Project is supported in part by DOE grant Grant No. DE-FG05-92ER40712

Paper: JHEP04(2023)140

2024 RHIC-AGS User Meeting, AI/ML Workshop

Machine Learning Application in Jet Quenching Analysis

Yilun Wu

Vanderbilt University

Outline

Background and Motivation

Neural Network Framework (feature engineering) for the Study

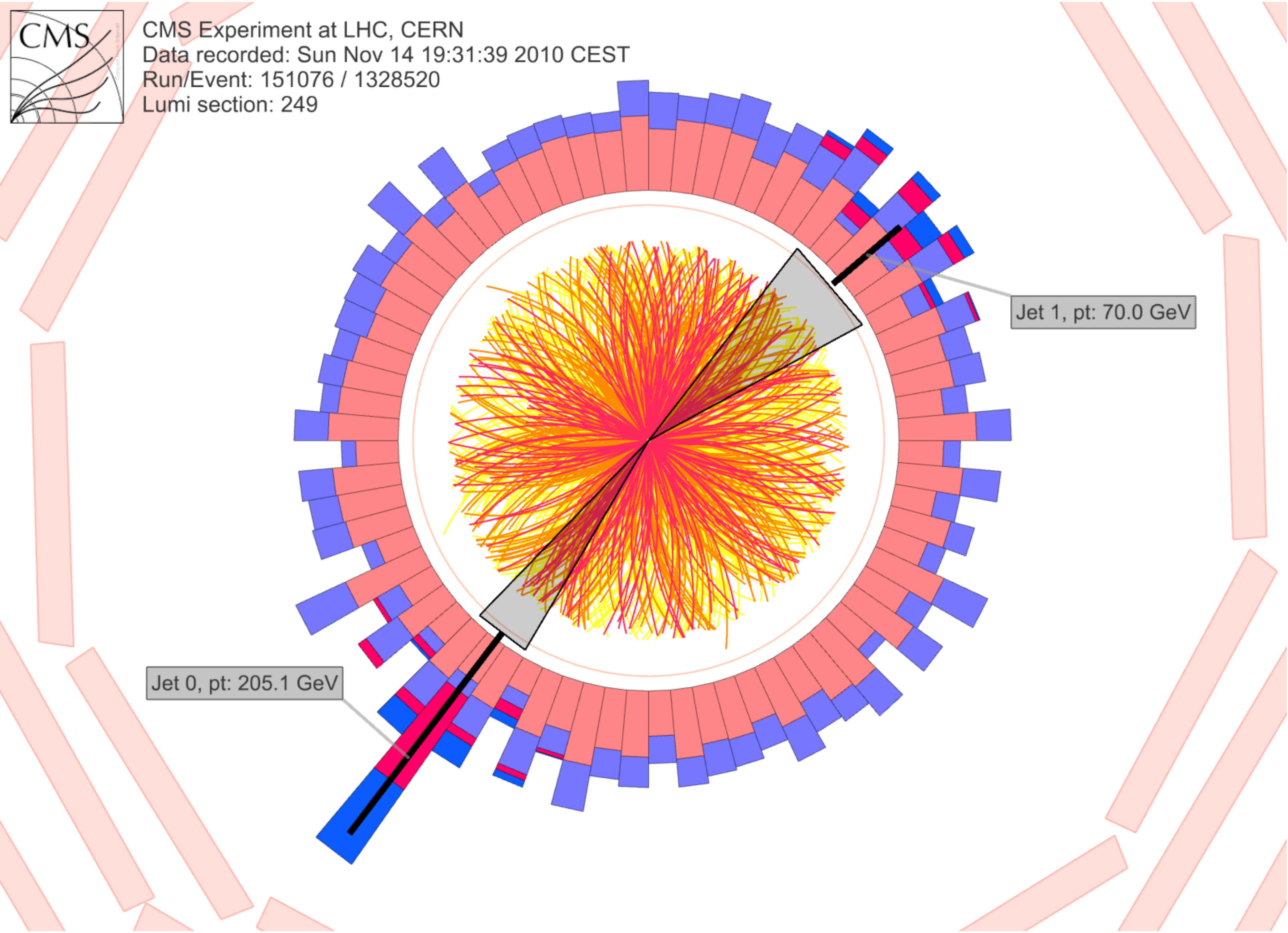
Design Simulation as a Realistic Approximation to Data

- ✓ Simulation of Thermal Background in HI Collisions and NN Training Results
- ✓ Simulation of Detector Effects on the NN Training Results

Summary and Outlook

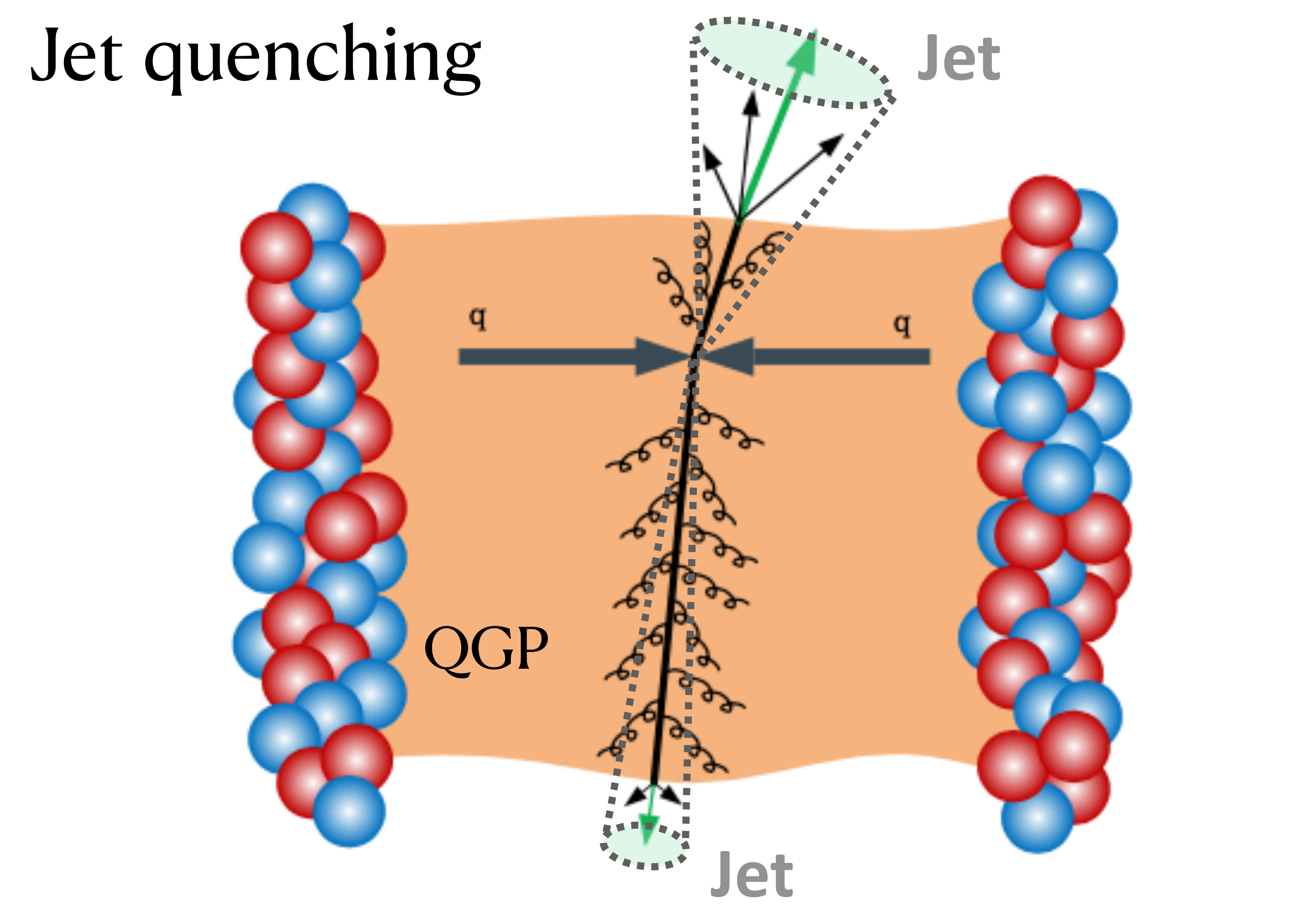
Jet Quenching Phenomenon

Heavy ion collision



QGP signature: Jet quenching phenomenon

- Jets interact with the QGP medium and lose energy.
- Back-to-back jets traverse different path length of the QGP medium.



Dijet Momentum Asymmetry

Motivation- why study quenching jet-by-jet?

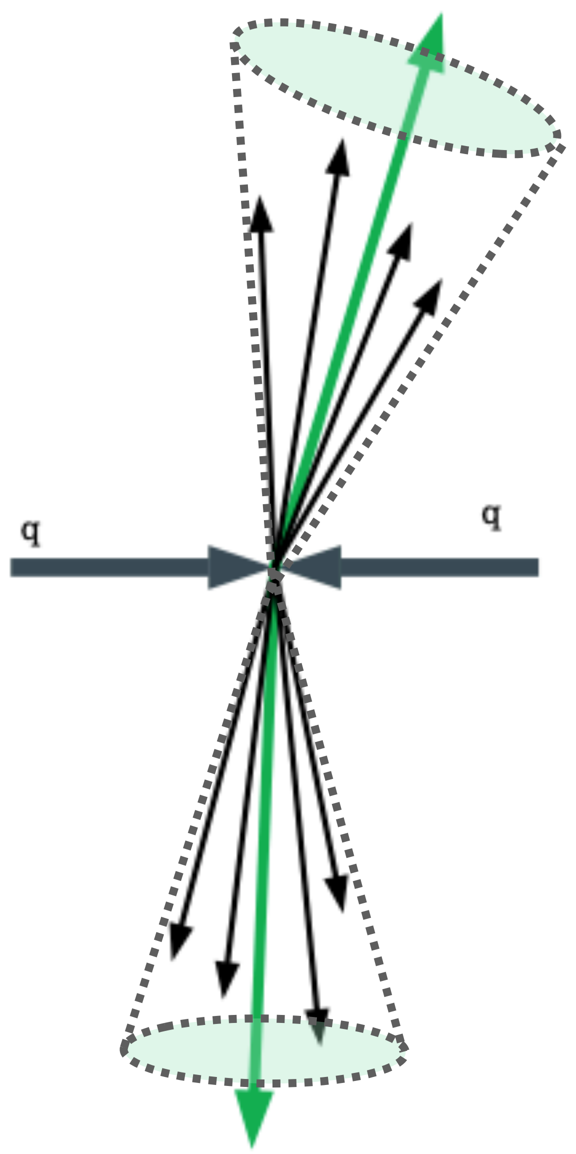
Jet Cone
Medium (QGP)

Jet-QGP interaction

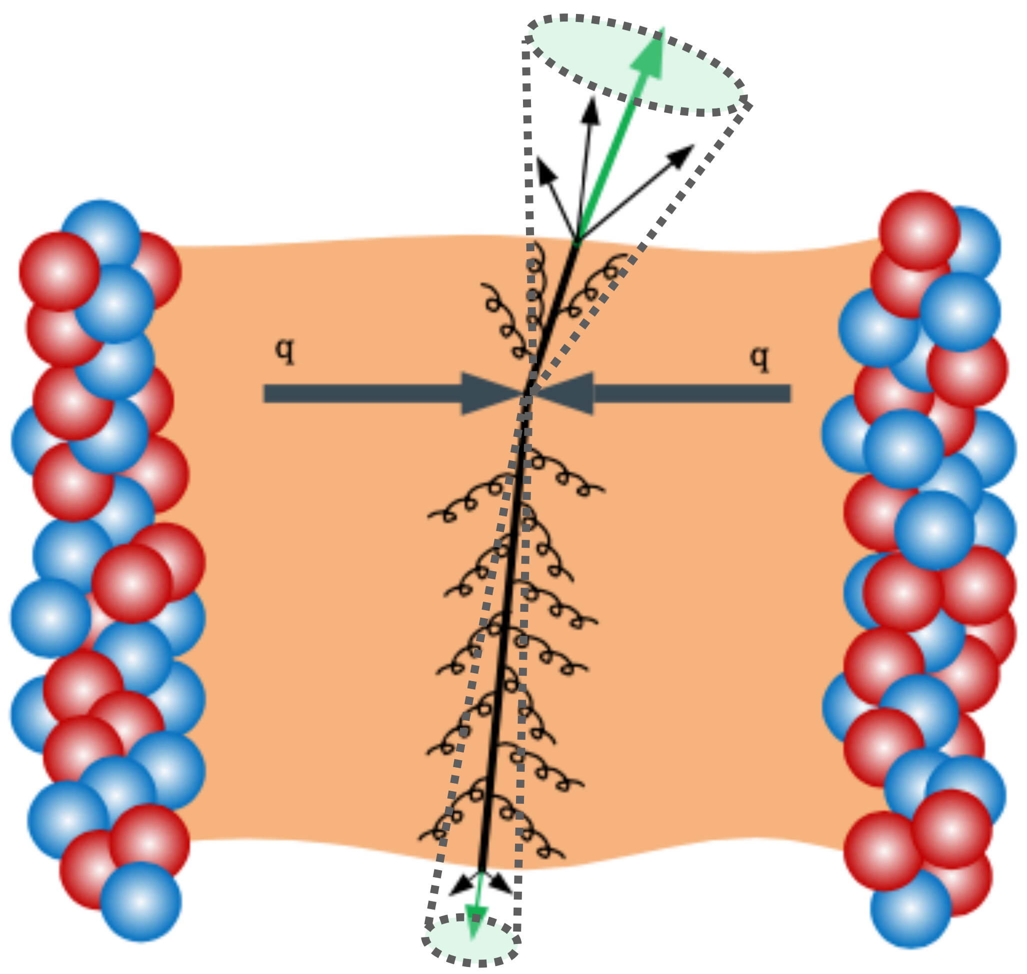
Parton Splitting,
Medium induced Radiation,
Medium Response...

What we measured

Jet loses energy as a whole
Internal structures of jets are modified



p+p
Vacuum jet



A+A
Quenched jet

- The physics of jet quenching is studied from **the difference between collision systems** of proton-proton (pp) and heavy-ion(AA) events.

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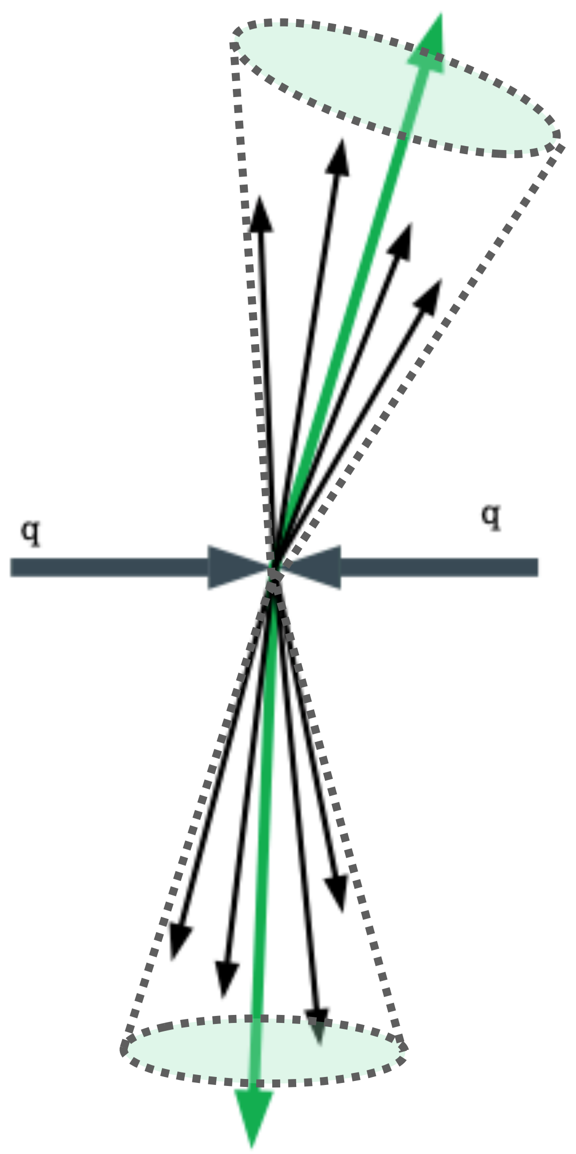

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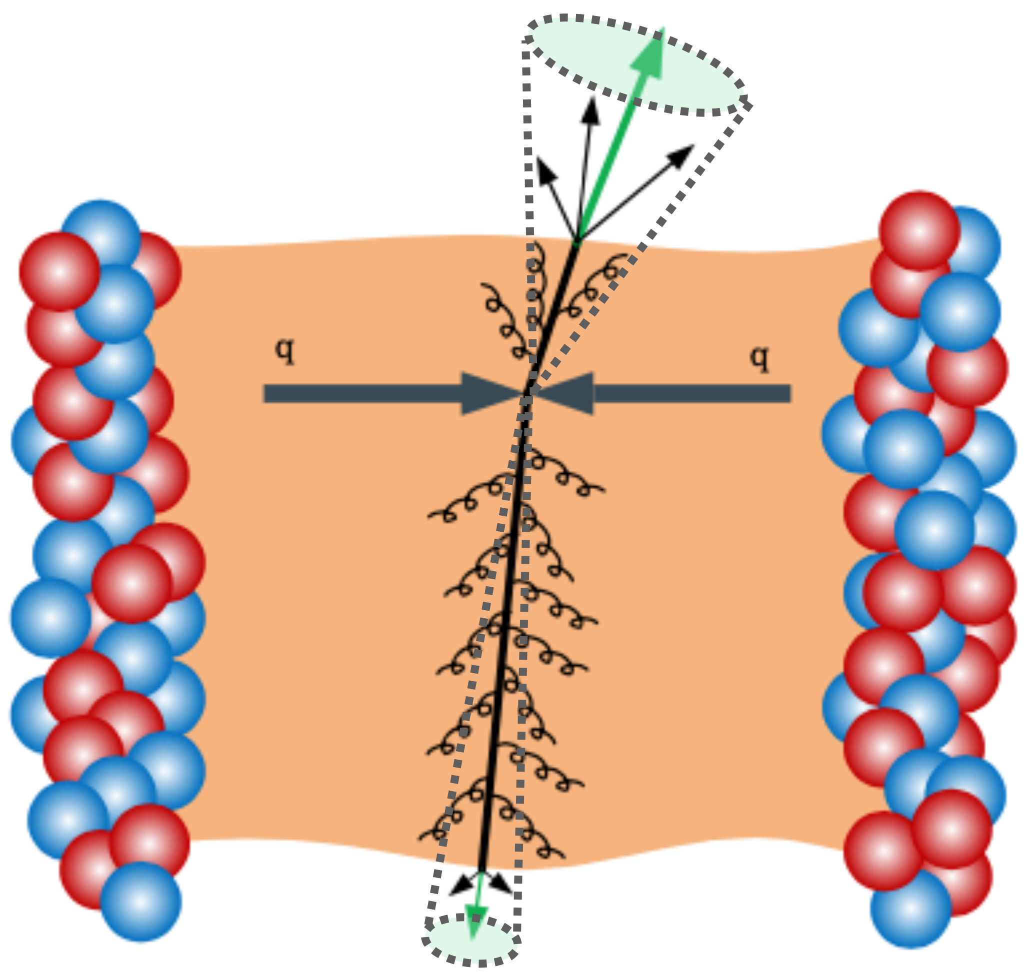


A+A
Quenched jet

- The physics of jet quenching is studied from **the difference between collision systems** of proton-proton (pp) and heavy-ion(AA) events.
- In practice, we **statistically average measured jet observables** over billions of collisions to achieve significant results.
- However, jets experience various levels of quenching due to complex mechanisms. **Many jets experience little quenching**, thus diminishing the significance of the results.

Motivation- why study quenching jet-by-jet?

