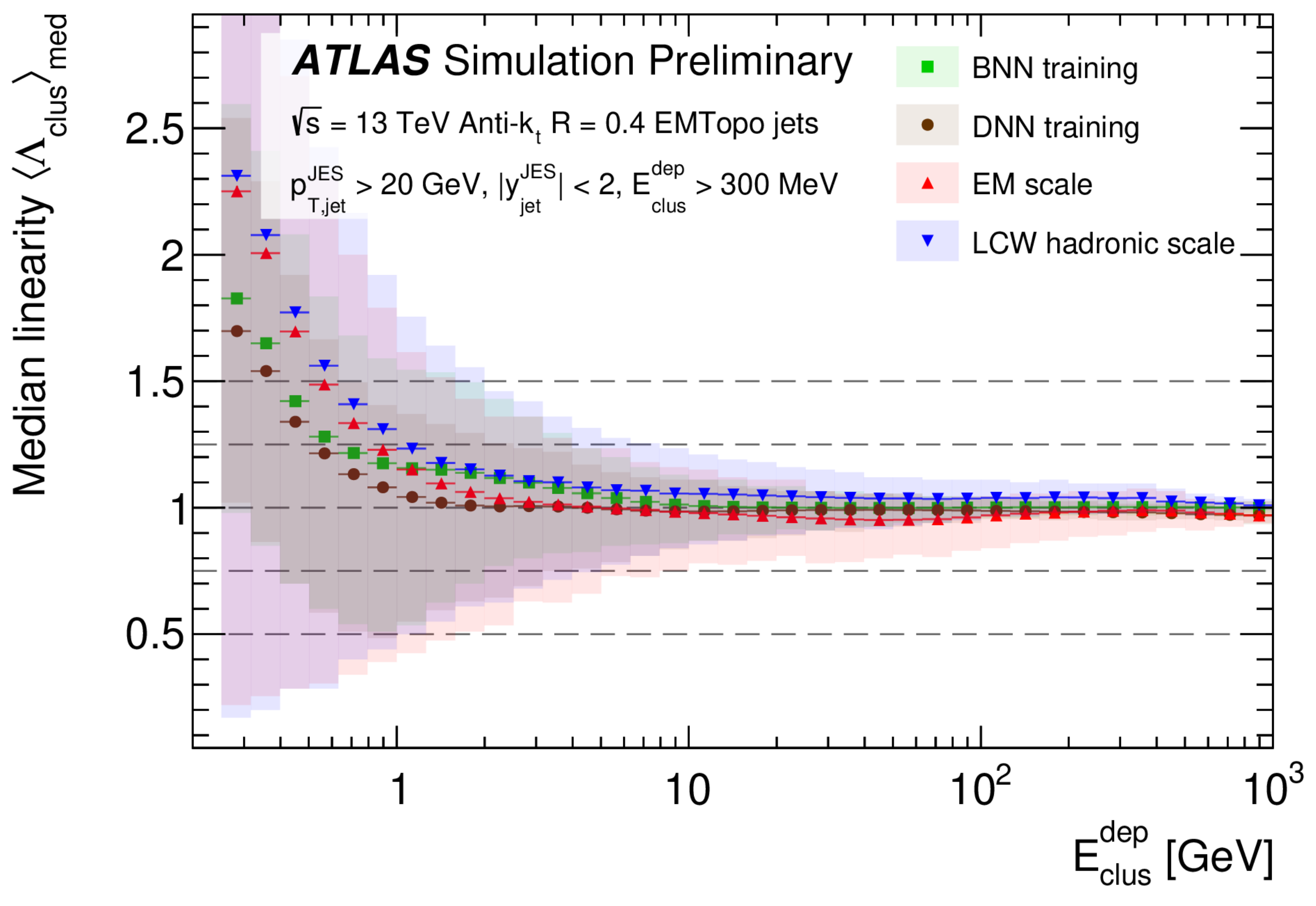
arXiv:1603.02934

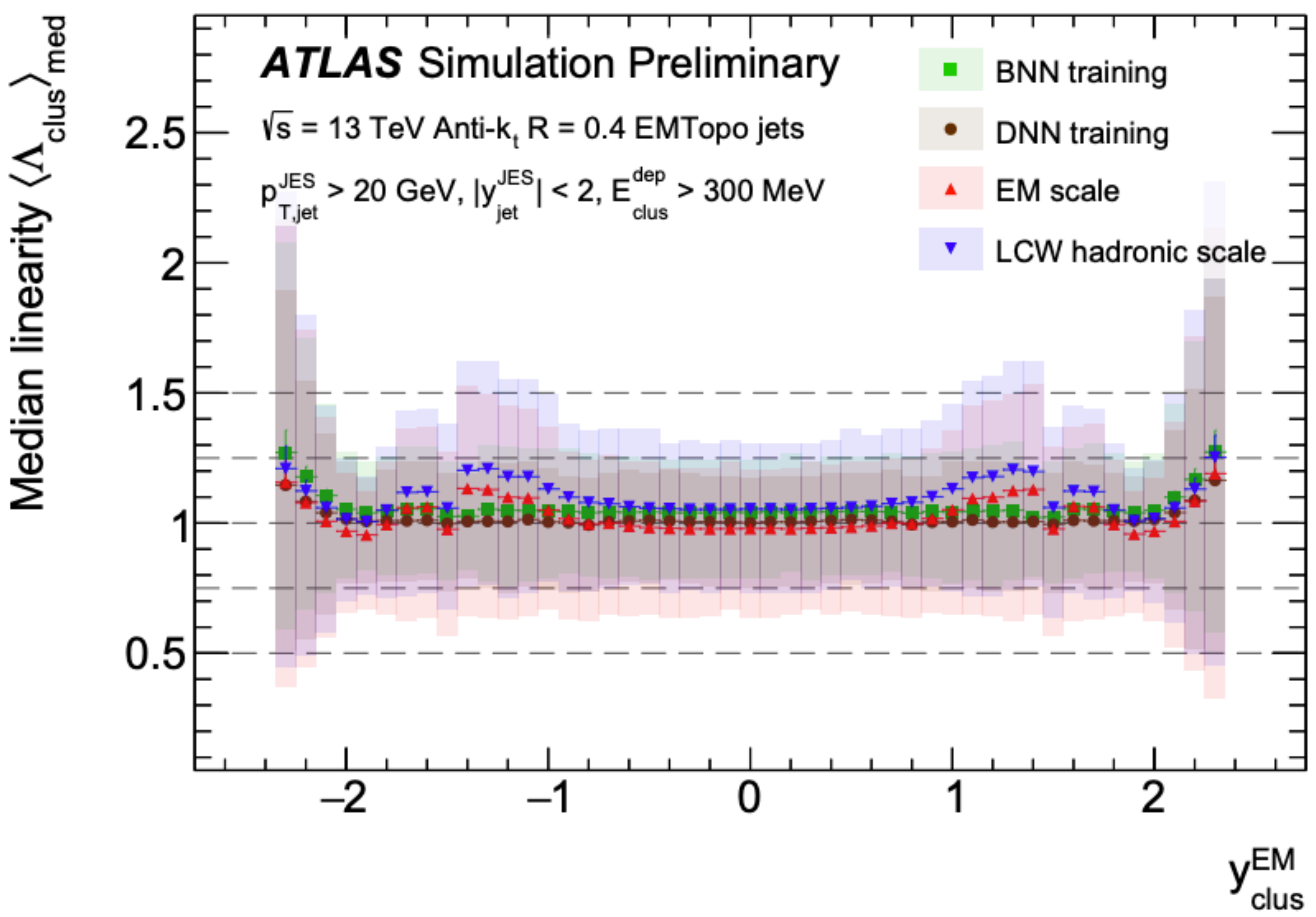
# Cluster Calibration with ML

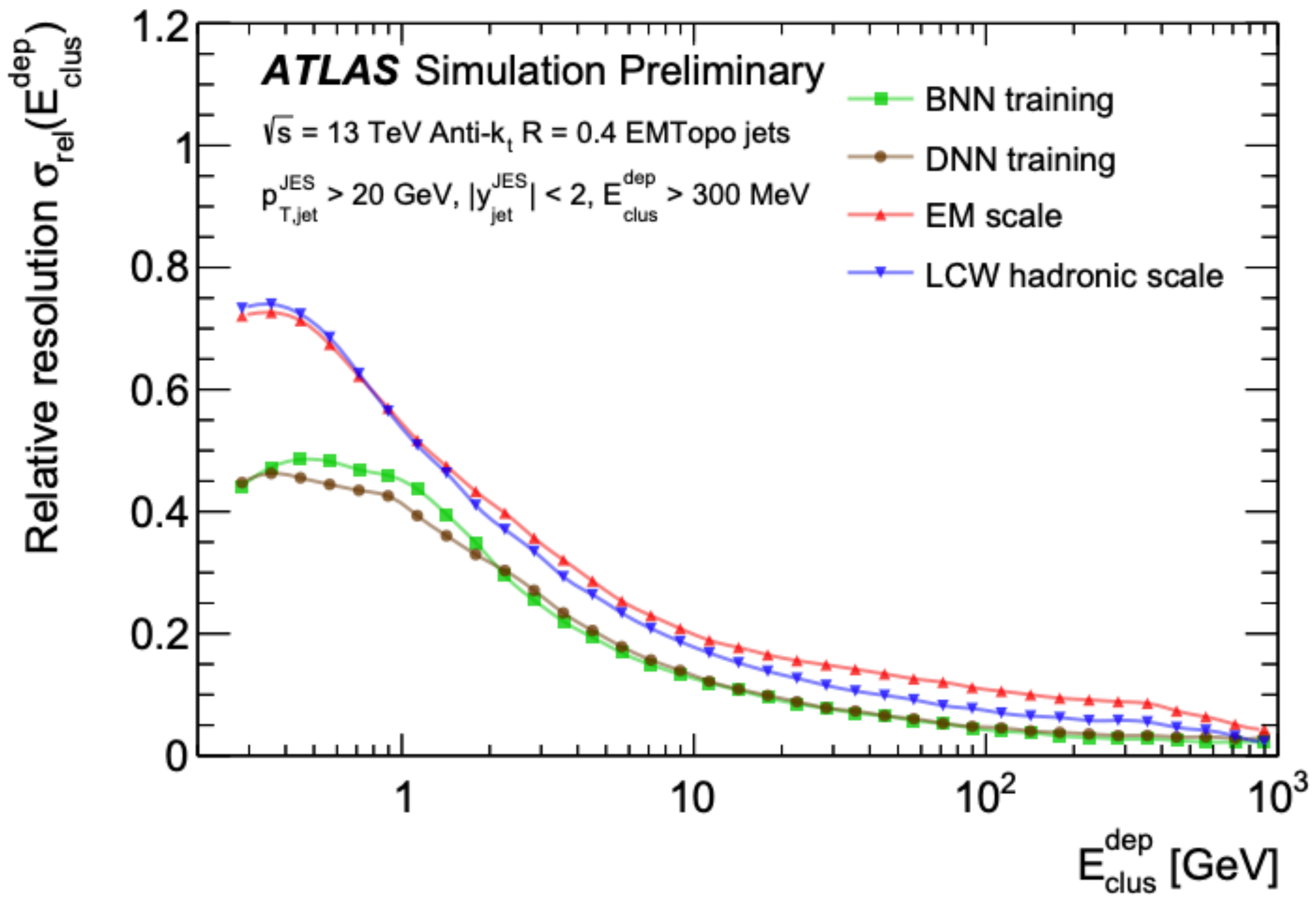
ATL-PHYS-PUB-2023-019

- Idea: Apply machine learning to Local Hadronic Calibration
  - to explore the applicability of neural networks to calorimetric calibration
  - so far done with the first of the three correction steps (non-compensation) and implicit classification

- Architecture
  - Using a regression technique, with similar input features as the ones used in LCW and also mu and NPV to include pileup information.
  - Deep and Bayesian Neural Networks (DNN, BNN)
  - DNN performs better than BNN.



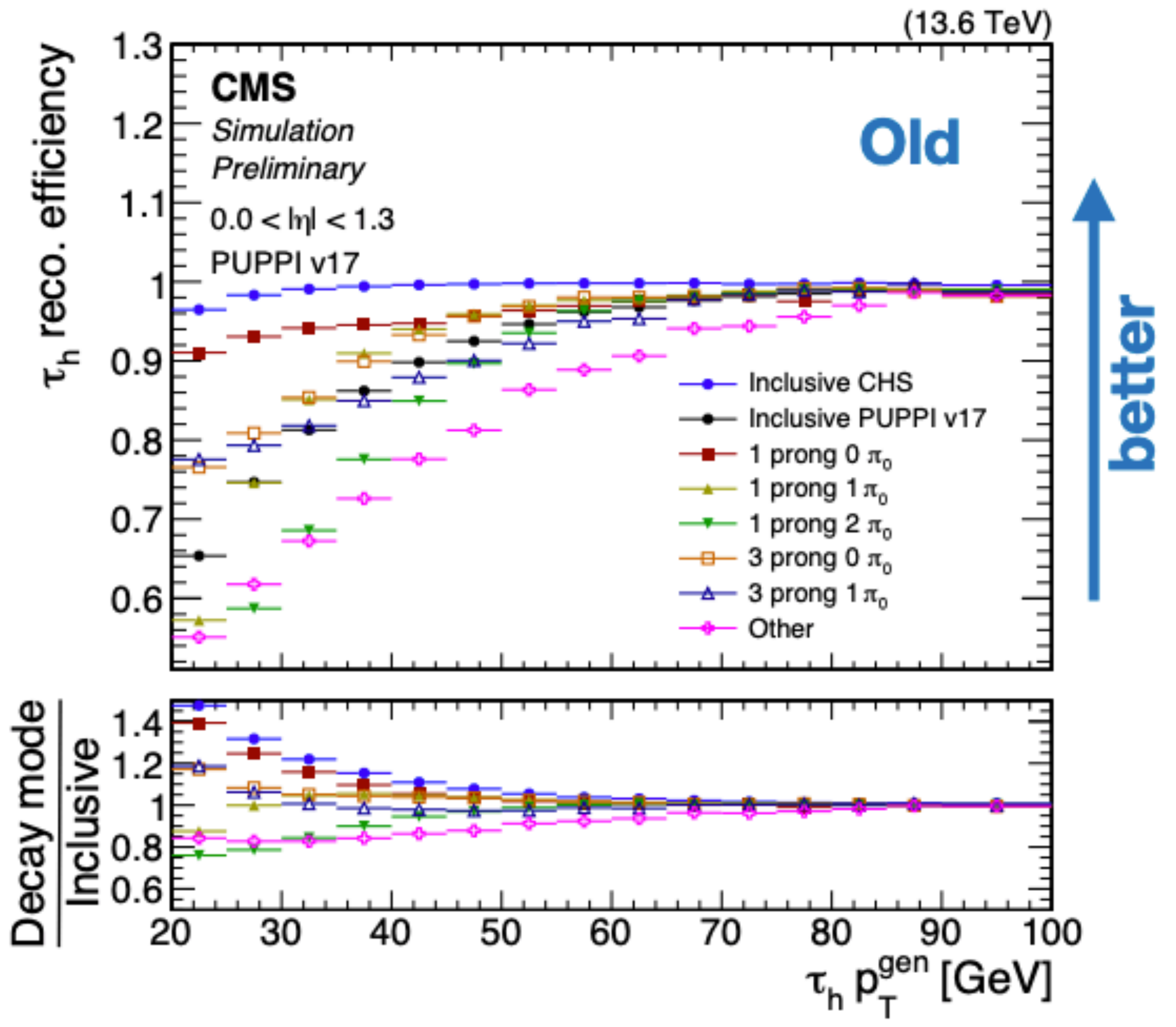



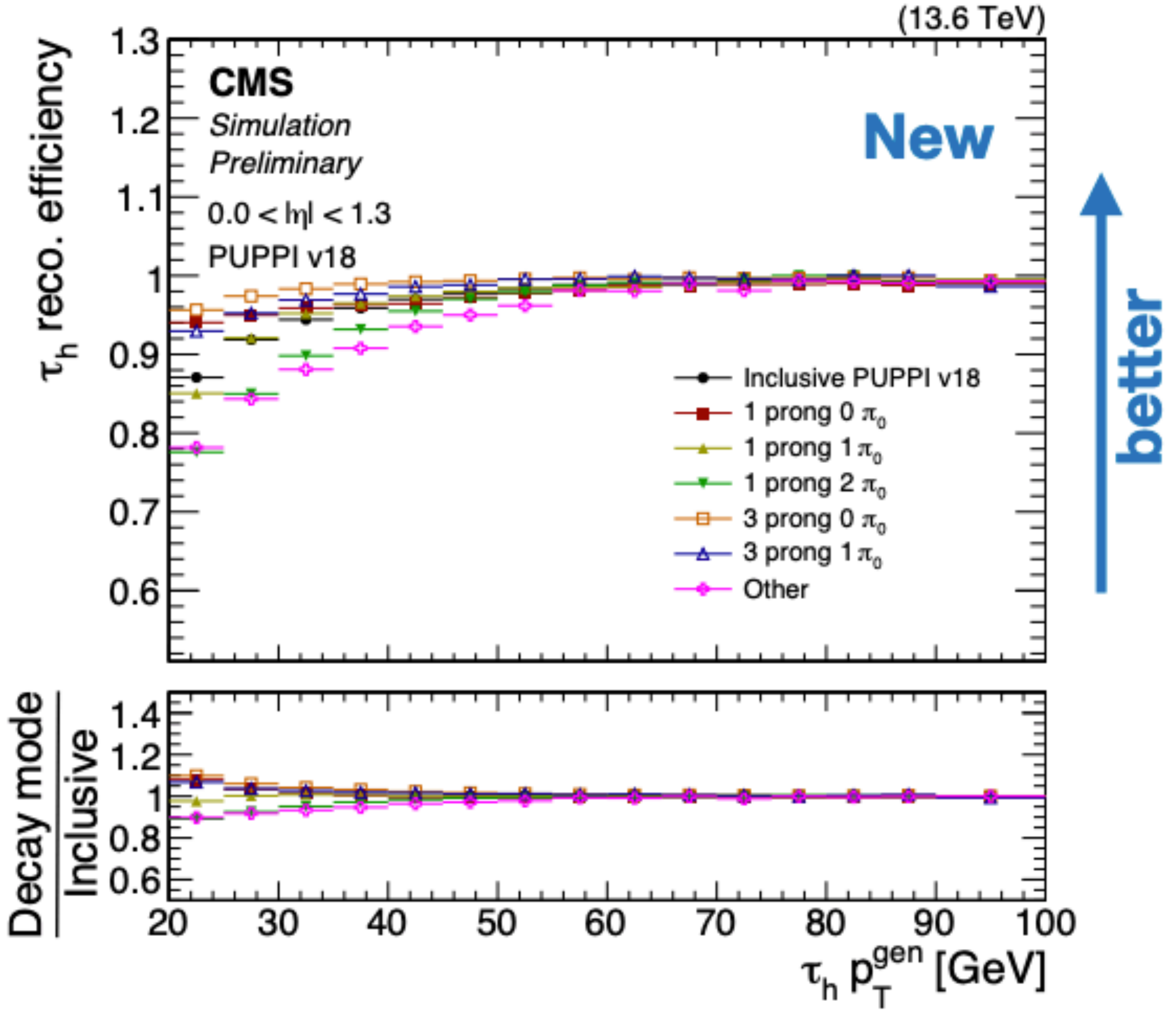



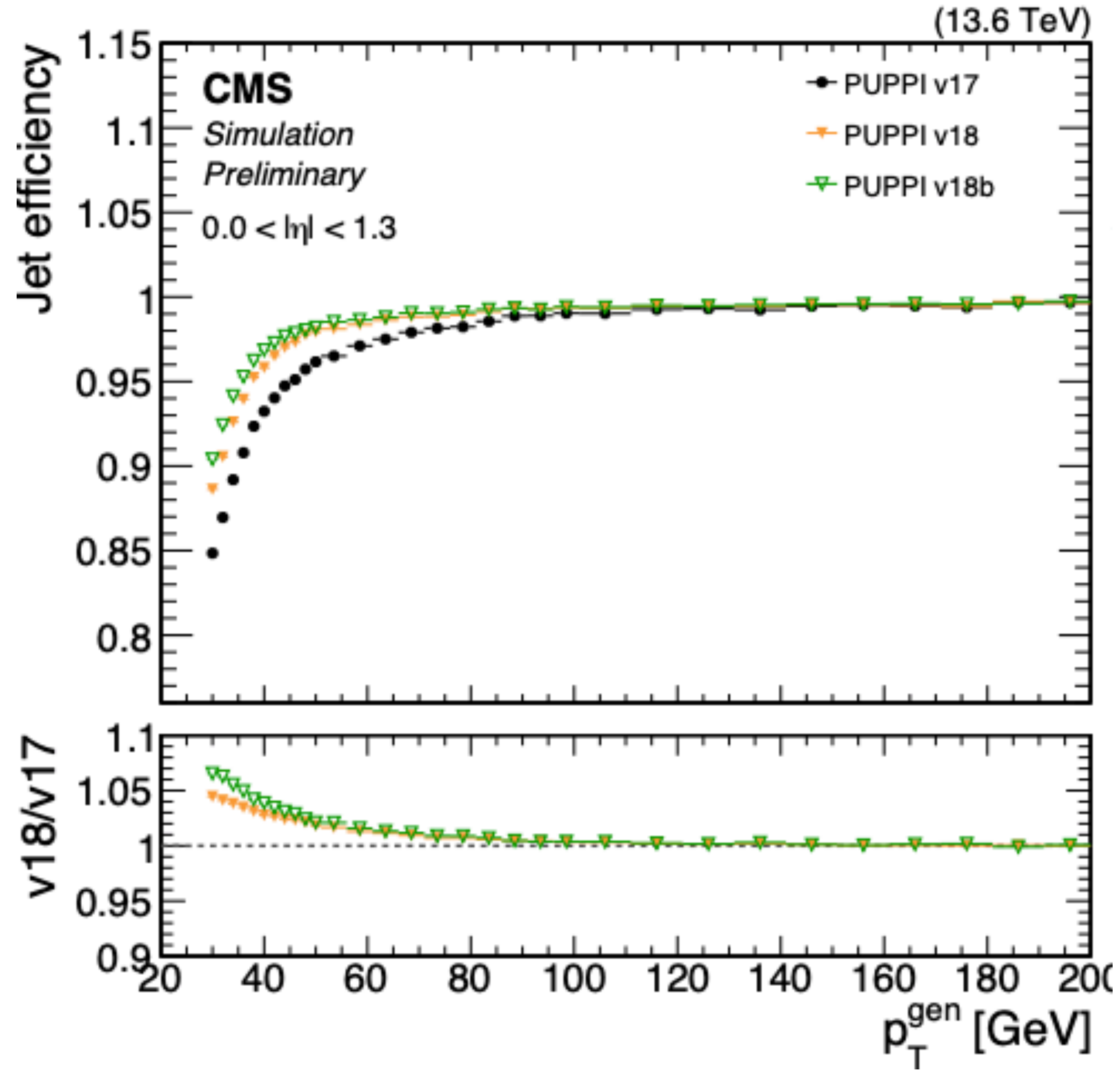

- Ratio of the calibrated energy over the deposited energy

# Optimisation of PU mitigation technique for $\tau_h$ identification

- PUPPI showed an inefficiency wrt to CHS at low pT
  - optimized track-vertex association (PUPPI v18)




- number of matched jets over the number of particle-level taus

- Fraction of particle-level jets with > 30 GeV that match within ΔR < 0.2 with a reconstruction-level jet with > 20 GeV.

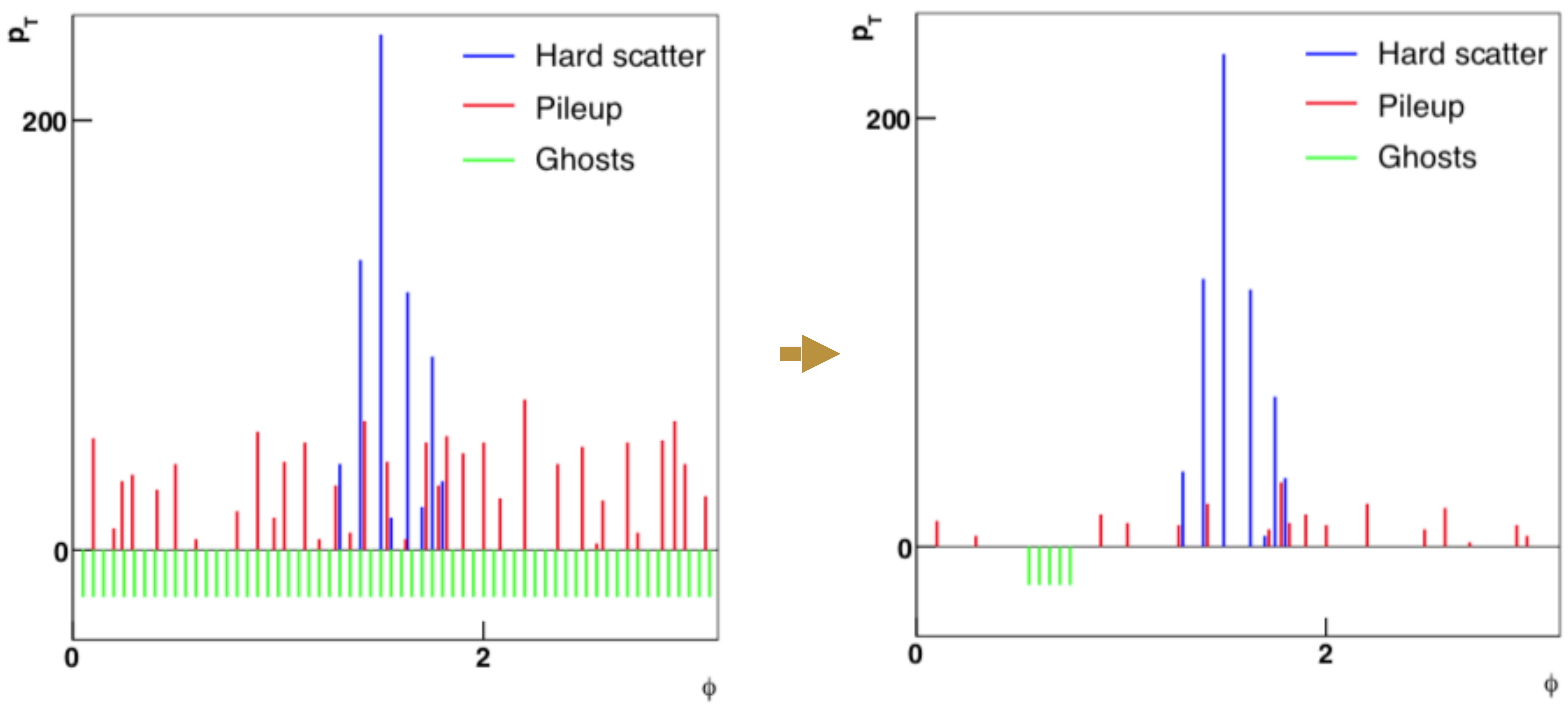
https://cds.cern.ch/record/2904356/files/DP2024_043.pdf

# CONSTITUENT SUBTRACTION (CS)

JHEP 1406 (2014) 092

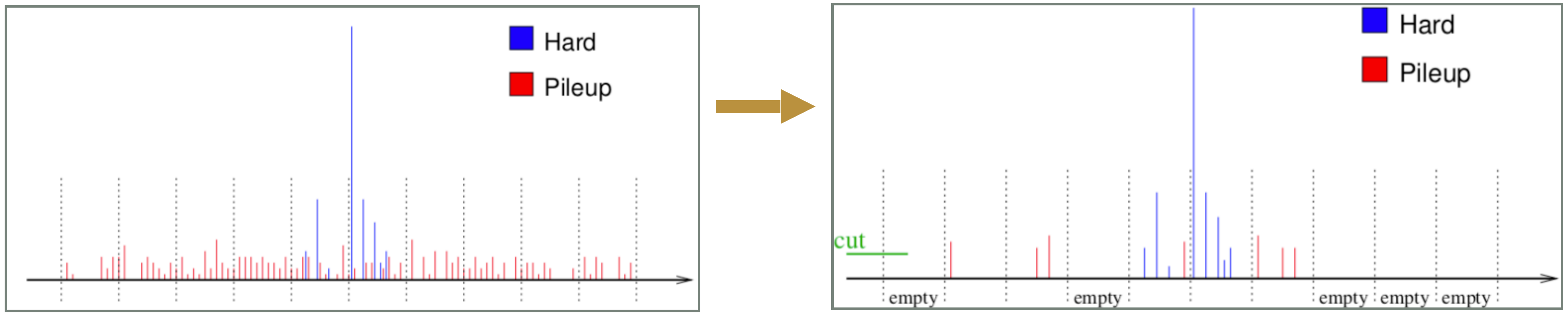
- A "constituent area" subtraction
- Add ghosts to the event with $p_T^g = A_g \times \rho$
  - $A_g$ is the area of the ghost (fixed $\Delta\eta \times \Delta\phi = 0.1 \times 0.1$)

- Subtract ghost's contribution from pT of closest constituent (in $\Delta R$)
  - Until $\Delta R$(ghost, constituent) > $\Delta R_{max}$
  - Algorithm built so that constituent's pT never goes negative



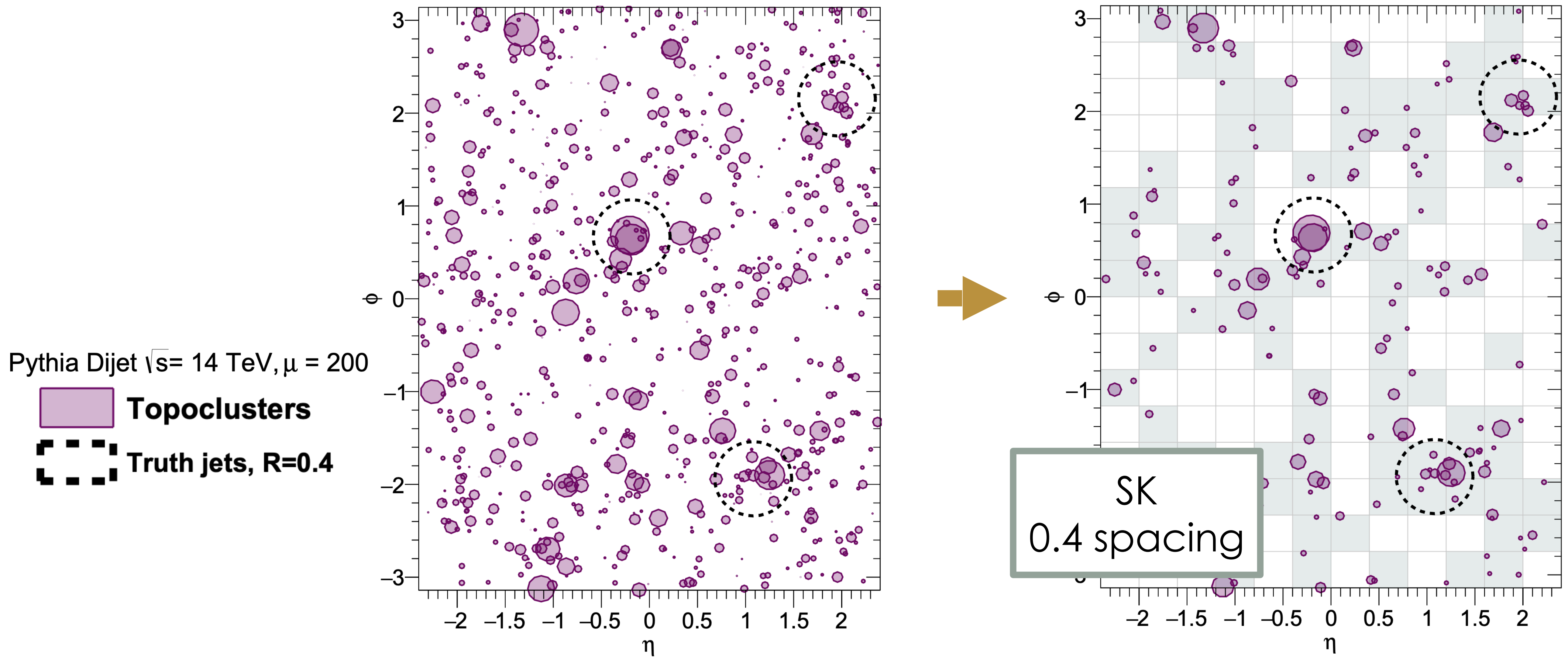
# SOFT-KILLER (SK)

- Removes low-$p_T$ constituents
- Applying a $p_T$ cut on particles on an event-by-event basis
- $p_T$ cut determined by putting constituents into an $\eta$-$\varphi$ grid, and requiring half of grid spaces to be empty after the cut




- Soft-Killer does not change remaining constituent's momenta
  - Combined with 'area' based correction (Vonoroi or CS)

ATLAS-CONF-2017-065



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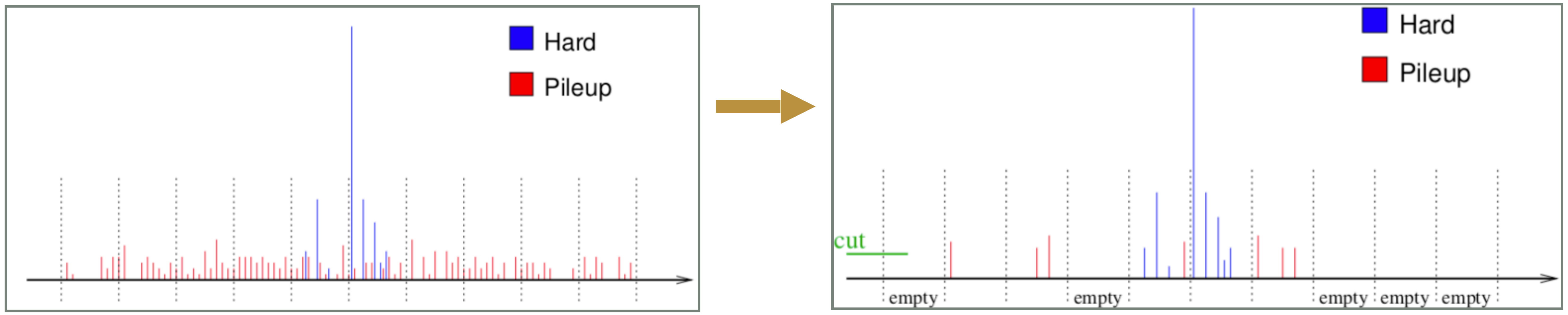


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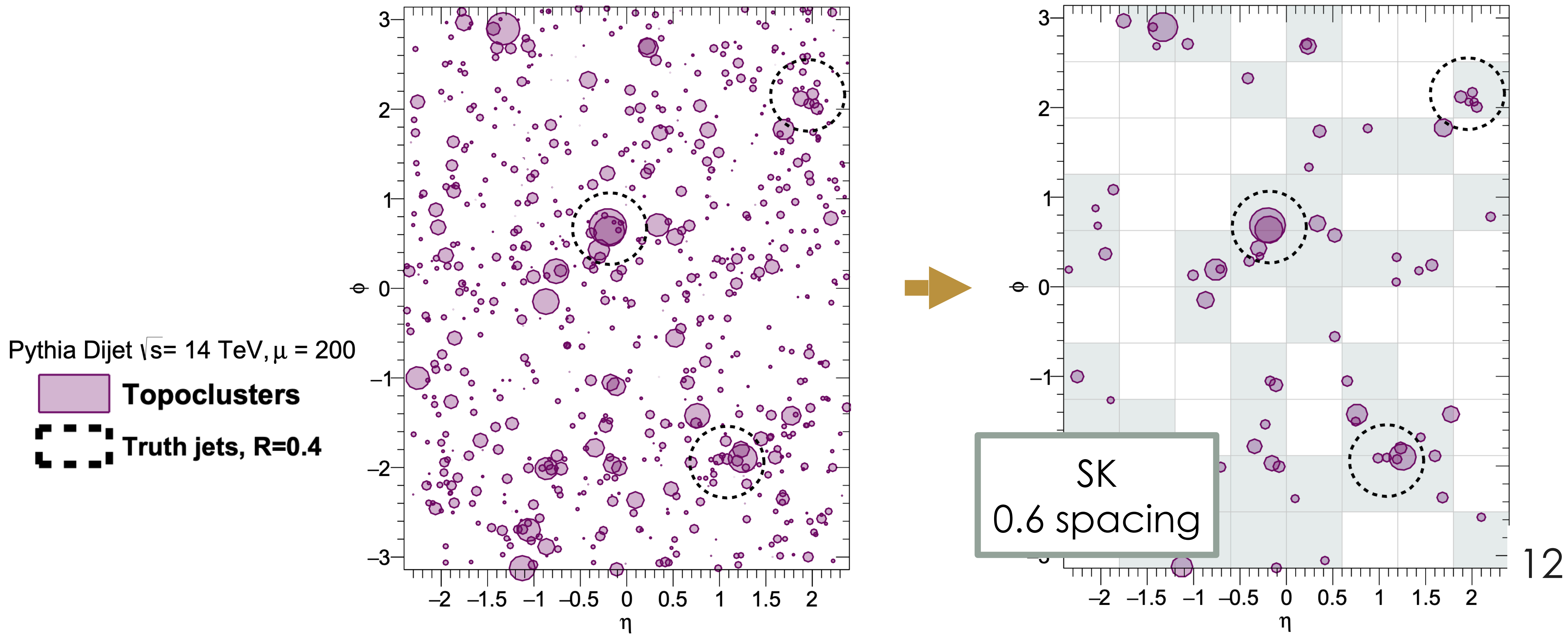
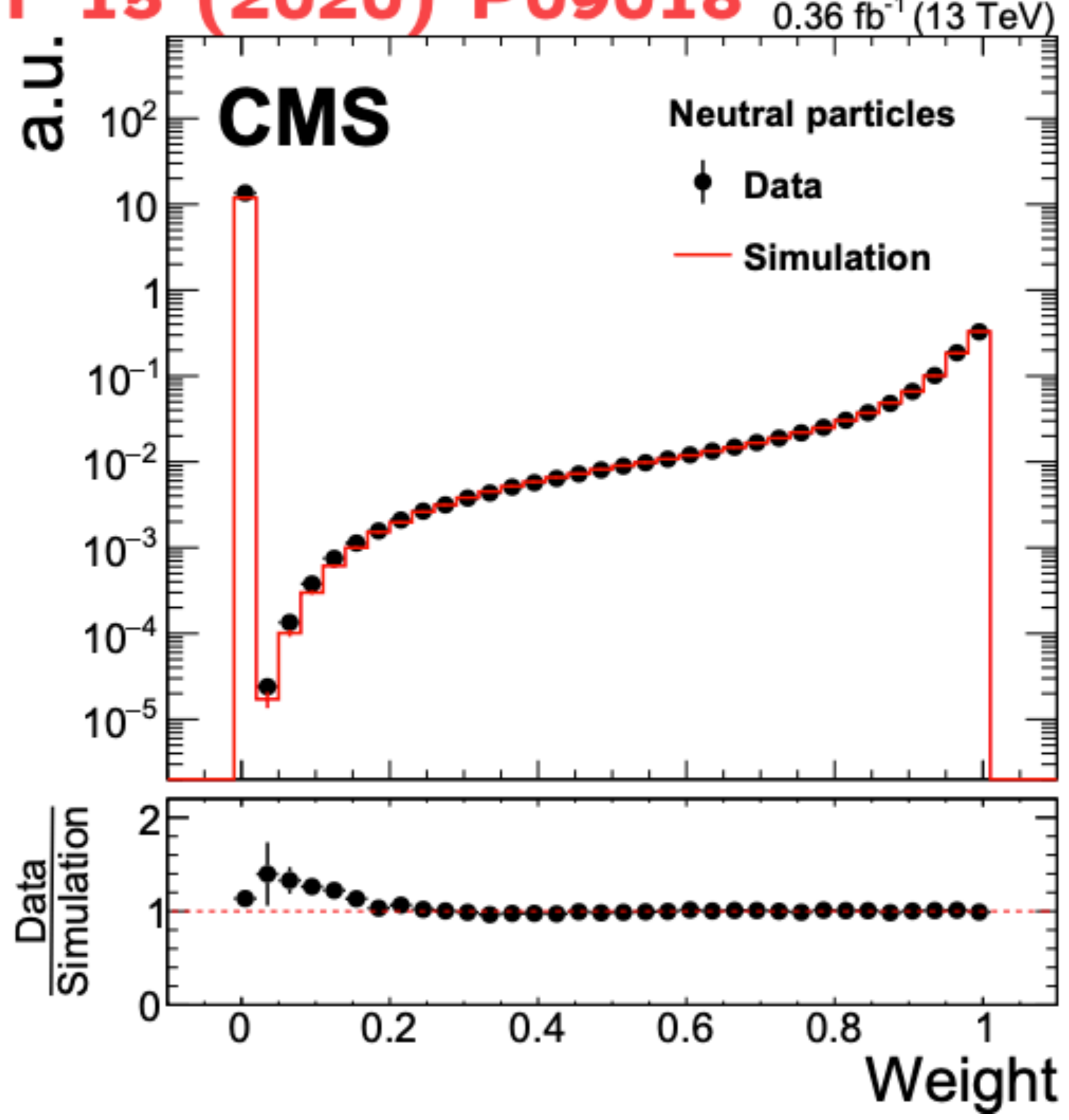
ATLAS-CONF-2017-065

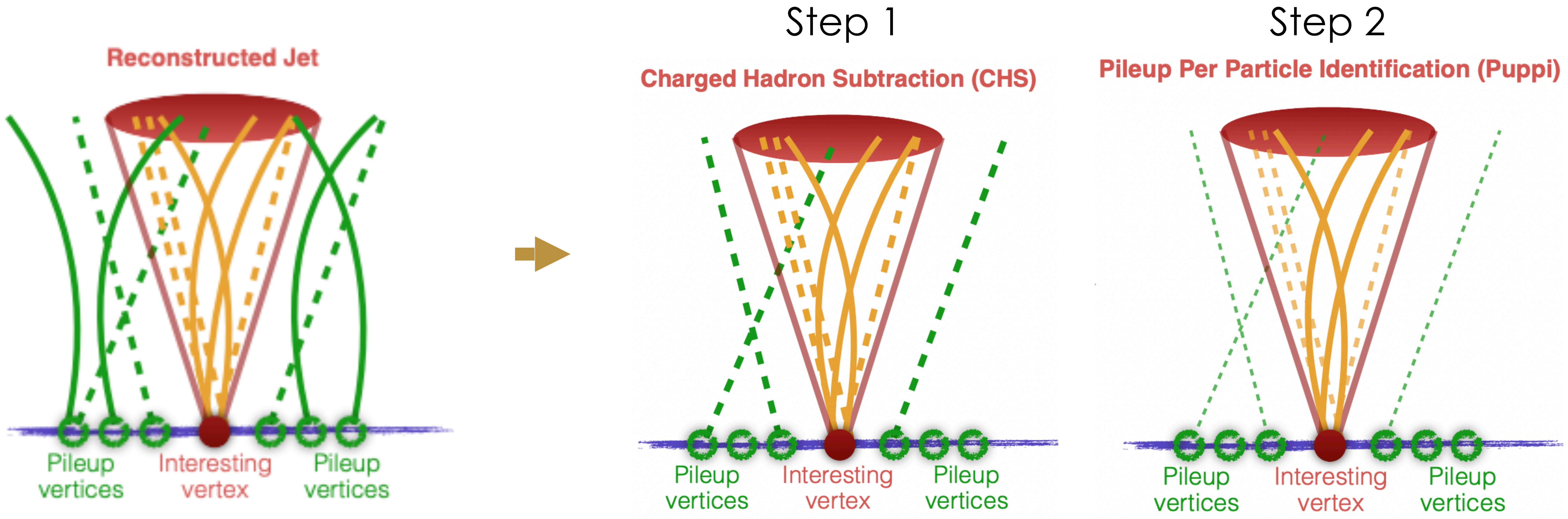


# PILE UP PER PARTICLE IDENTIFICATION: PUPPI

- Per-particle weight for each neutral particle related to the likelihood this particle to originate from PU or not
- Scale 4-momentum for neutral particles before clustering
- Charged particles similar to CHS
- Baseline PU suppression in CMS

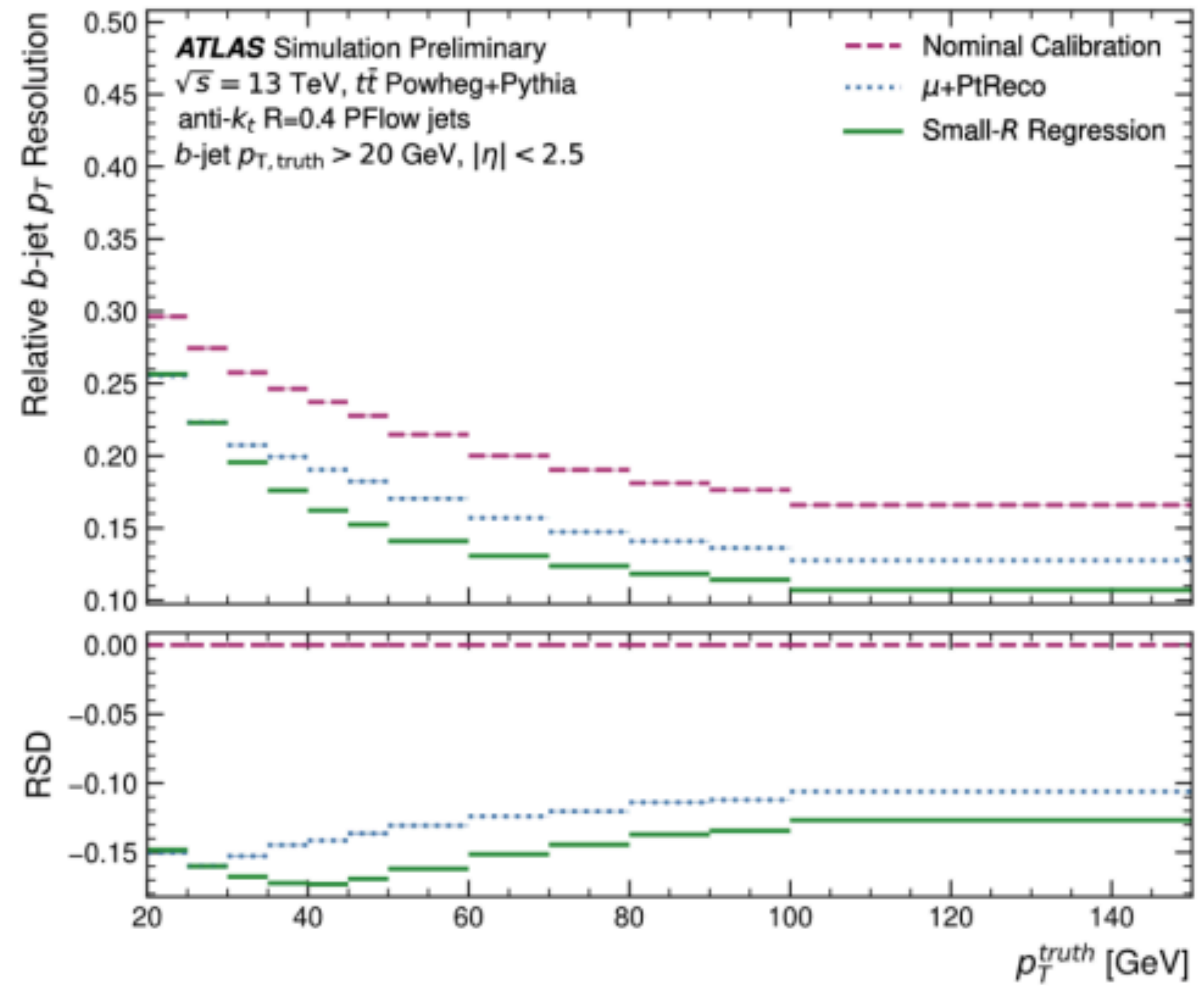
JINST 15 (2020) P09018

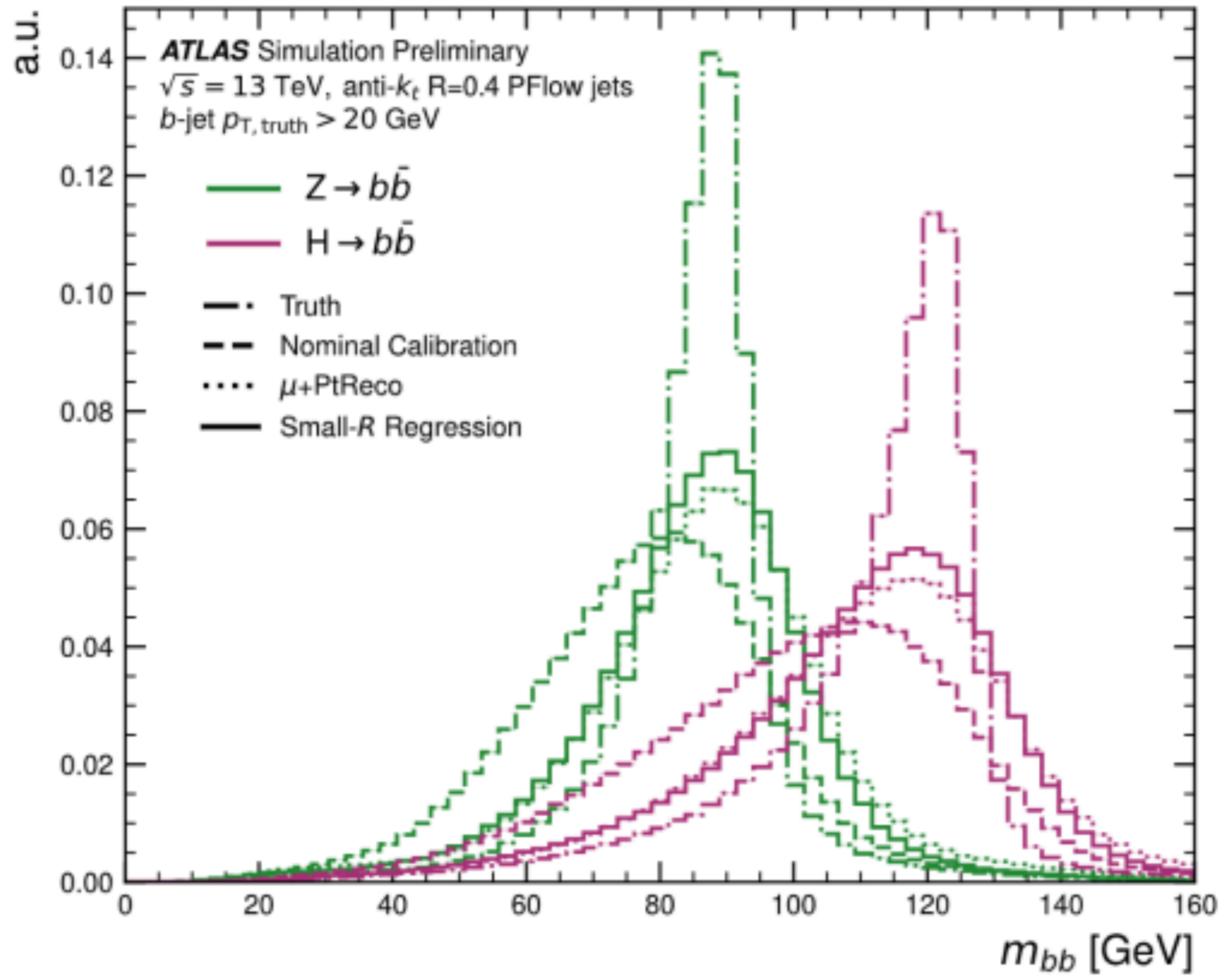


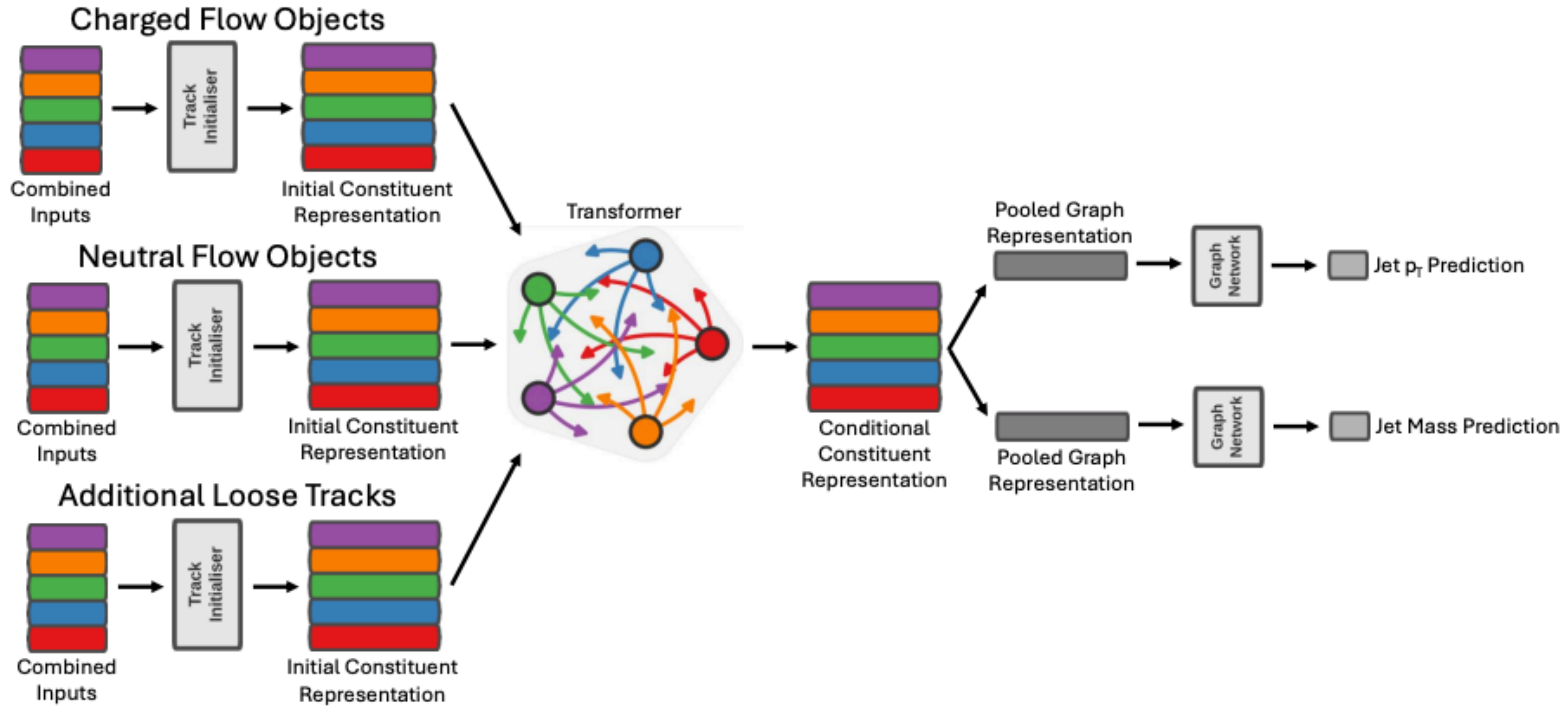



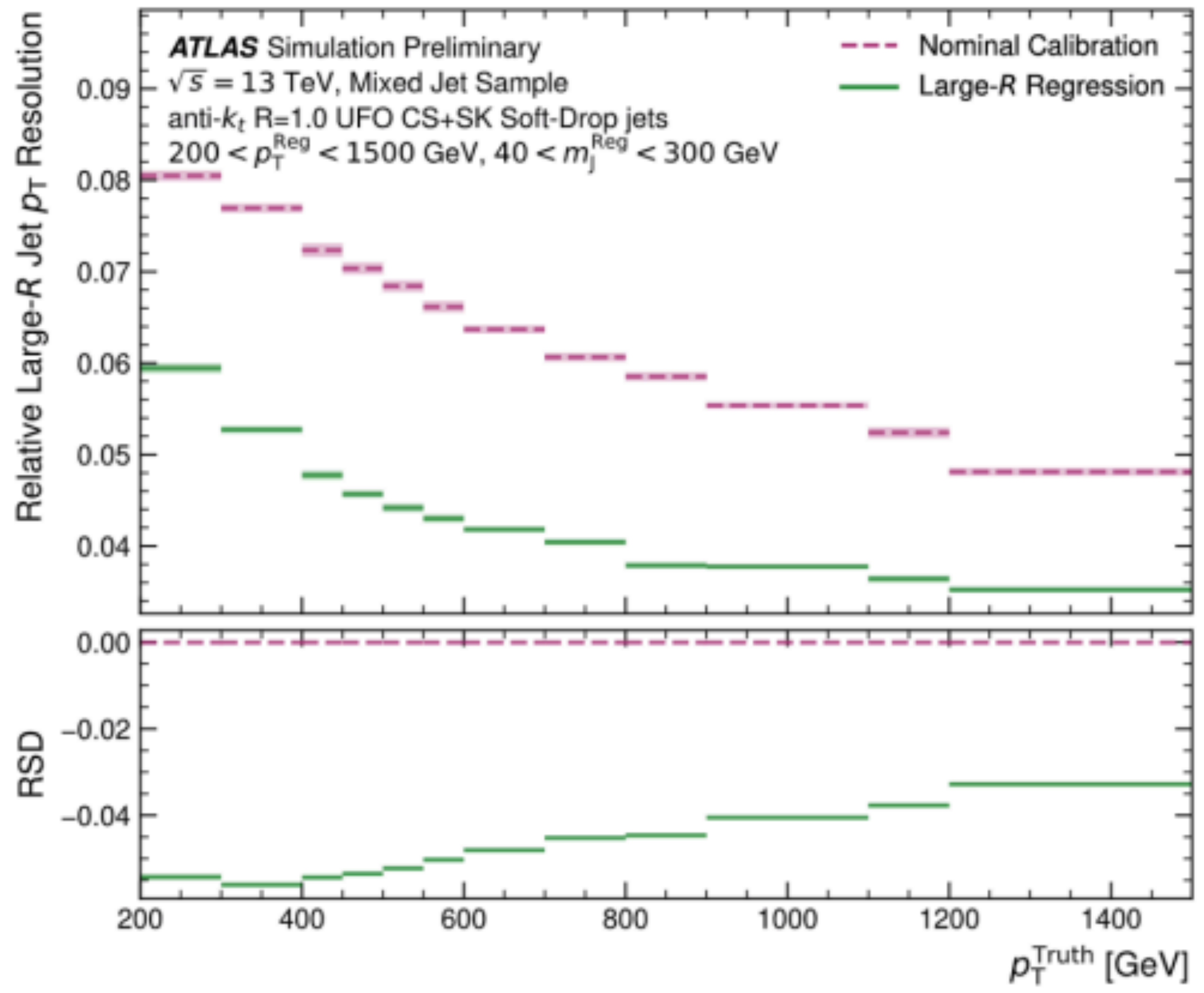
# b-JES calibration

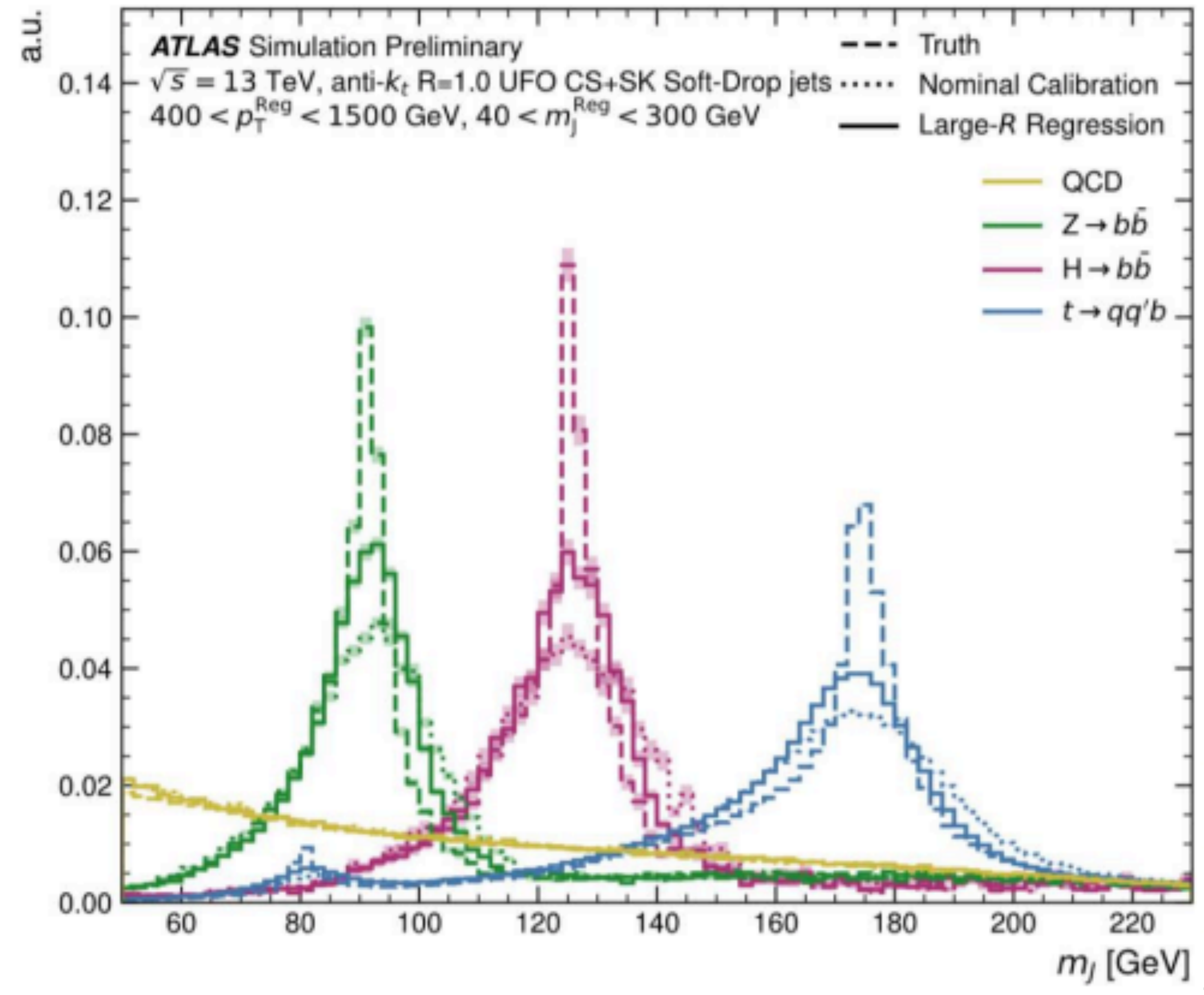
- b-jets differ from light quark and gluon jets due to high mass and large semileptonic branching fraction
- Transformer architecture
  - Target: Truth/Reco Ratio
    - Small-R: Only pT
    - Large-R: Mass and pT