Jet Cone
Medium (QGP)

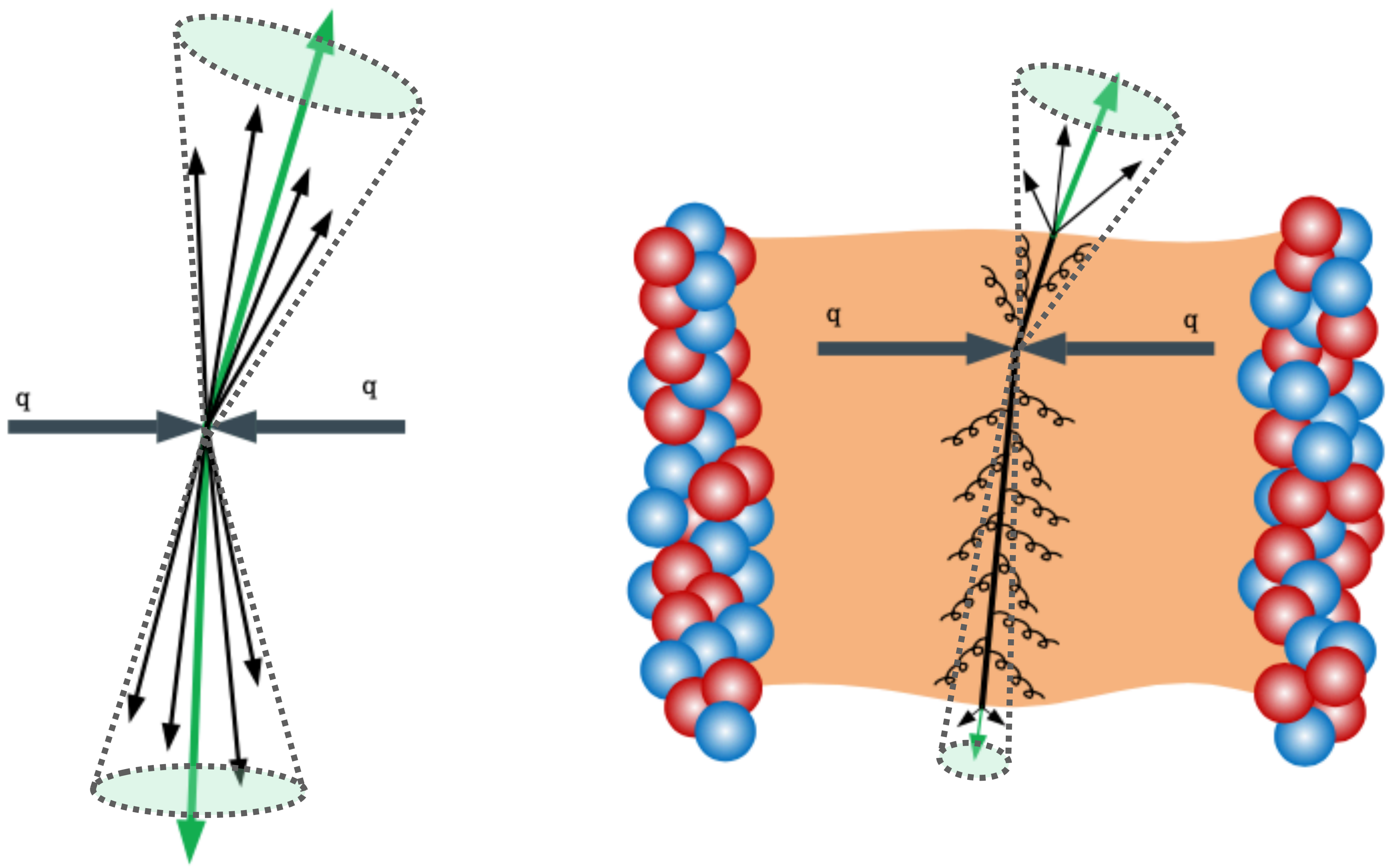
Jet-QGP interaction

Parton Splitting,
Medium induced Radiation,
Medium Response...

→

What we measured

Jet losses energy as a whole
Internal structures of jets are modified



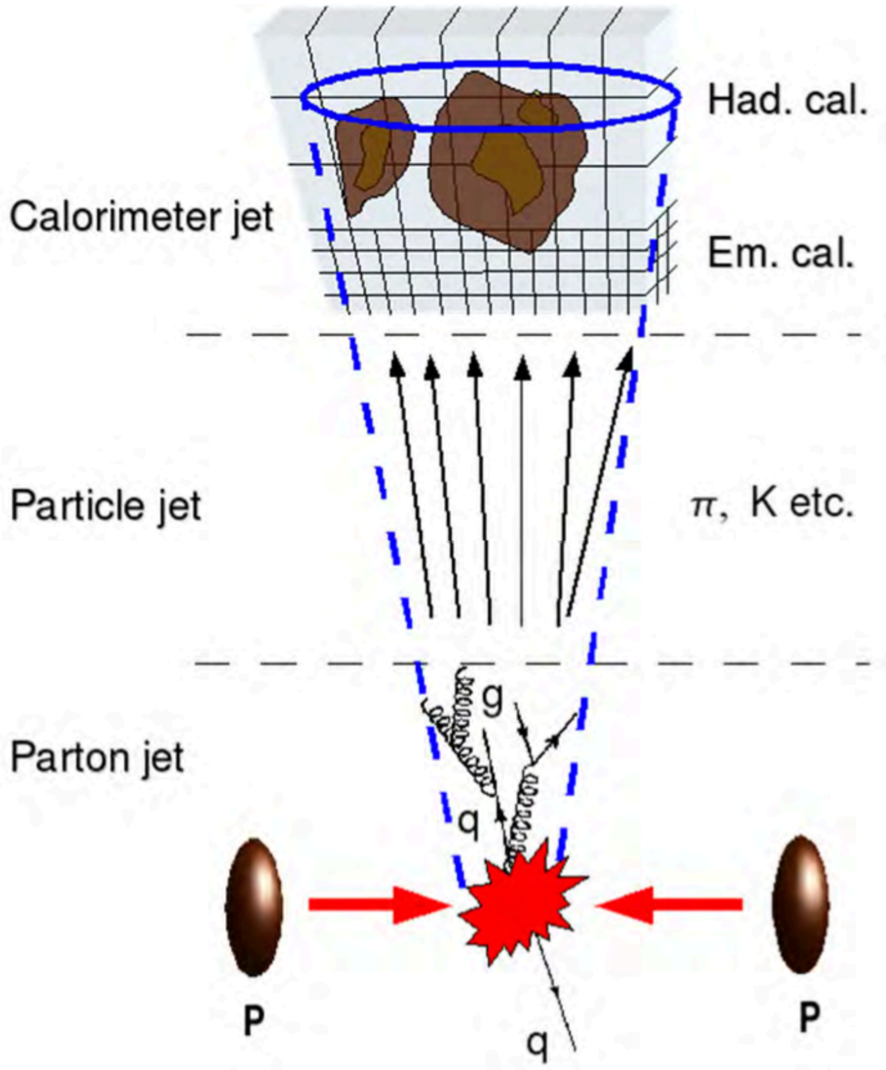
p+p
Vacuum jet

A+A
Quenched jet

- The physics of jet quenching is studied from **the difference between collision systems** of proton-proton (pp) and heavy-ion(AA) events.
- In practice, we **statistically average measured jet observables** over billions of collisions to achieve significant results.
- However, jets experience various levels of quenching due to complex mechanisms. **Many jets experience little quenching**, thus diminishing the significance of the results.
- **Train the neural network (NN) to discriminate pp jets from AA jets. The trained NN can identify jet quenching level on a jet-by-jet basis.**

Previous Works on ML applied to Jets Quenching Study

Jet—from initial parton to detected collimated spray of hadrons



★ **Jets are complex evolving objects that enable different learning algorithm to be applied.**

- L. Apolinário, N.F. Castro, M. C. Romão, et al., JHEP11(2021)219
  - Convolutional Neural Network (CNN) for **jet pixel images**
  - Recurrent Neural Network (RNN) for **jet Lund planes**
  - Dense Neural Network (DNN) for **global jet momentum** and **constituent numbers**
- YLD, D. Pablos and K. Tywoniuk, JHEP03(2021)206
  - Input: **Jet images, jet fragmentation function, jet shape**, with other features as well
  - Network: Fully connected CNN
  - Output: jet energy loss
- Y. S. Lai, J. Mulligan, M. Płoskoń, et al., JHEP10(2022)011
  - Explored the optimal ML classifier and Jet Observable designed for ML

Input: Choose the measurements of jet observables that signify the quenching effects

Global jet observable
Internal jet structures

Binary Classification & Supervised Learning
Quenched jets: 1 Unquenched jets:0

❖ Neural Network of Choice:
❖ CNN, RNN, DNN,…

Train the neural network (NN) to discriminate pp jets from AA jets, so the NN can learn from jet quenching.

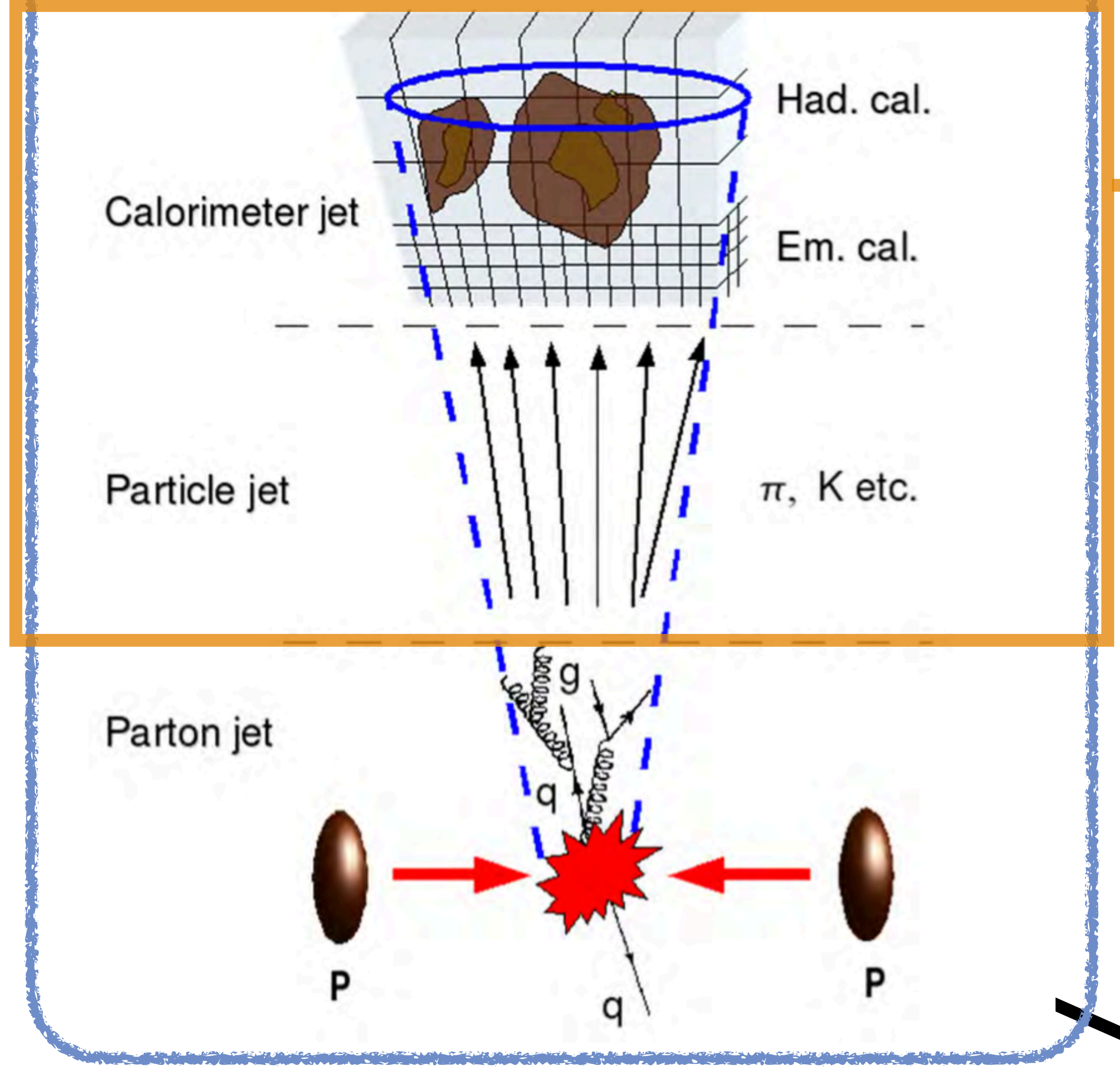
Training
Learning loss minimization

Output:
Quenching level prediction/
Energy loss prediction

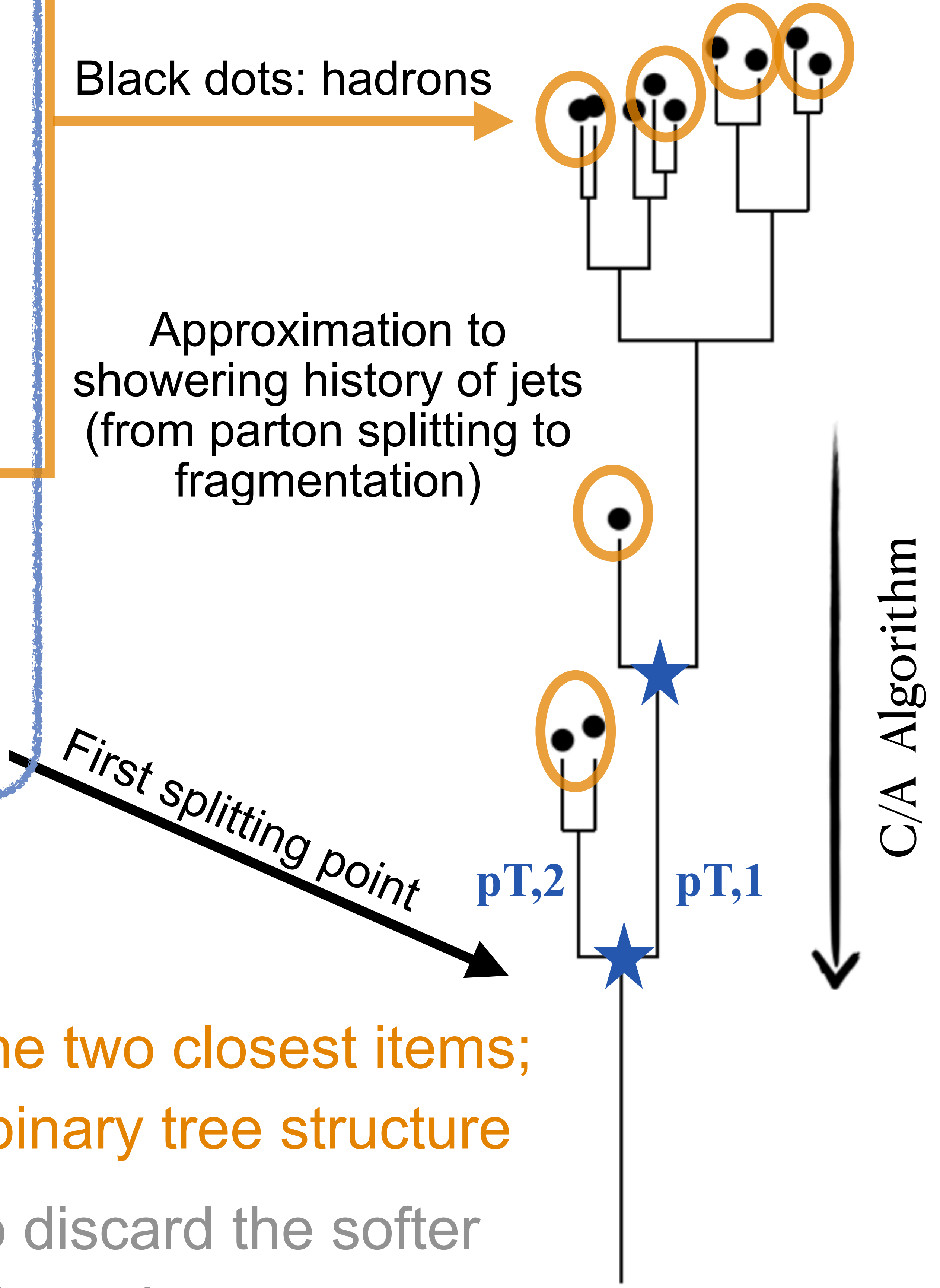
Background and Motivation | Feature Engineering | GEN Level Simulation | Detector Effects Simulation

Jet Substructures with Showering History as NN Input

Jet—from initial parton to detected collimated spray of hadrons



Jet in a binary tree structure



1st step: each time cluster the two closest items; eventually get the binary tree structure

2nd step: use the soft drop to discard the softer splitting of the two branches

Jet Substructures with Showering History as NN Input

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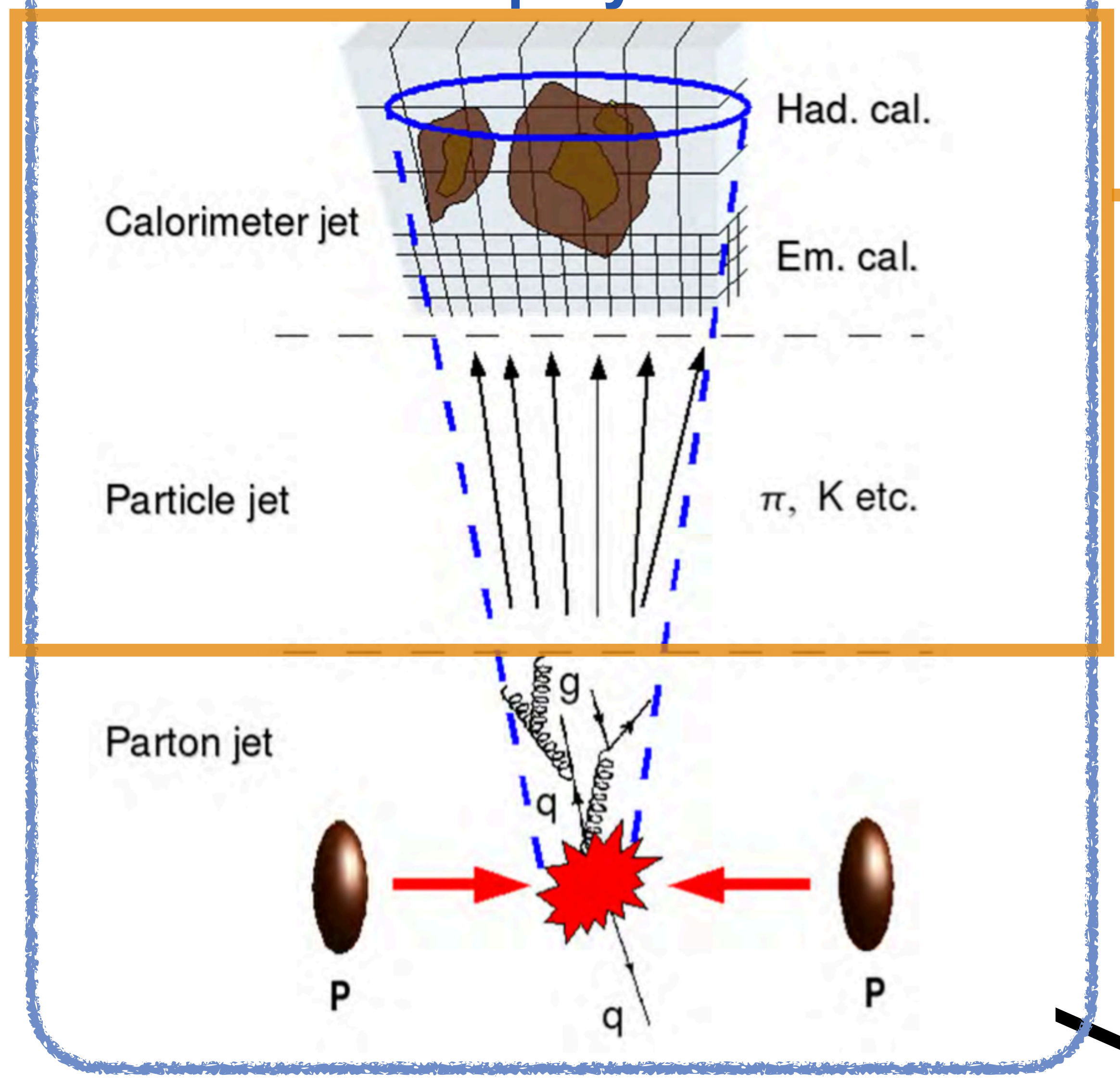
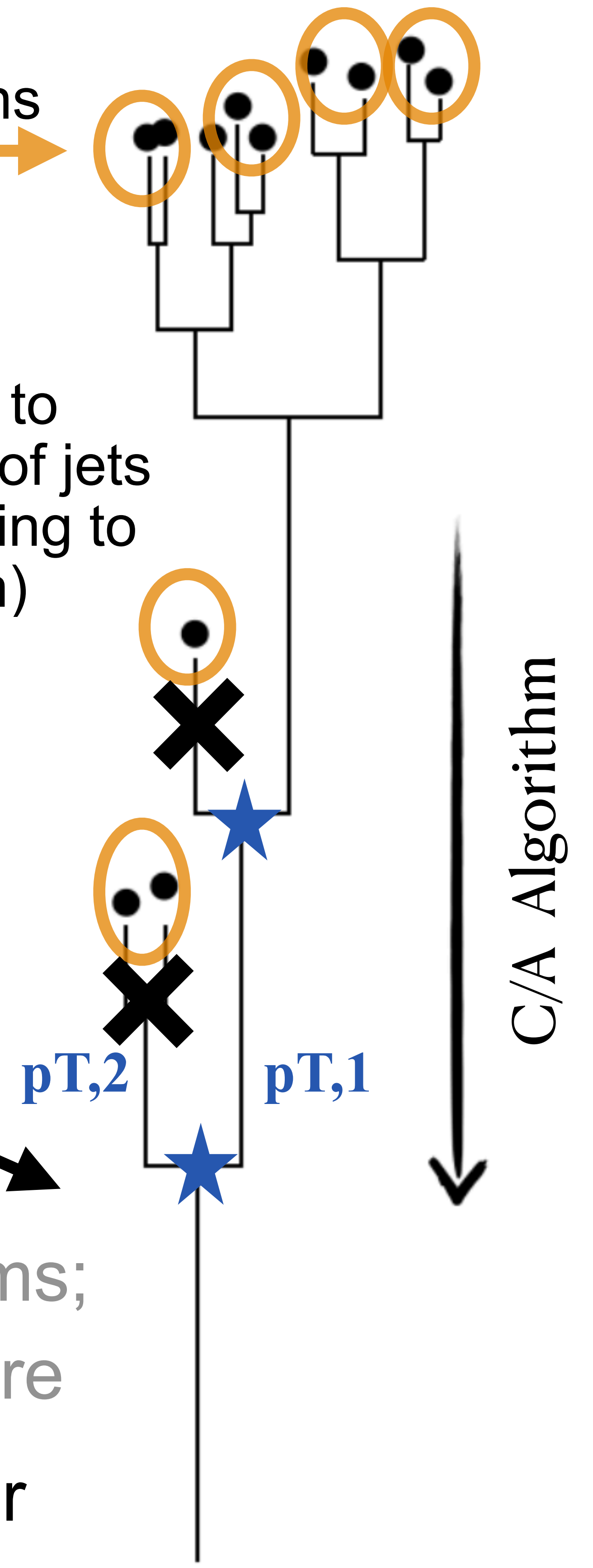