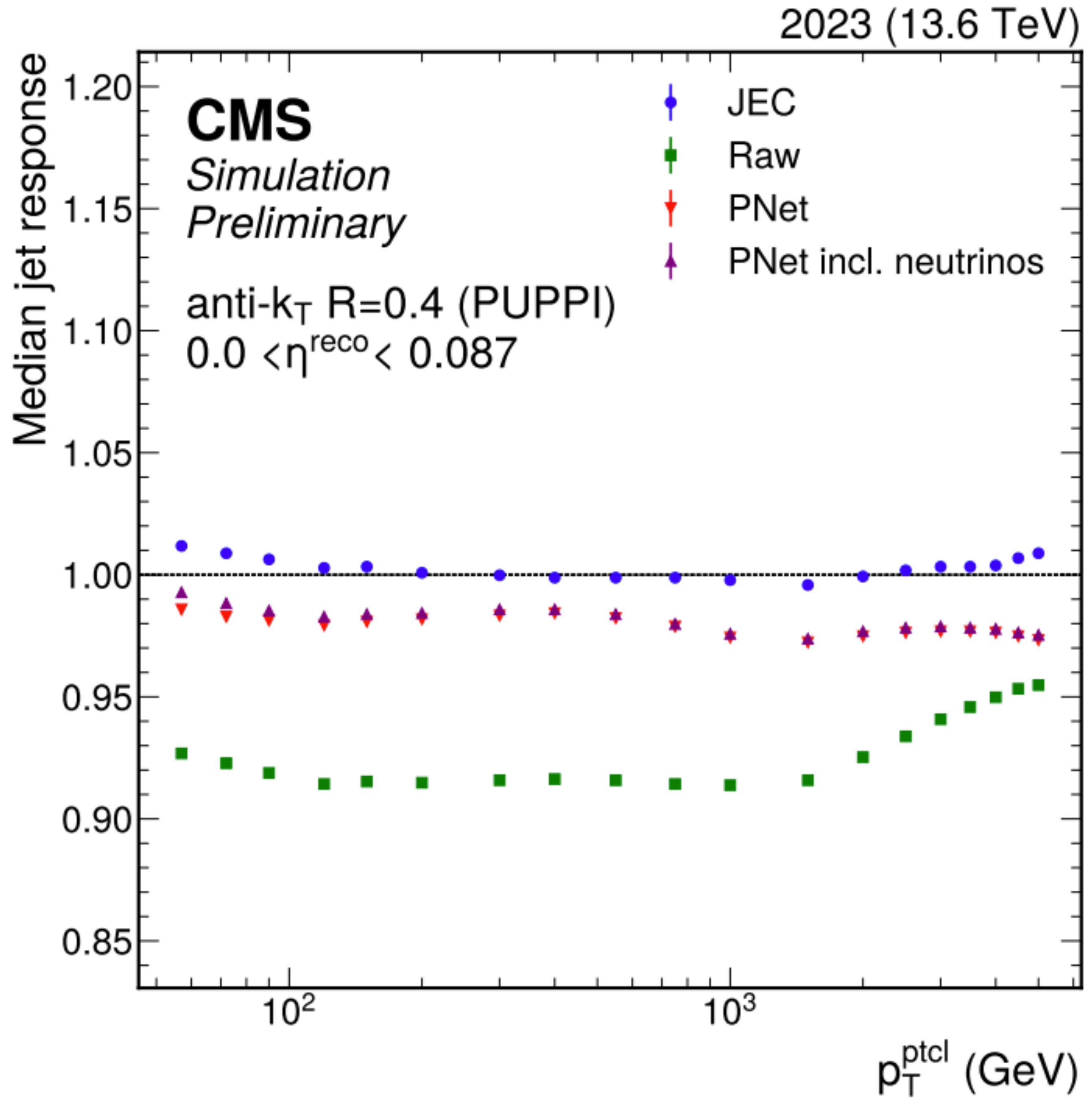



# ParticleNet pT regression

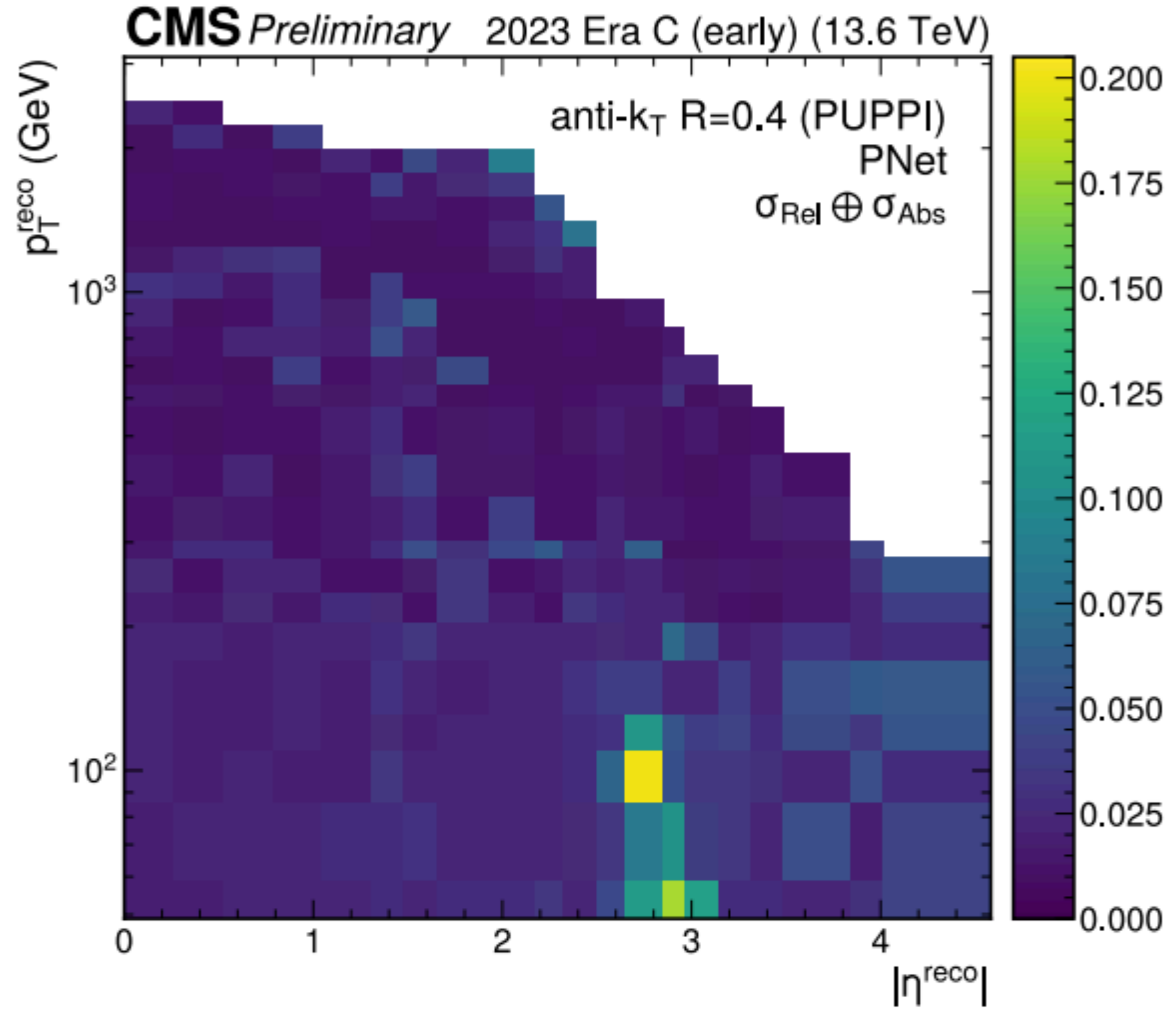
DP-2024-064

- ParticleNet architecture: jets treated as unordered set of particles on which a permutation-invariant graph neural network is used.
- Based on Dynamic Graph Convolutional Neural Network (DGCNN)
  - Node: PF candidate and Secondary Vertex in jet (PUPPI weights used as feature)

- Accomplish multiple tasks simultaneously:
  - Jet classification
  - Jet pT regression
  - Jet energy resolution estimation




- Residual Corrections Closure
  - the standard residual corrections are applied
  - Complete calibration with data gives a non-closure of 2-5% in | η | < 2.5

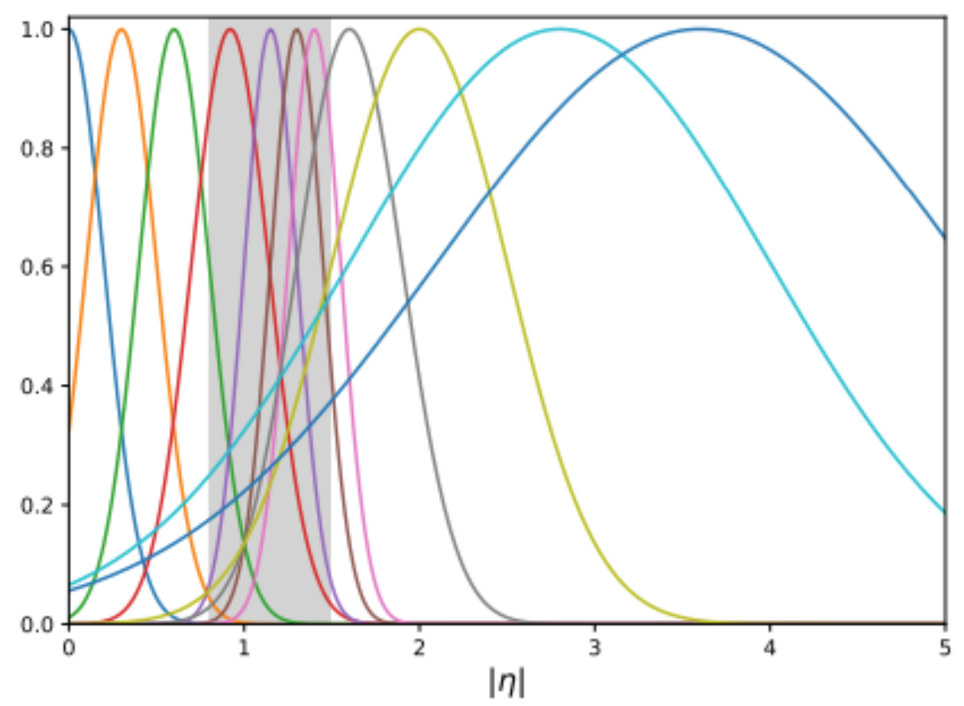


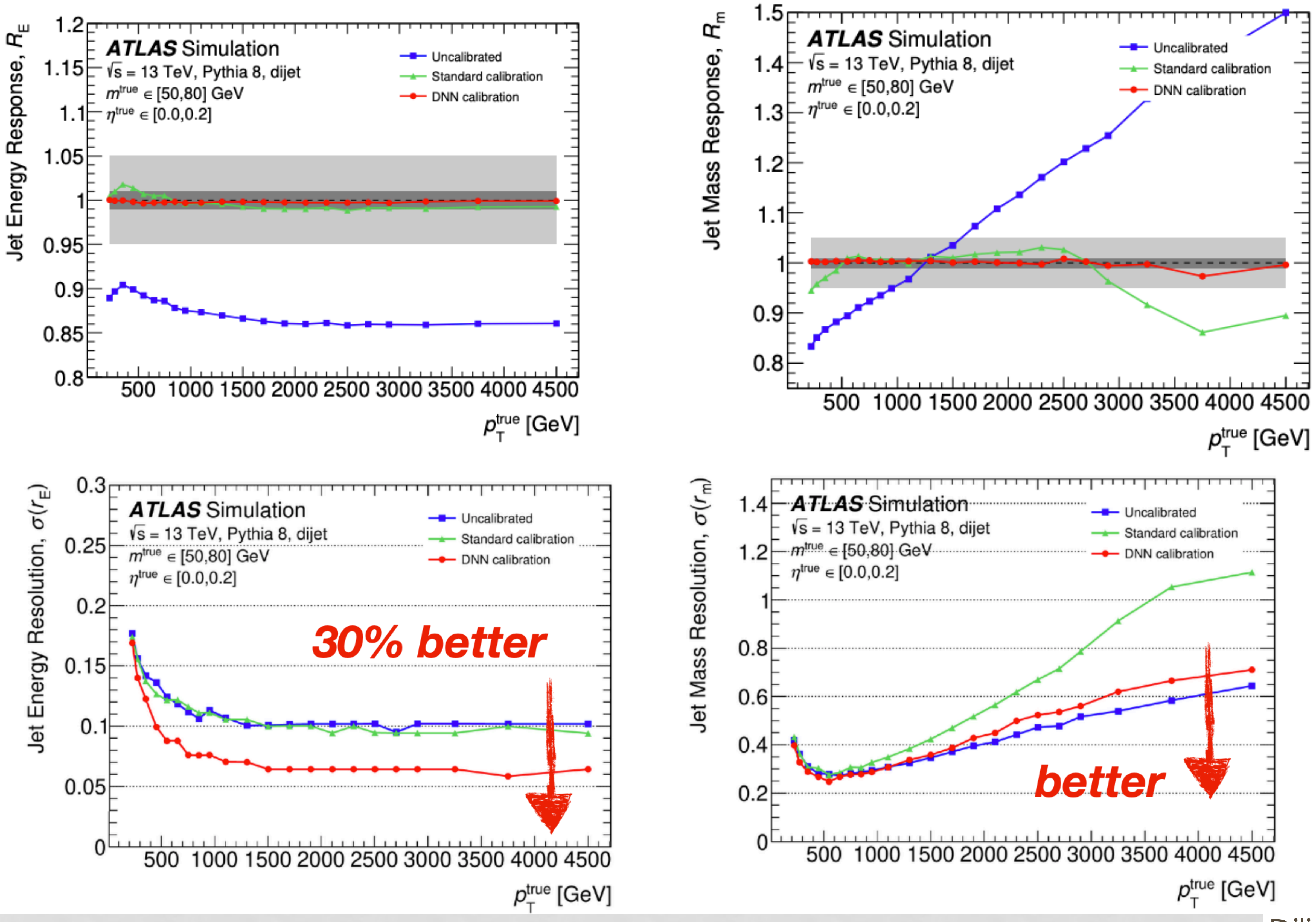
# Simultaneous JES+JMS using DNN

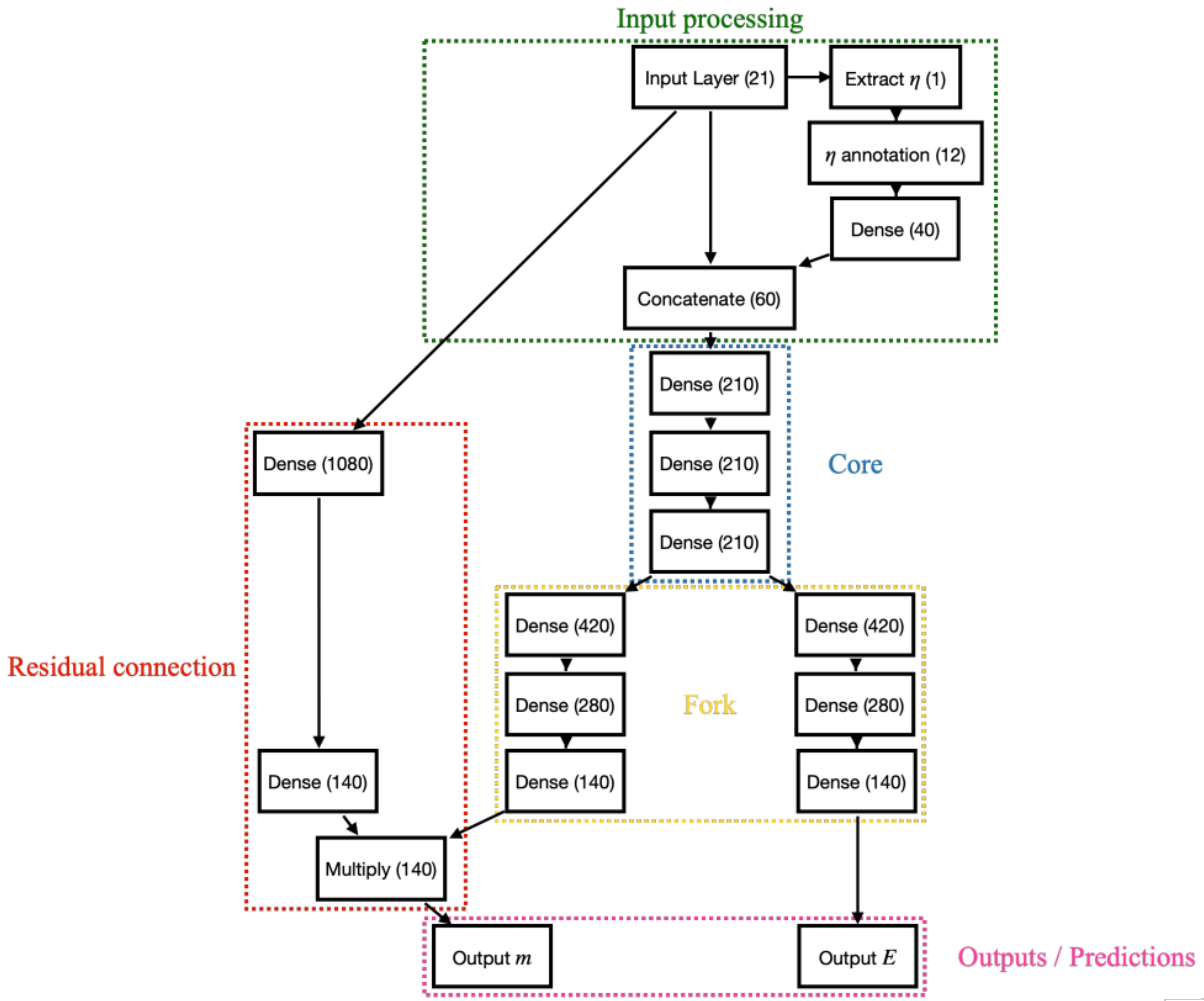
submitted to MLST

- The asymmetric response in energy and mass requires dedicated calibration for both
- both remain highly correlated though
- A combined calibration approach is desirable

- complex DNN with η annotation (adding 11 Gaussian η-dependent weights to input)
- inputs: jet kinematics E, m, η, 8 jet substructure variables, 7 detector-level energy or pT fractions, Pile-Up environment NPV, μ

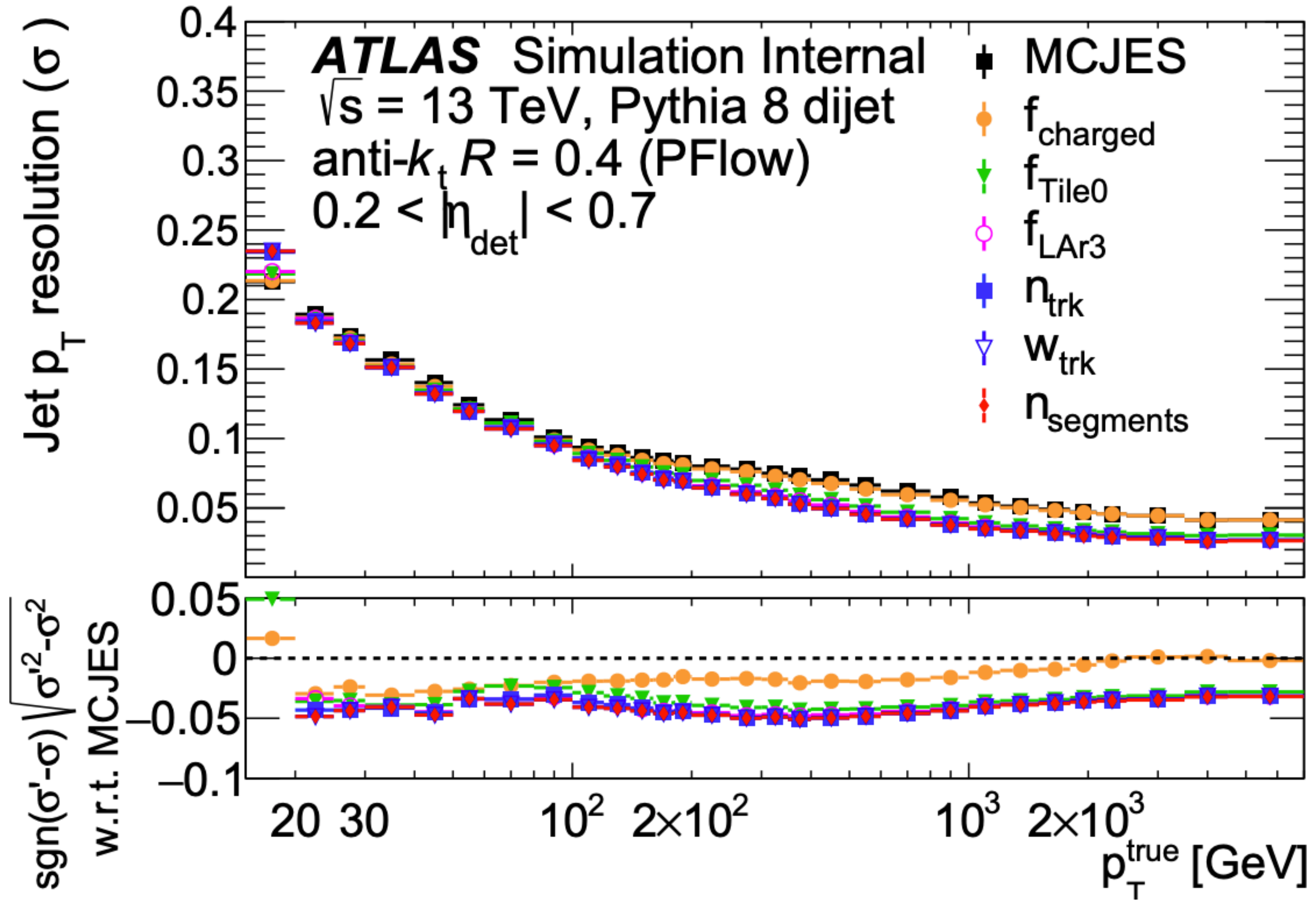


# Global Neural Network Calibration (GNNC)

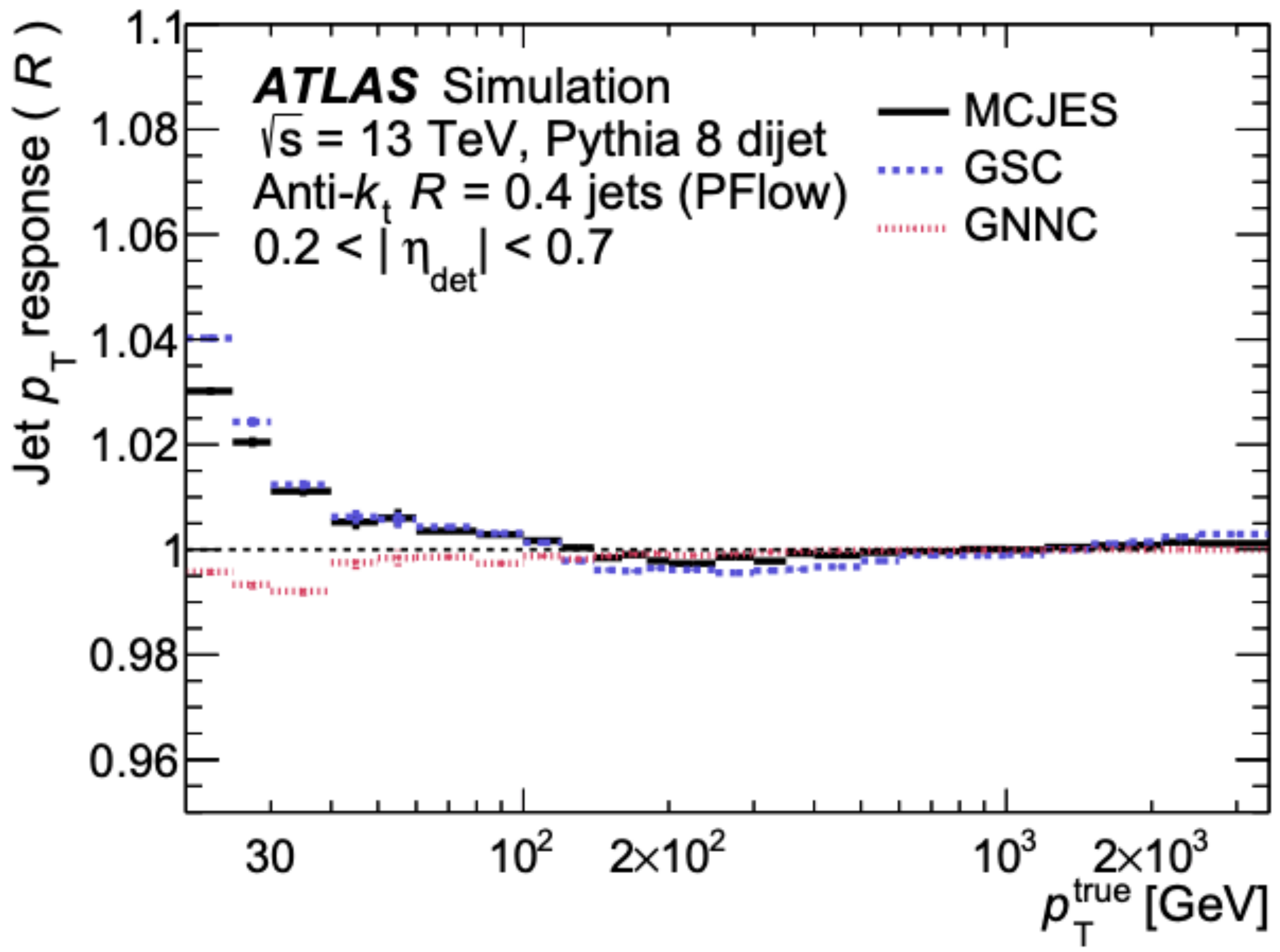
- The energy response depends on jet features related to their quark/gluon nature.
- The resolution can be improved by removing these dependencies

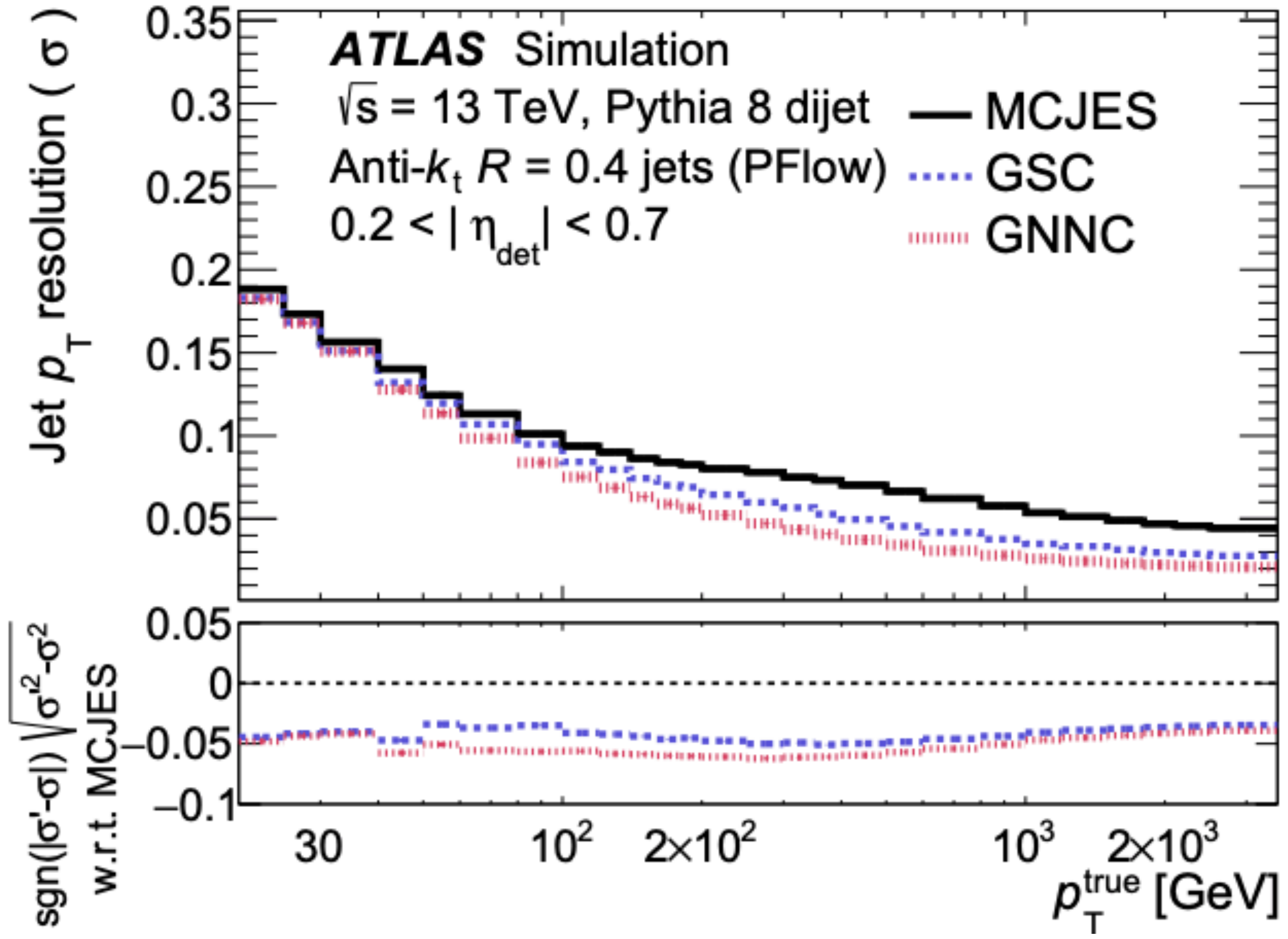



- Global Sequential Calibration (GSC)
  - Correct sequentially with respect to 6 non-correlated visible features

**Global Neural Network Calibration (GNNC)**

- Replace the multiple GSC steps with 1 Deep Neural Network (DNN)-based calibration
  - Trained to predict the $p_T$ response
  - Corrects for more features and take correlations of input variables into account

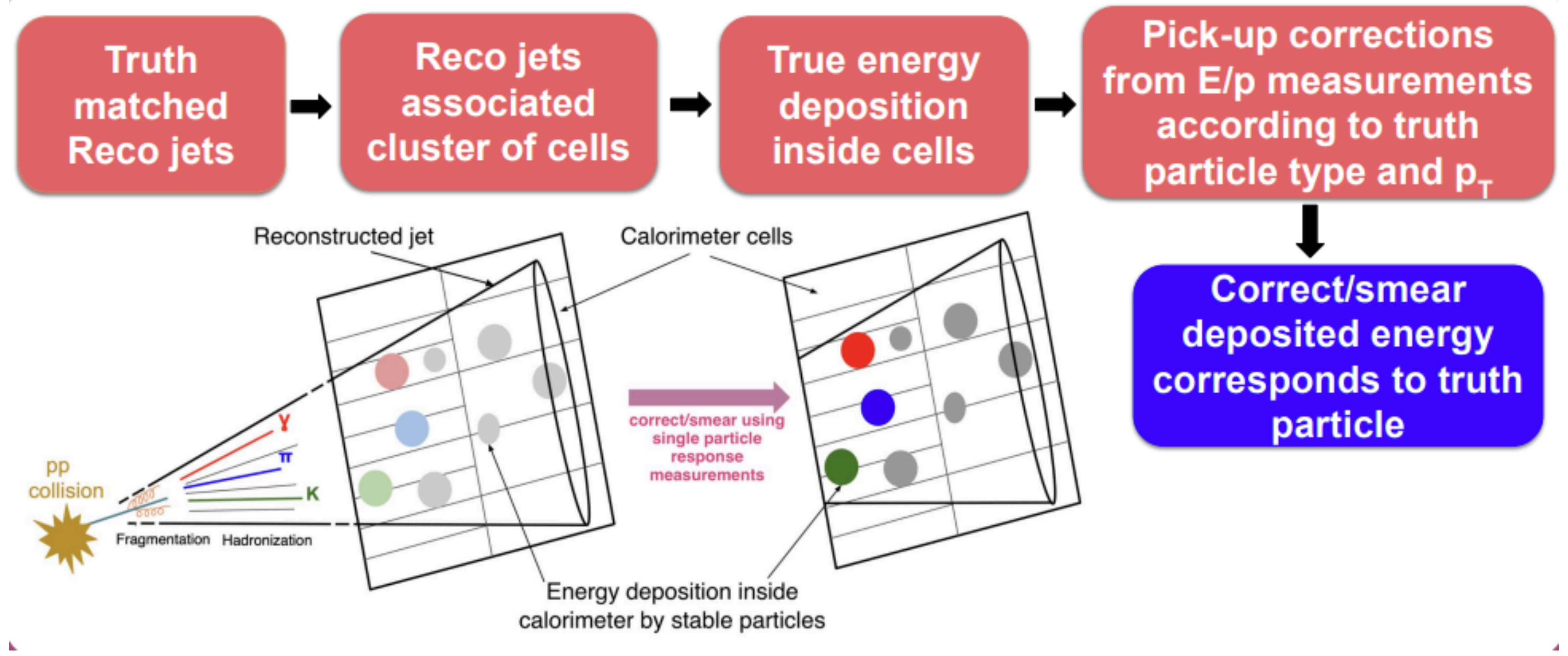


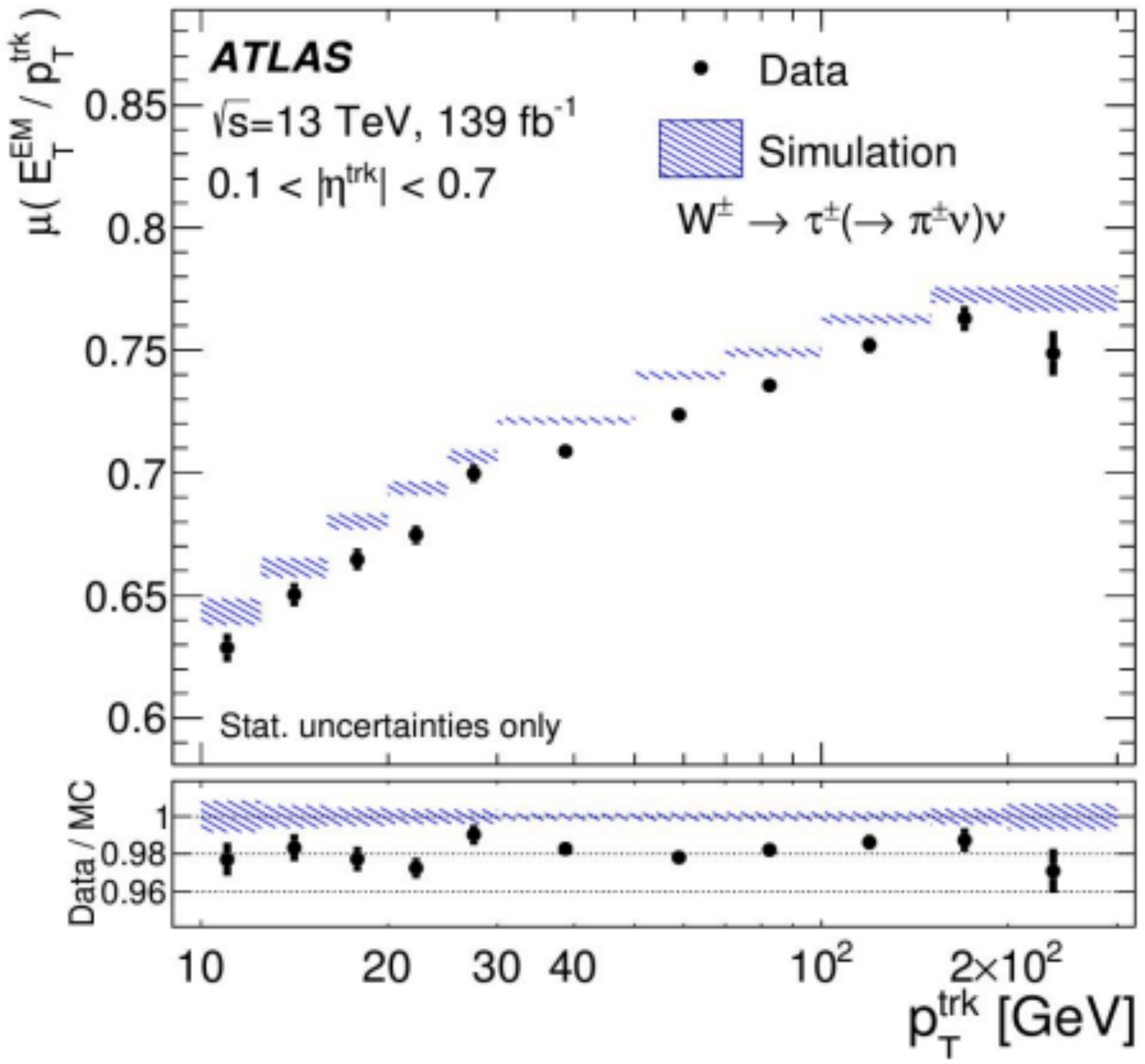
# Jet Energy Scale Uncertainty using Single Particle Response (E/p) Measurements

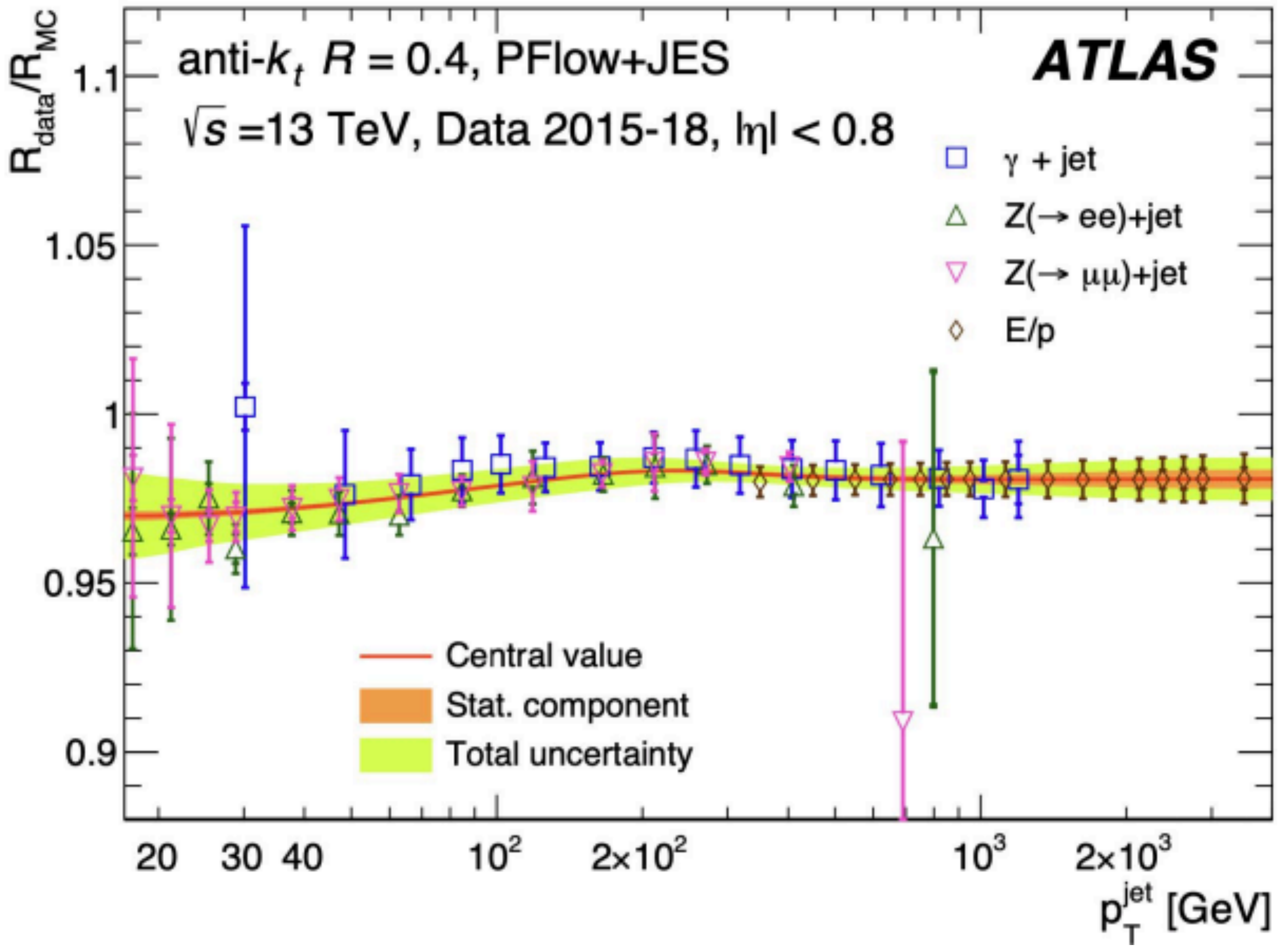
https://atlas.web.cern.ch/Atlas/GROUPS/PHYSICS/PAPERS/JETM-2022-06/

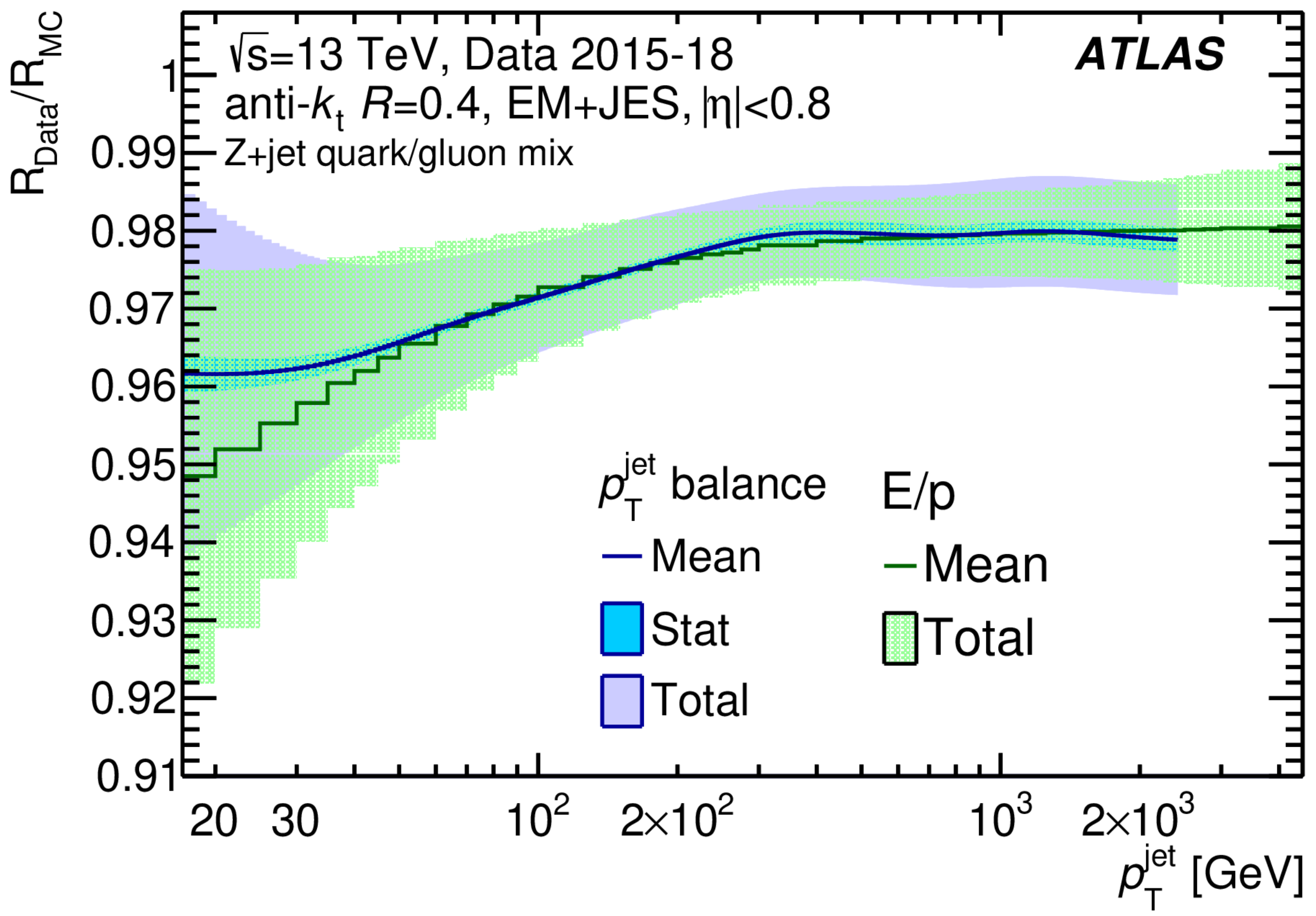
- Single Particle Response (E/p) Measurement:
  - Ratio of the average energy deposited by an isolated charged particle in the calorimeter (E) to the momentum of its inner detector track (p)
  - Traditionally measured in minimum bias collisions using isolated tracks (2) , limited kinematic reach (up to 20 GeV)
  - New Run 2 measurement with $W \to \tau\nu$ events with small uncertainties extends the kinematic reach up to 300 GeV




submitted to EPJC



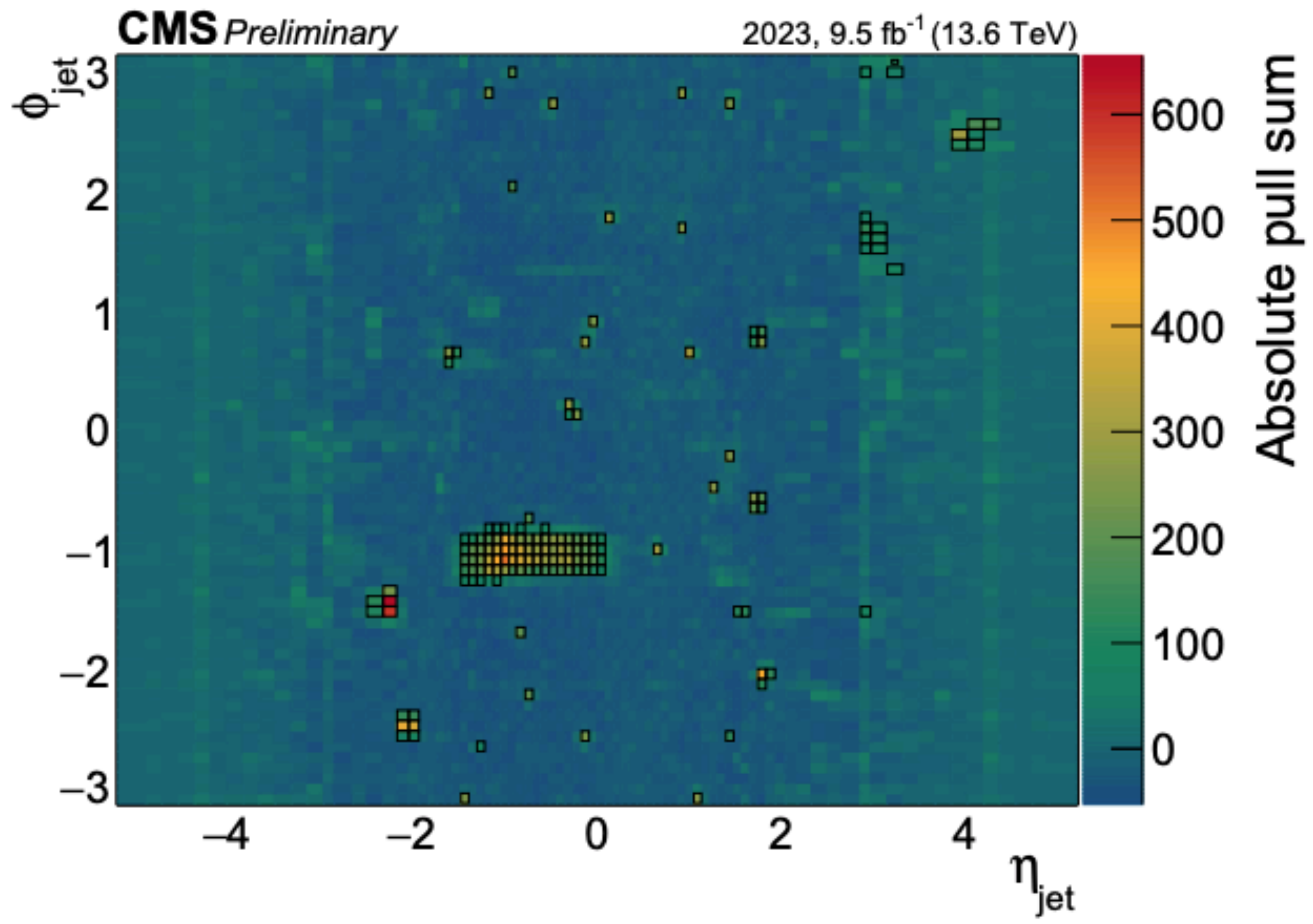



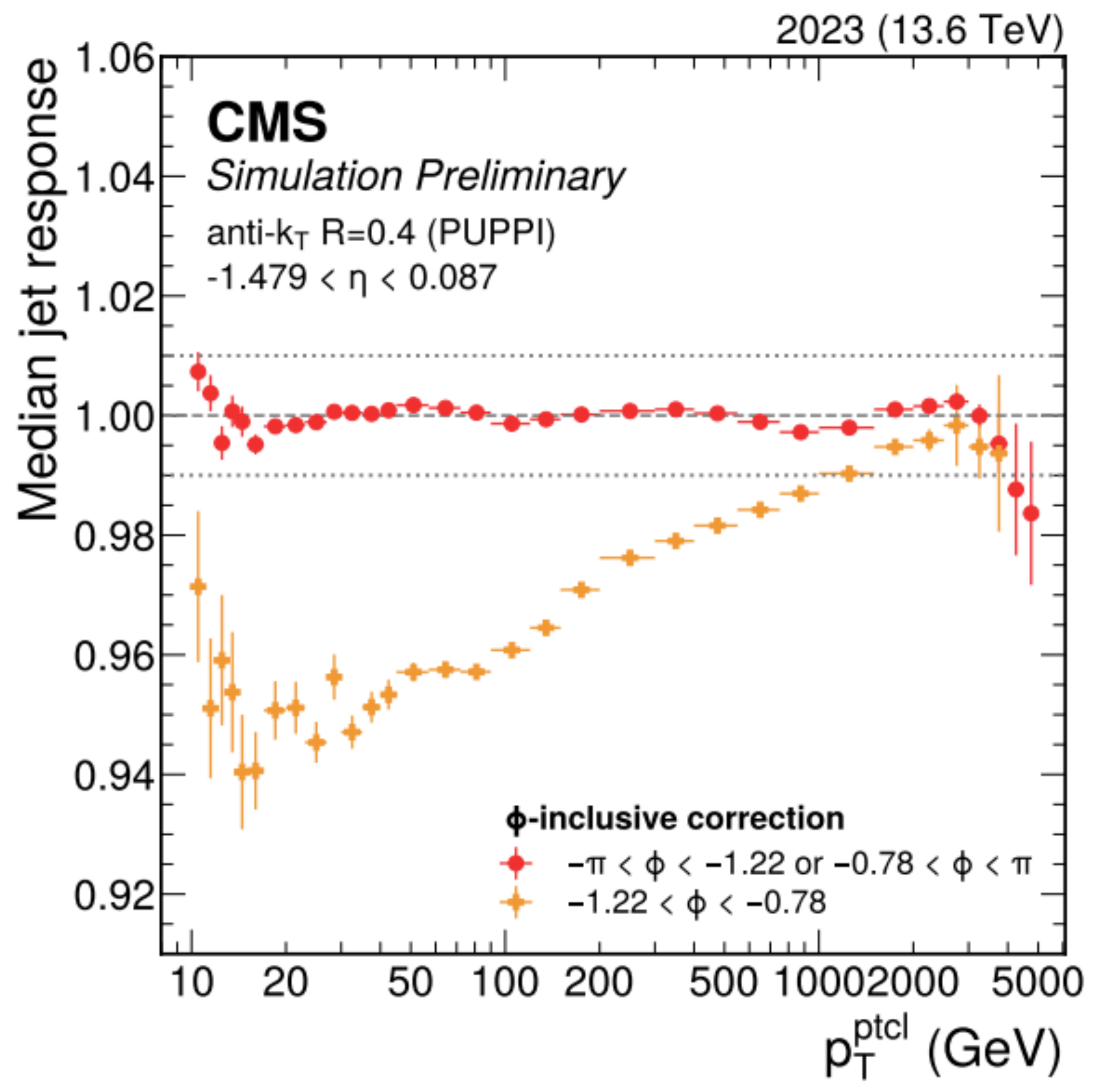



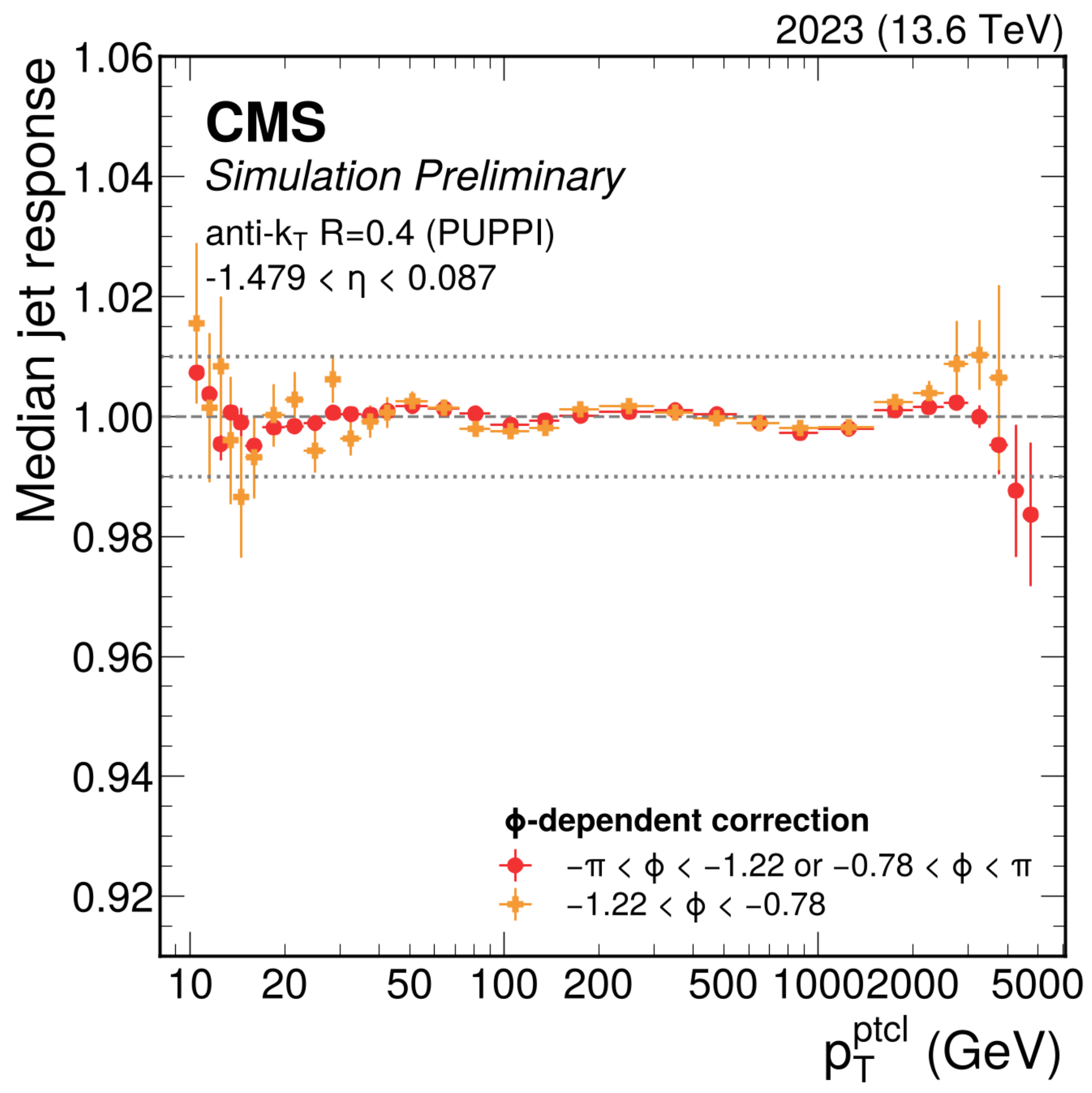
# Barrel Pixel layer 3 & 4

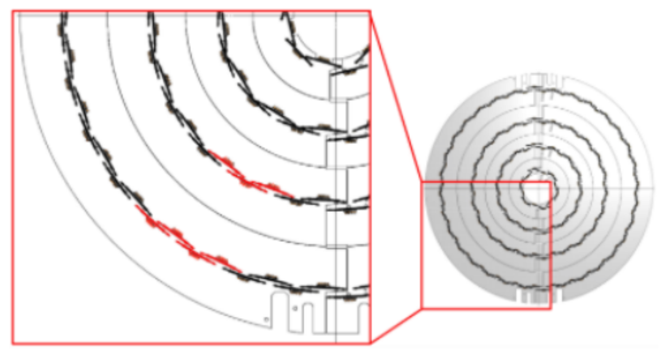
DP2024_039

- On 2023: 27 modules (1.5% of the total) in the Barrel Pixel Layers 3 & 4 became inoperable (issue in distributing the LHC clock signals). They cover a sector spanning approximately 0.4 radians (~23 degrees) in at negative pseudorapidity



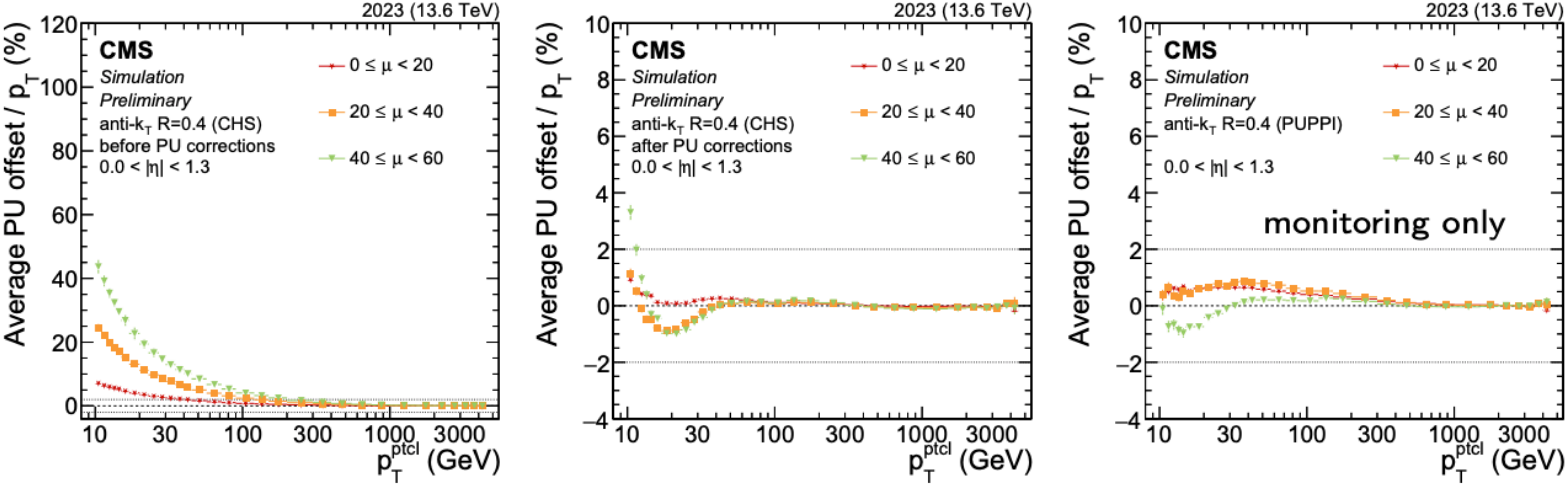



# PU correction in CMS

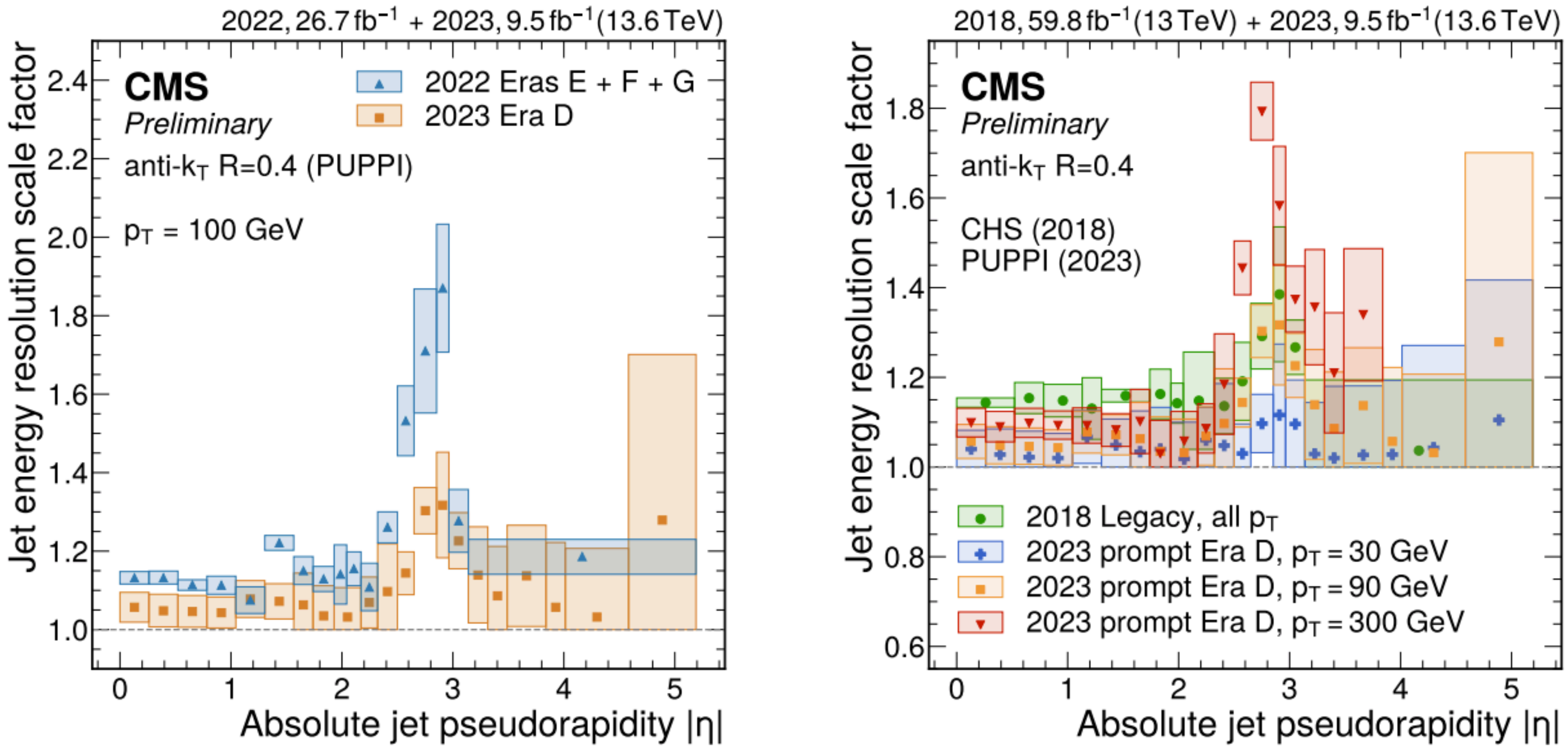
DP2024_039



# JER Scale Factors CMS

DP2024_039

- JER is determined in simulation by matching reconstructed and particle jets in $\Delta R$. Data/simulation scale factors are derived from dijet events using similar in-situ techniques as for residual corrections.

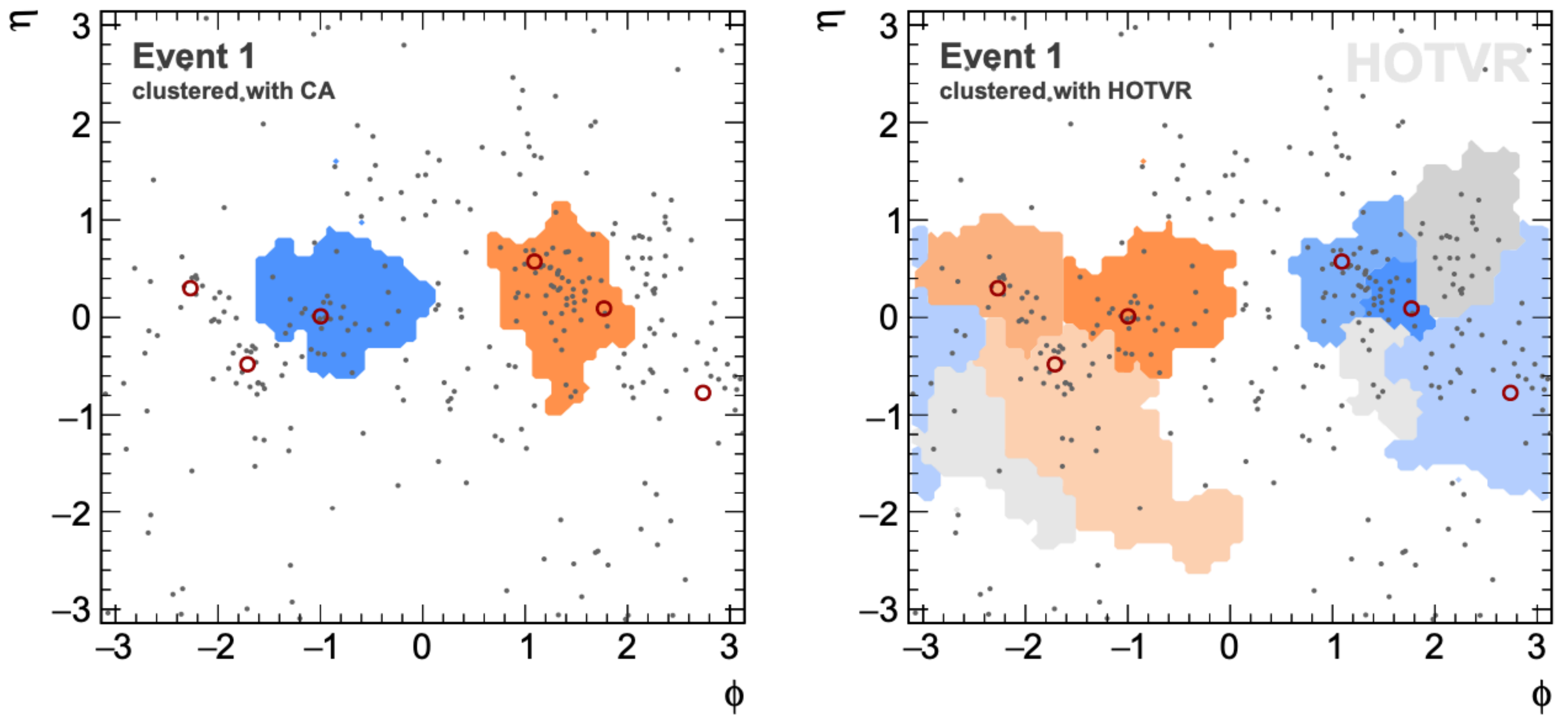



The central value is obtained from pT balance in 2022, while MPF is used in 2023.