Jet in a binary tree structure

Black dots: hadrons

Approximation to showering history of jets (from parton splitting to fragmentation)

First splitting point



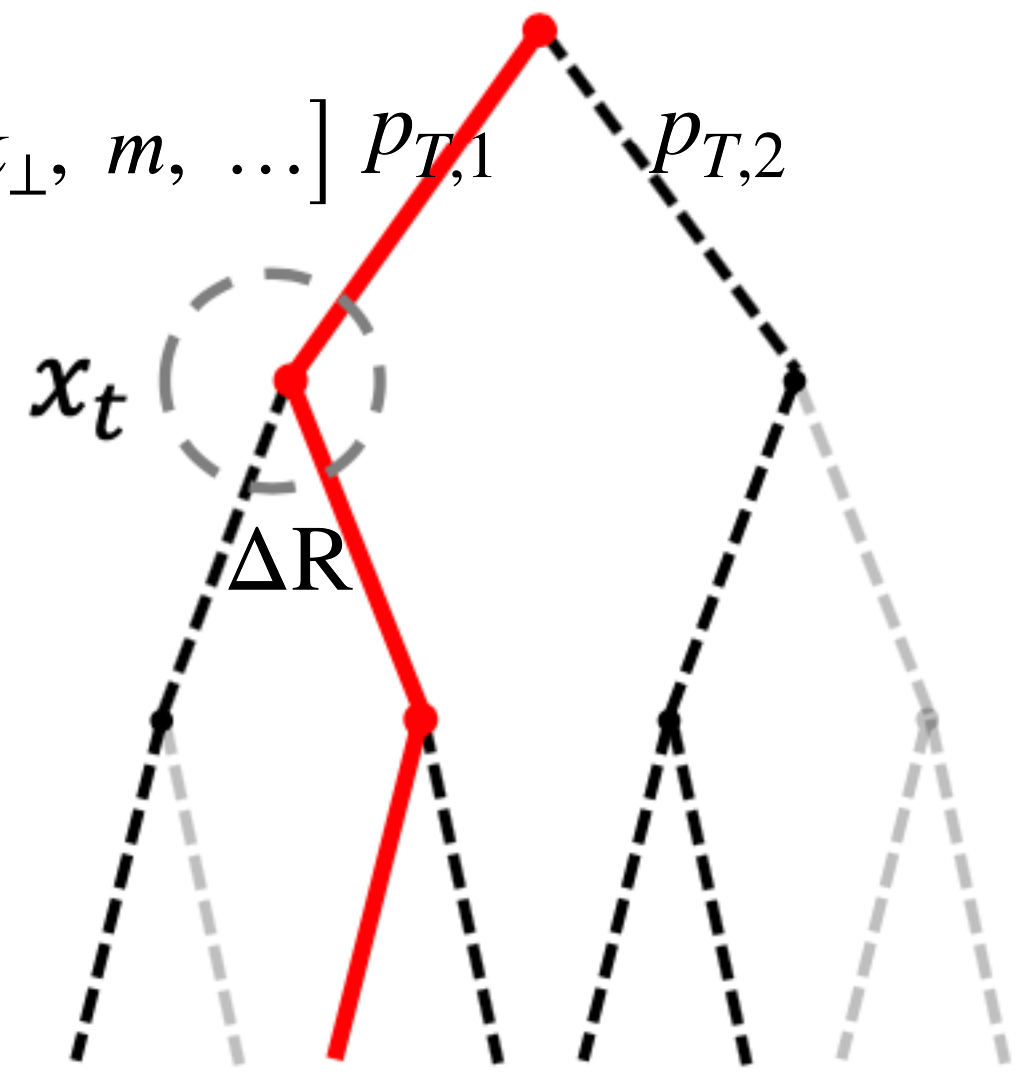
1st step: each time cluster the two closest items; eventually get the binary tree structure

2nd step: use the soft drop to discard the softer splitting of the two branches

Hardest branch of the jet

$$x_t = [z,\ \Delta R, k_\perp,\ m,\ \dots]$$

$$z = \frac{\min(p_{T,1}, p_{T,2})}{p_{T,1} + p_{T,2}}$$



Jet substructure variables are defined at the splitting points of the jet. They are sensitive to jet-induced medium response. Thus, they are good tools to study the jet energy loss in medium

How to do feature engineering?

Jet observable that represents the <u>internal structure</u> of a jet:

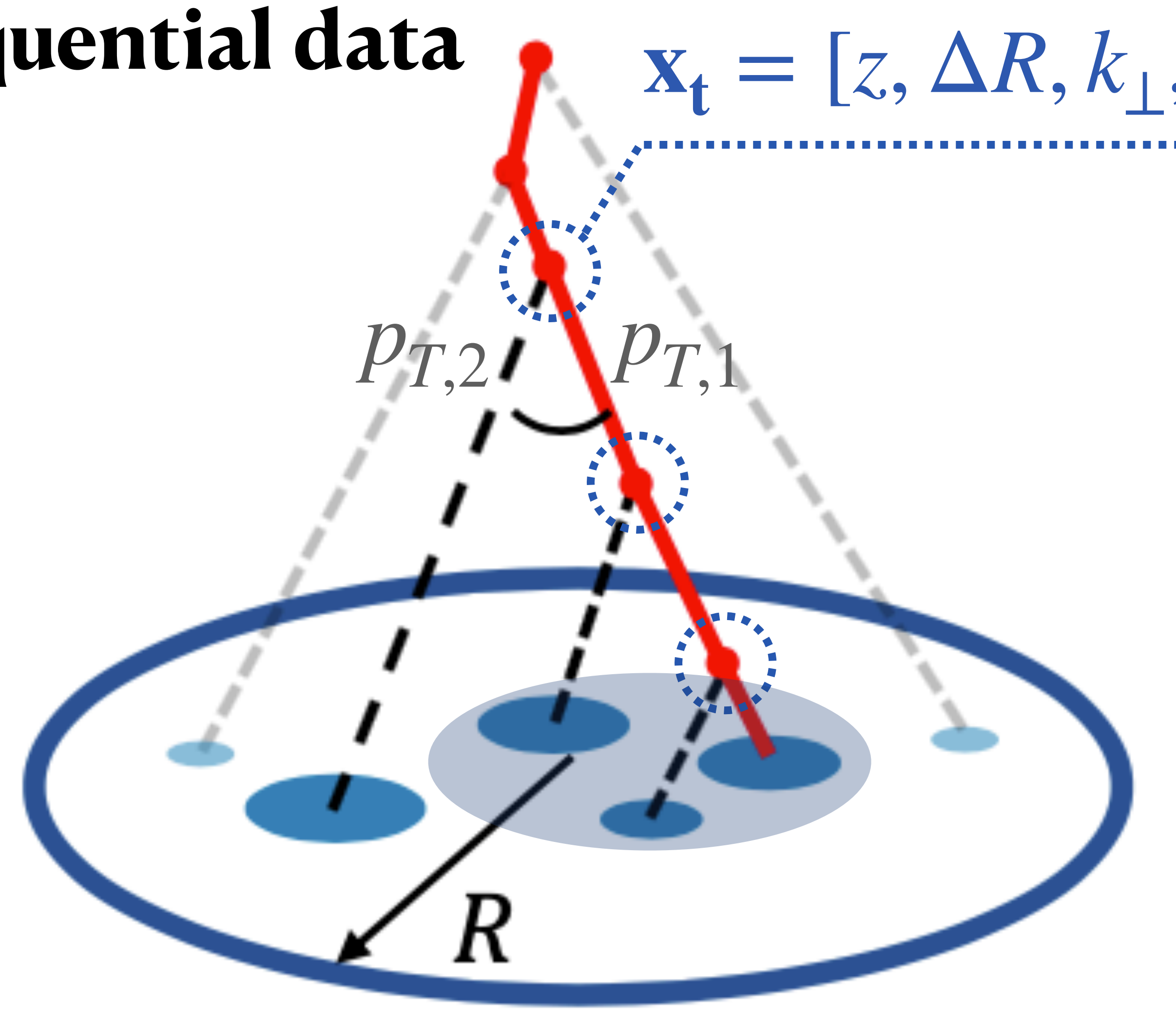
- **Jet substructure**

Input

Long Short-Term Memory Neural Network

- learning from sequential data
- Improved RNN (Recurrent Neural Network)

Sequential data $\mathbf{x_t} = [z, \Delta R, k_\perp, m, \ldots]$



Jet substructures

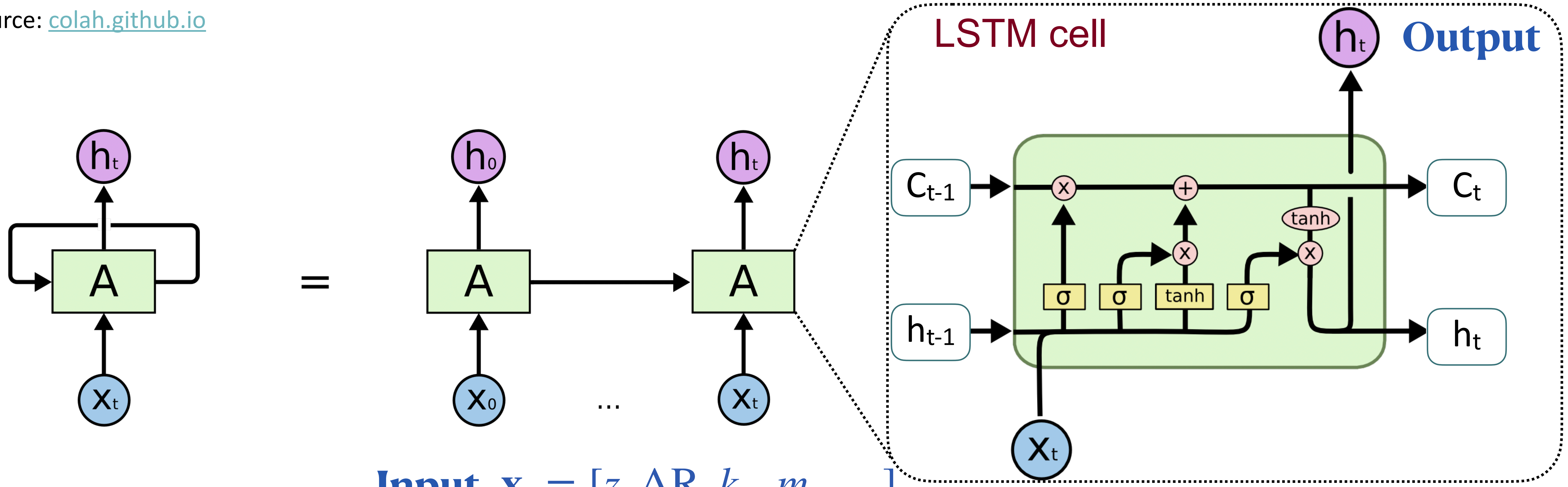
$$z = \frac{\min(p_{T,1},\ p_{T,2})}{p_{T,1} + p_{T,2}}$$ Shared momentum ratio

$$\Delta R = \sqrt{(\varphi_1 - \varphi_2)^2 + (\eta_1 - \eta_2)^2}$$ Angular separation

$$k_\perp = p_{T,2} * \Delta \mathrm{R}$$ Perpendicular momentum

$$m = inv\_mass(j_1, j_2)$$ Invariant mass

Image source: colah.github.io



Input $\mathbf{x_t} = [z, \Delta \mathrm{R}, k_\perp, m, \ldots]$

Before Starting Training the NN...

Background and Motivation ✓

Neural Network Framework (feature engineering) for the Study ✓

Design Simulation as a Realistic Approximation to Data

✓ Simulation of Thermal Background in HI Collisions and NN Training Results

✓ Simulation of Detector Effects on the NN Training Results

Summary and Outlook

Generator Level Events for Training

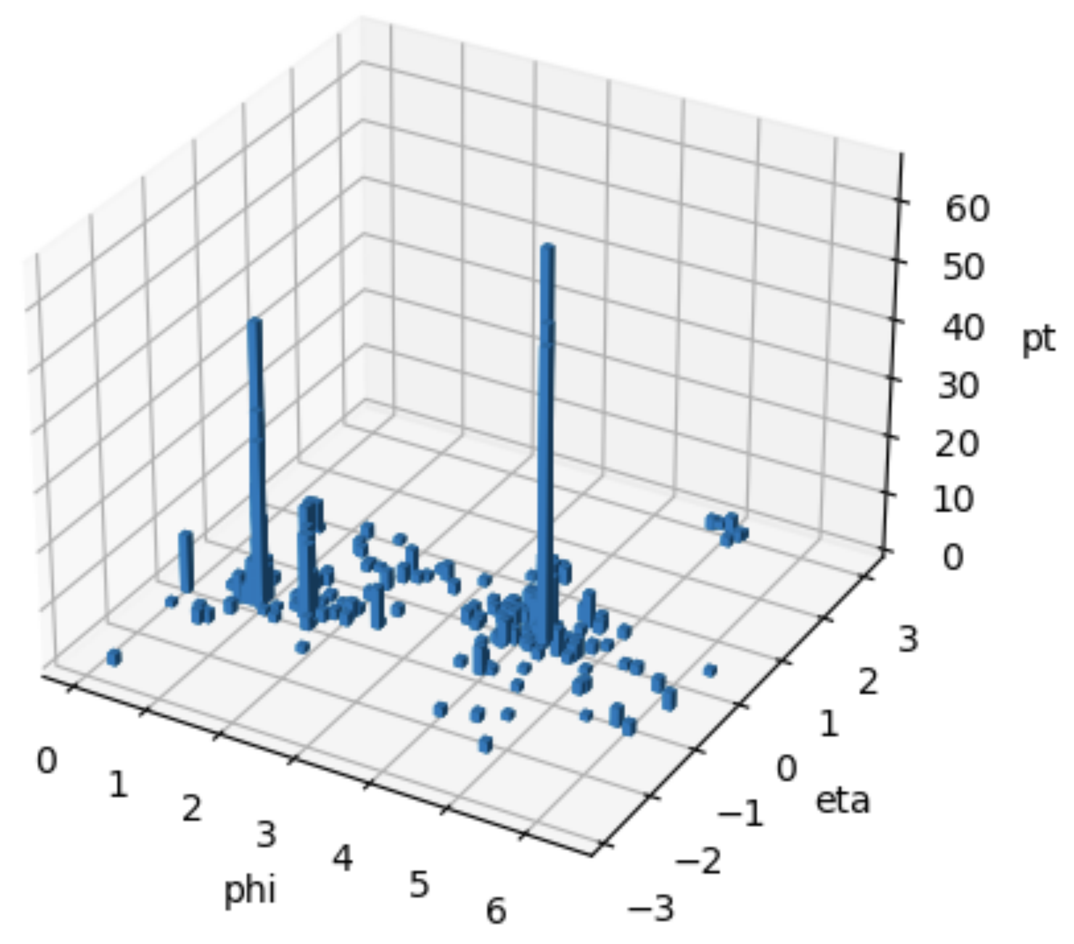
In data, we need to subtract underlying event per event in heavy-ion collisions.
To be as realistic as possible, we apply the same process in simulation.

JEWEL simulation for dijet events:

Non-quenched jets (vacuum class)

Quenched jets (medium class)

0-10% Centrality

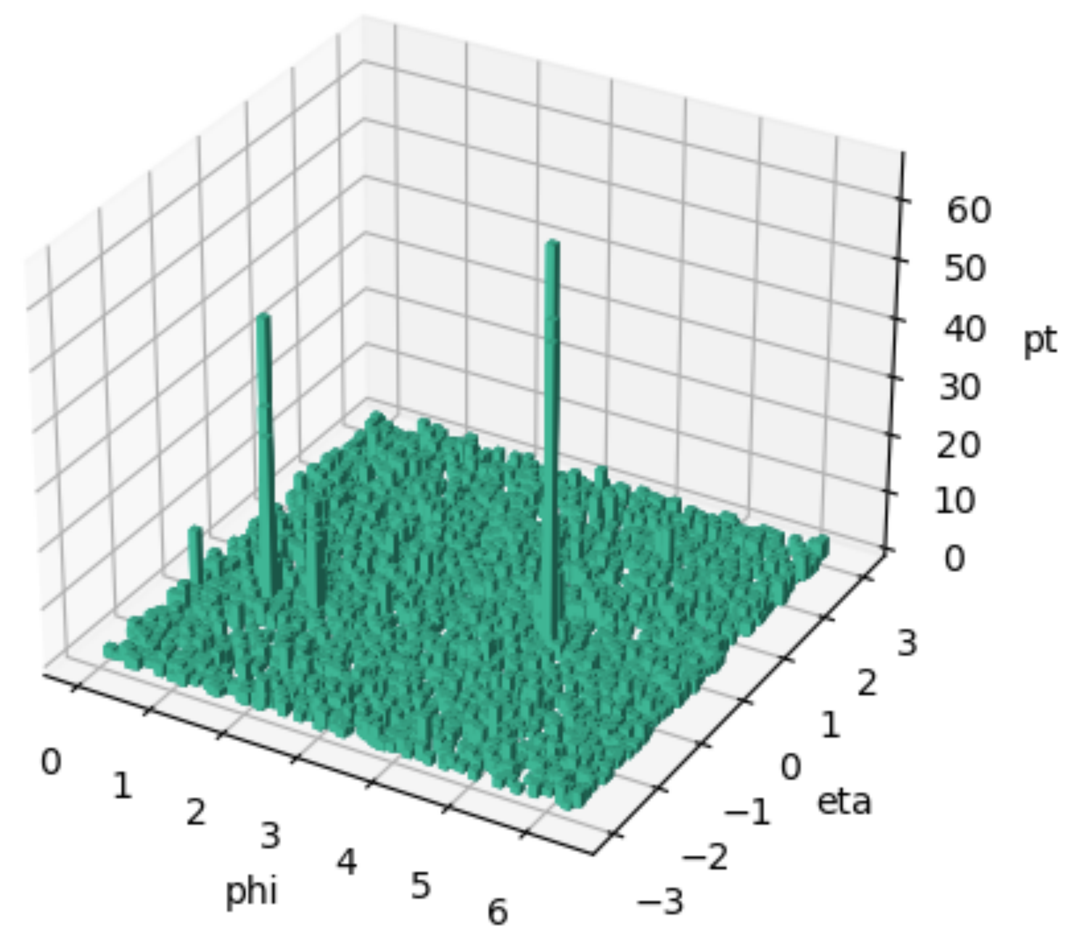


dijet hard event

Embedding the simulated event with a thermal background:

*Thermal Bkg is simulated by the PYTHIA+ANGANTYR model

+ Uncorrelated thermal background

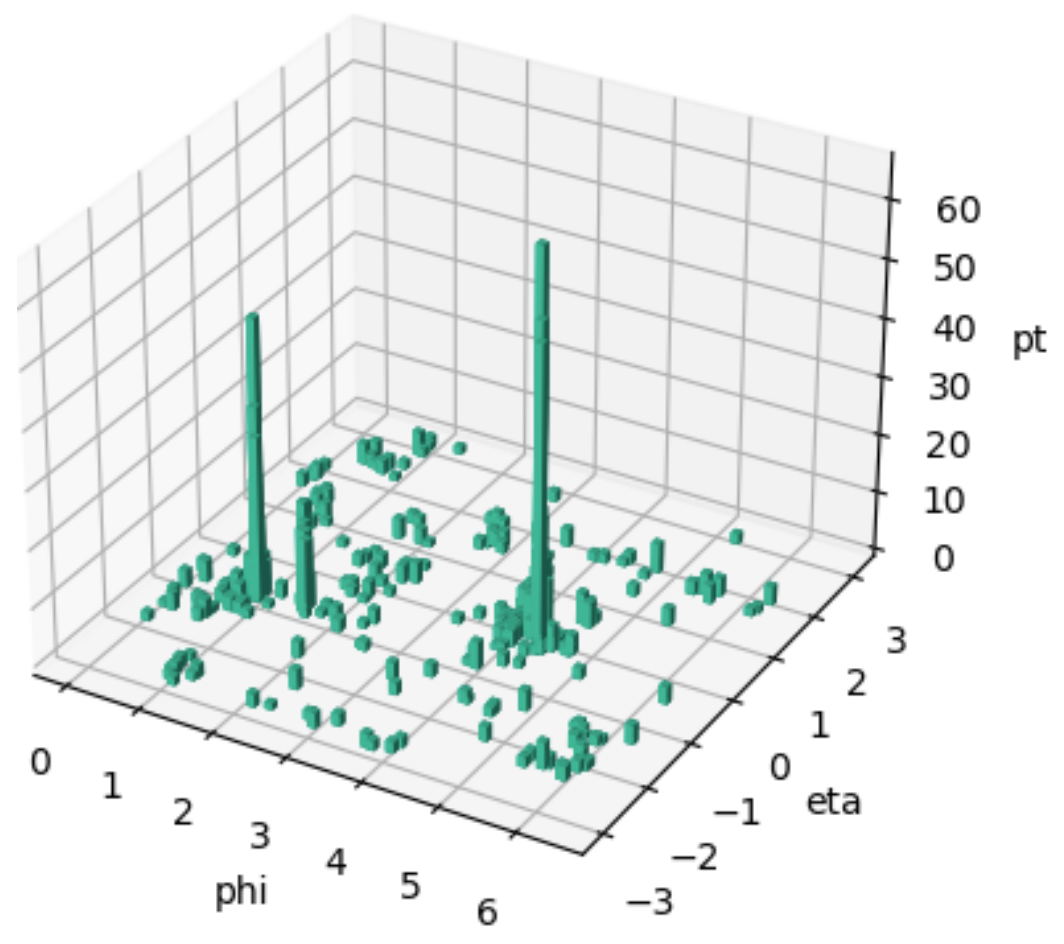


mixed event

Background subtraction algorithm:

Event-wide Constituent Subtraction

We use the jets reconstructed from the bkg-subtracted events for training.