# Top tagging with variable-sized jets in CMS

DP-2024_038

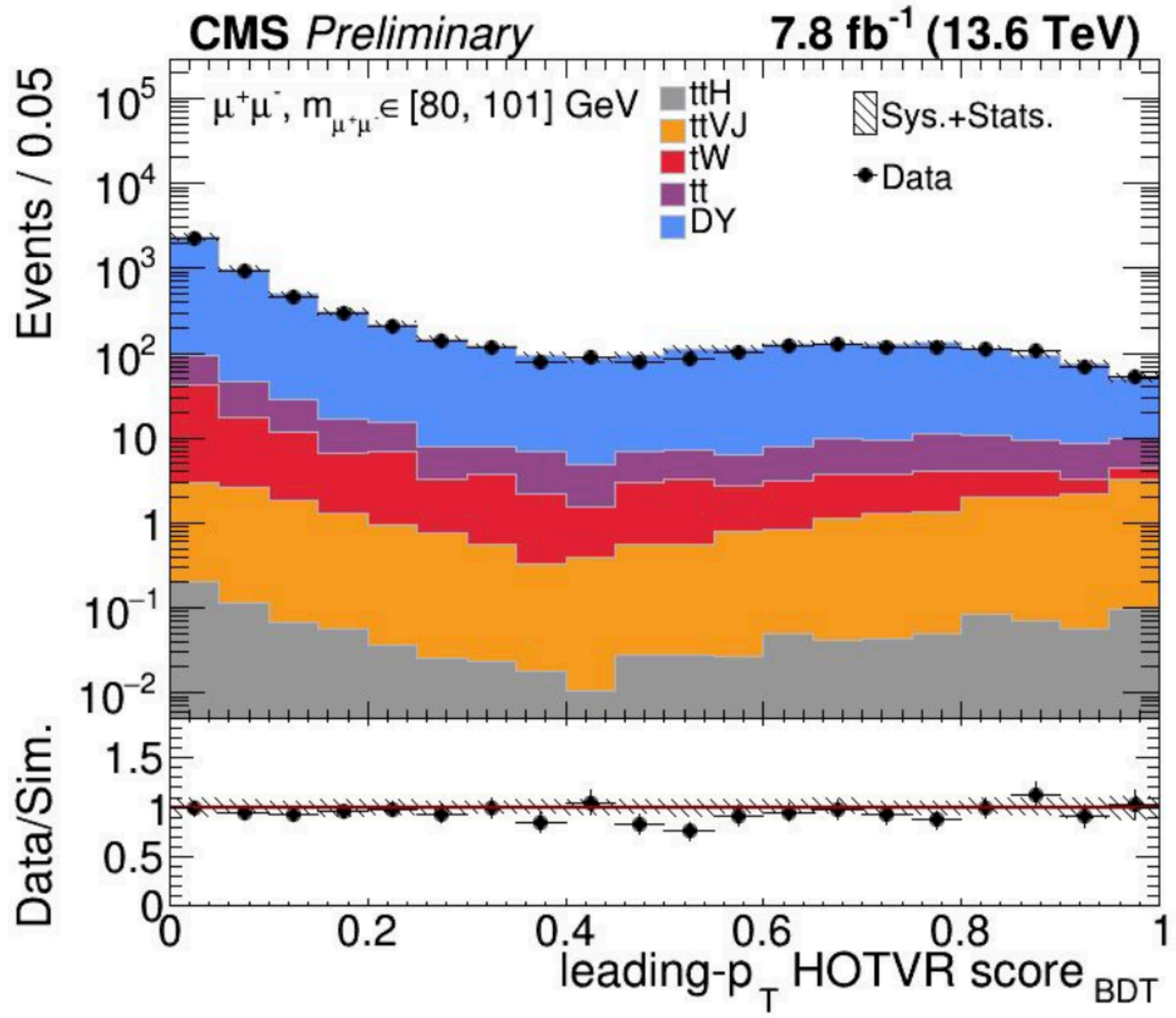
- HOTVAR: Heavy Object Tagger with Variable Radius is a variable distance parameter jet clustering algorithm
  - leading to broader jets at low pT and narrower jets at high pT.
- Variable-R clustering especially useful for multiscale problems like 4 top final states
  - $R = \rho/pT$; $\rho$ = 600 GeV for top quark tagging



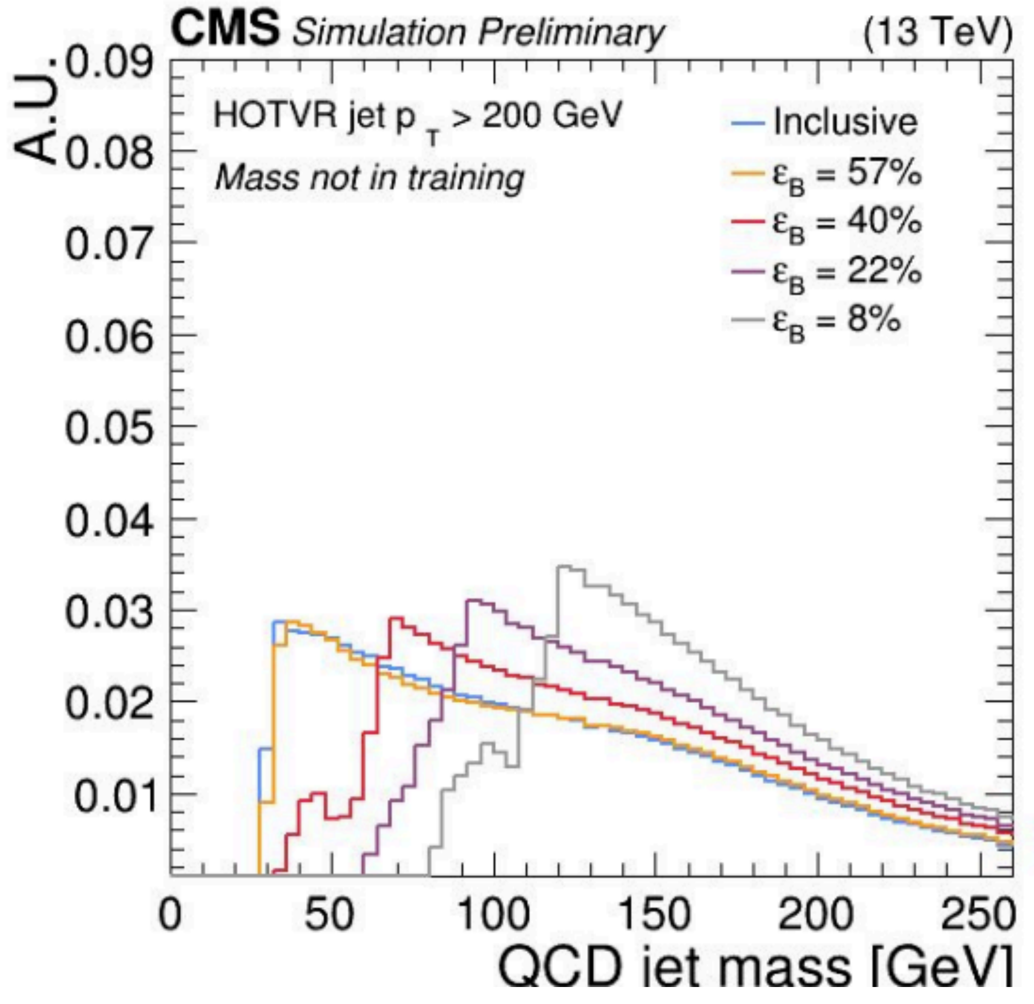

- **BDT for top quark tagging on HOTVR jets**

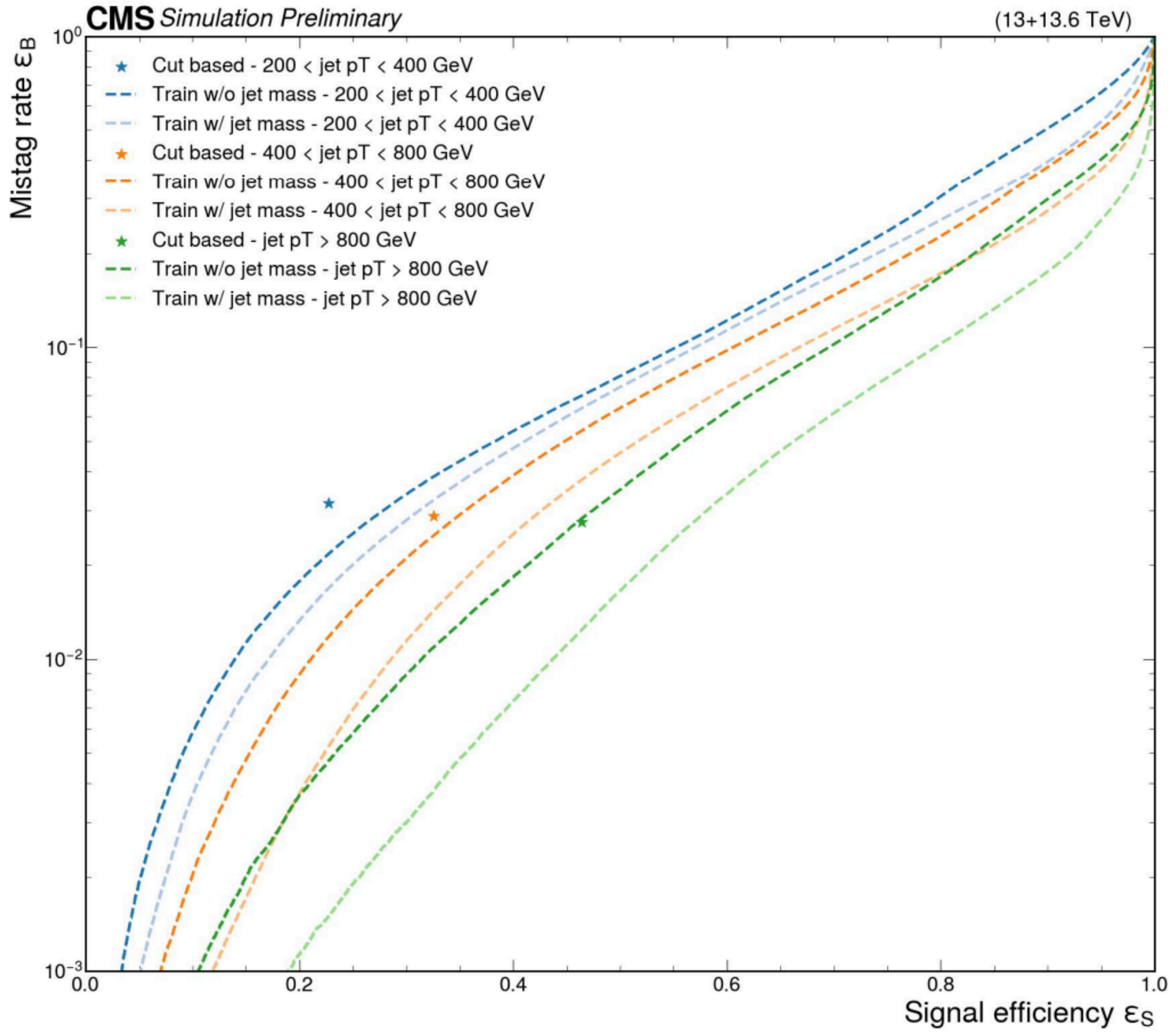
| HOTVR Variables | Cut | Description |
|---|---|---|
| mass | [140, 220] GeV | Jet Mass. |
| $N_{subjets}$ | > 2 | Number of subjets. |
| $Mass_{min\ ij}$ | > 50 GeV | Minimum pairwise subjets mass. |
| $f_{pT}$ | < 0.8 | Fractional pT. |
| $\tau3/\tau2$ | < 0.6 | N-subjettiness τ3 over τ2. |

The BDT model is tested and validated in data using Z+jets enriched region




- **Correlation with mass**



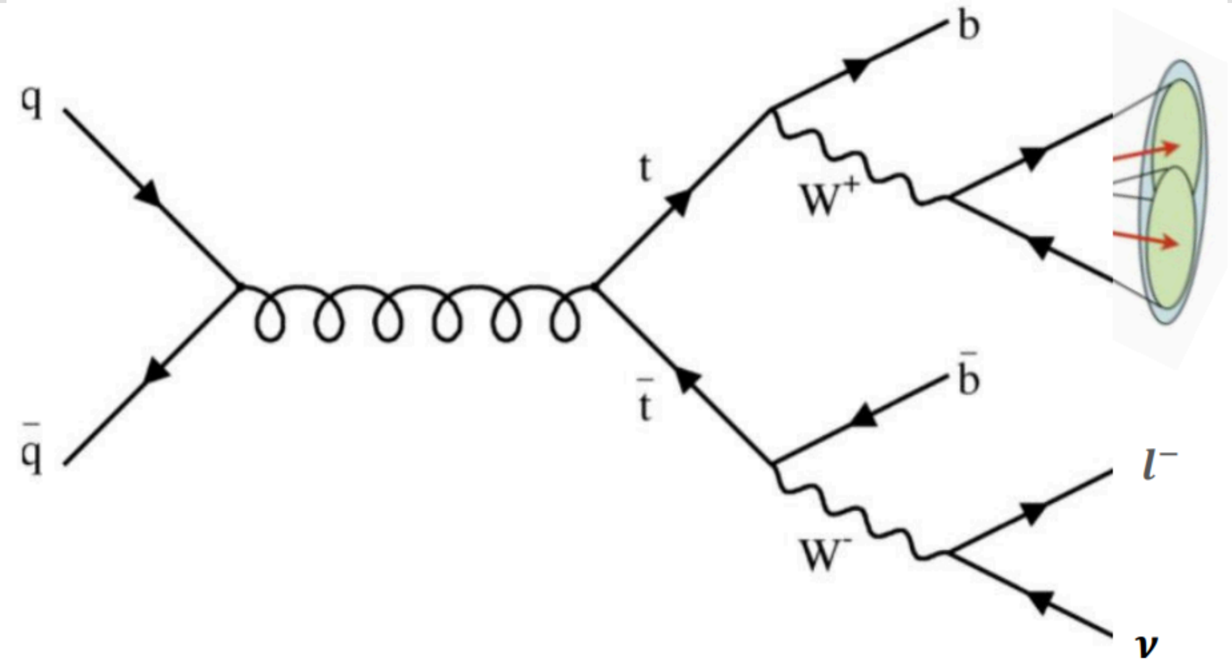



# Charge tagger

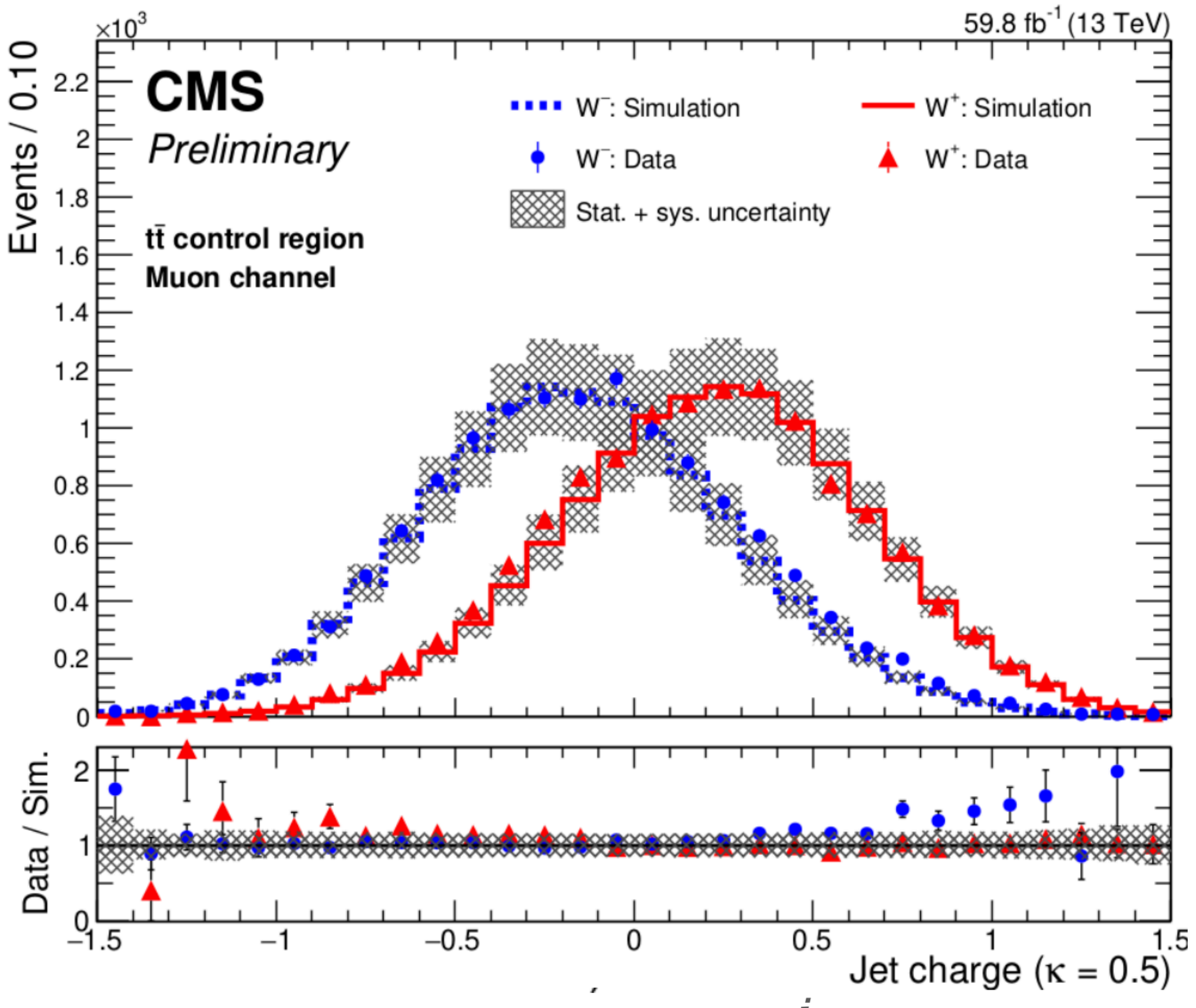
DP-2024-044

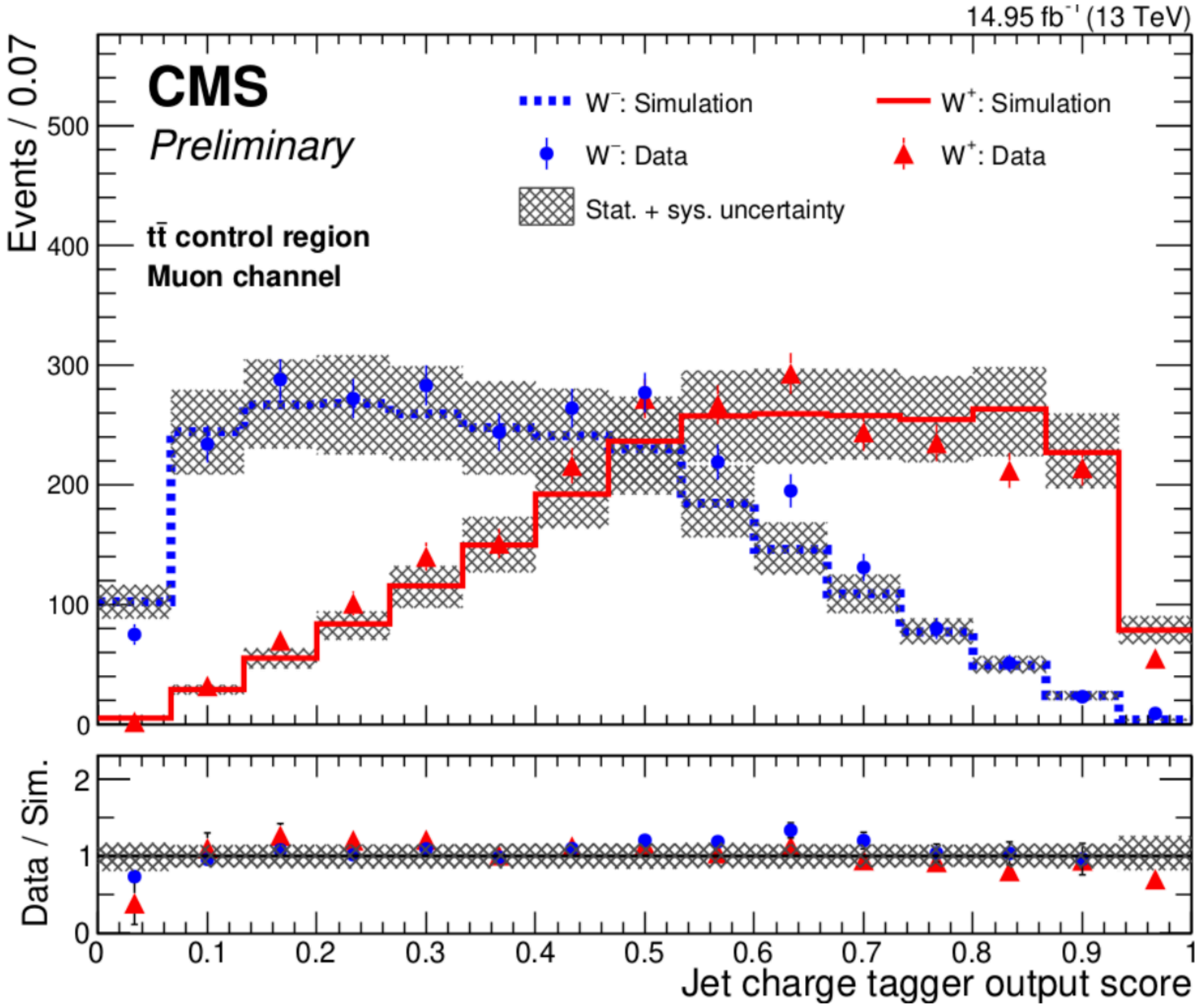
- Using ParticleNet architecture trained on W's from $t\bar{t}$ production
  - Dynamic Graph Convolutional Neural Network (DGCNN) based on the ParticleNet
  - jet as a "particle cloud"

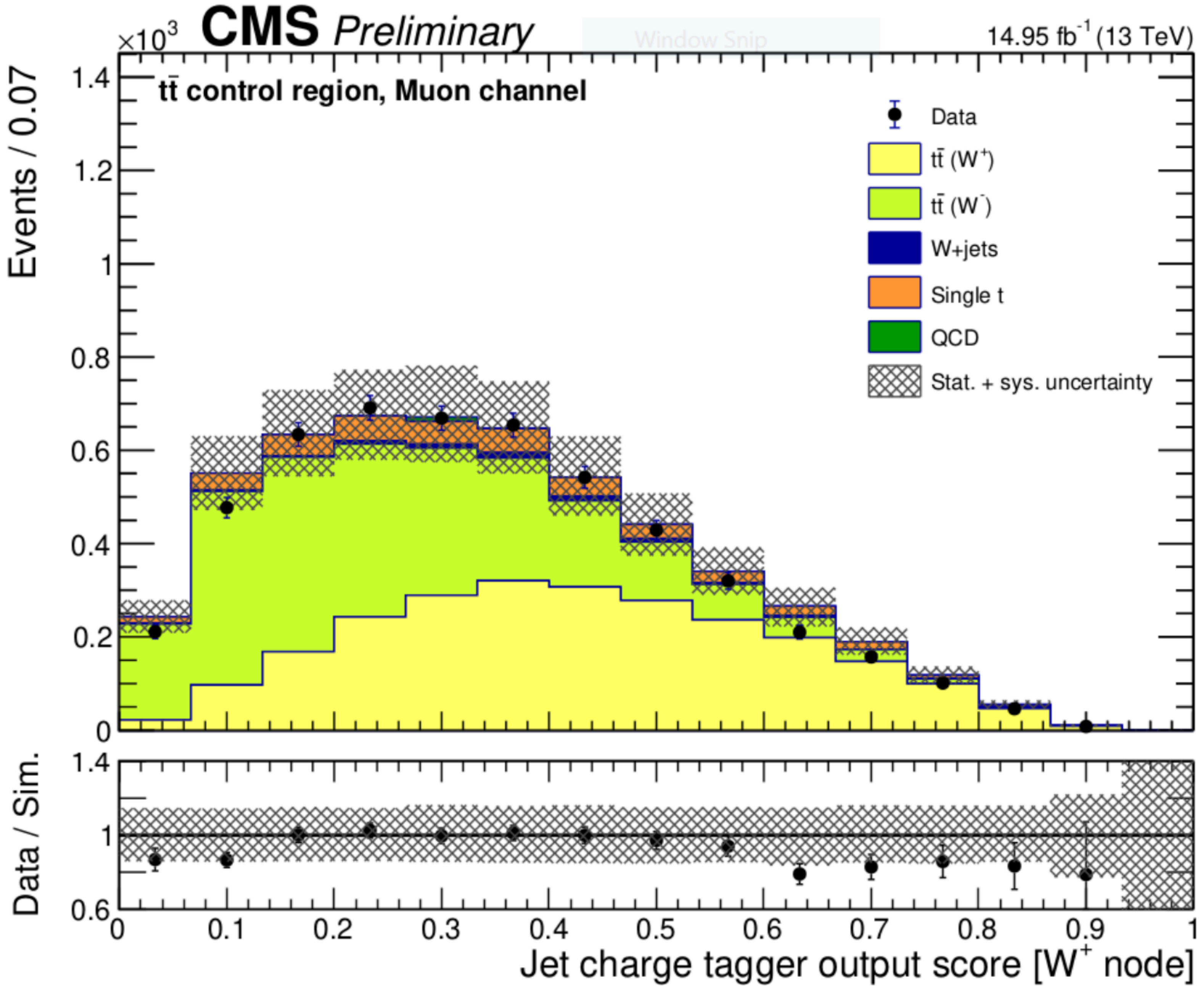
| Variable | Description |
|---|---|
| ΔR | angular separation between the particle and the jet axis $\sqrt{(\Delta\eta)^2+(\Delta\phi)^2}$ |
| Δη | difference in the pseudorapidity between the particle and the jet axis |
| Δϕ | difference in the azimuthal angle between the particle and the jet axis |
| log E | logarithm of the particle's energy |
| log $p_T$ | logarithm of the particle's $p_T$ |
| log E/log $E^{jet}$ | logarithm of the particle's energy relative to the jet energy |
| log $p_T$/log $p_T^{jet}$ | logarithm of the particle's $p_T$ relative to the jet $p_T$ |
| Jet constituents charge | electric charge of the particle |




- Very good agreement between data and simulation



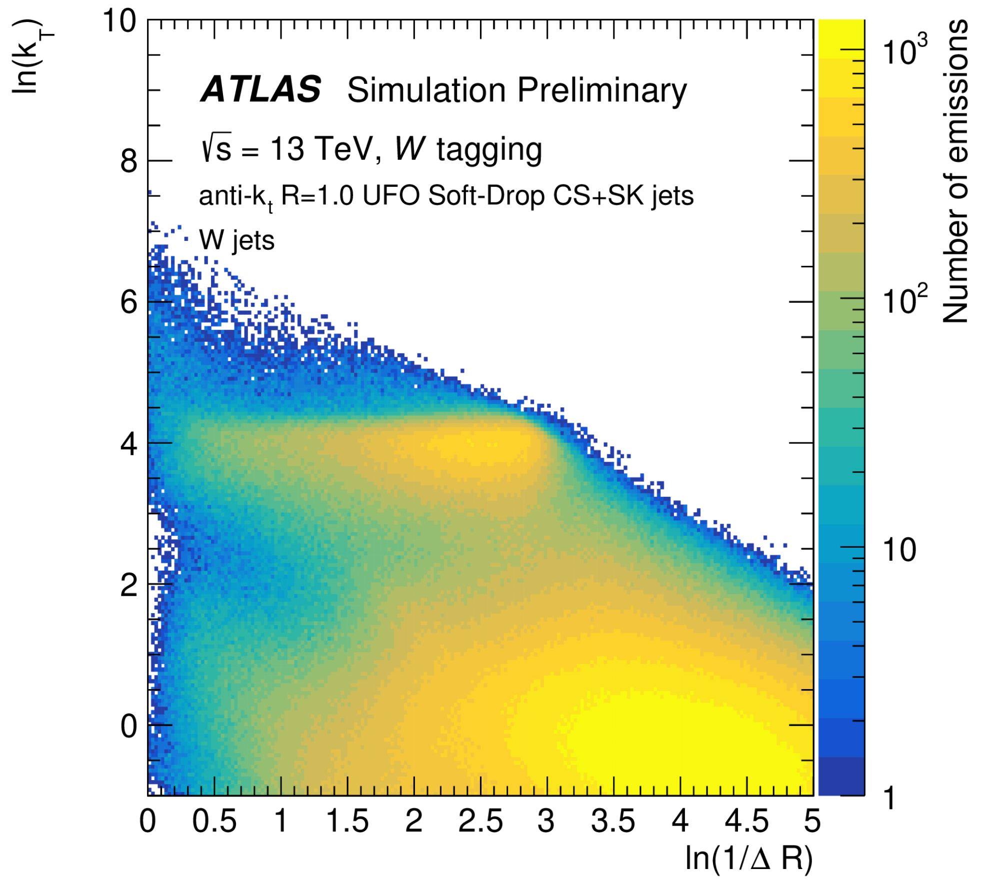

- Jet Charge $Q_\kappa = \frac{\sum_i q_i (p_T^i)^\kappa}{(p_T{}^{jet})^\kappa}$

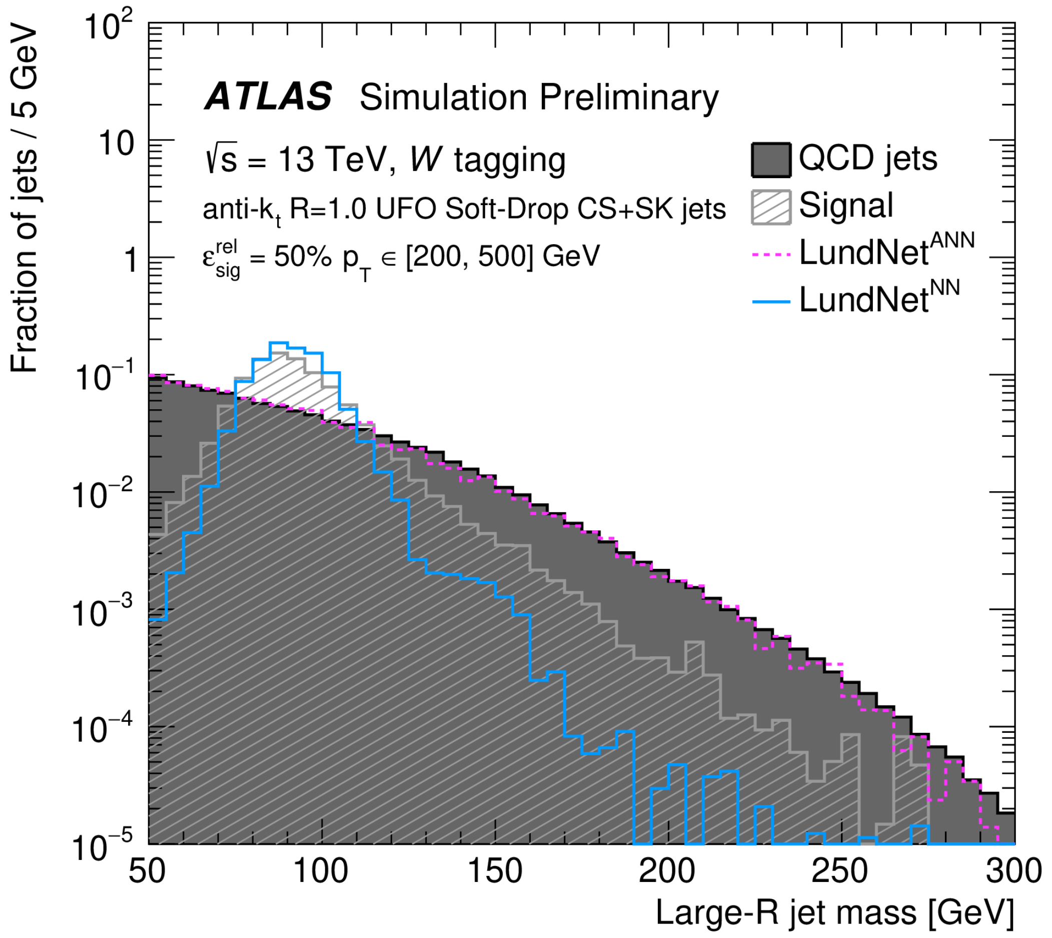
# Jet Tagging highlights in ATLAS

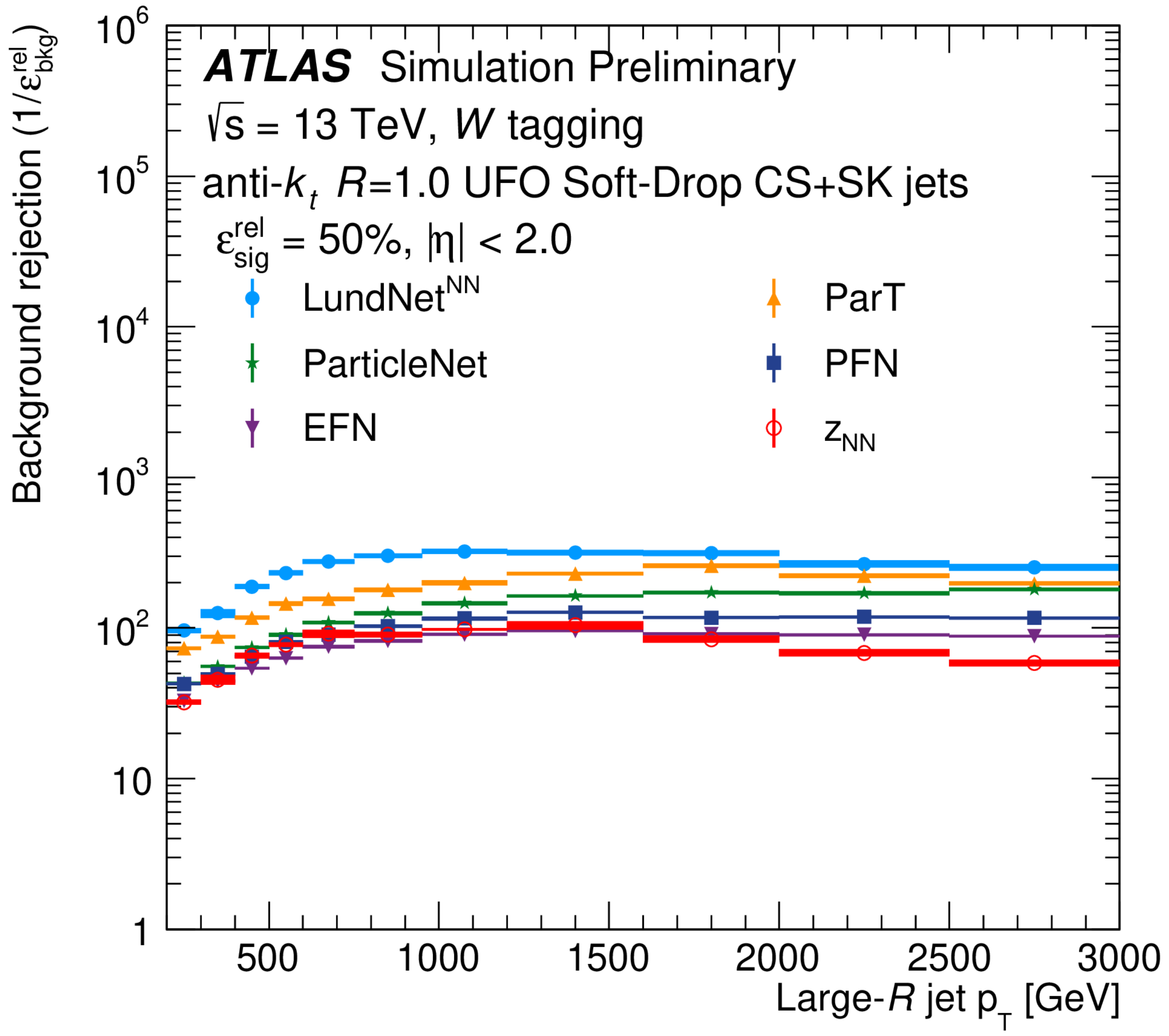
Lund Plane tagger: Graph-neural network inspired by ParticleNet on the Lund-plane points

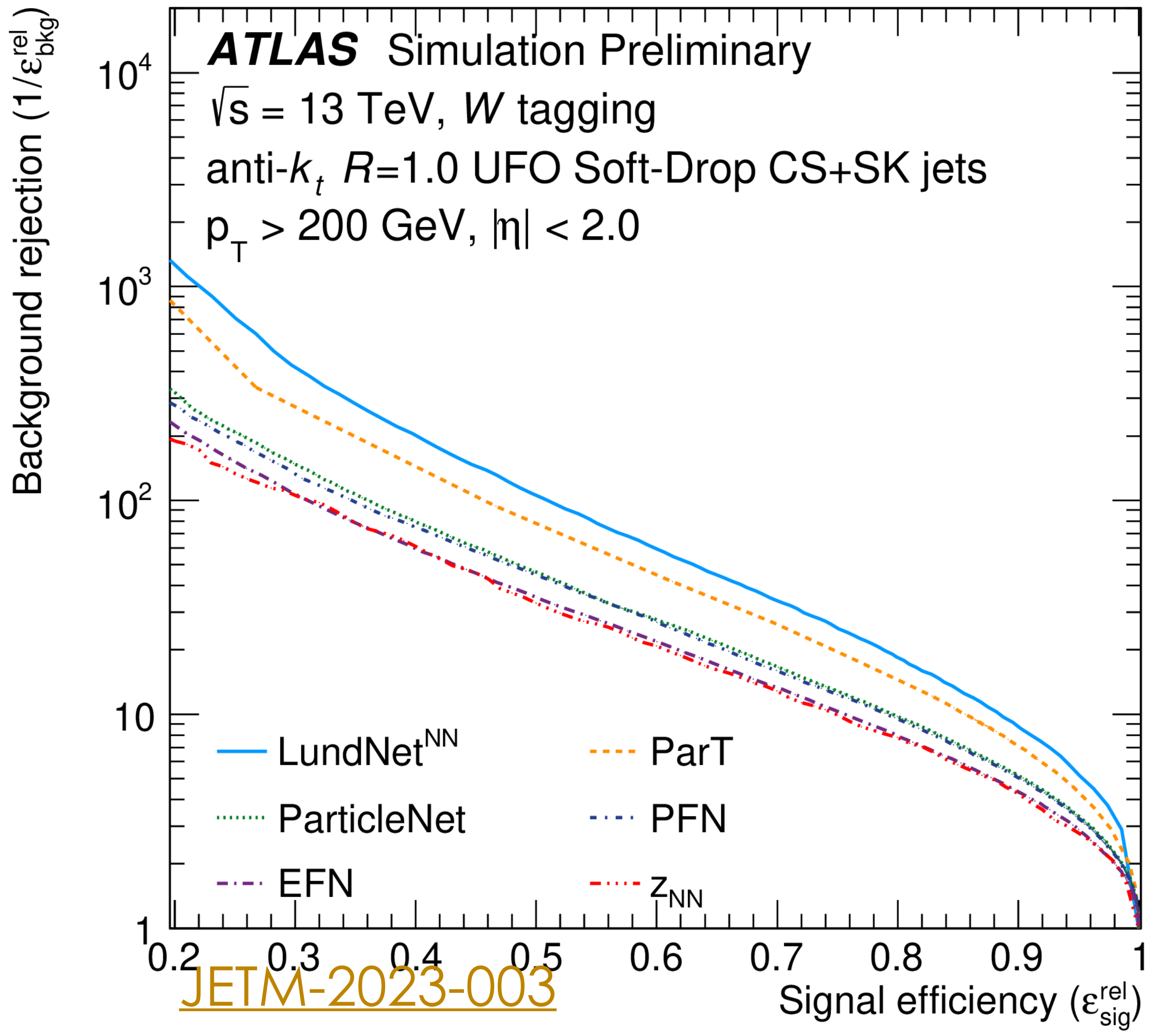
ATL-PHYS-PUB-2023-017

## W-tagging



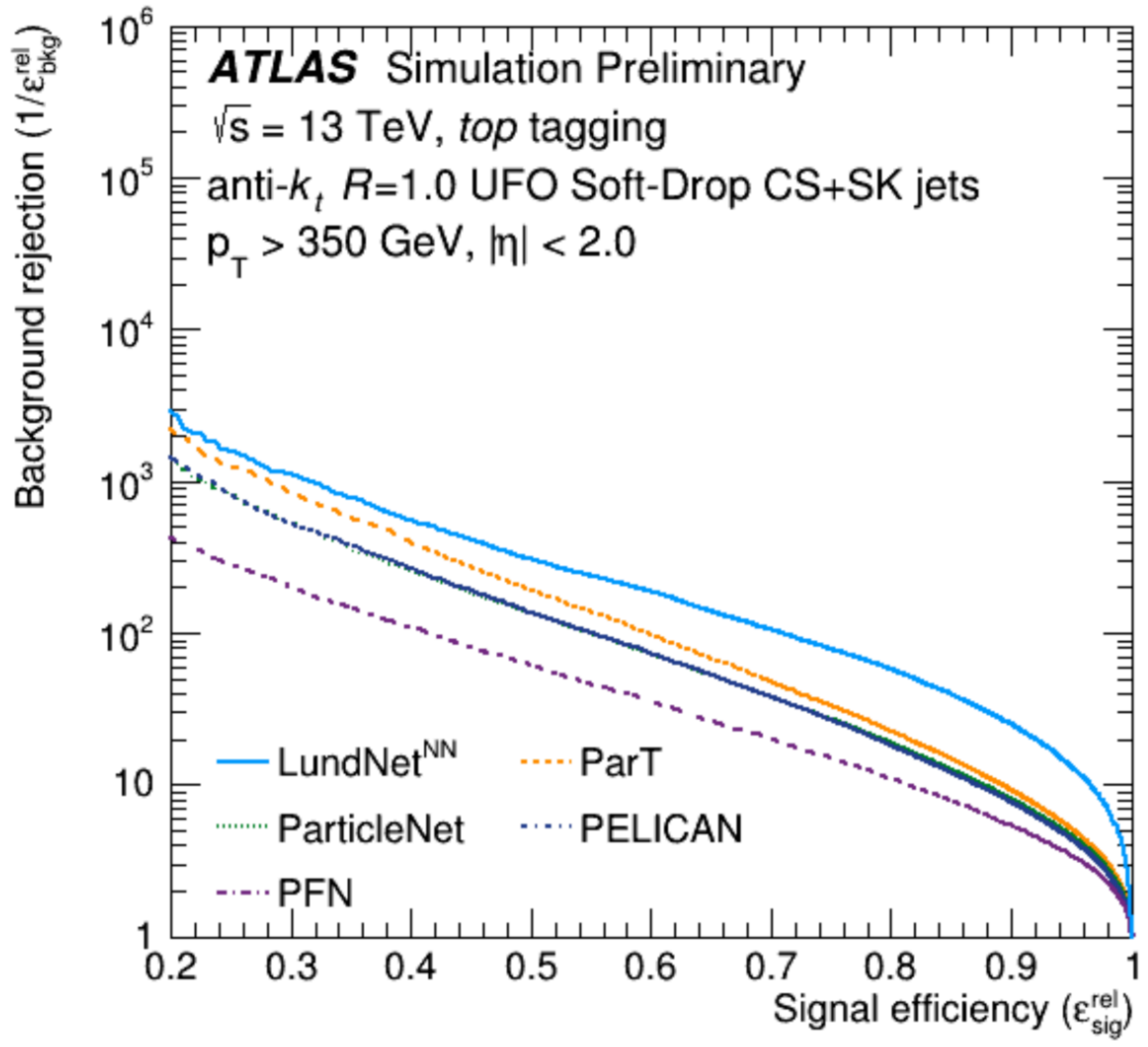



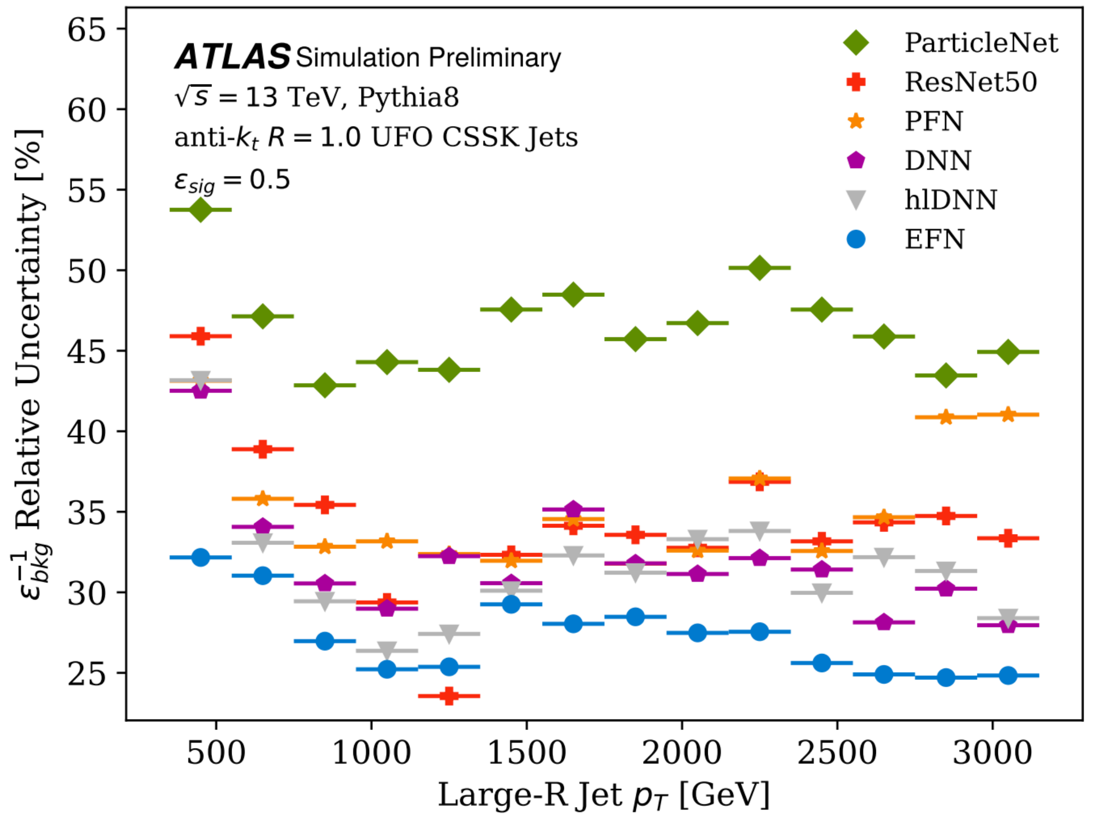




JETM-2023-003

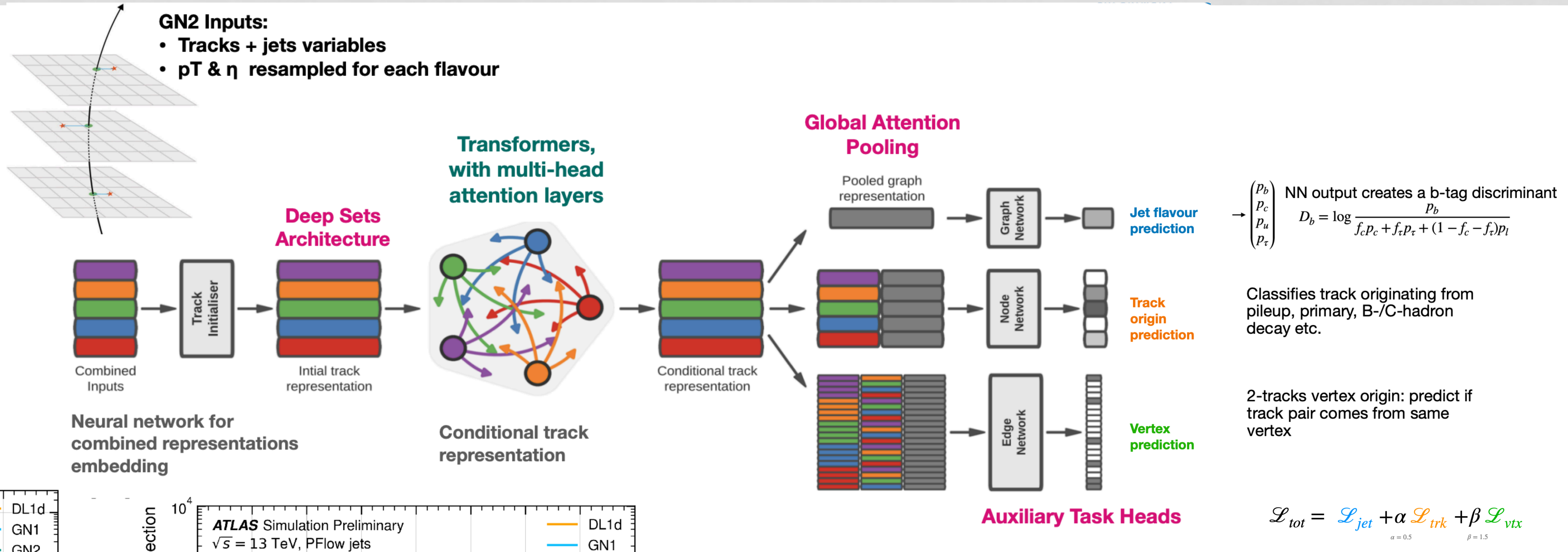
## Top-tagging

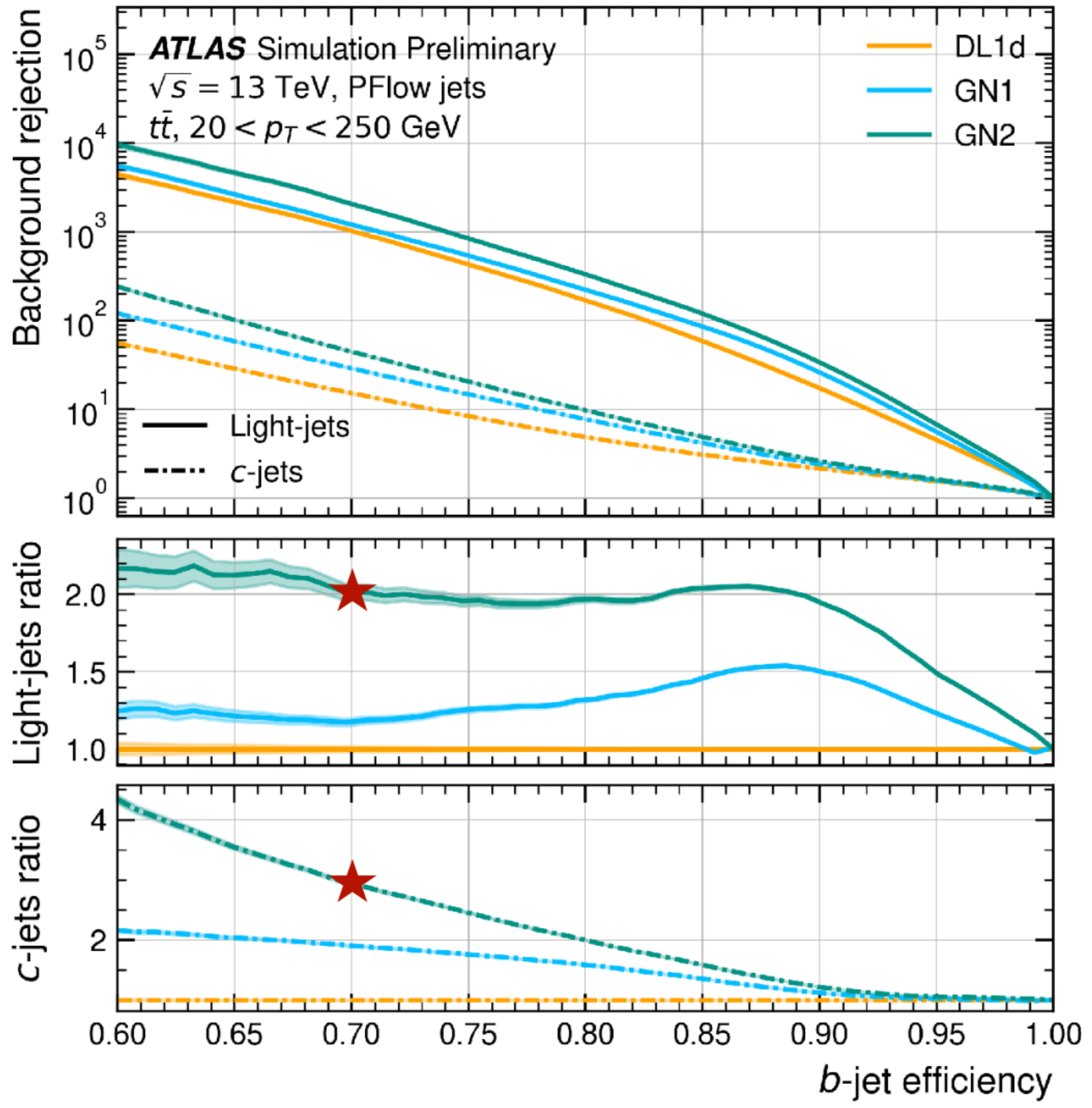


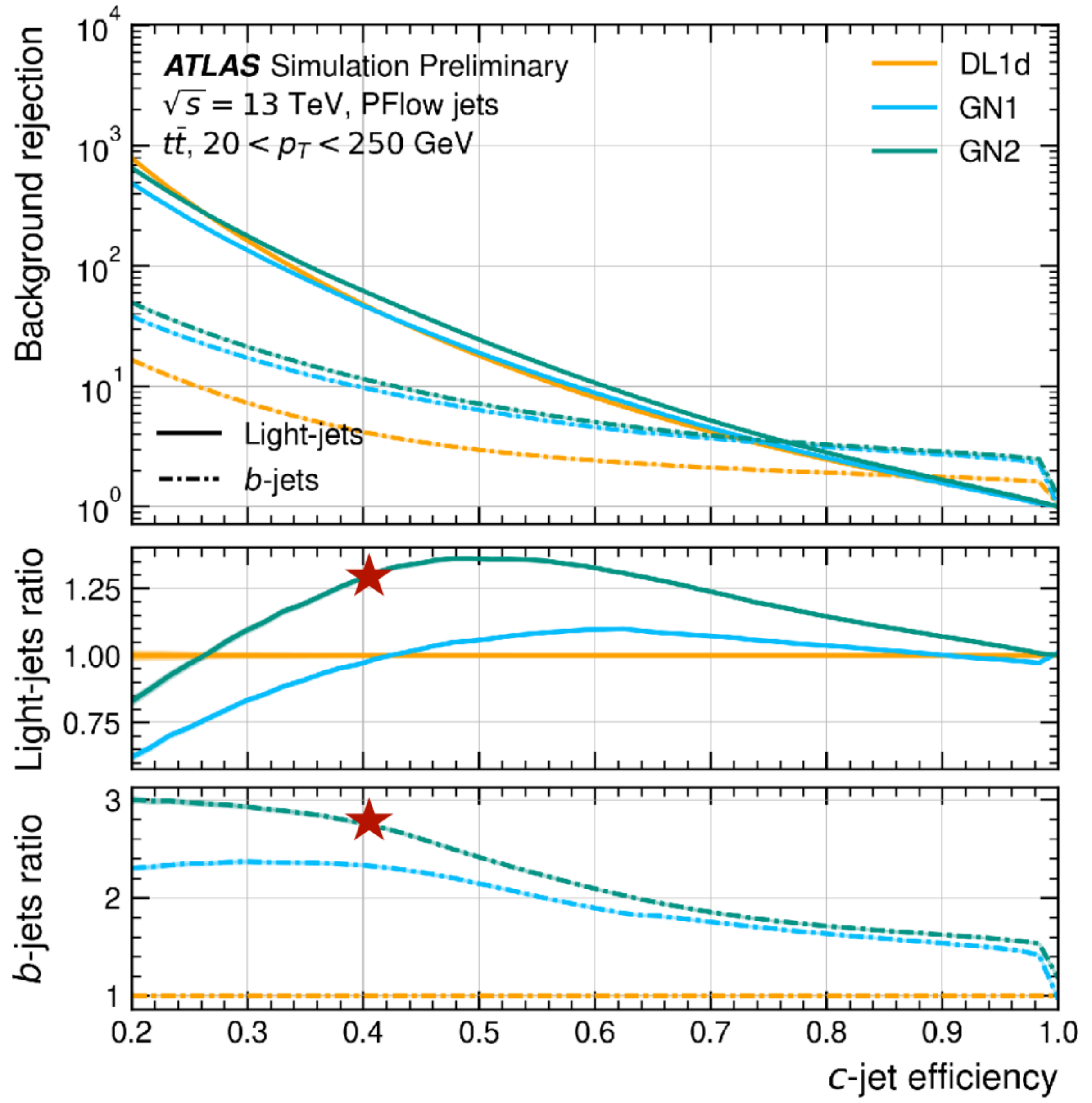



# GN2 Flavour Tagging ATLAS

- GN2 architecture:
- All-in-one GNN based



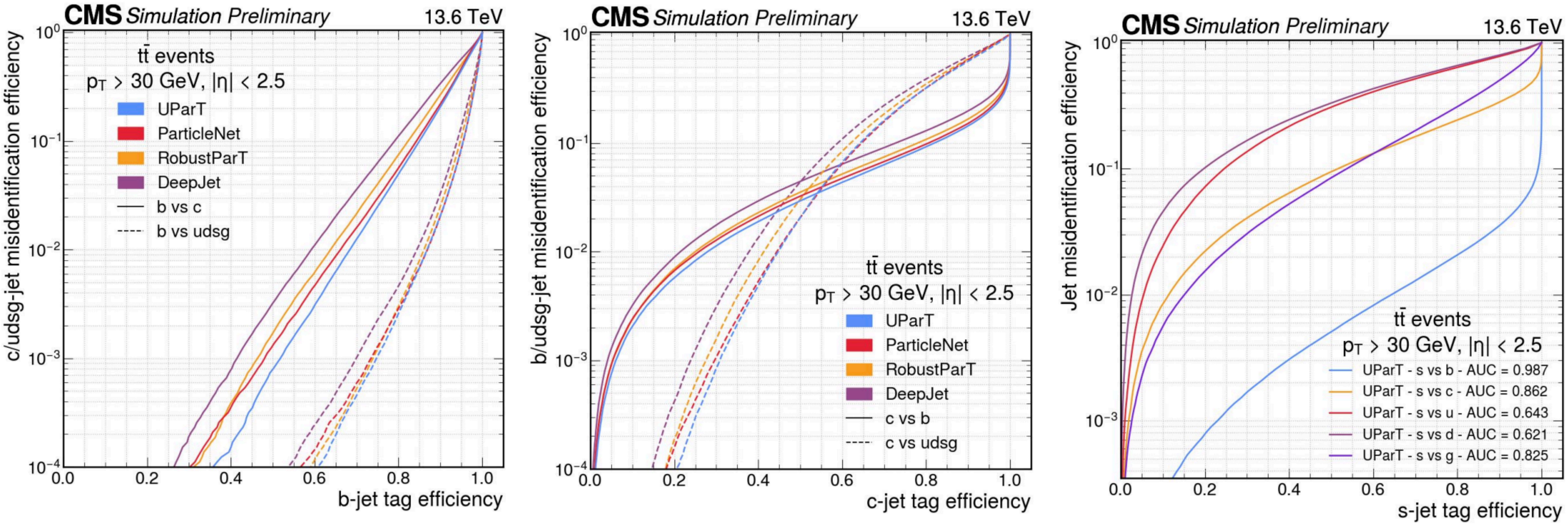



# Flavour Tagging highlights in CMS

DP-2024-066

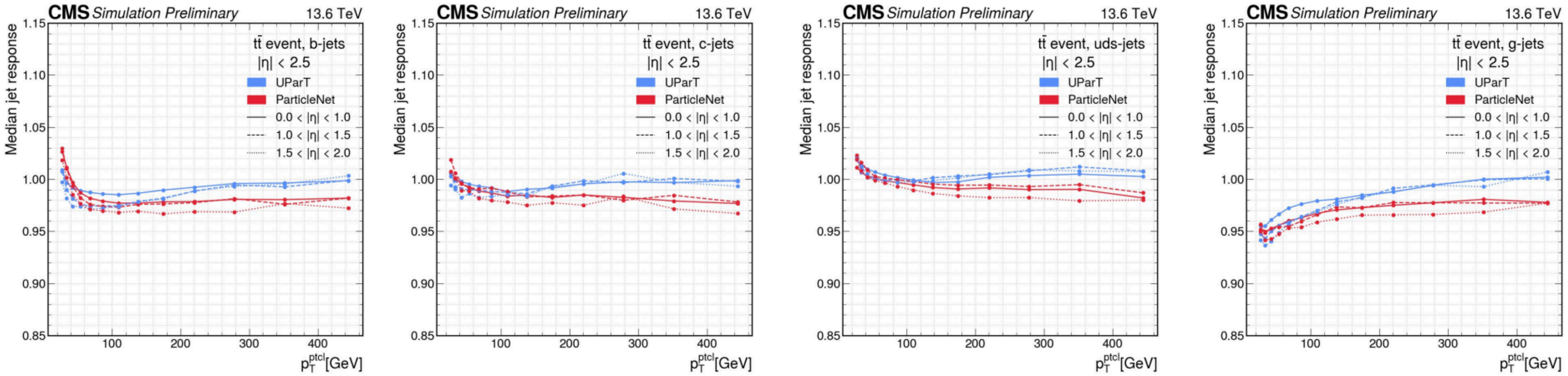
- UParT: A ParticleTransformer model for AK4 jet tasks, performing:
  - heavy flavour and $\tau_{had}$ identification
  - flavour aware jet energy regression
  - jet energy resolution estimation.
- Introduces an s-jet classifier allowing for the first time to identify jets originating from s-quarks in CMS.



# Flavour Tagging highlights in CMS

DP-2024-066

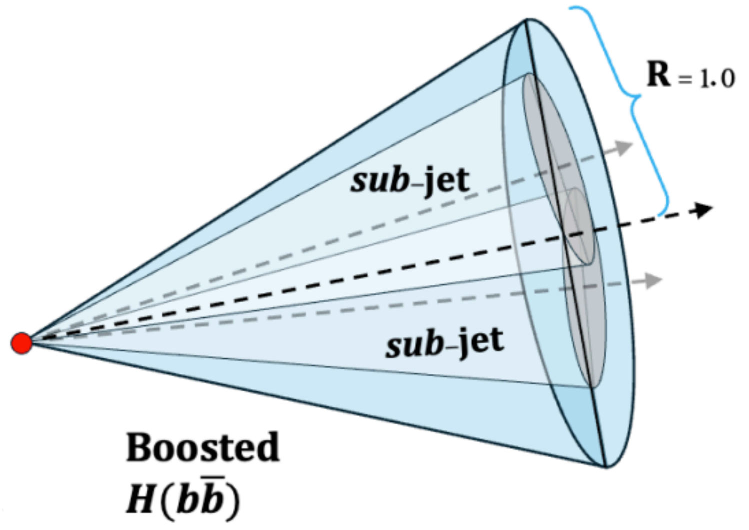
- UParT: A ParticleTransformer model for AK4 jet tasks, performing:
  - heavy flavour and $\tau_{\text{had}}$ identification
  - flavour aware jet energy regression
  - jet energy resolution estimation.
  - Introduces an s-jet classifier allowing for the first time to identify jets originating from s-quarks in CMS.