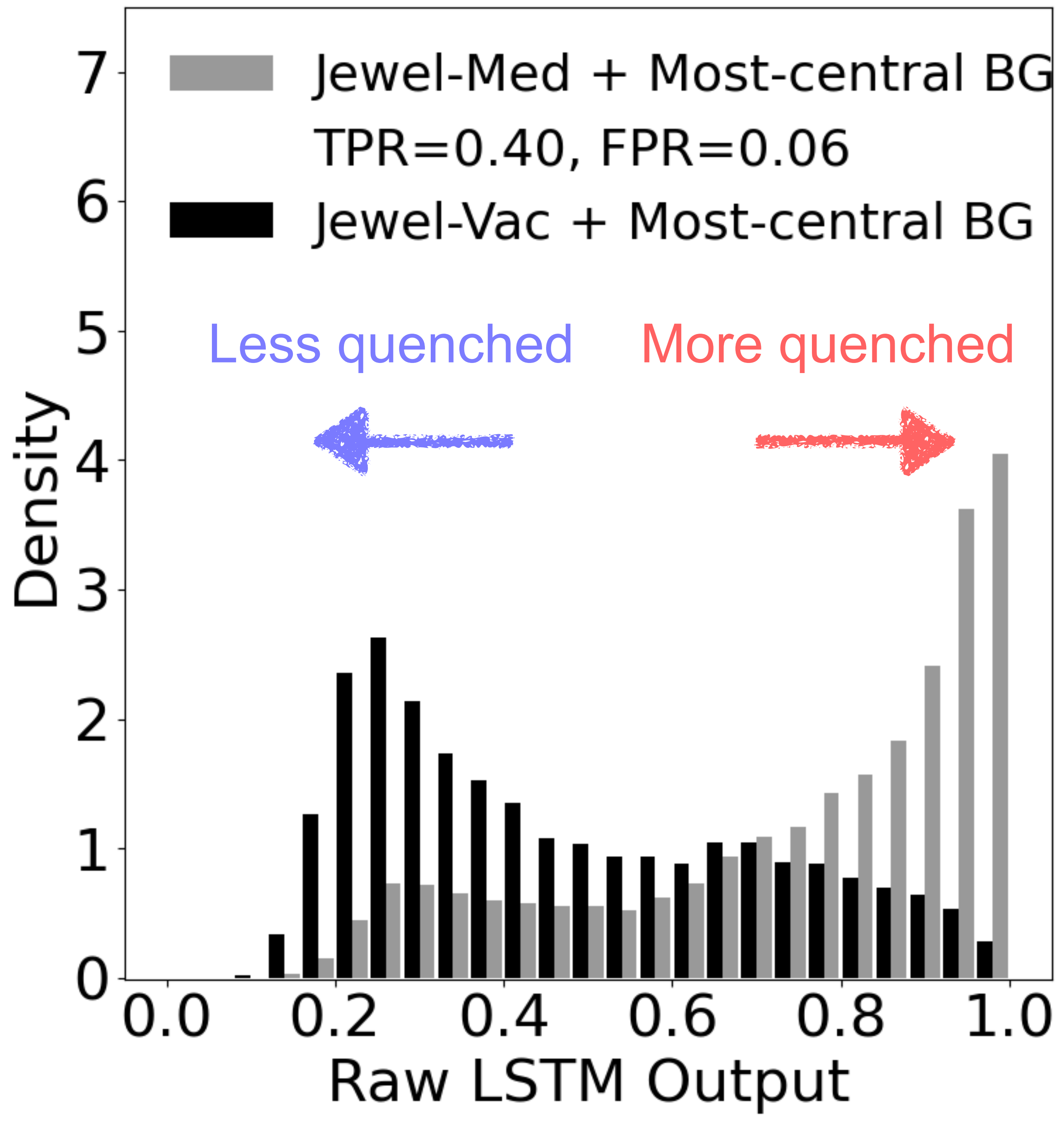
bkg-sub event

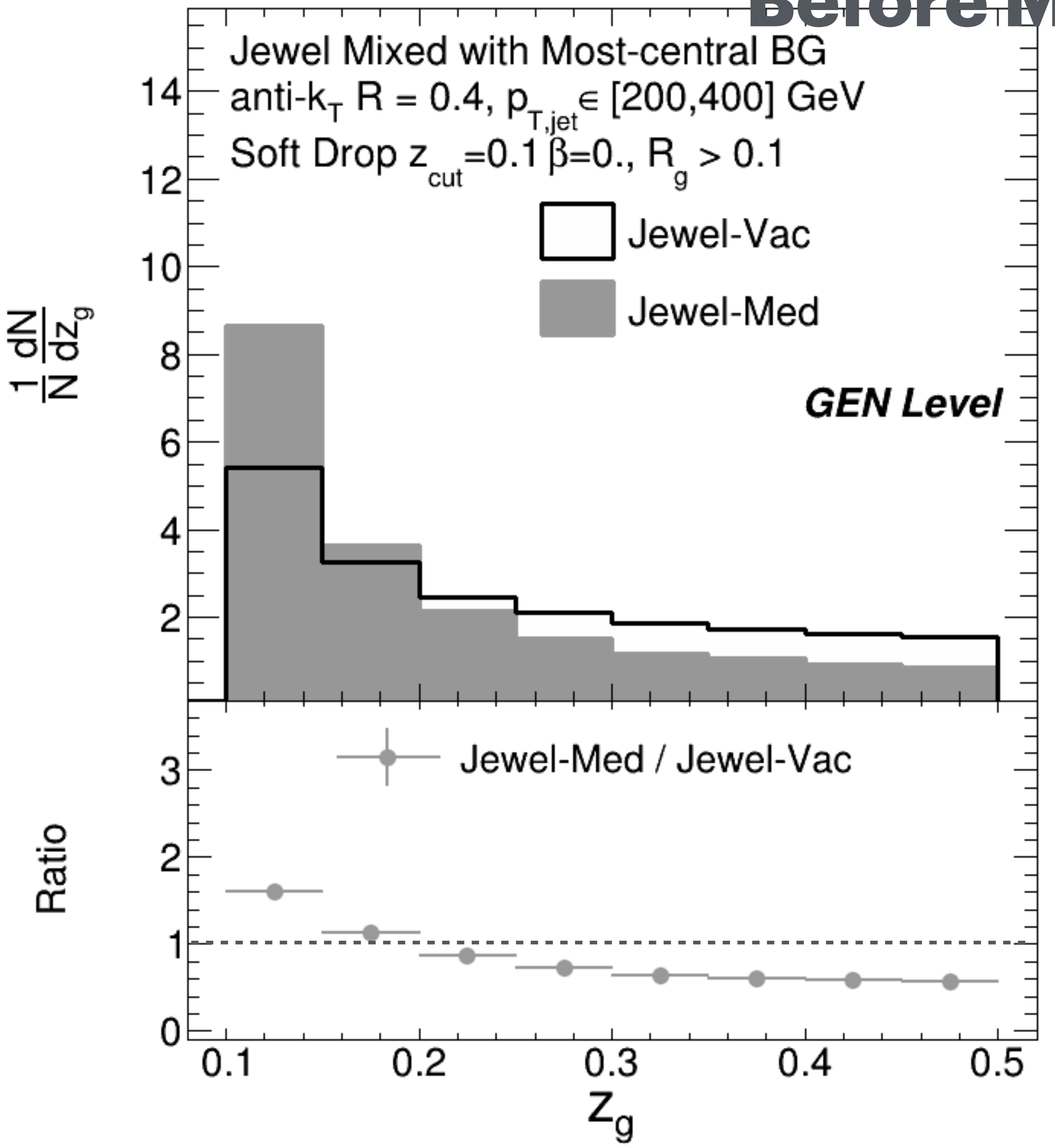
Background and Motivation | Feature Engineering | GEN Level Simulation | Detector Effects Simulation

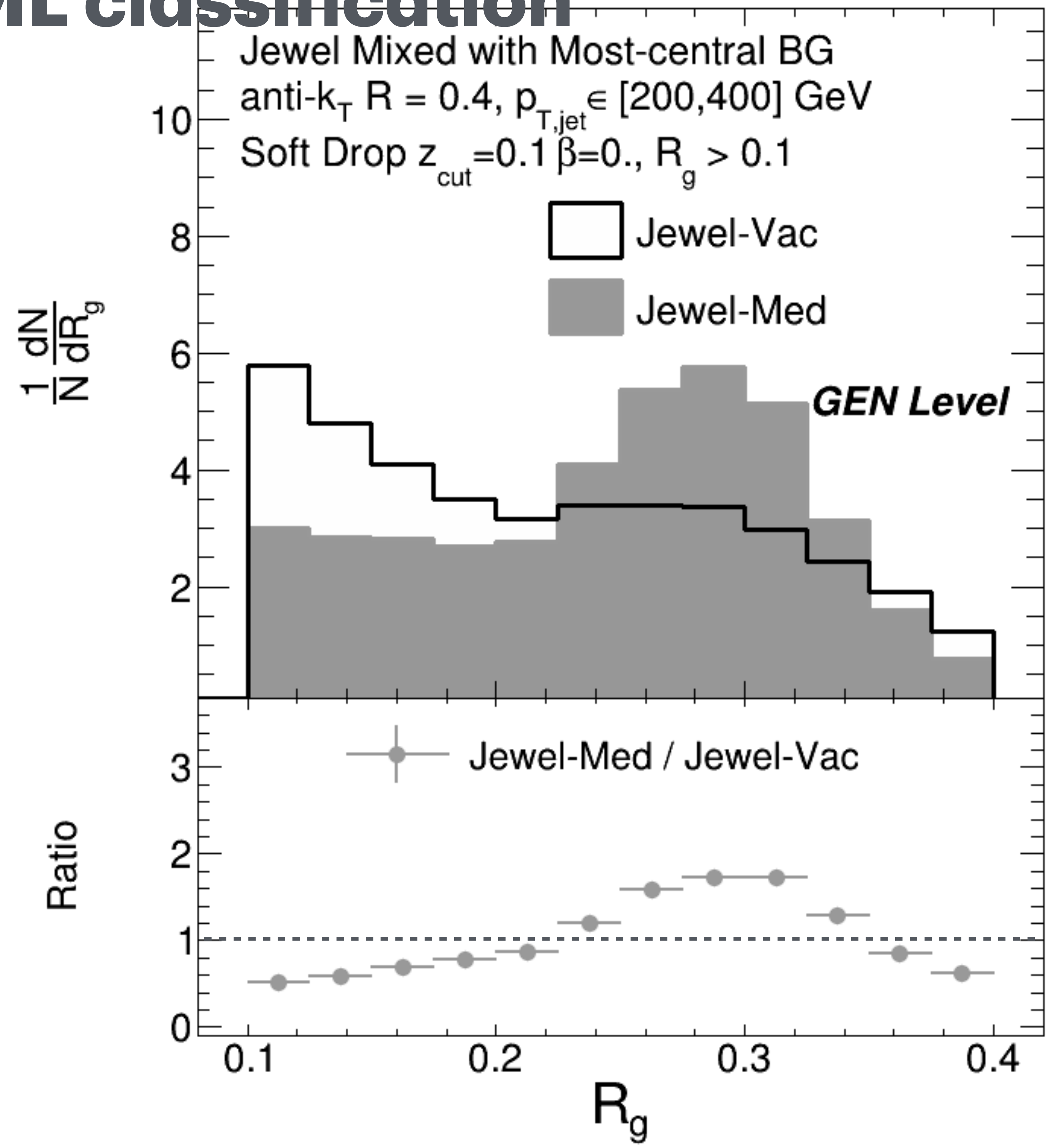
ML Classified Quenched Jets — Jet Substructures

Paper: *JHEP04(2023)140*

Before ML classification

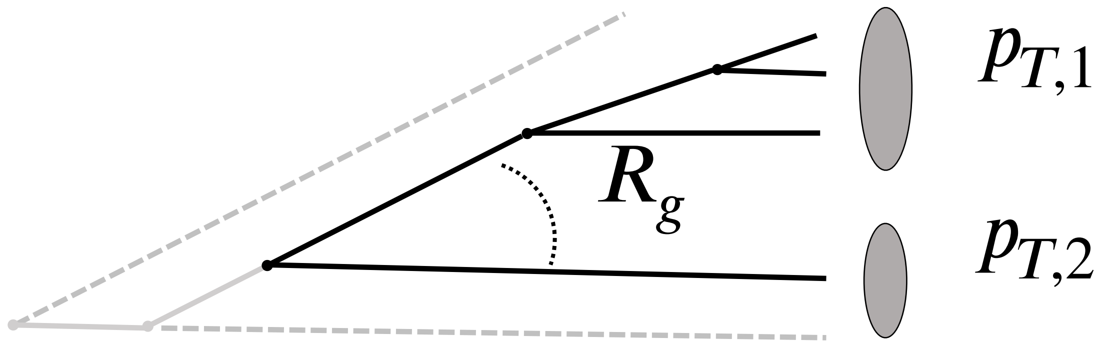






Quenchness: The LSTM output for each medium jet. If the value is closer to 1, then the jet is more quenched. And vice versa.

$$z_g = \frac{\min(p_{T,1},\ p_{T,2})}{p_{T,1} + p_{T,2}}$$



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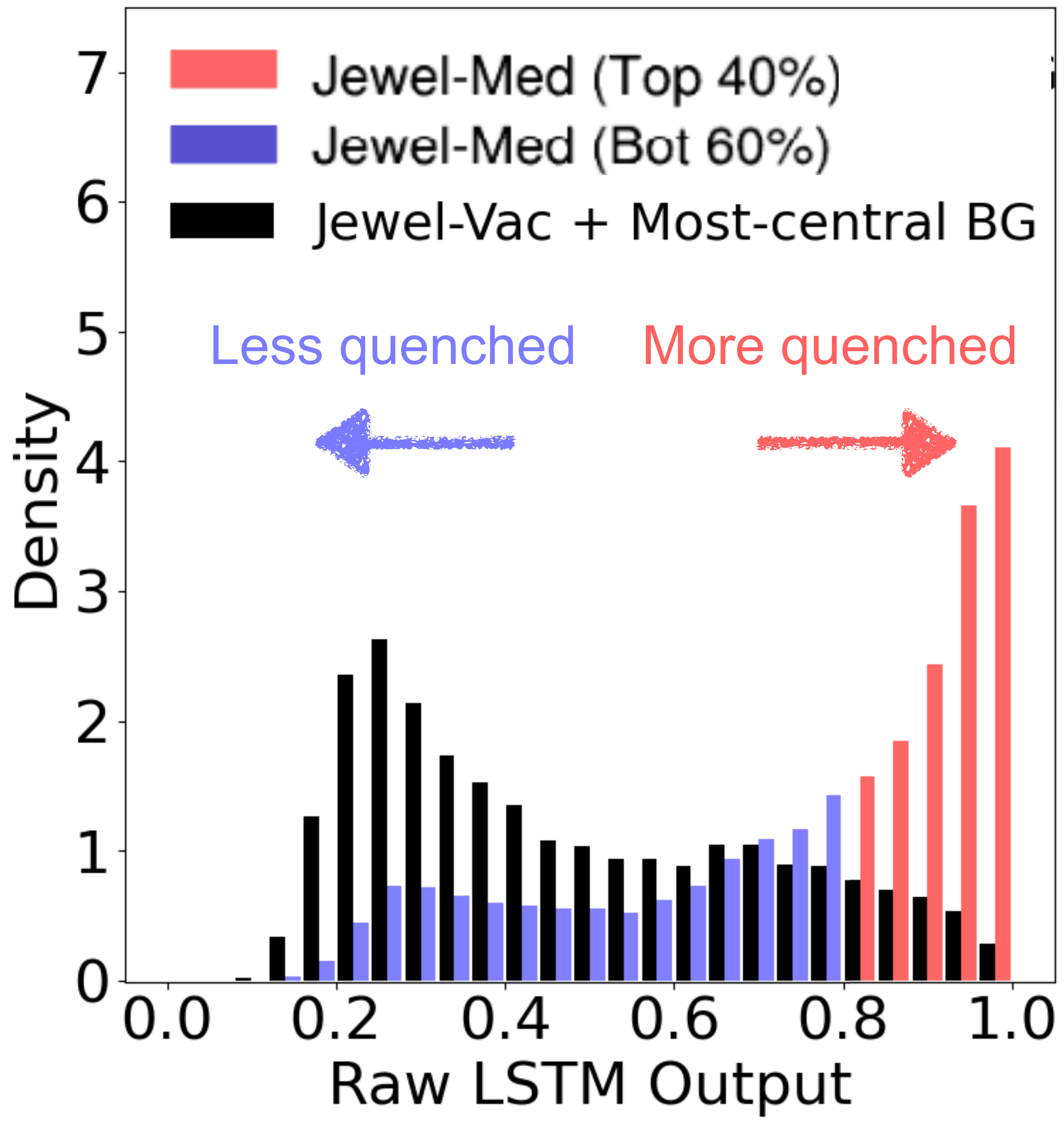
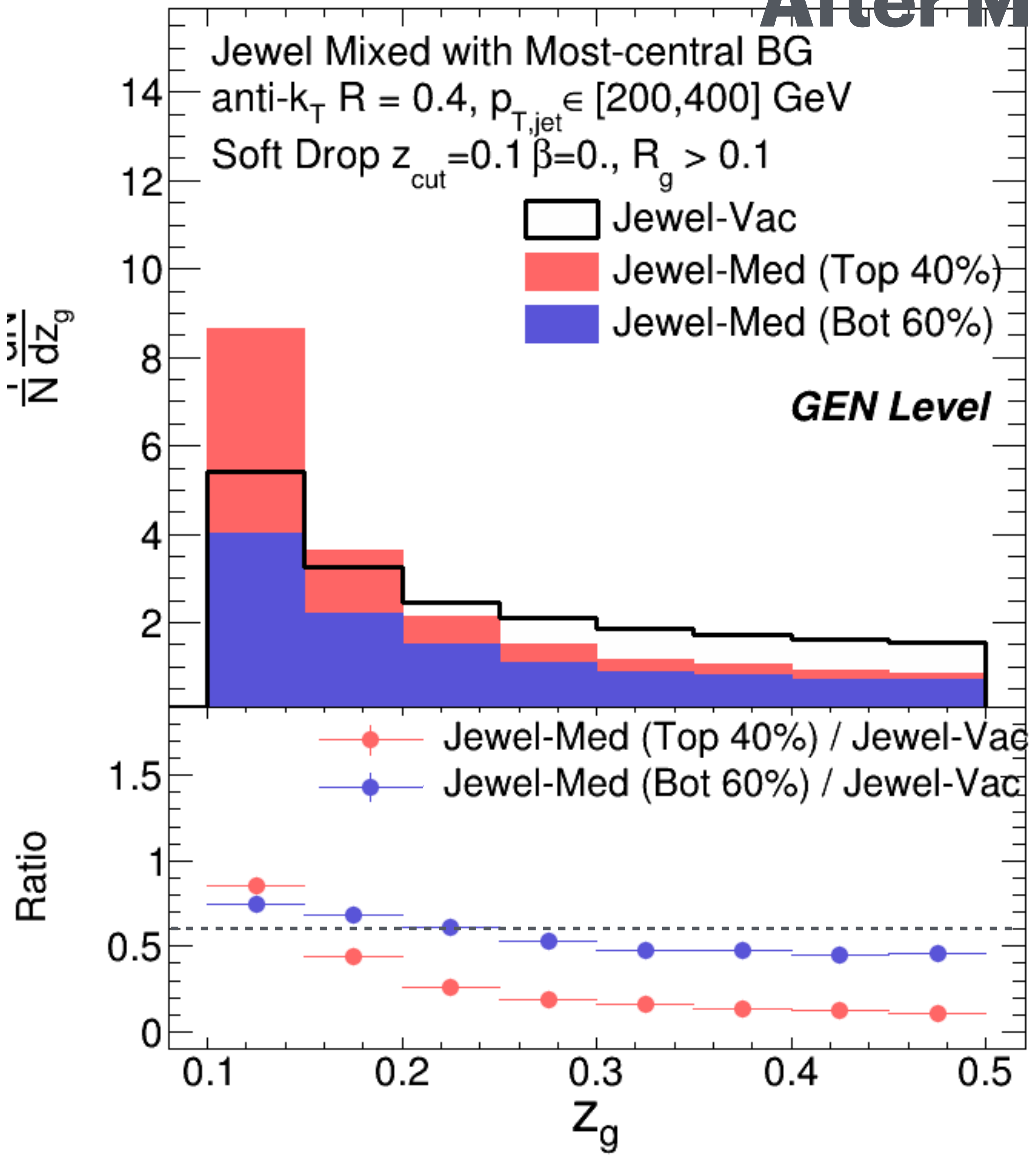
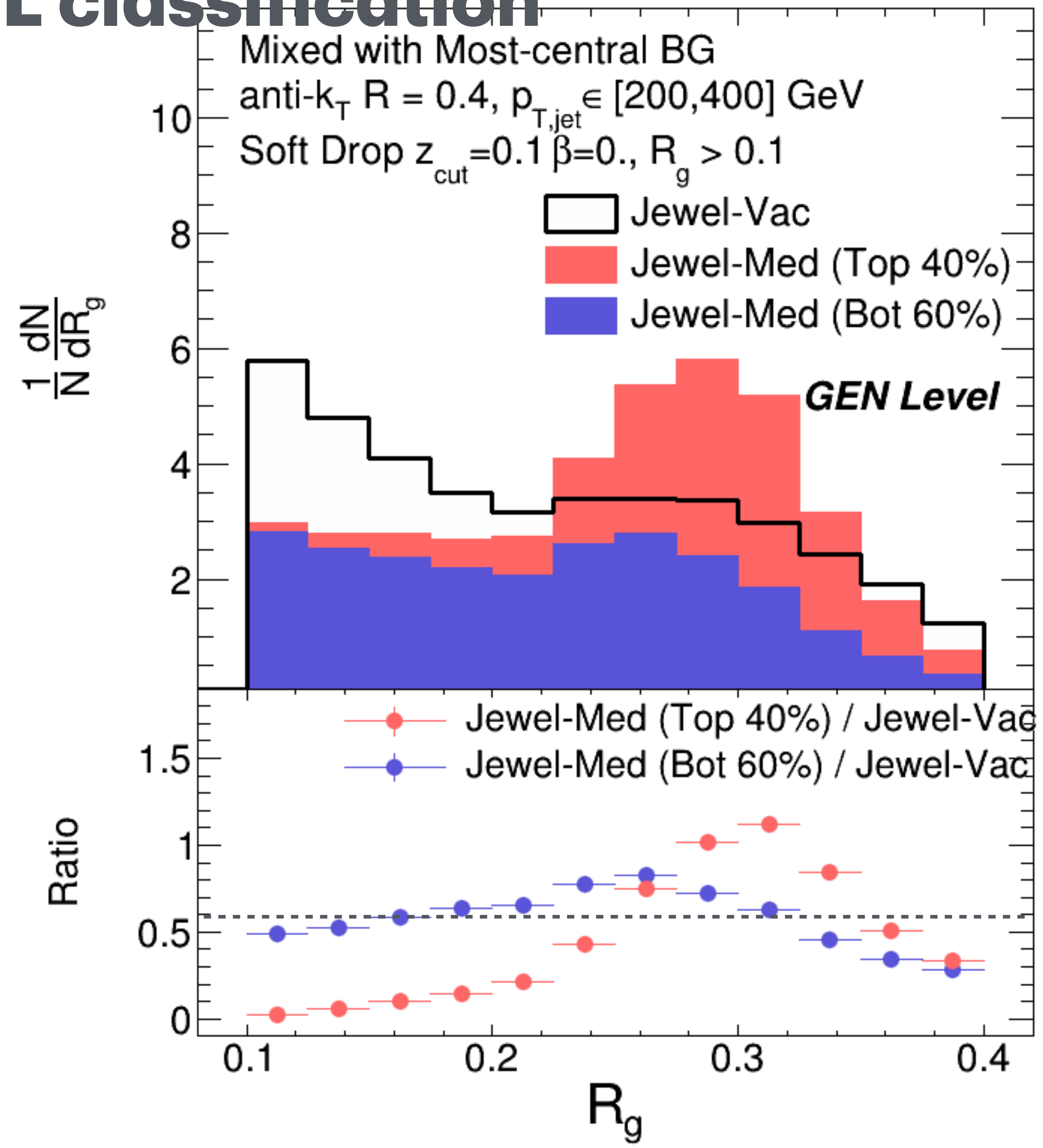


After ML classification





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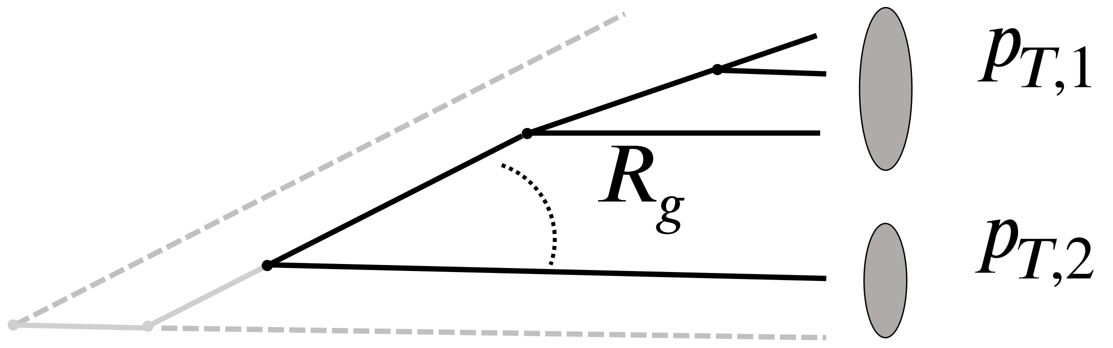

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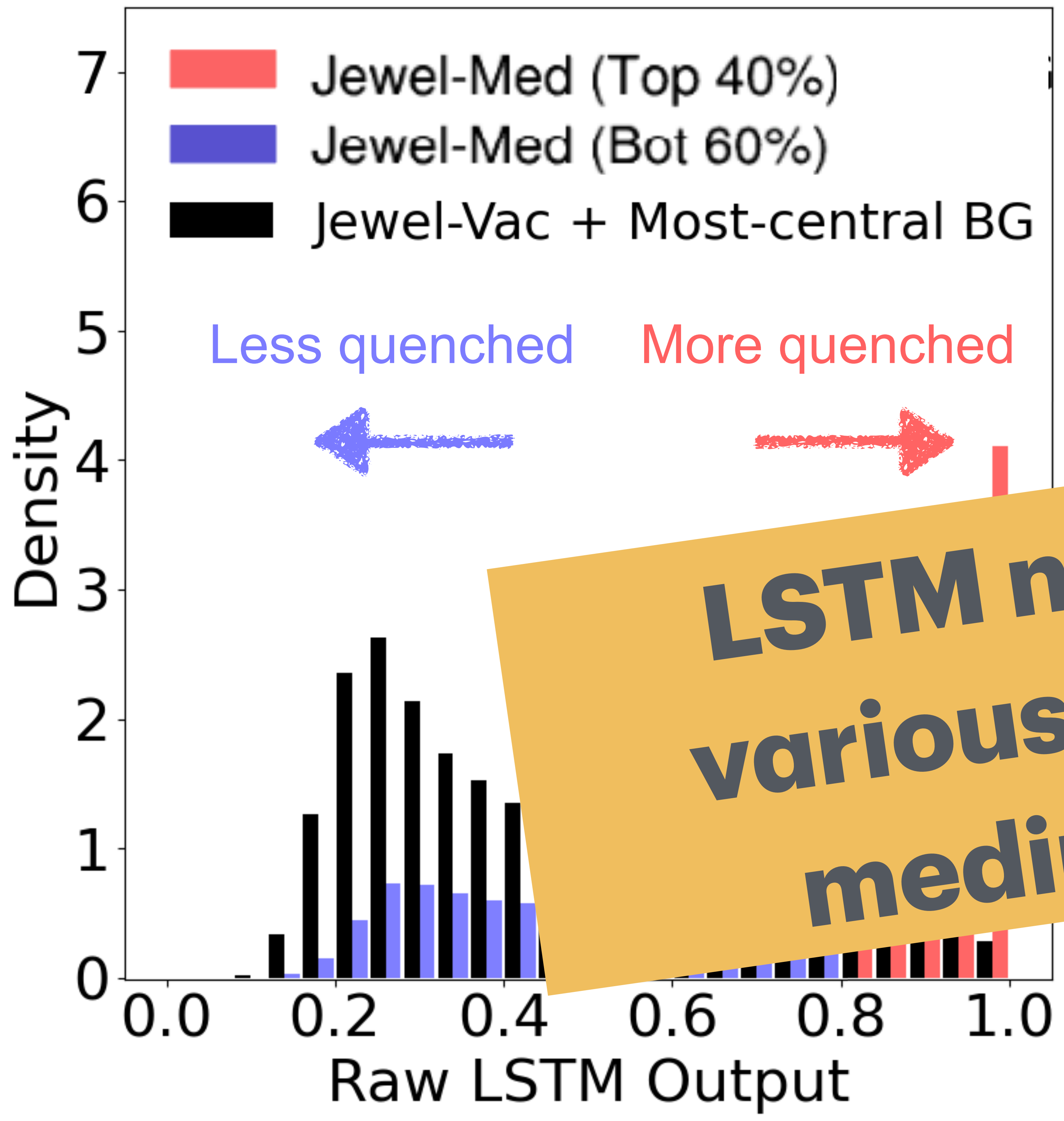

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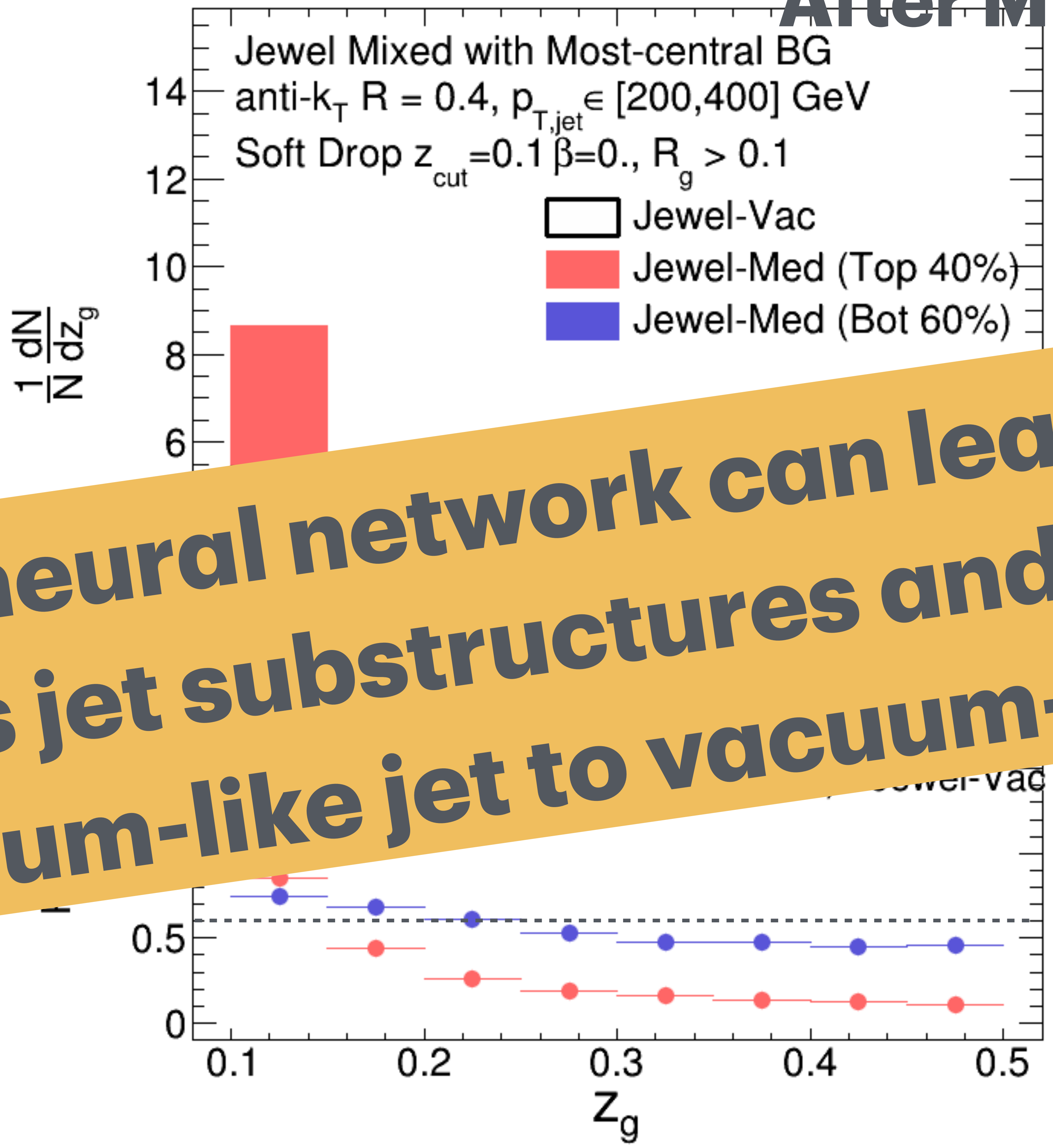

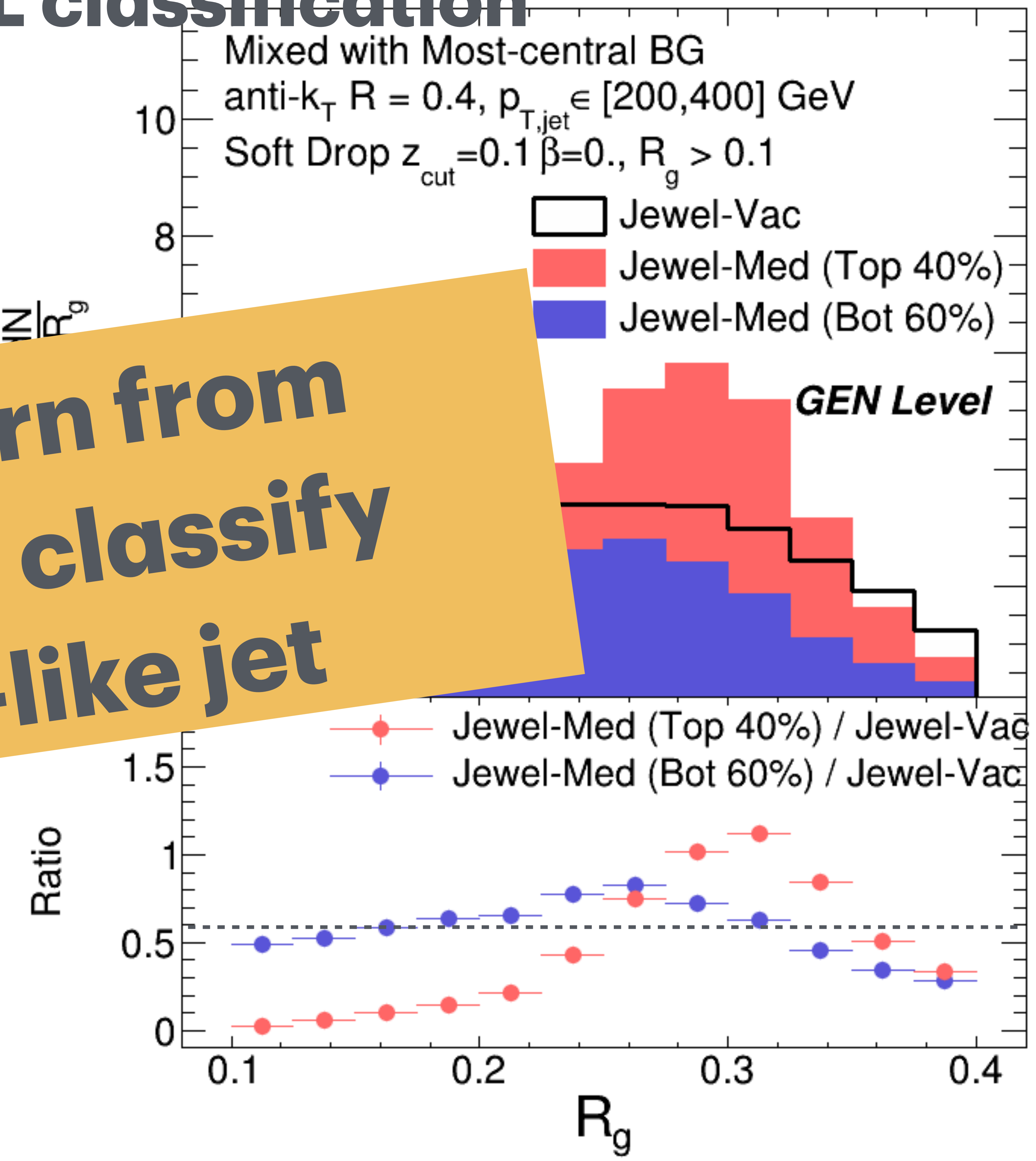

LSTM neural network can learn from various jet substructures and classify medium-like jet to vacuum-like jet

Quenchness: The LSTM output for each medium jet. If the value is closer to 1, then the jet is more quenched. And vice versa.

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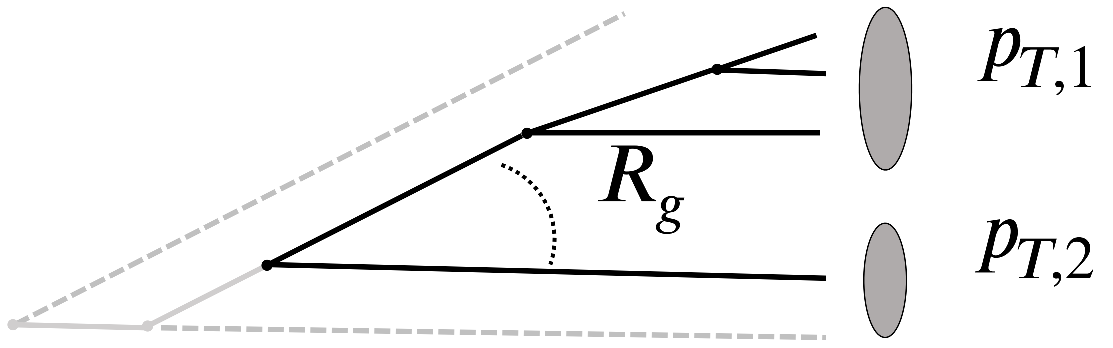


Other Observables for ML Classified Quenched Jets

Our LSTM neural network can learn from various jet substructures, and **classify jets from heavy-ion collisions based on the diverse extents they quenched to.**

To better interpret ML's application in jet quenching study, **we use the LSTM outputs to analyze other jet observables**.