# GN2X – H(bb/cc) tagger

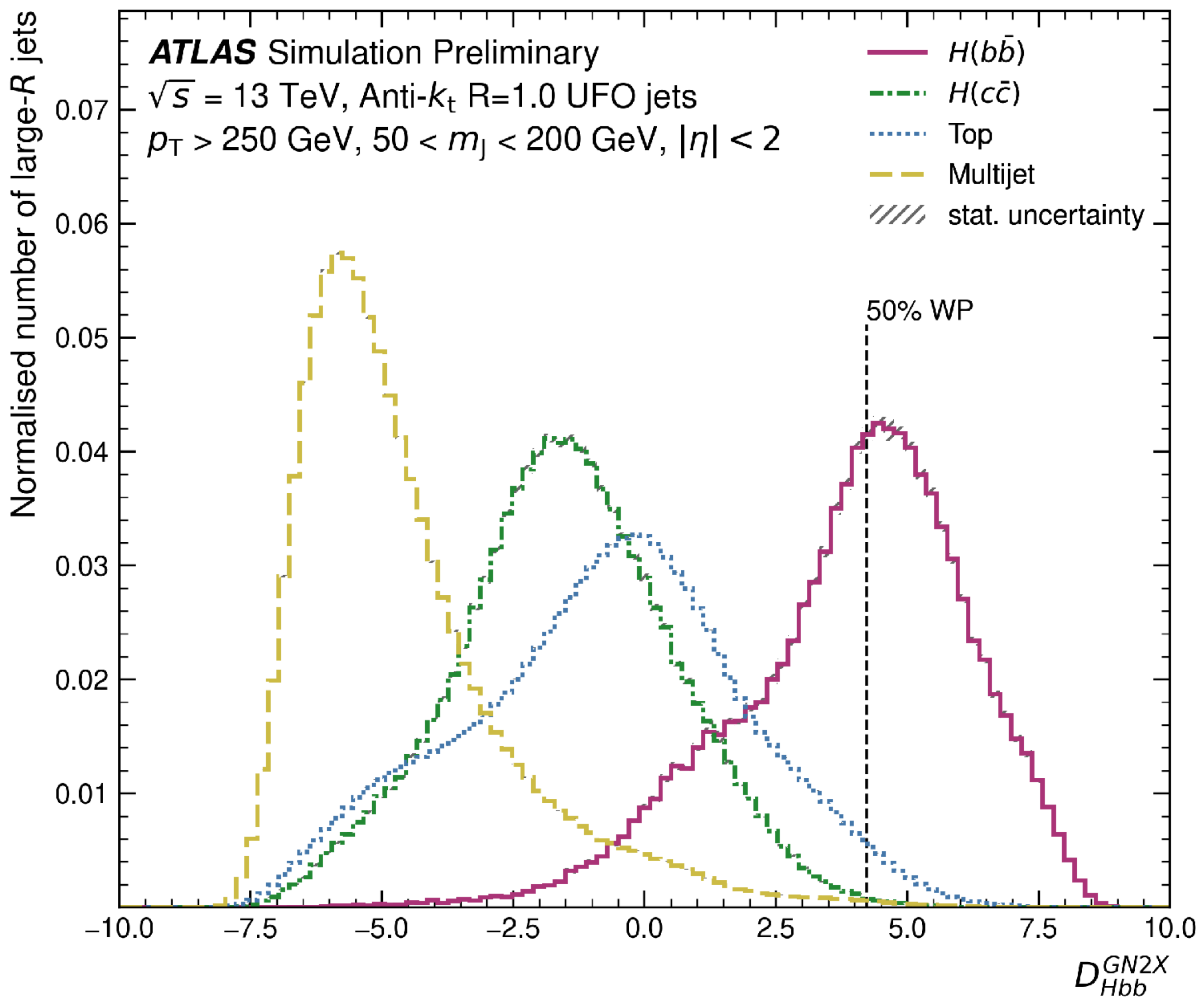
ATL-PHYS-PUB-2023-021

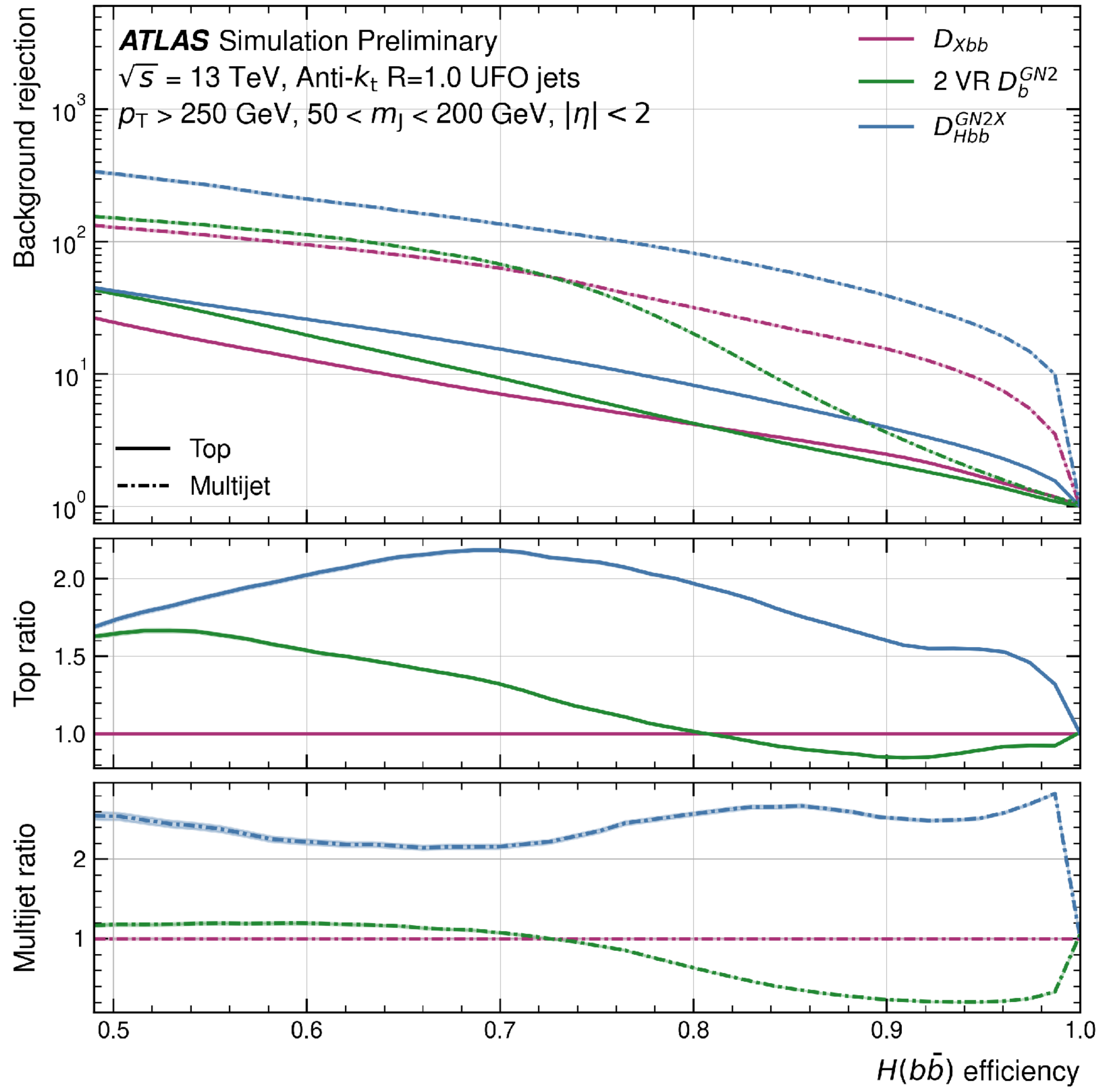
- Transformer based Xbb tagger
- Discriminate between boosted H →bb, H → cc, hadronic top and QCD jets
- trained on mass decorrelated Higgs sample

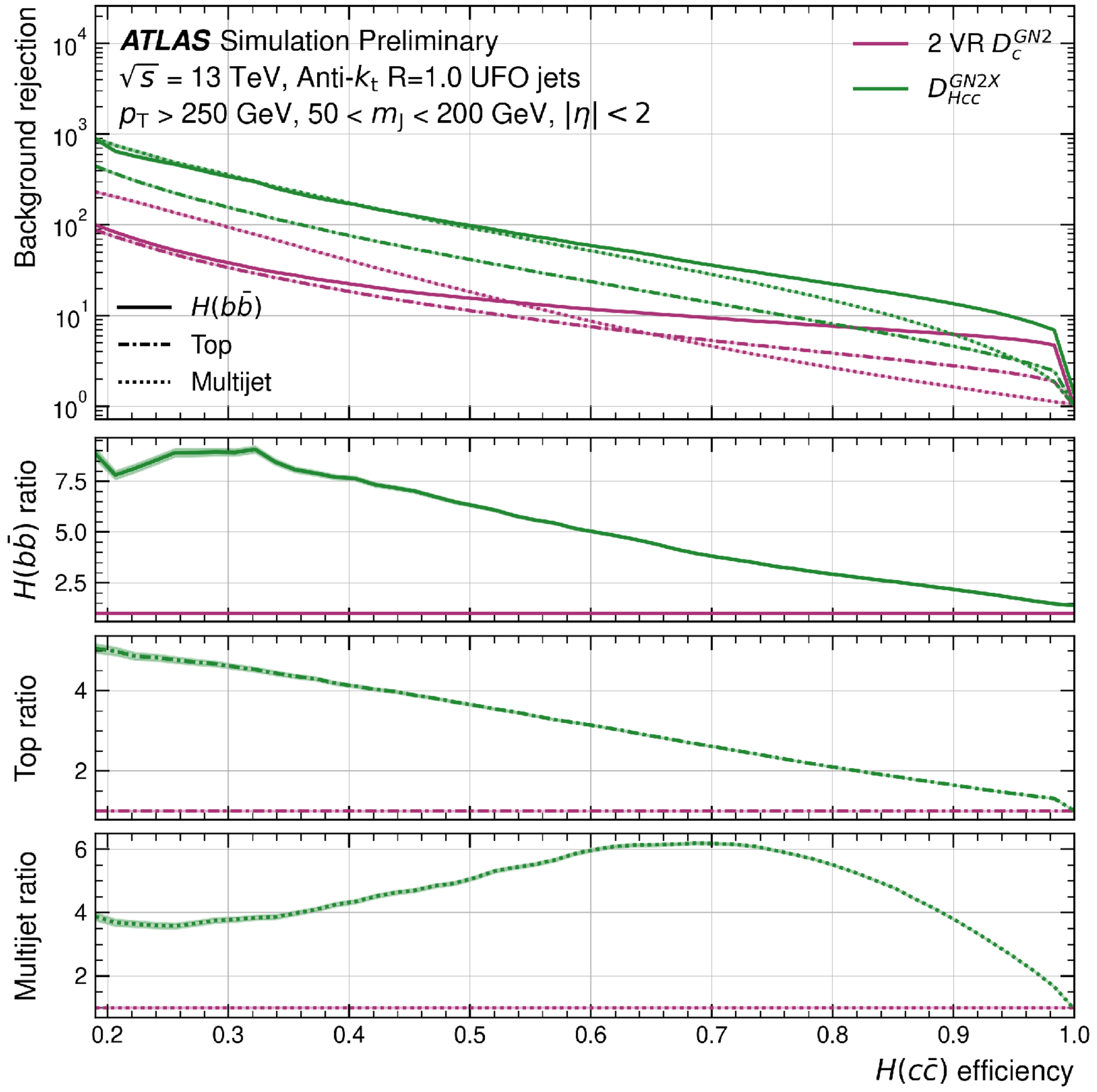



- DXbb is the usual tagger used in ATLAS (combining flavour tagging discriminants)
- GN2X uses constituent-level quantities

- GN2X Discriminant



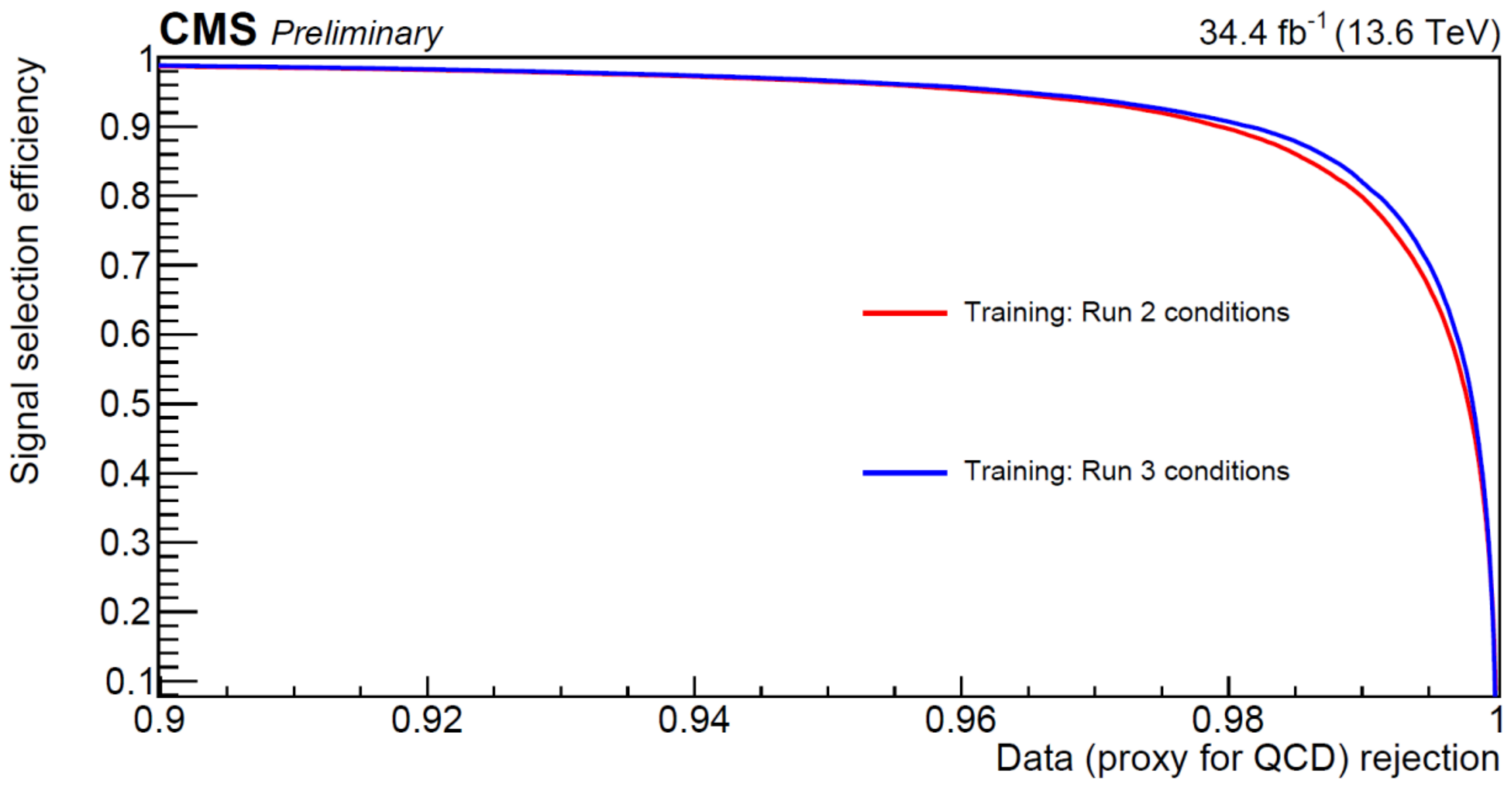



# ParticleNet-MD

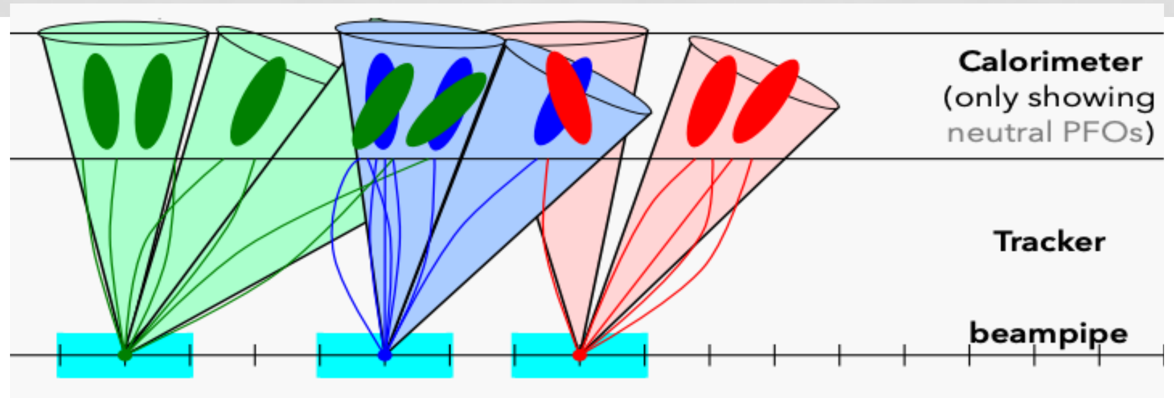
DP2024_055

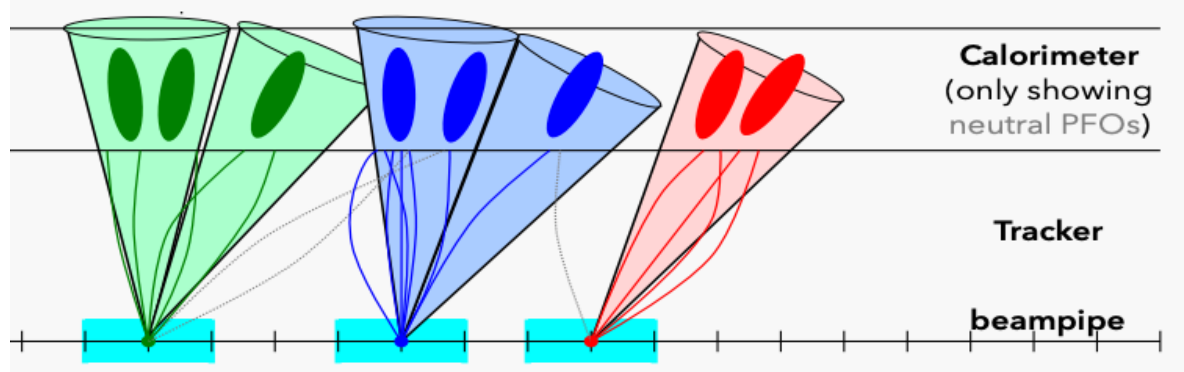
- ParticleNet-MD tagger: A mass-decorrelated boosted jet tagger for identifying two-prong hadronic decays of a highly Lorentz-boosted particle decaying to bb, cc or qq.
- The main background: QCD multijet estimated with a data-driven technique



# Using pile-up for physics

[submitted to JHEP](submitted to JHEP)

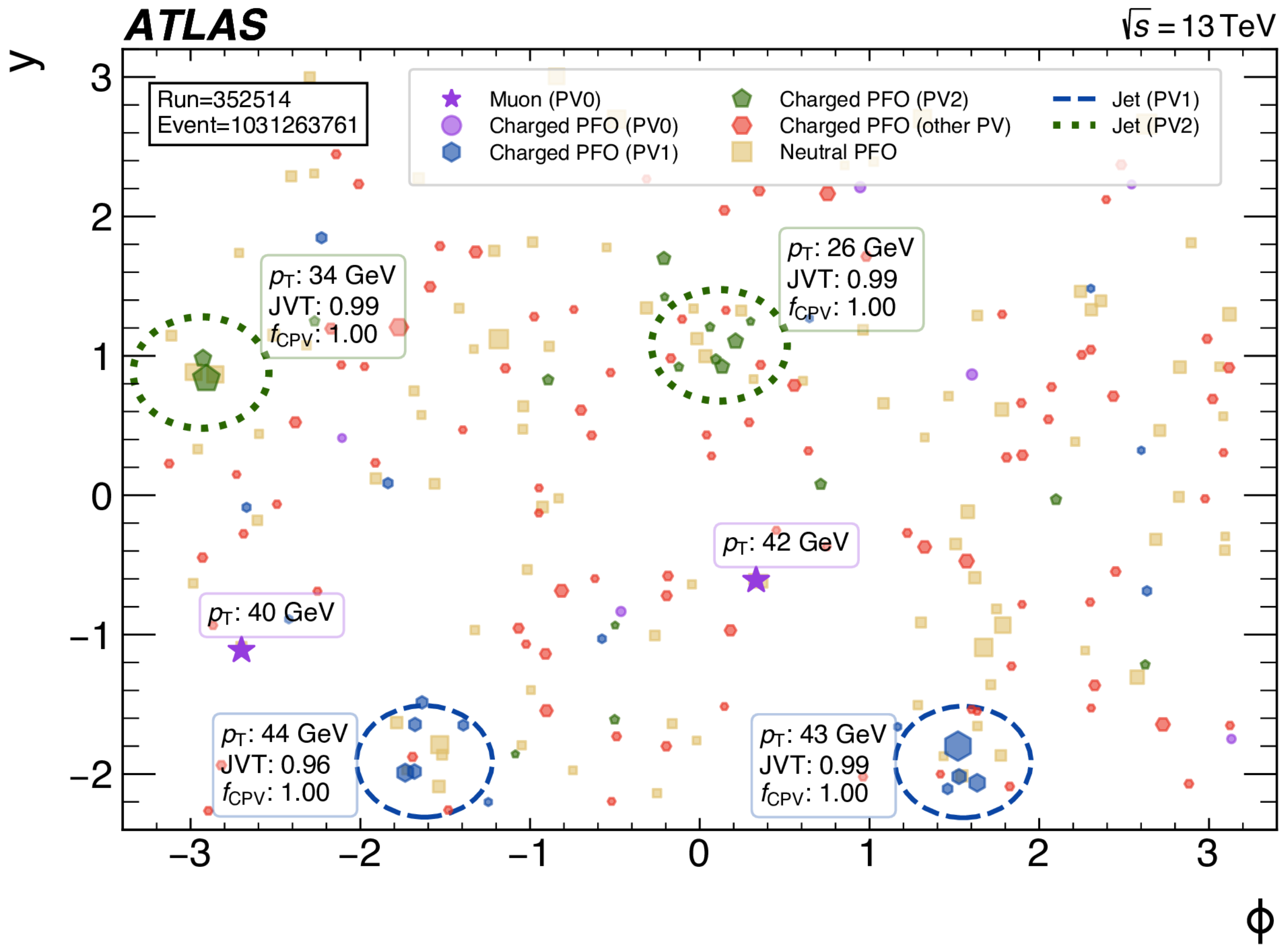


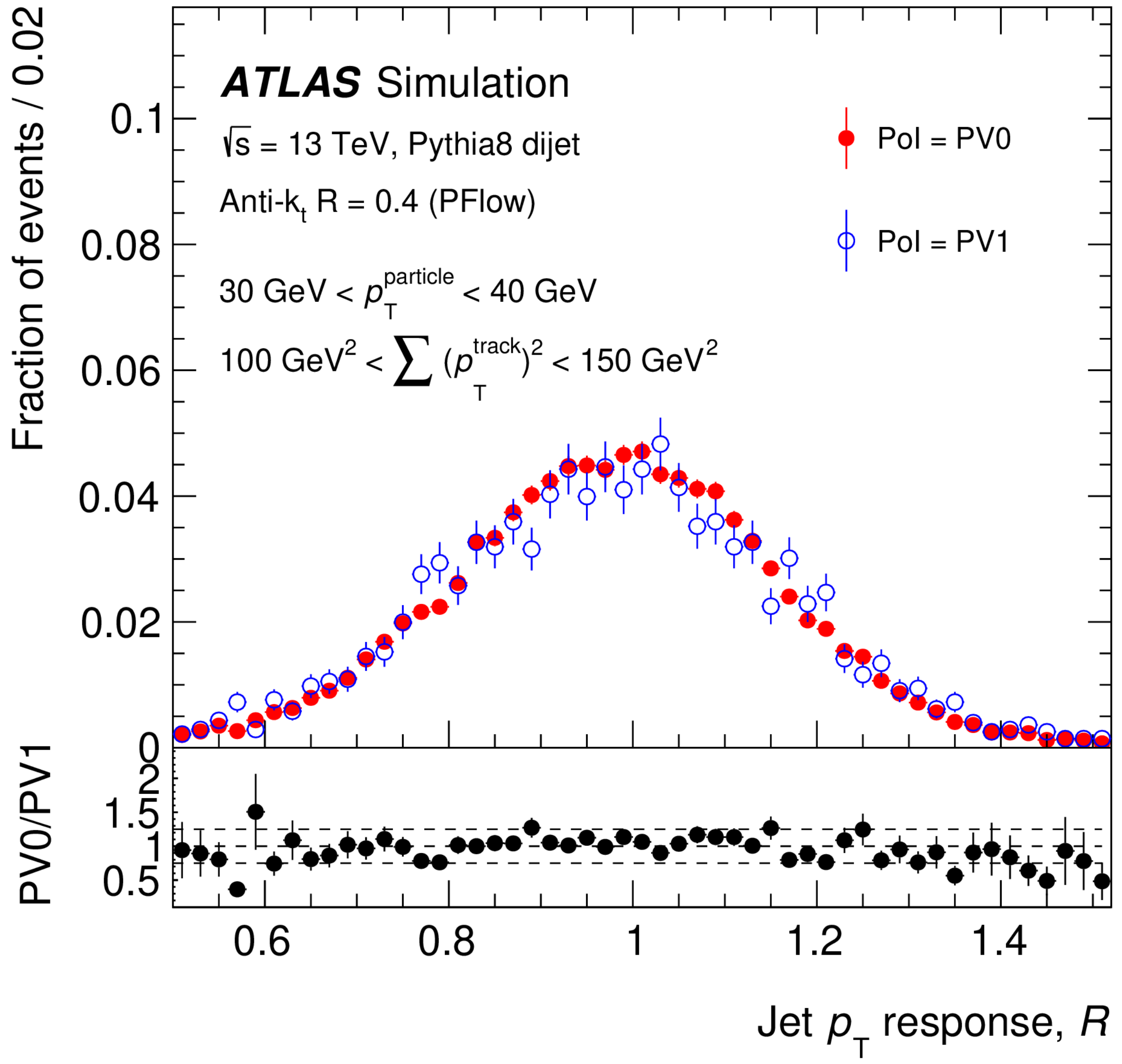

- Reconstructing Flow jets by-vertex

1. Run jet reconstruction once per vertex
    1. Charged PFOs uniquely associated with a given vertex
    2. Neutral PFOs have no vertex link → clustered once for each vertex
2. jet-vertex-tagger → removes the majority of "combinatorial" jets
3. Remaining overlaps are handled using a ΔR-based approach

Example of a bunch crossing containing a muon-triggered collision (PV0) and two distinct dijet pileup collisions (PV1 and PV2)




- Check the Jet Response
    - Reconstructed vertices ranked by $\sum (p_T^{track})^2$ → requirement on this variable ensures similar charged activity between selected PVs
    - Jet response consistent when generated dijet process is PV0 (leading vertex) vs PV1 (subleading vertex)

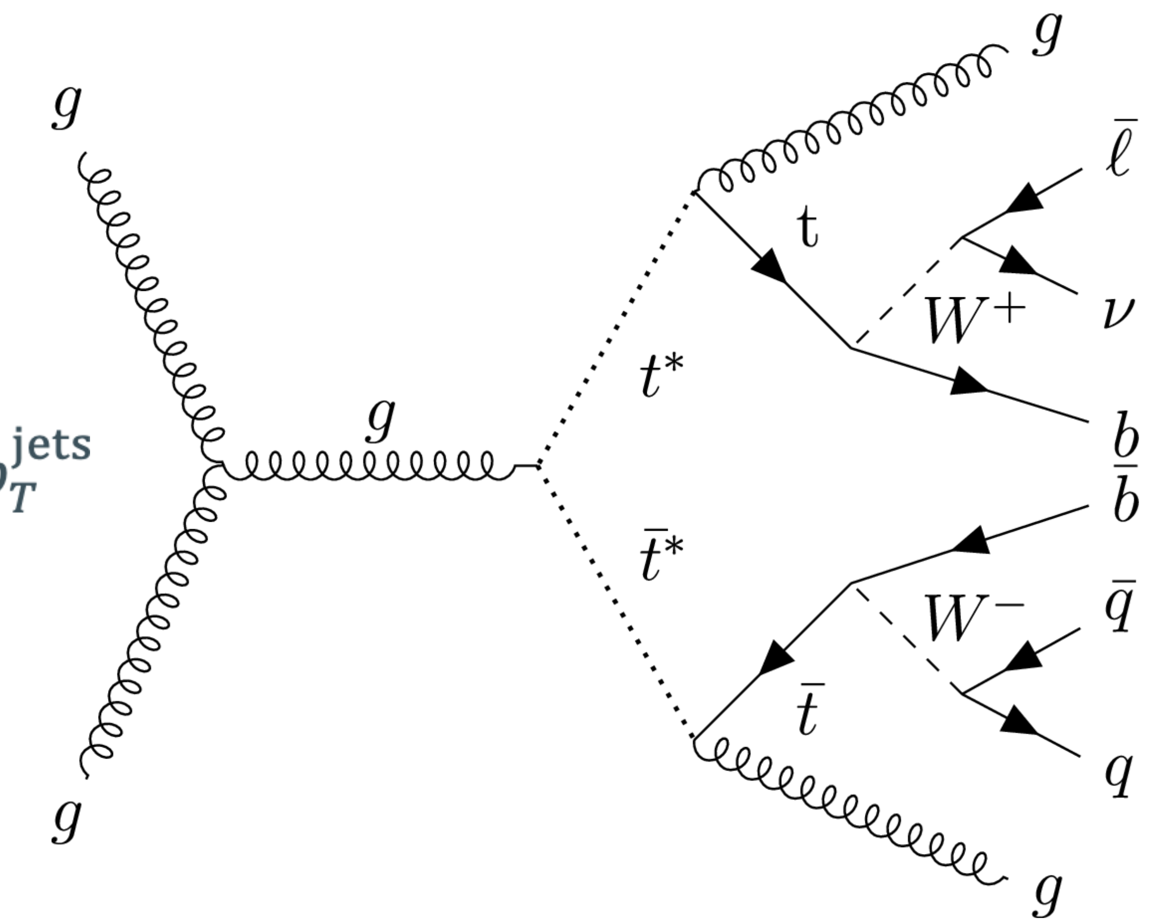


# Search for pair production of heavy particles decaying to a top quark and a gluon in the lepton+jets final state

- Search for pair production of excited top partners: $t^*\bar{t}^* \rightarrow tg\bar{t}g$
- HOTVR jets: allow access to wide range of jet momenta, due to variable radius

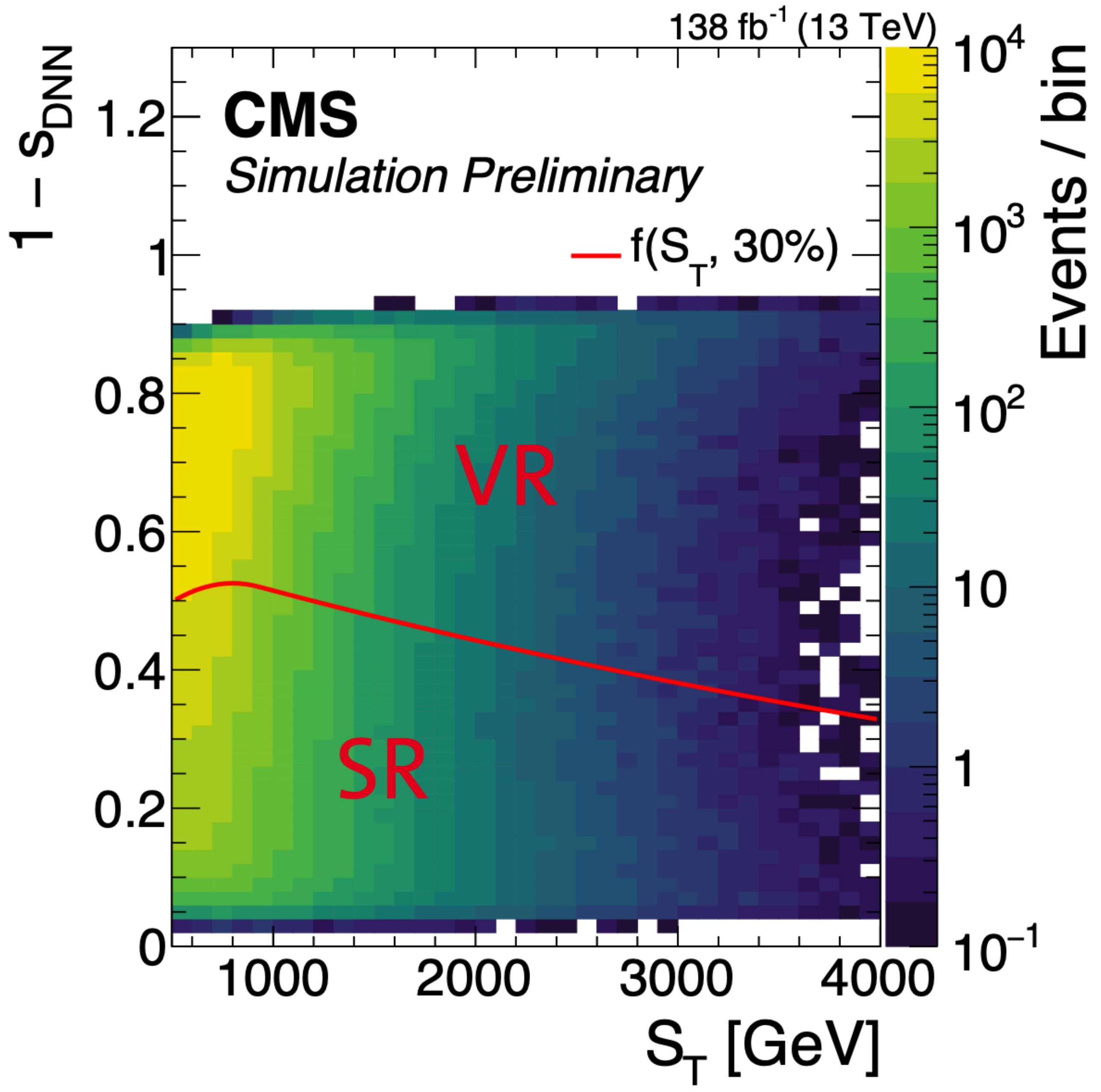
- Final state similar to $t\bar{t}$, with two additional jets
- Mass reconstruction challenging: instead use energy sum as sensitive variable

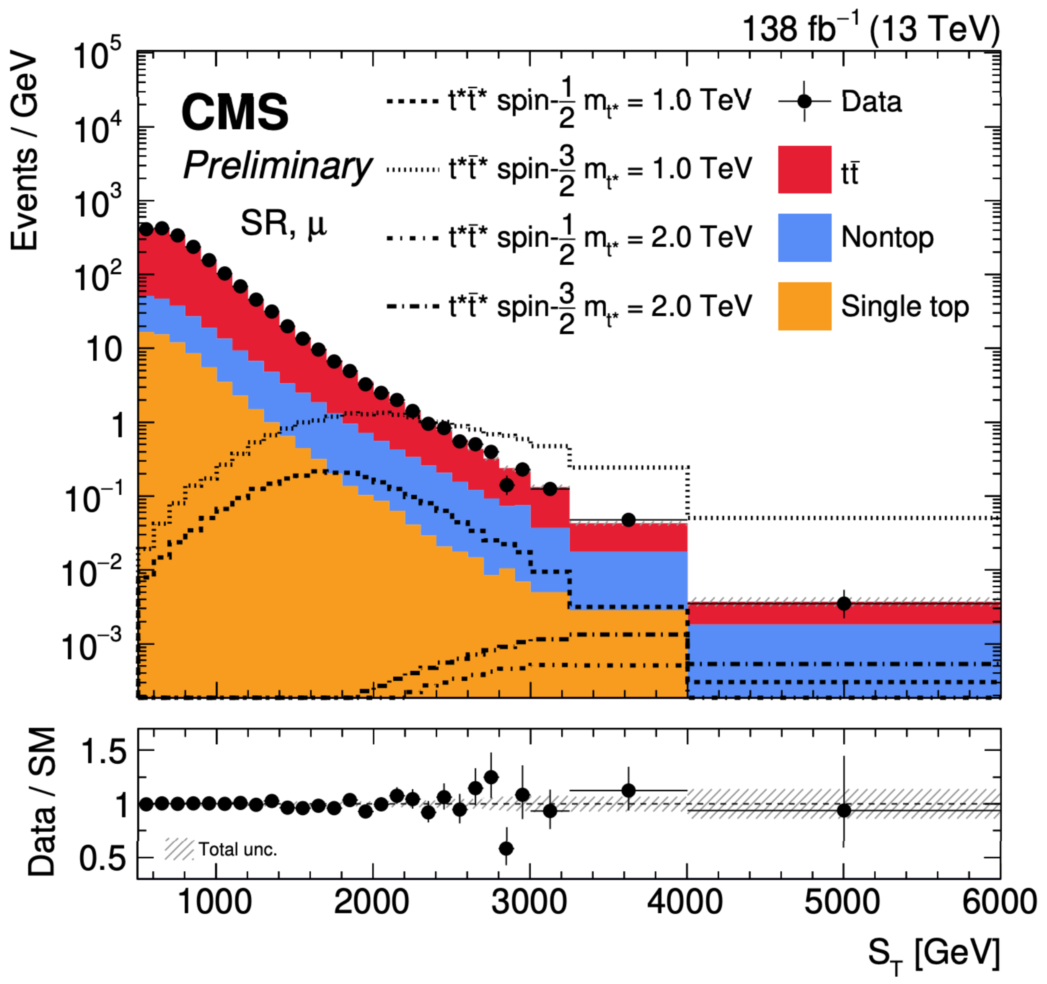
$$S_T = p_T^{\ell} + p_T^{\text{miss}} + \sum p_T^{\text{jets}}$$