✓ Jet shape

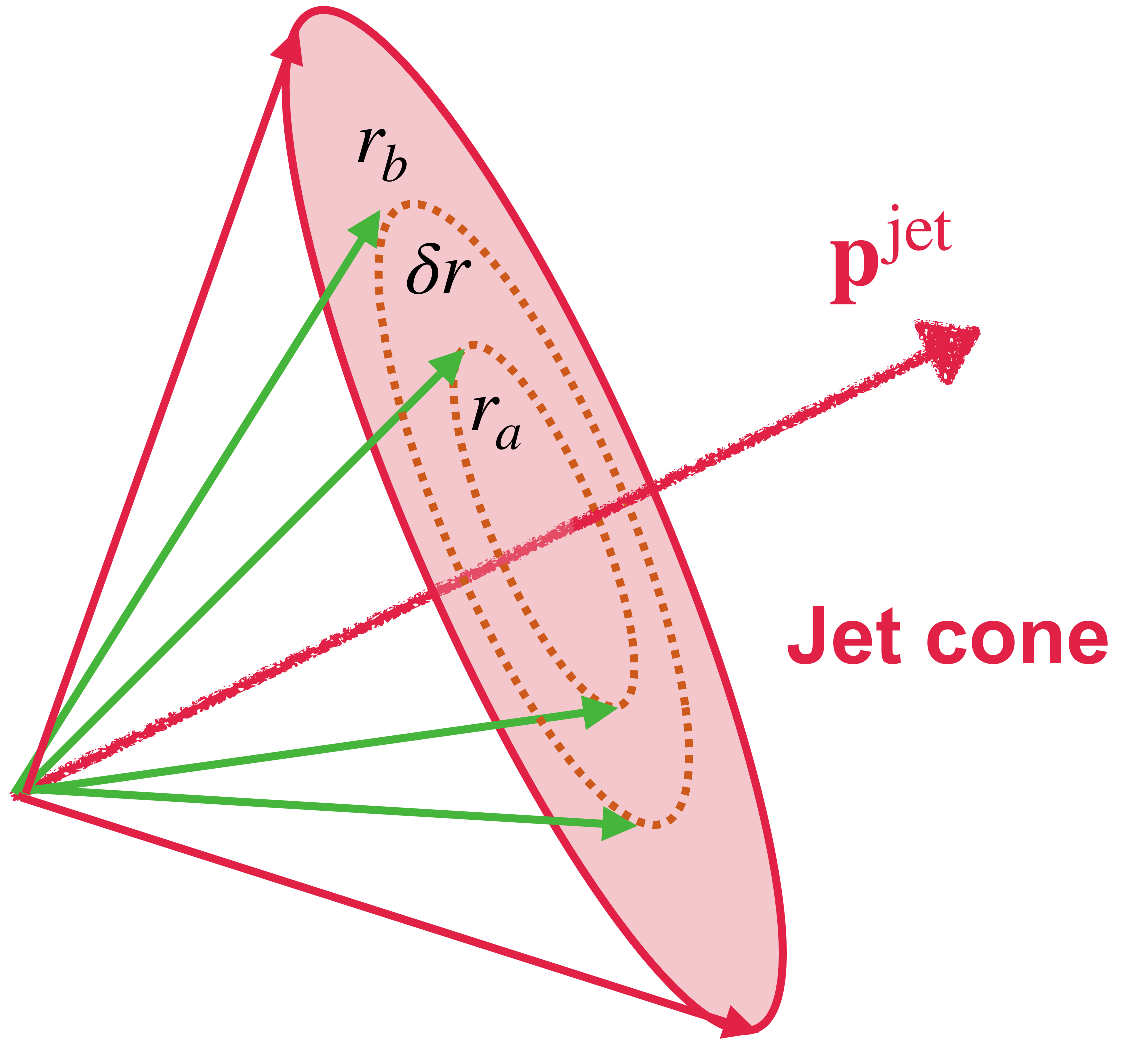
✓ Jet fragmentation function

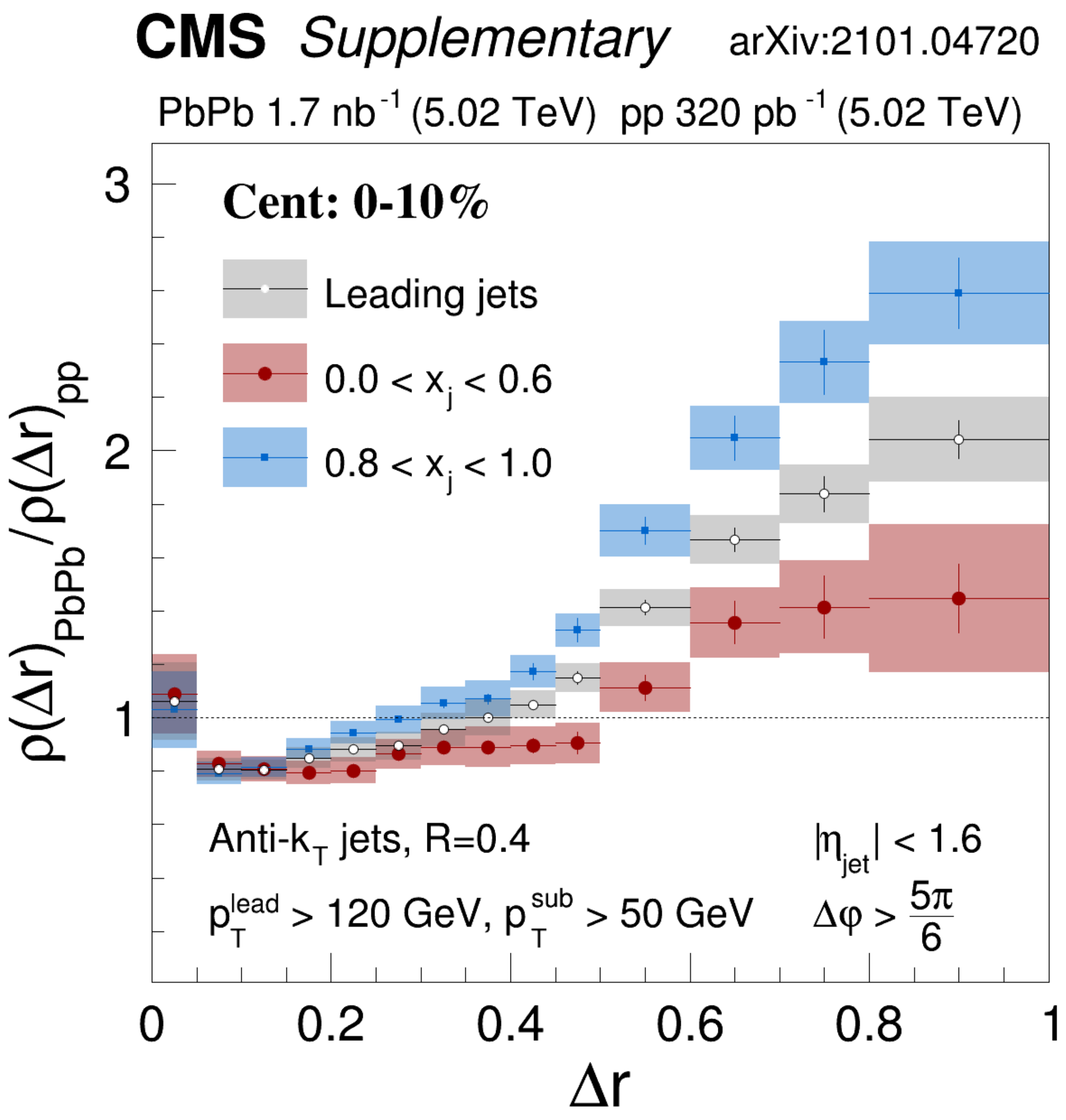
Jet Quenchness ML Results — Jet Shape

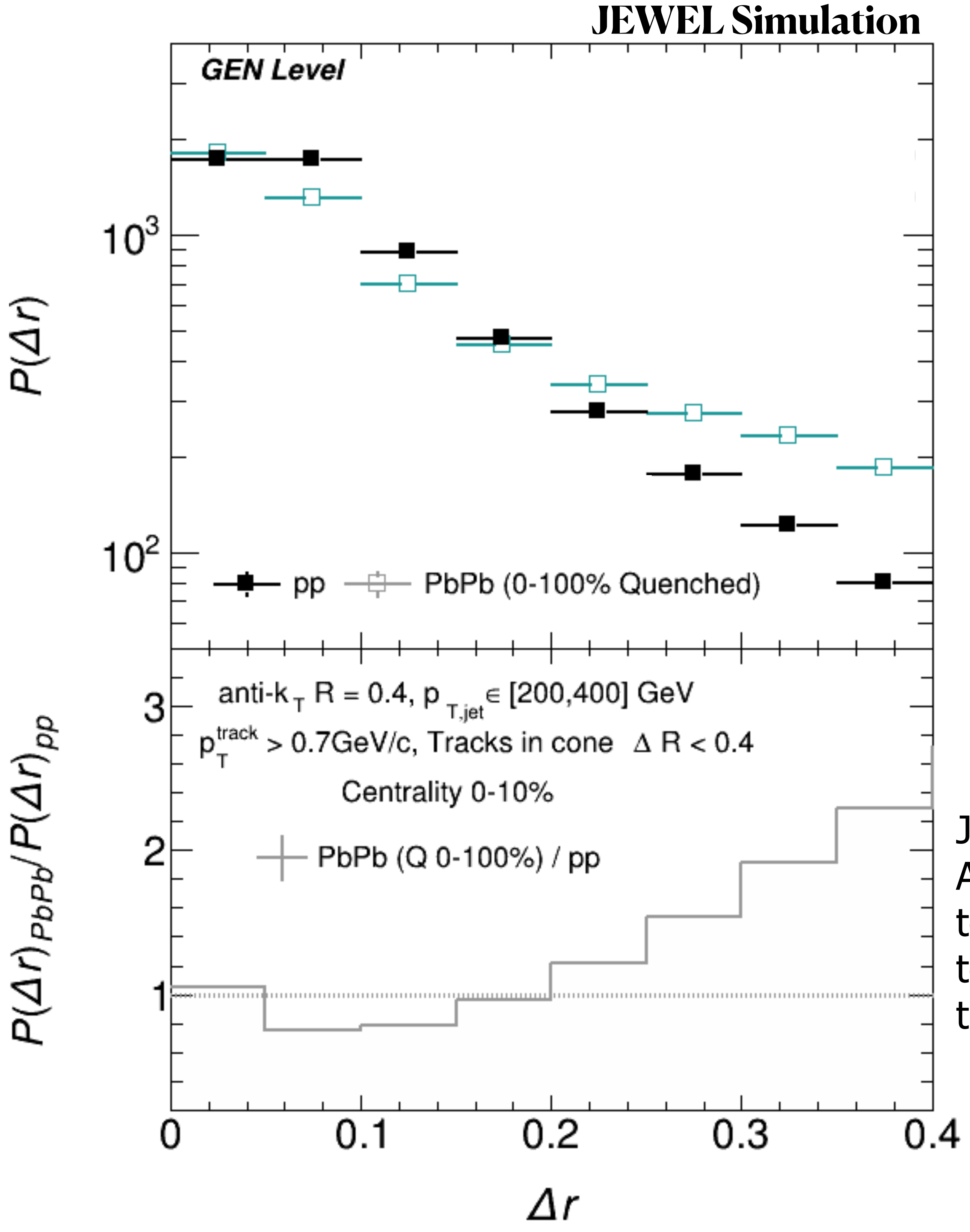
- The jet radial momentum profile (integrated jet shape),

$$P(r) = \frac{1}{\delta r}\frac{1}{N_{\text{jet}}}\sum_{\text{jets}}\sum_{\text{tracks}\in[r_a,r_b)} p_T^{\text{track}},$$

provides information about the radial distribution of the momentum carried by the jet constituents (fragments).



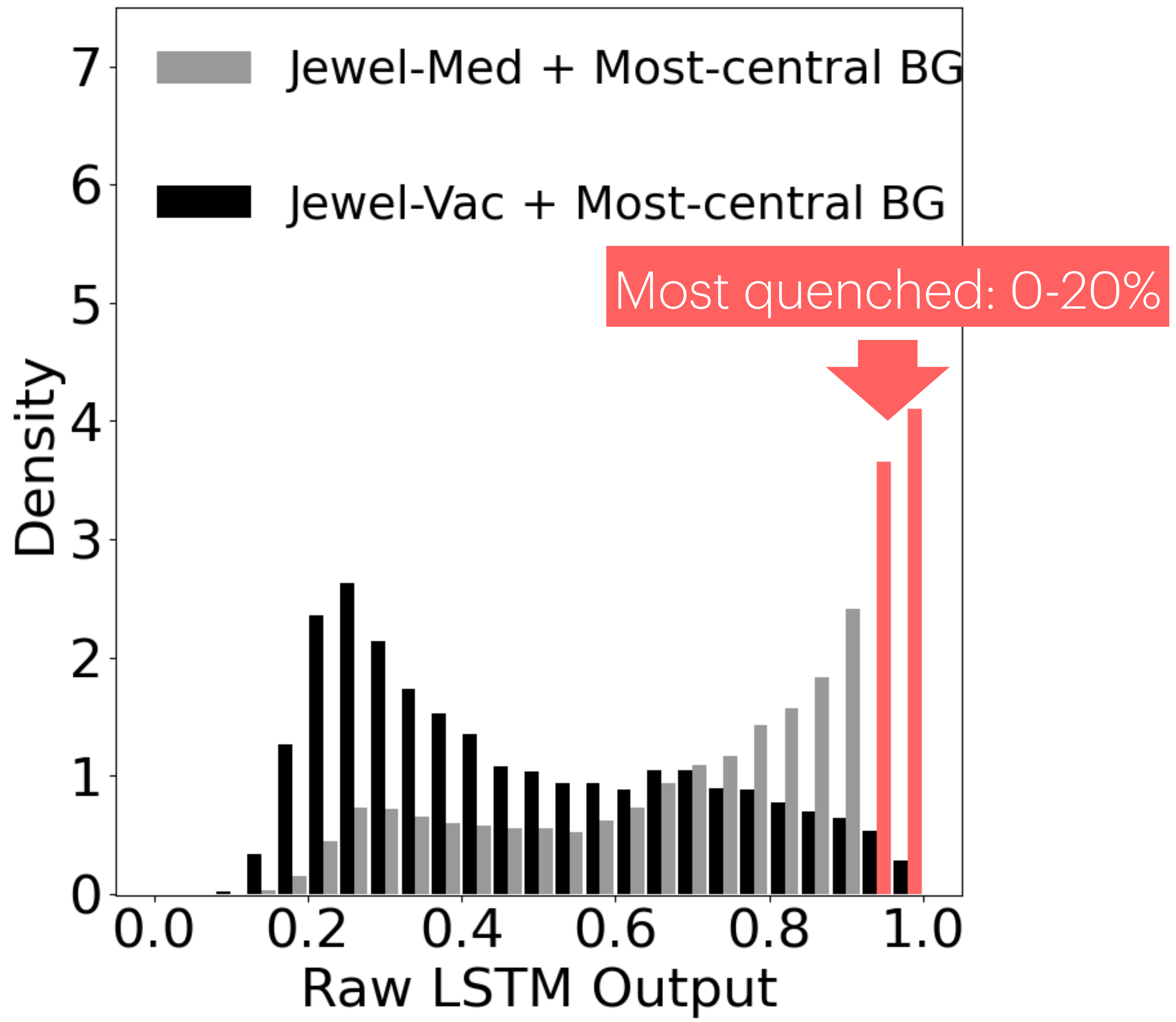




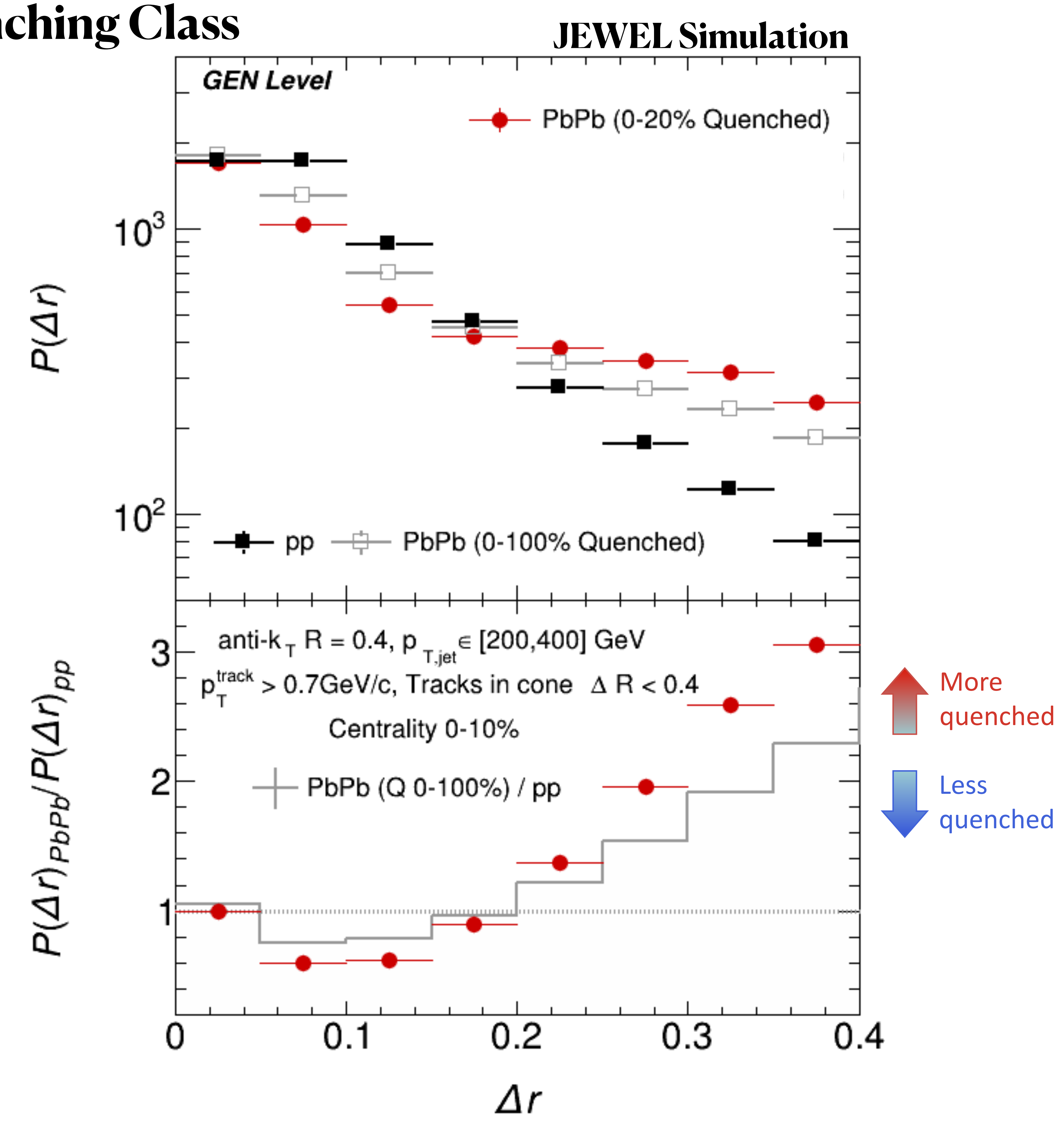
Jet shape ratio:
A redistribution of jet energy to softer particles extending to large angles away from the jet axis

Jet Quenchness ML Results — Jet Shape

1st (Most) Quenching Class



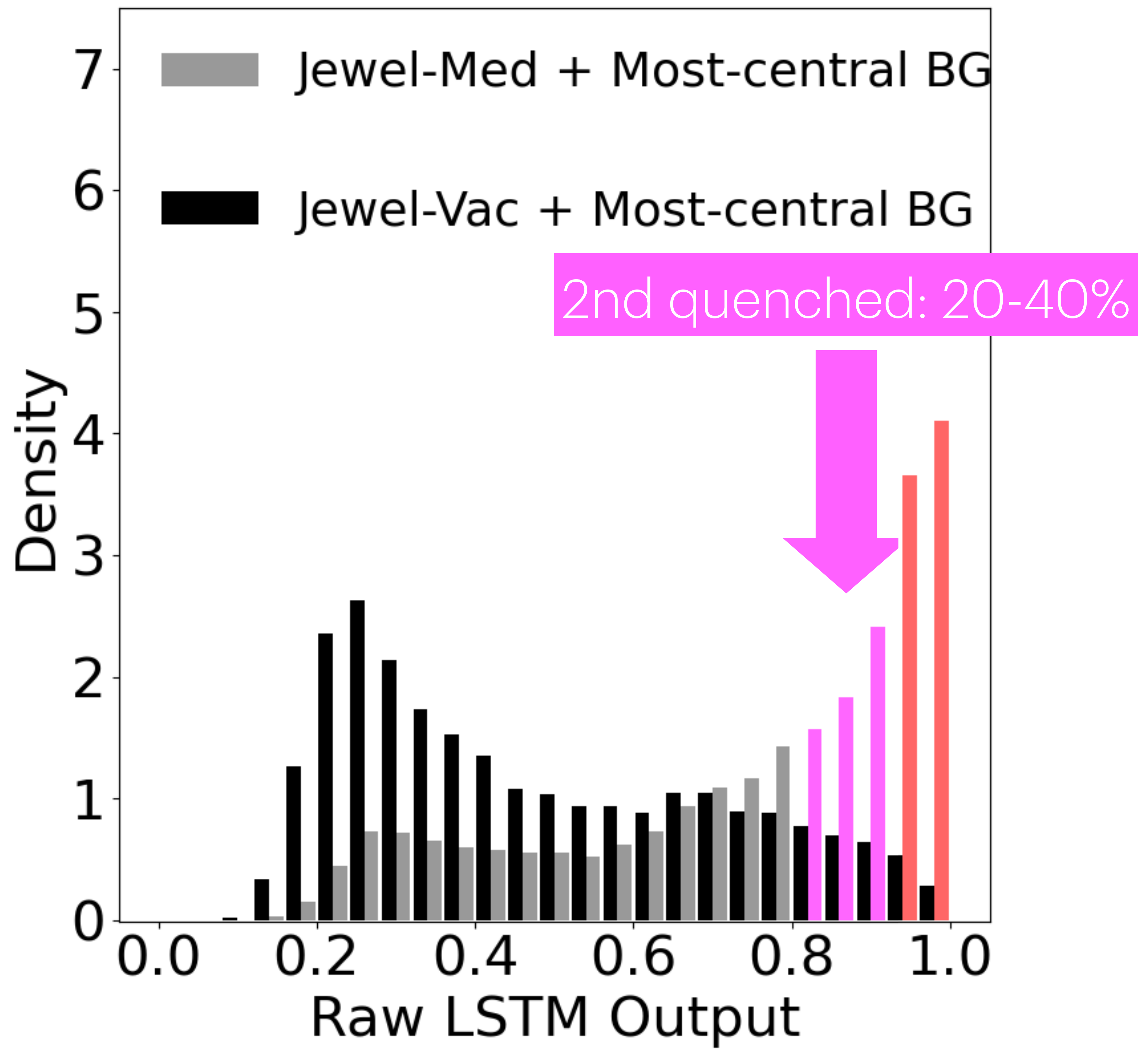
Quenchness: The LSTM output for each medium jet.
If the value is closer to 1, then the jet is more quenched.
Vice versa.