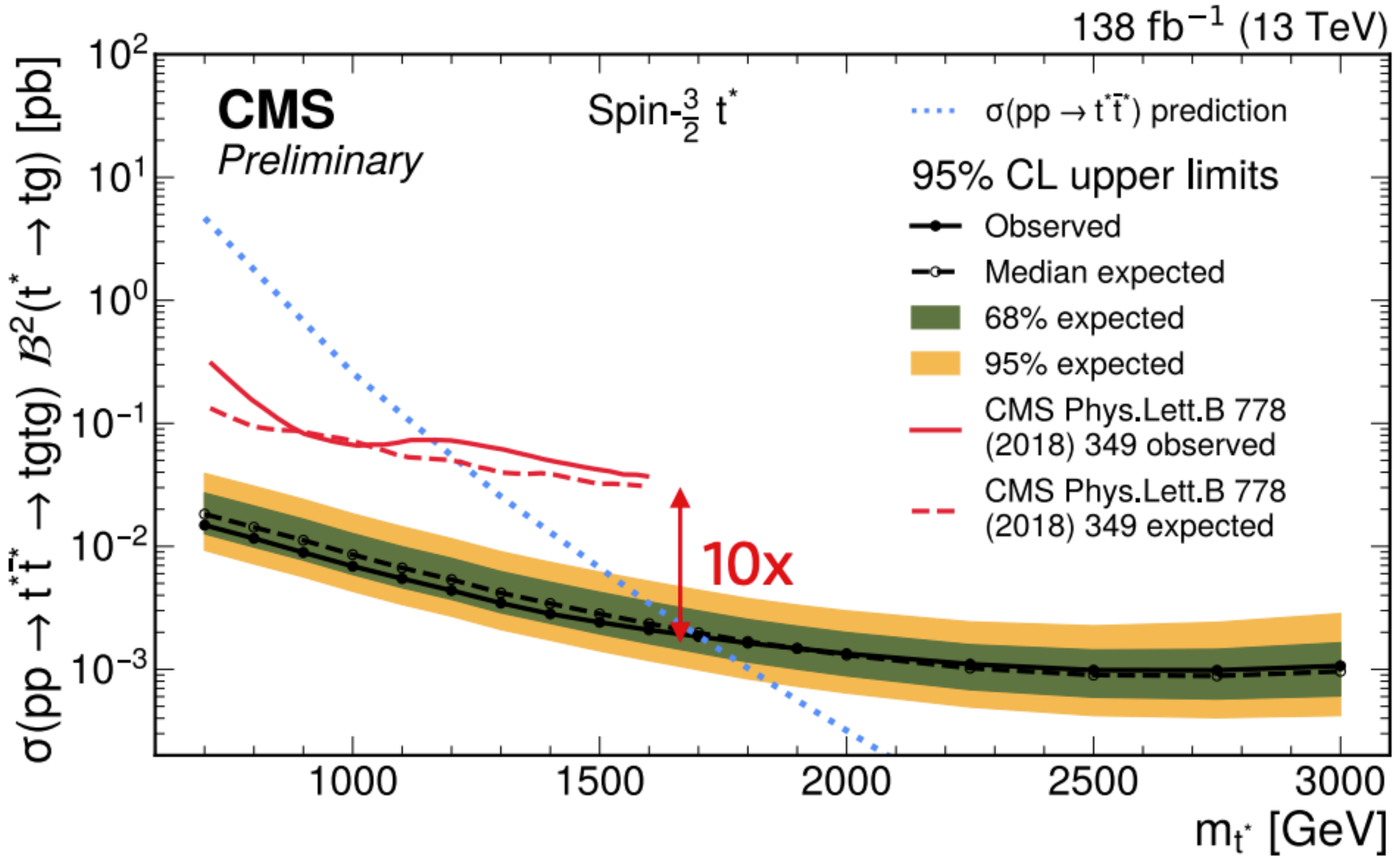



- Event classification with DNN
  - Discriminating $t^*\bar{t}^*$ from $t\bar{t}$
  - DNN inputs include jet substructure

decorrelated tagger by introducing a ST dependent threshold



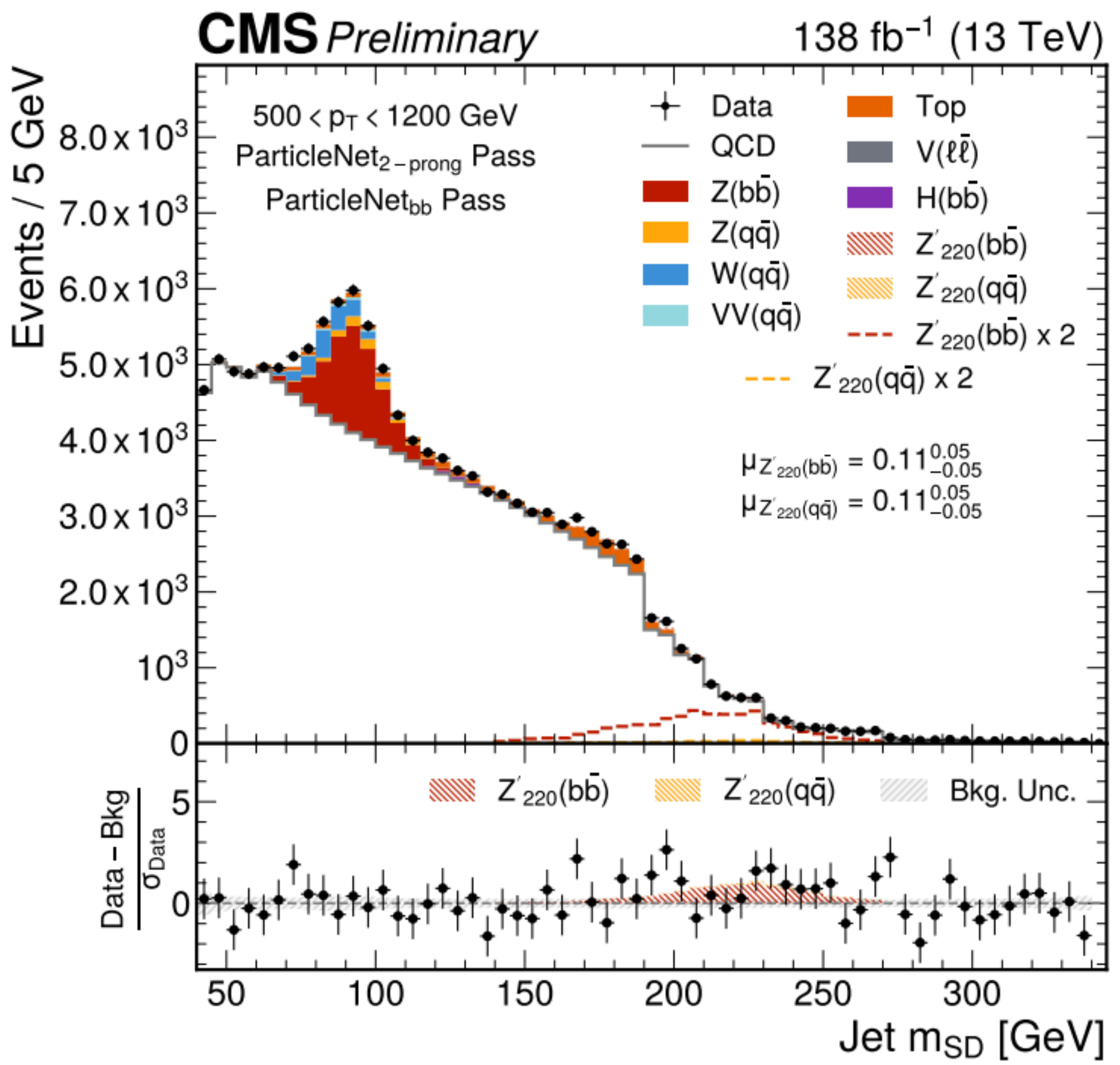



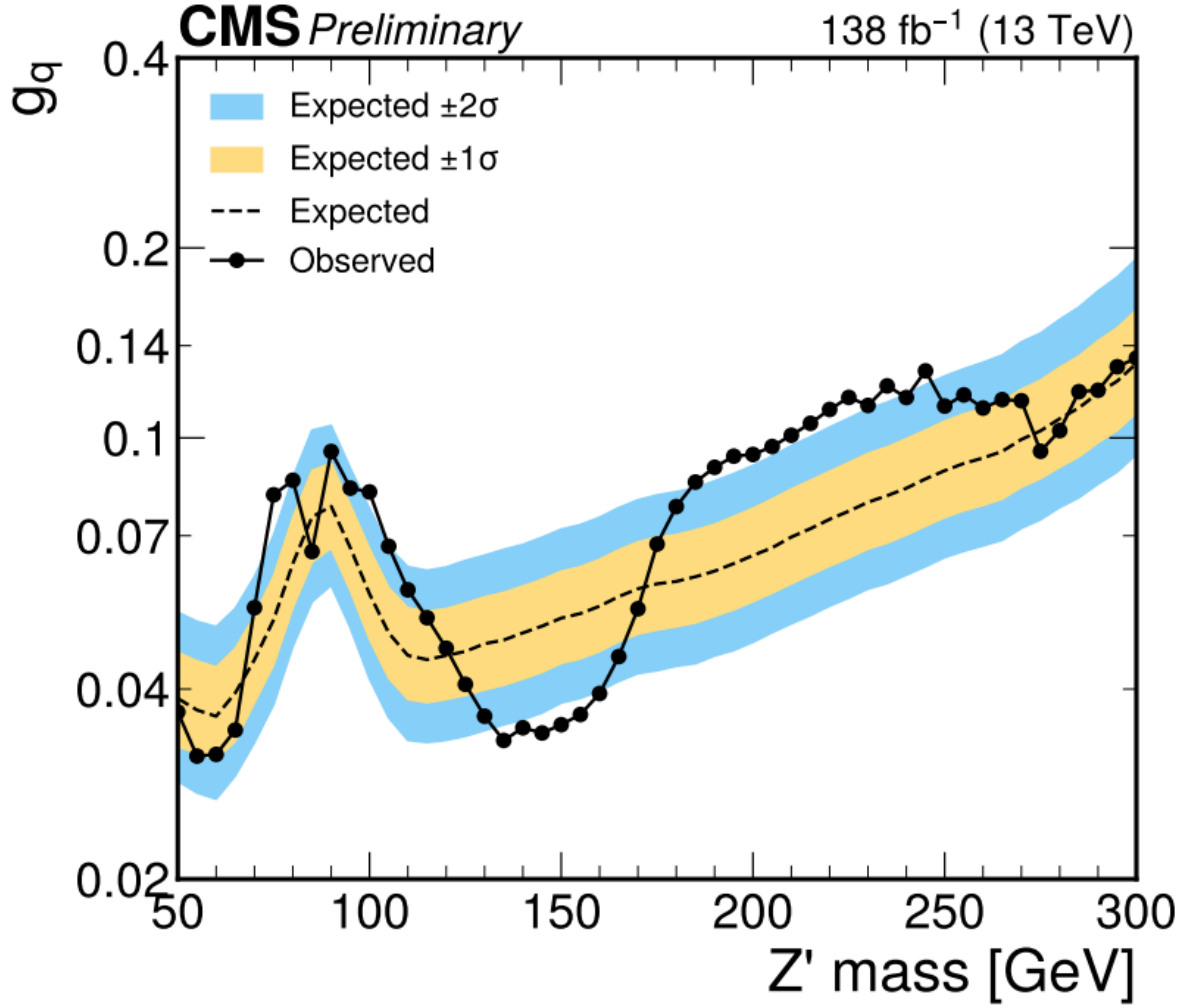



# Boosting Searches

- Search for boosted low-mass resonances decaying to a merged dijet system
  - targets resonances with masses from 50 to 300 GeV
  - produced in association with large initial-state radiation

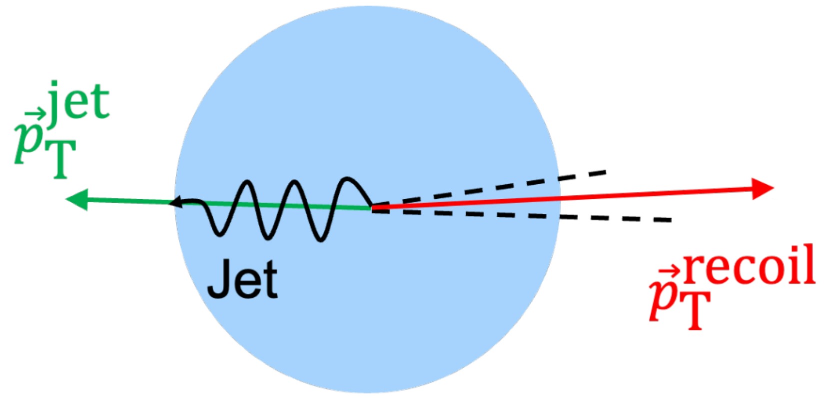
- ParticleNet to identify these two-prong jets
- QCD background is data-driven

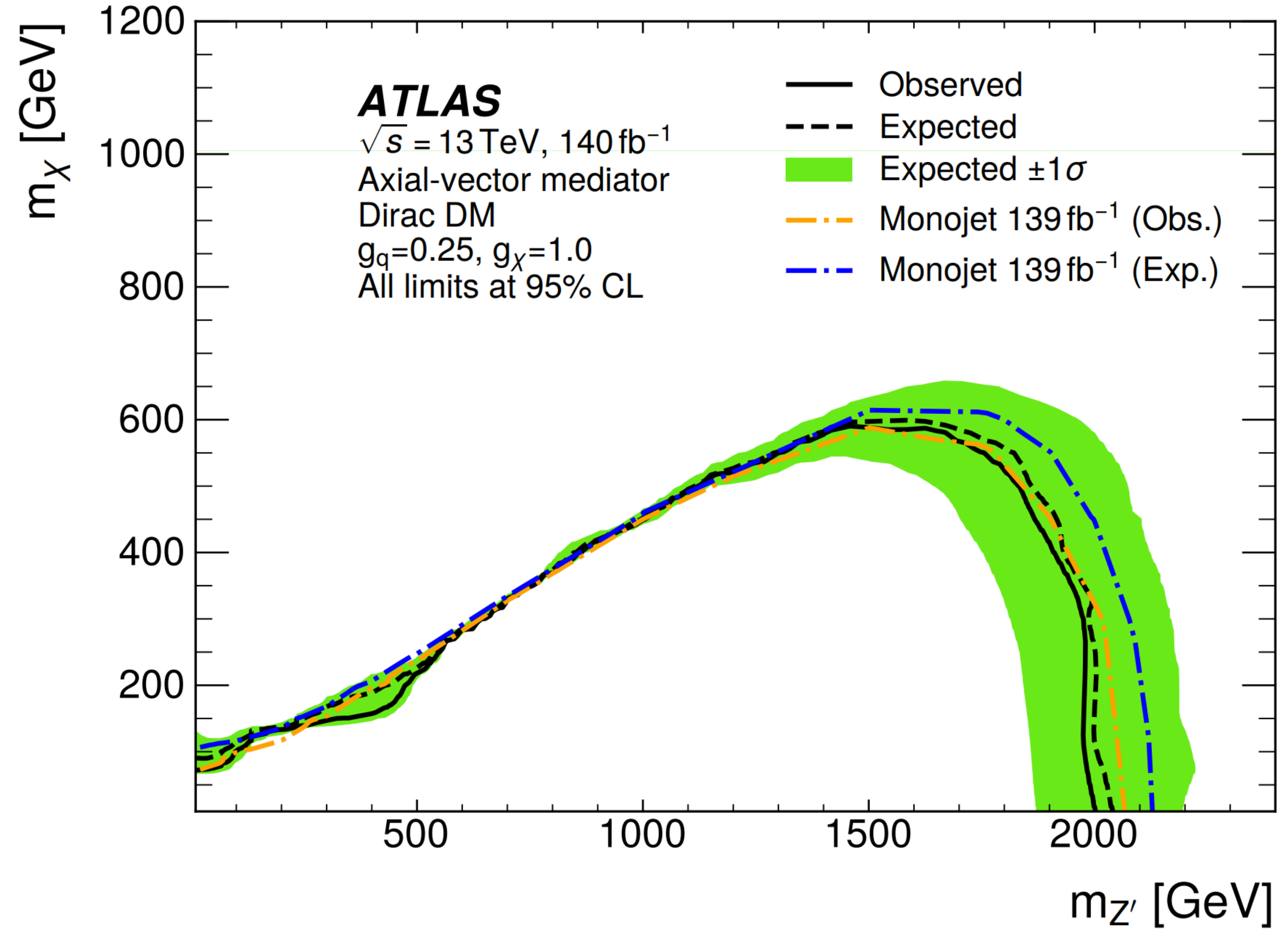


# Measurements

- First inclusive **particle-level measurement of** $p_T^{miss}$, using full ATLAS Run-2 dataset

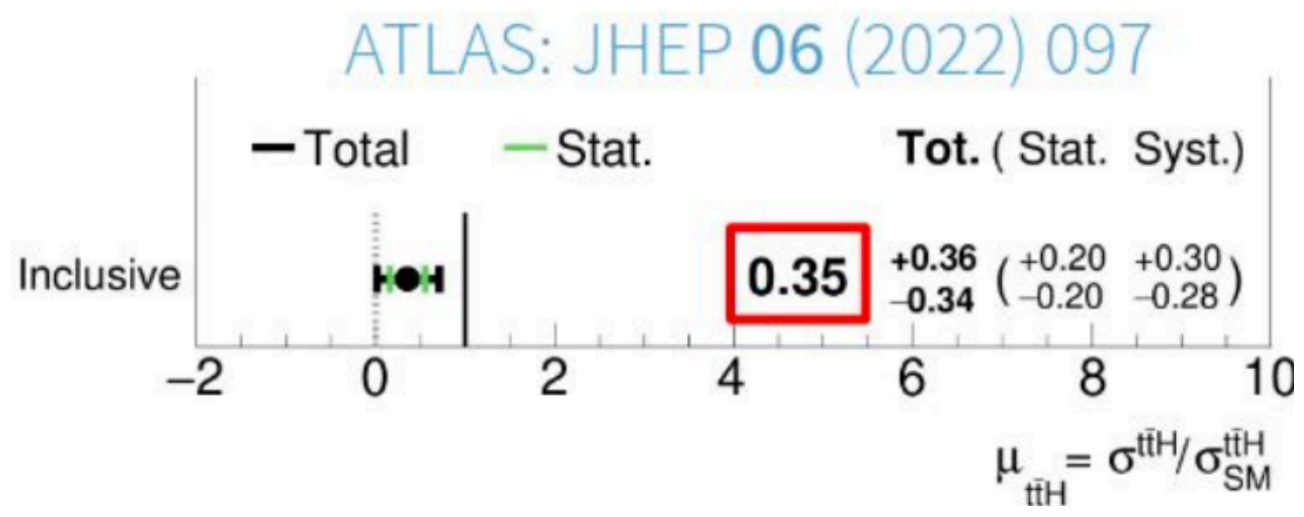



particle-level measurements can be as powerful as dedicated BSM searches in terms on constraining power!

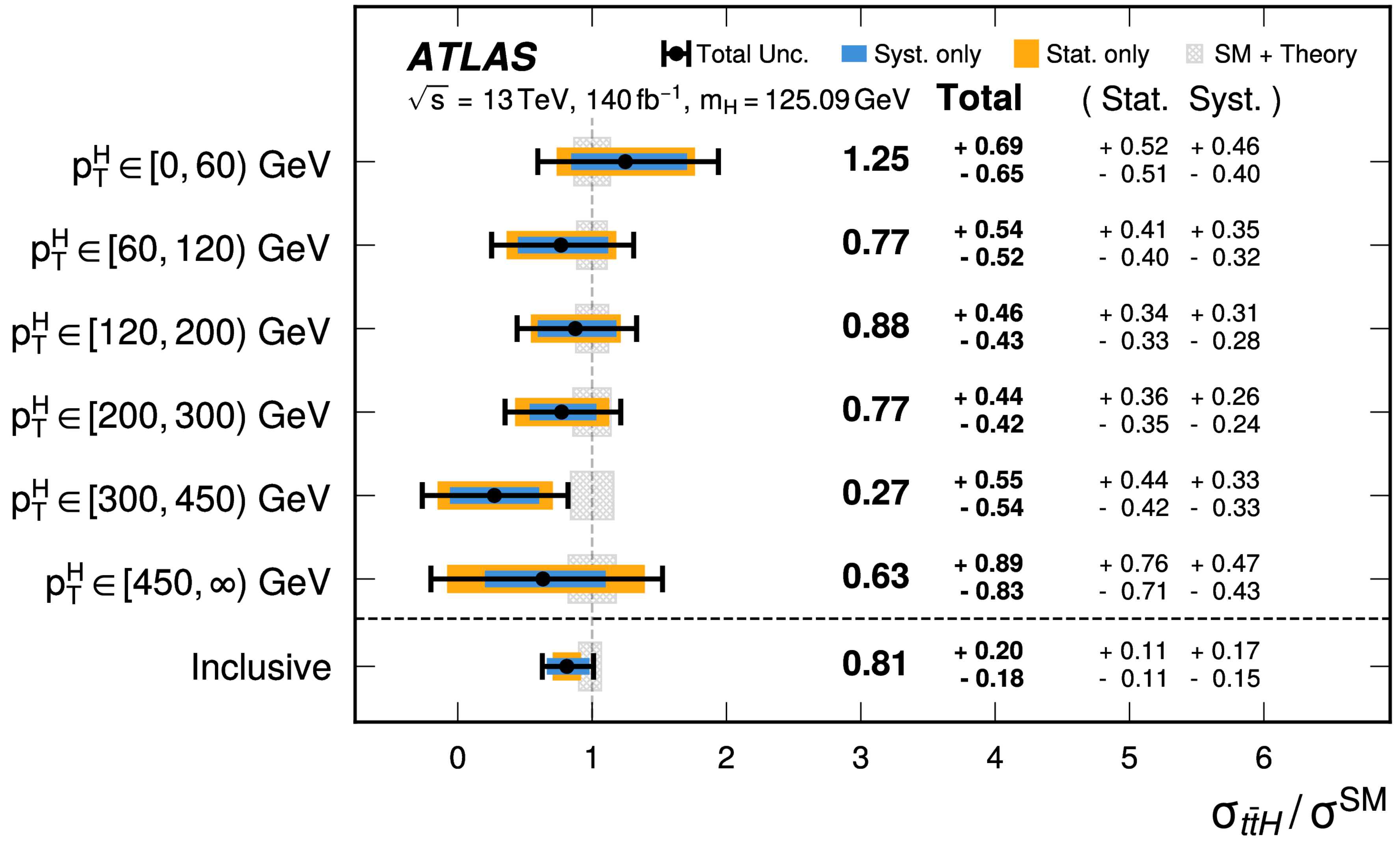
More details on Yoran talk

- **Precision Higgs -** $ttH(bb)$




- Particle-flow jets for Small-R
- Reclustered for Large-R
- Improved tagging of b-jet

submitted to EPJC



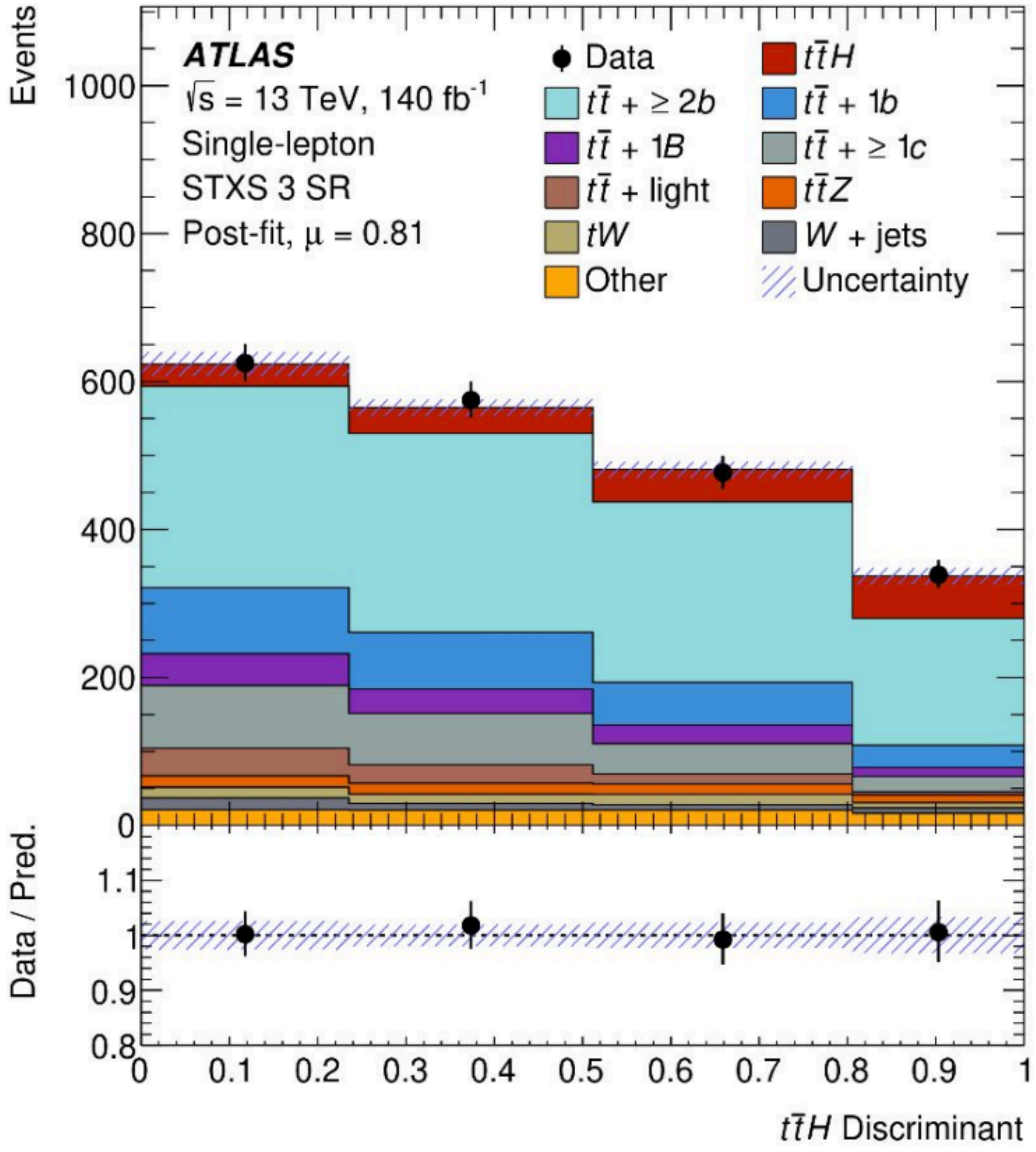

Improve precision and 4.6σ observed significance in ttH(bb) alone!

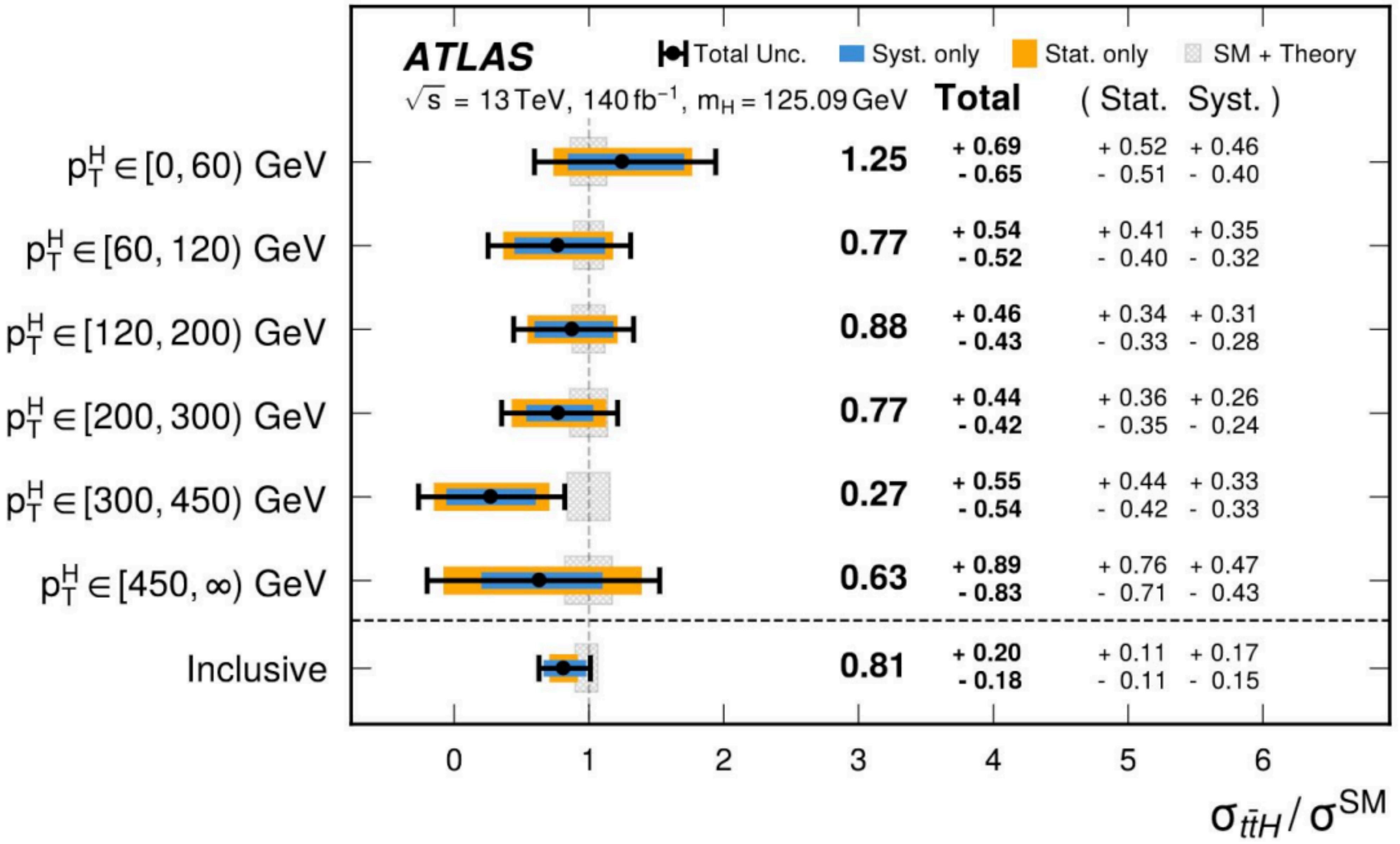
More details on Kulin talk

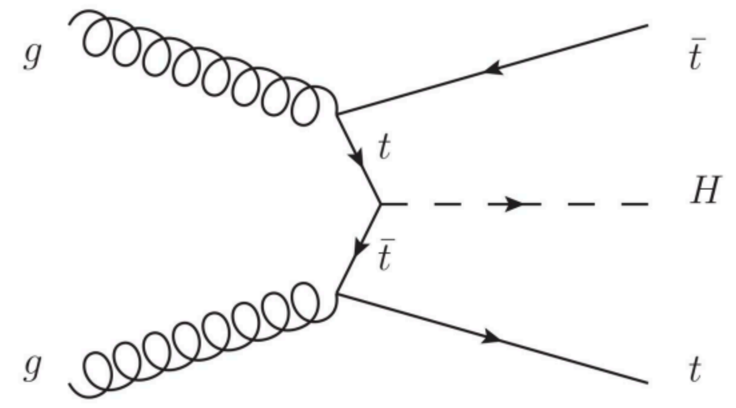
# Measurements

- **ttH with H to bb with Full Run2**

State-of-the art NN classifier using transformers with attention mechanism




**$p_T$(H) measurement limited statistically**

Inclusive cross-section:

$$\sigma_{t\bar{t}H} = 411\ ^{+101}_{-92}\ \text{fb} = 411 \pm 54(\text{stat.})\ ^{+85}_{-75}(\text{syst.})\ \text{fb}.$$

→ dominated systematically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