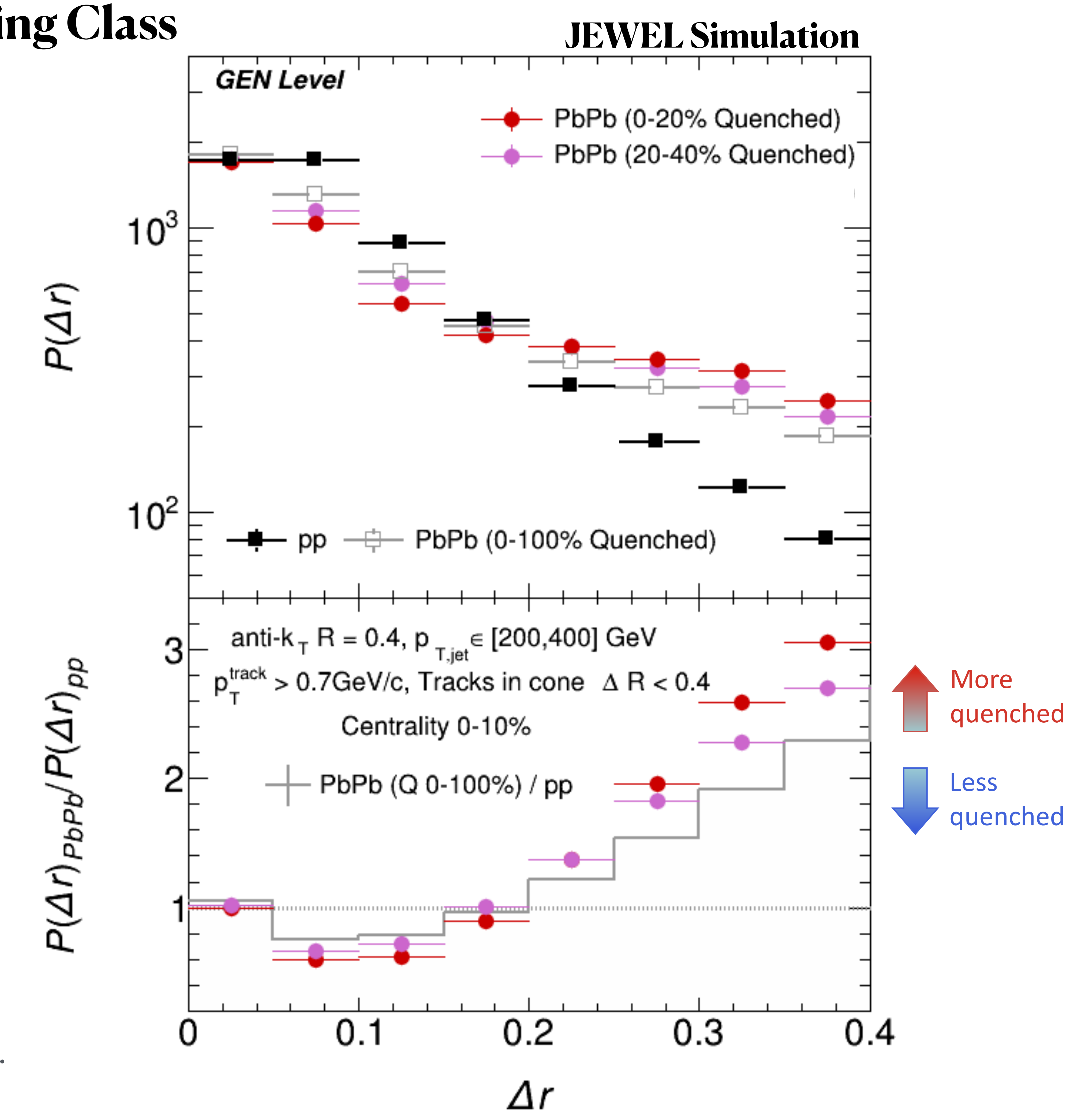


Background and Motivation | Feature Engineering | GEN Level Simulation | Detector Effects Simulation

Jet Quenchness ML Results — Jet Shape

2nd Quenching Class





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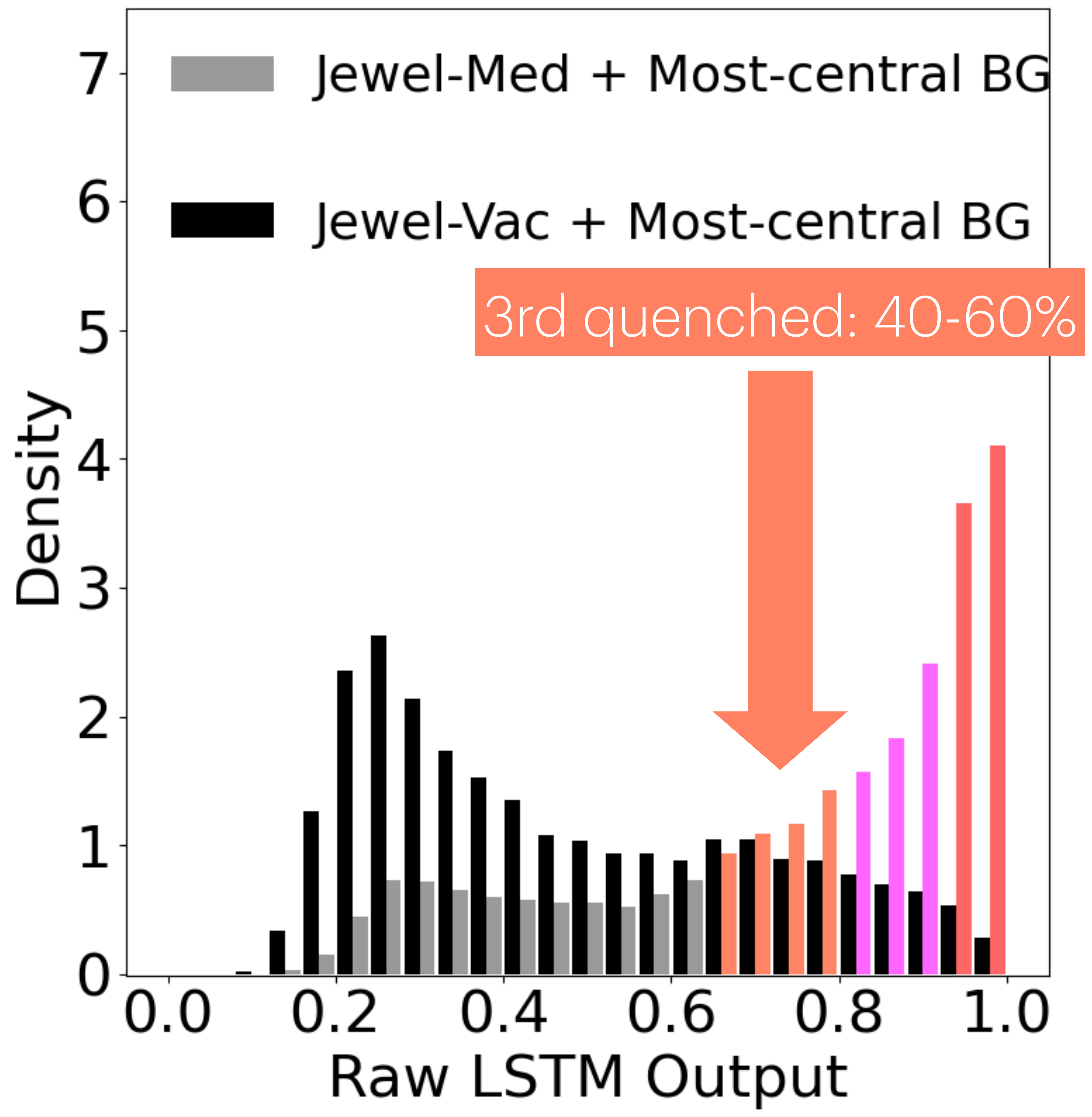
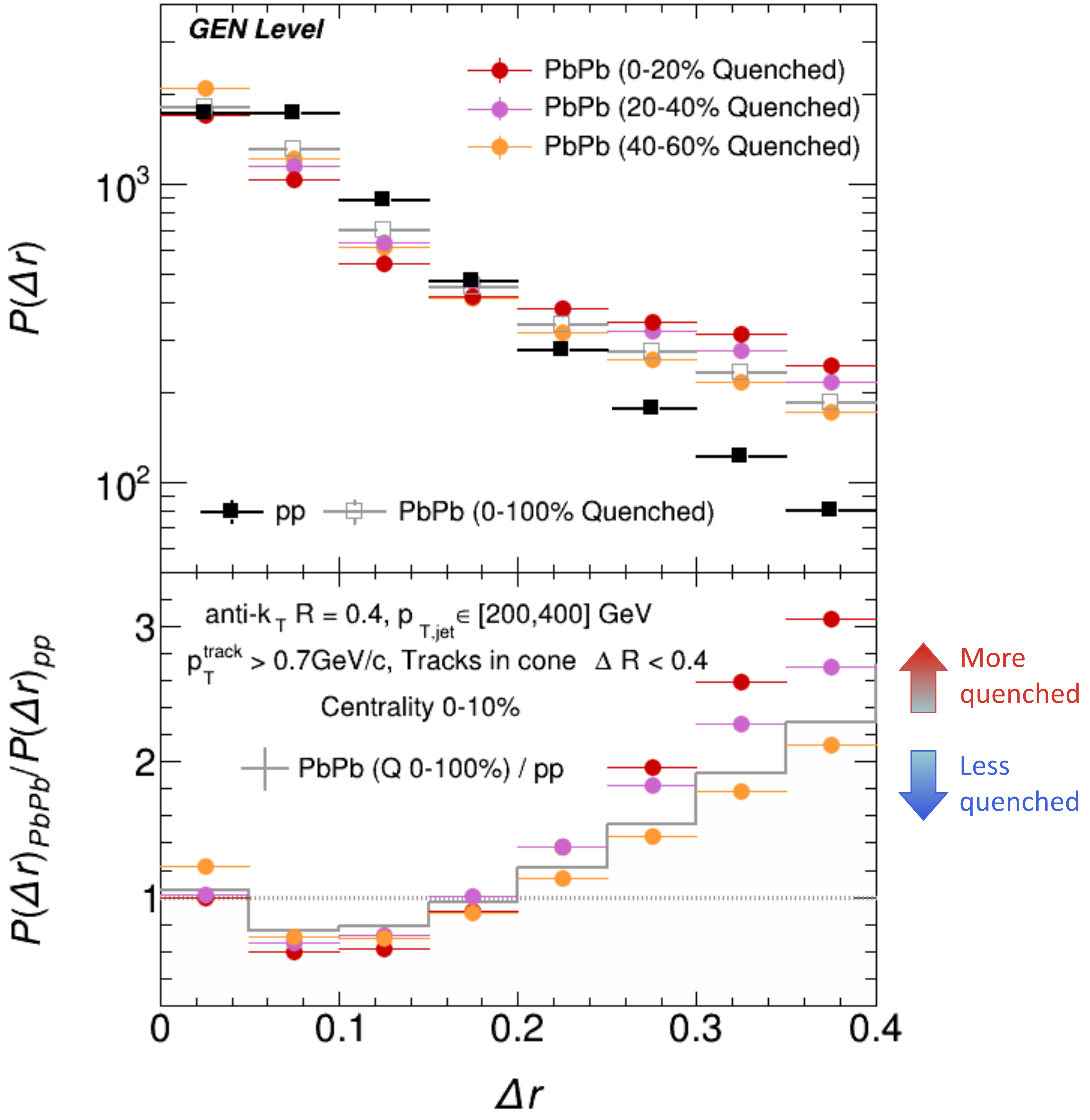
Vice versa.

Jet Quenchness ML Results — Jet Shape

3rd Quenching Class





Quenchness: The LSTM output for each medium jet.
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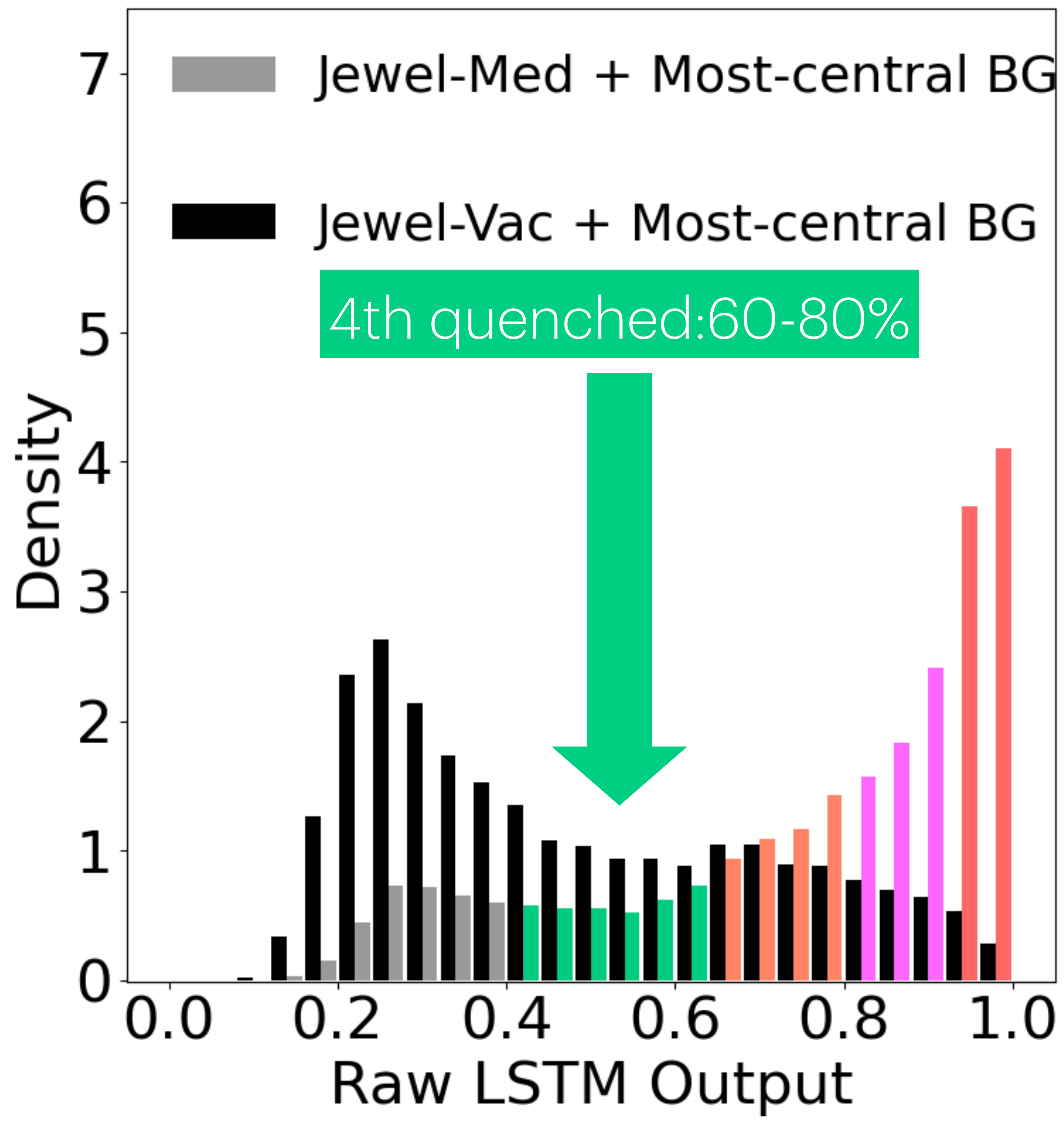
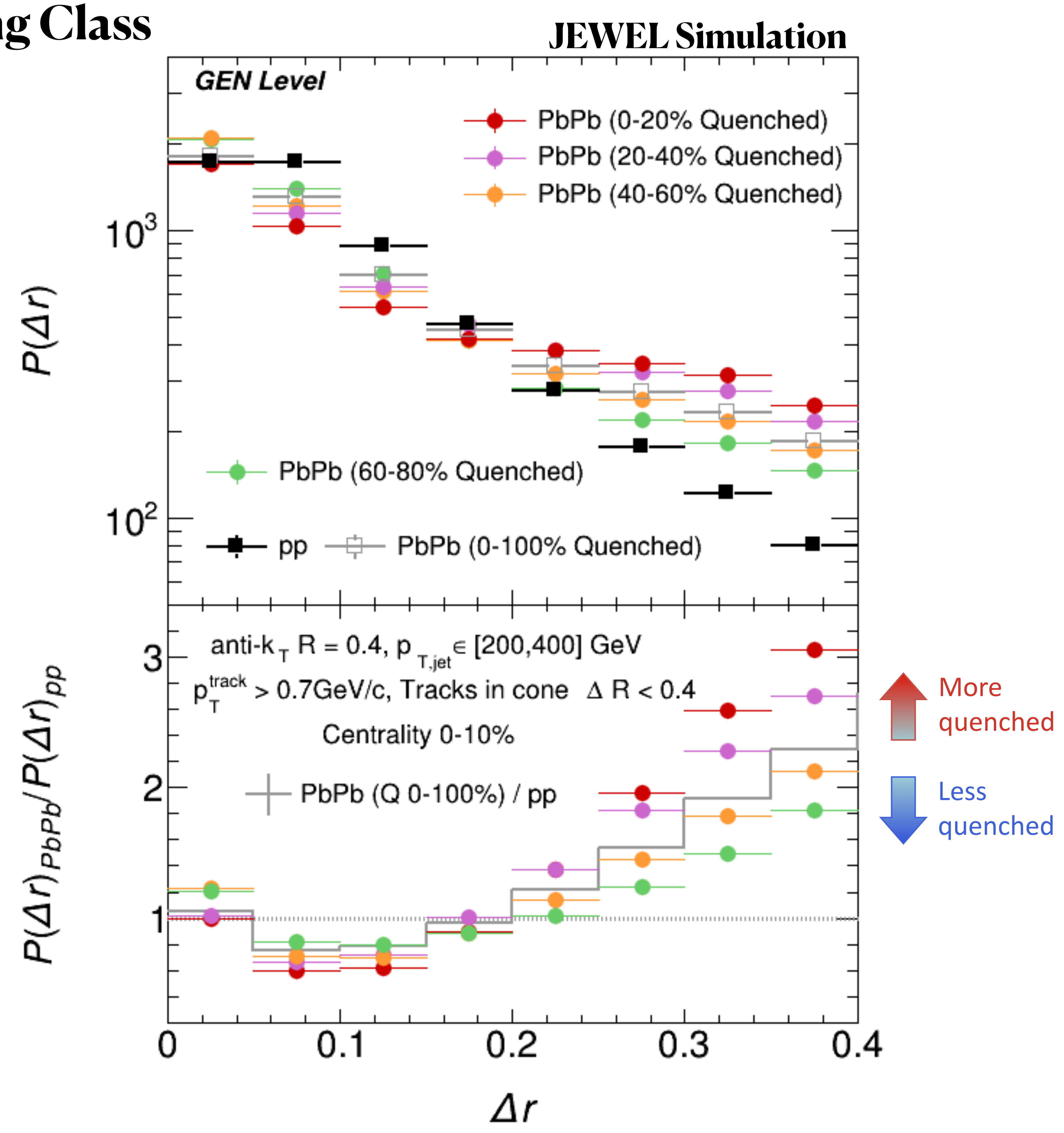
Jet Quenchness ML Results — Jet Shape



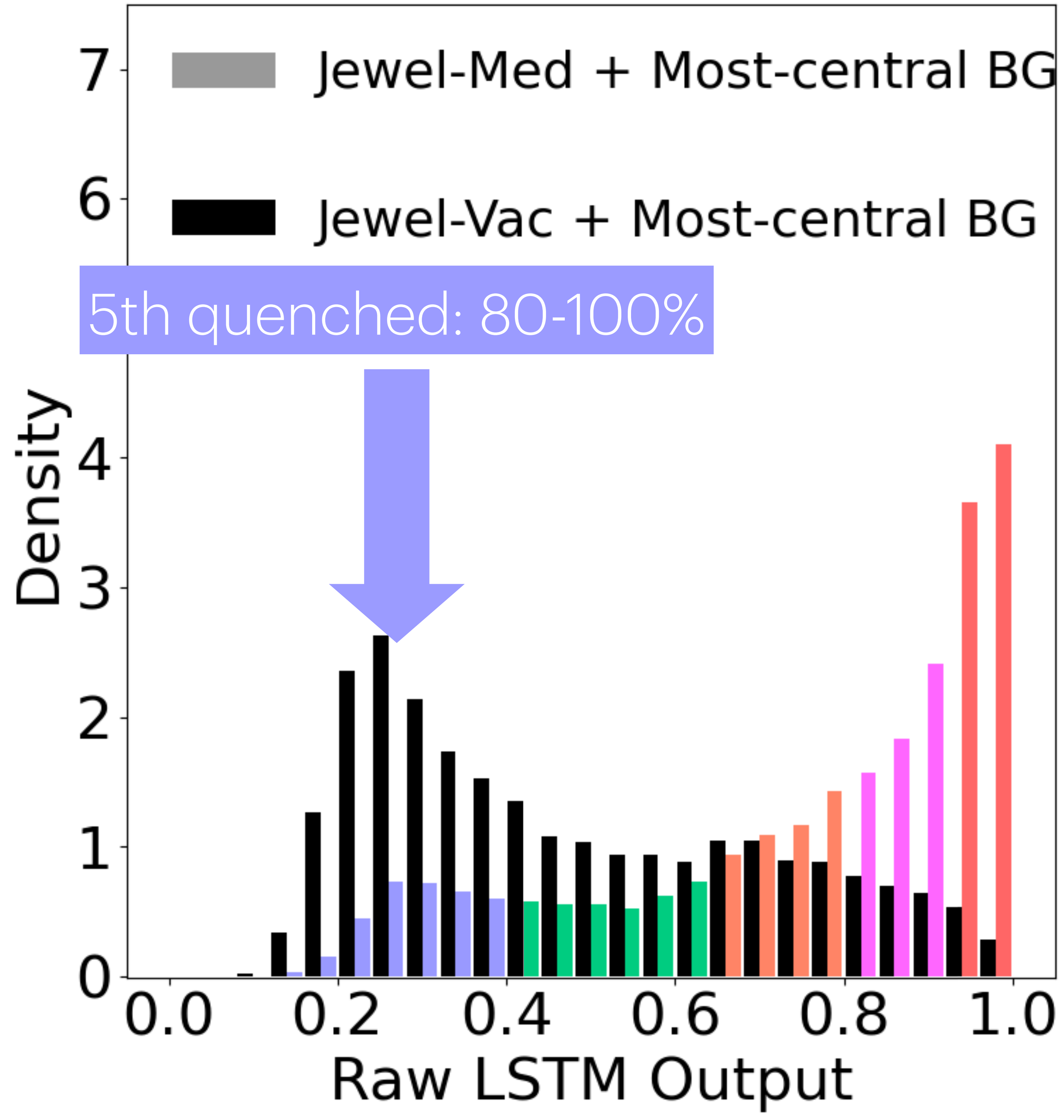
4th Quenching Class



Quenchness: The LSTM output for each medium jet.
If the value is closer to 1, then the jet is more quenched.
Vice versa.

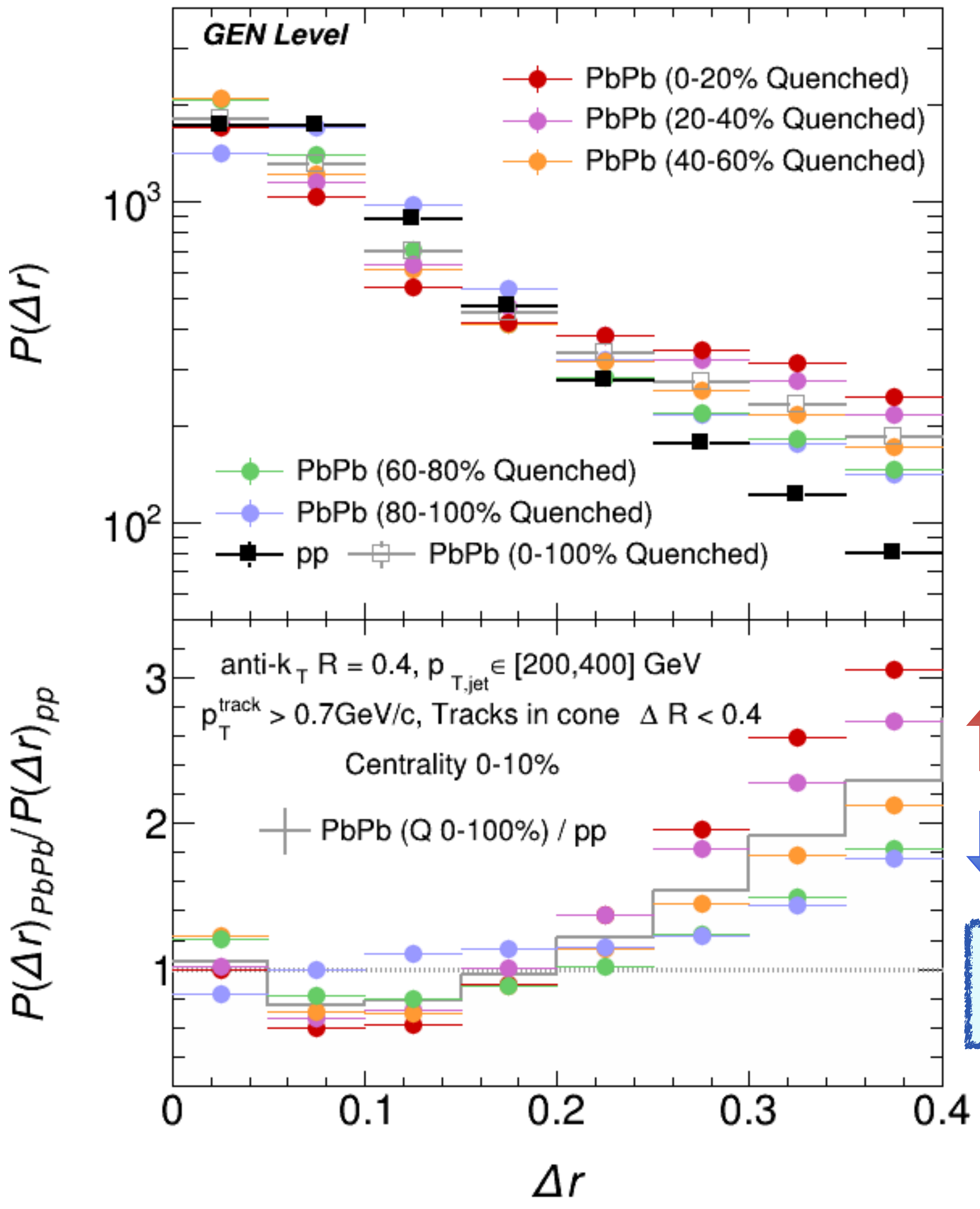
Jet Quenchness ML Results — Jet Shape

5th (Least) Quenching Class



Quenchness: The LSTM output for each medium jet.
If the value is closer to 1, then the jet is more quenched.
Vice versa.

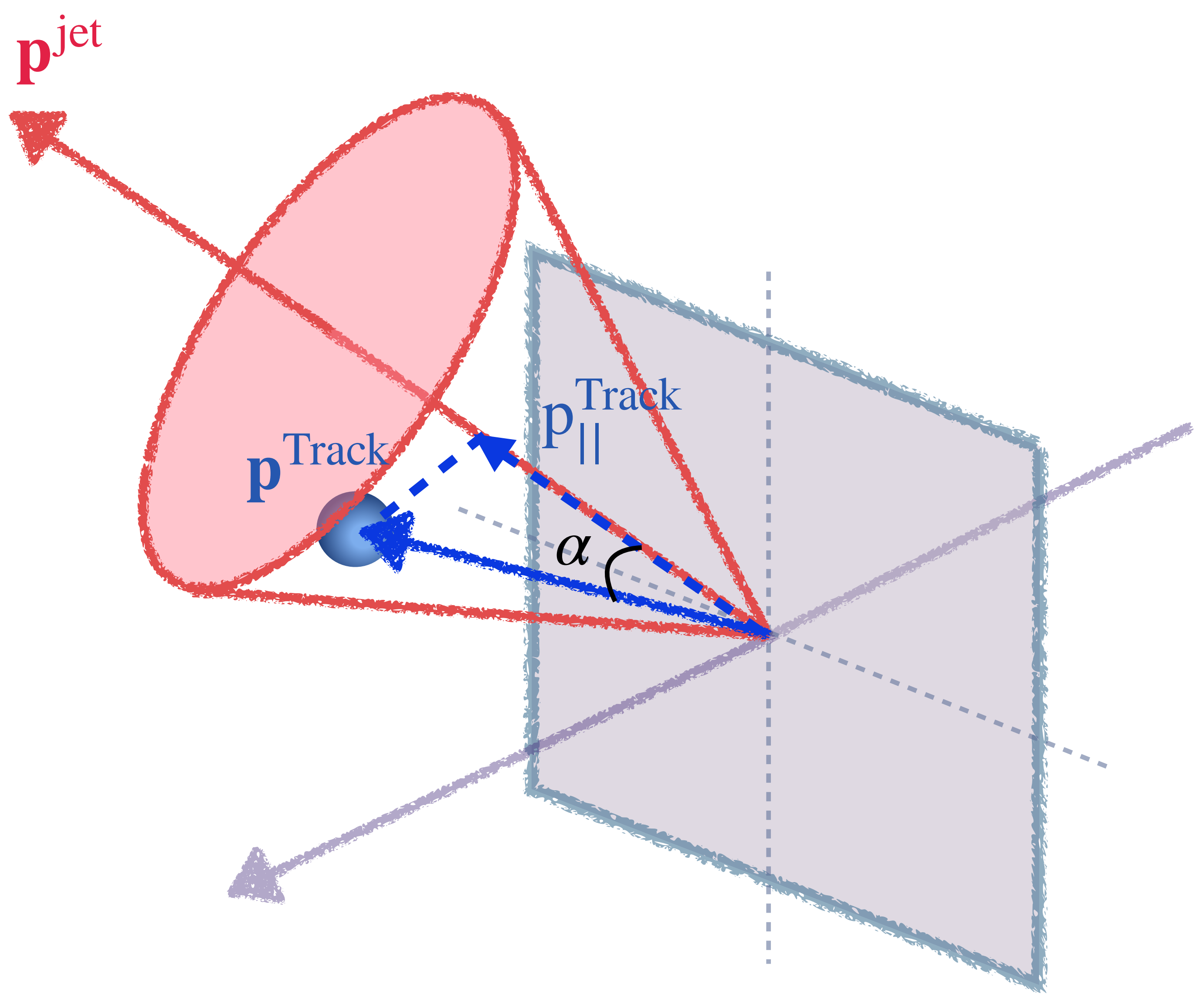
JEWEL Simulation



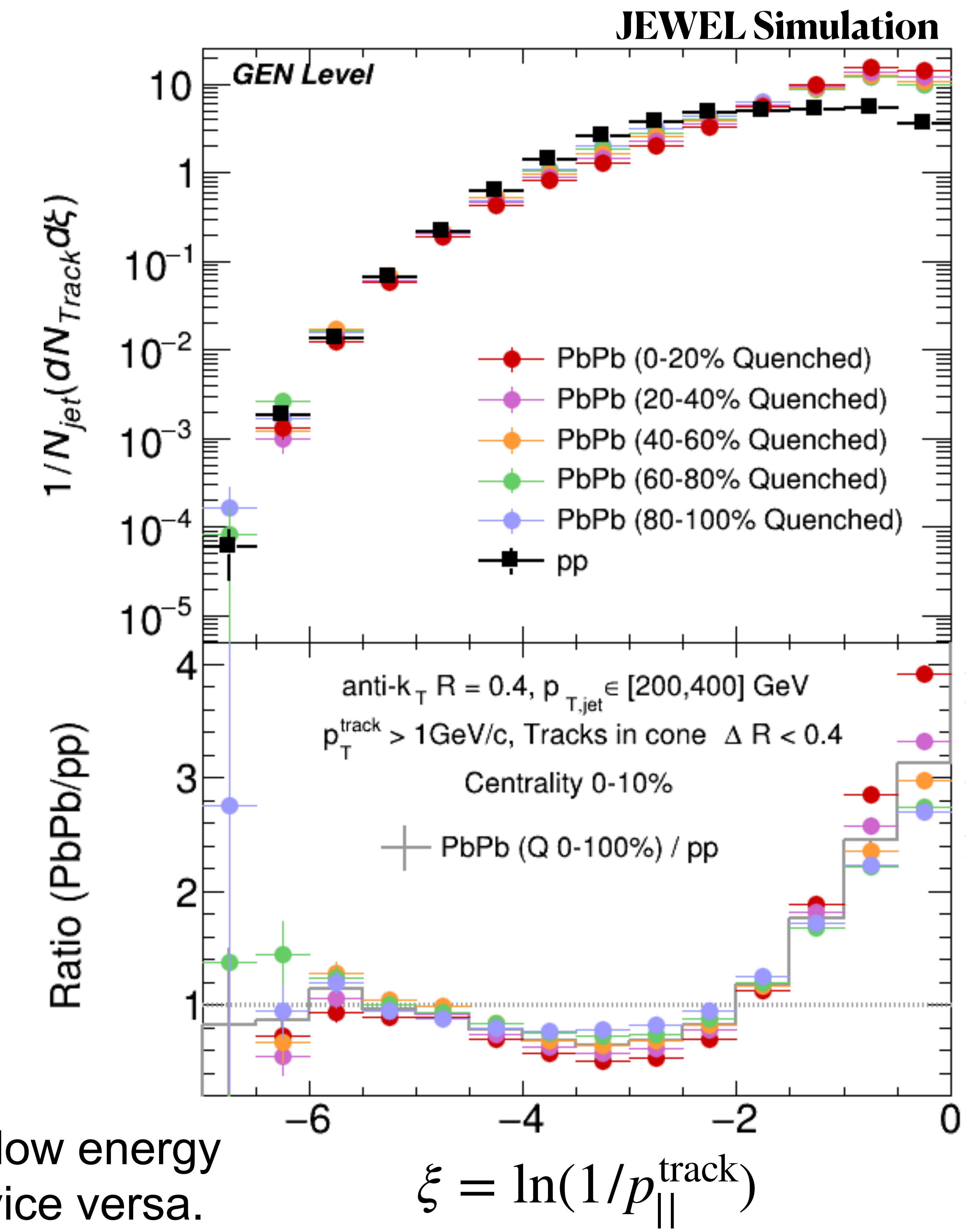
Jets are ordered based on their quenching levels.

Jet Quenchness ML Results — Jet Fragmentation Function

$\xi = \ln(1/p_{||}^{\mathrm{track}})$: the probability of finding one hadron inside jet cone containing certain a longitudinal energy.



Large ξ values correspond to low energy particles within the jet cone, vice versa.



NN predicts that strongly quenched jets have more soft tracks than weakly quenched jets

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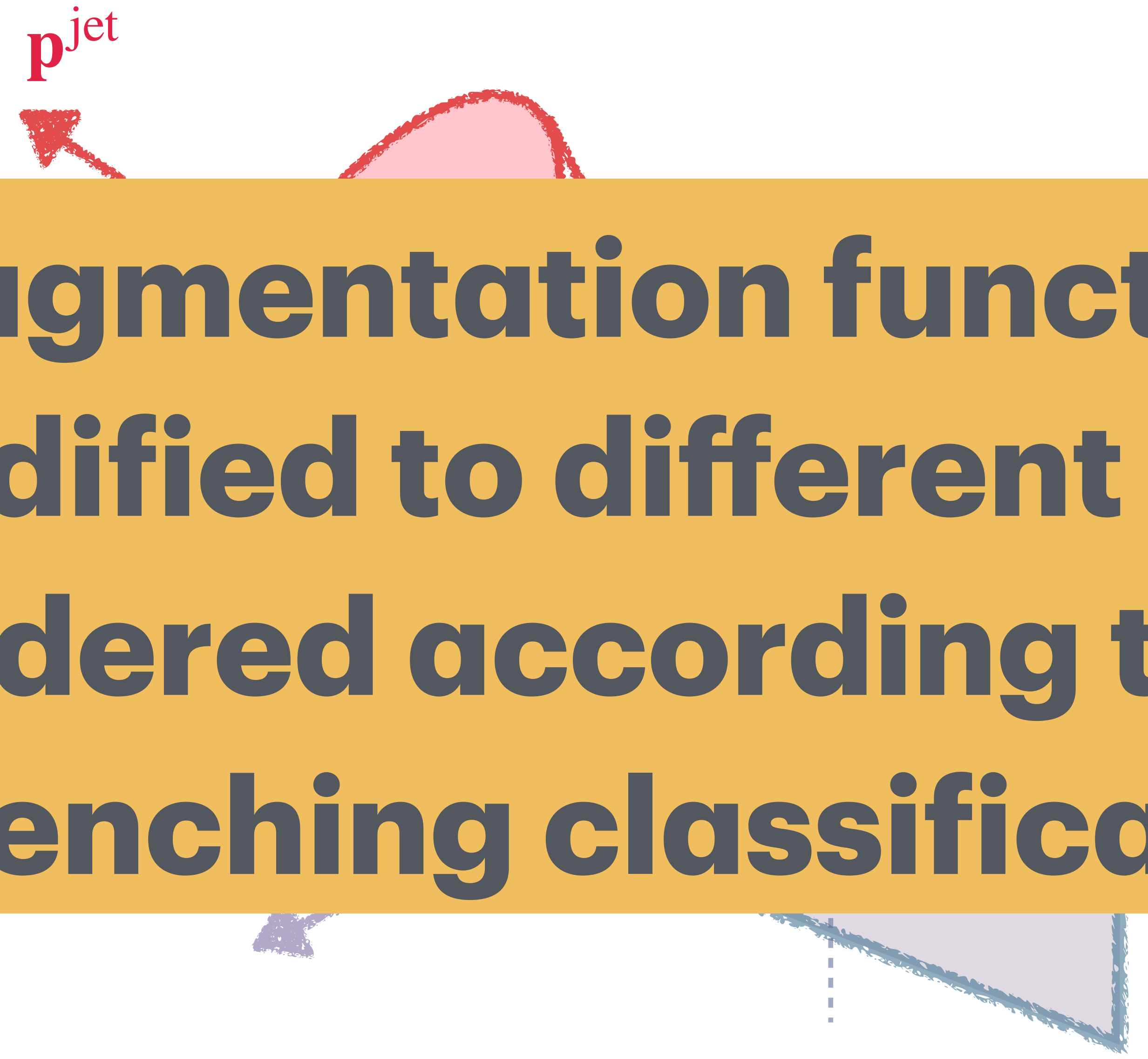
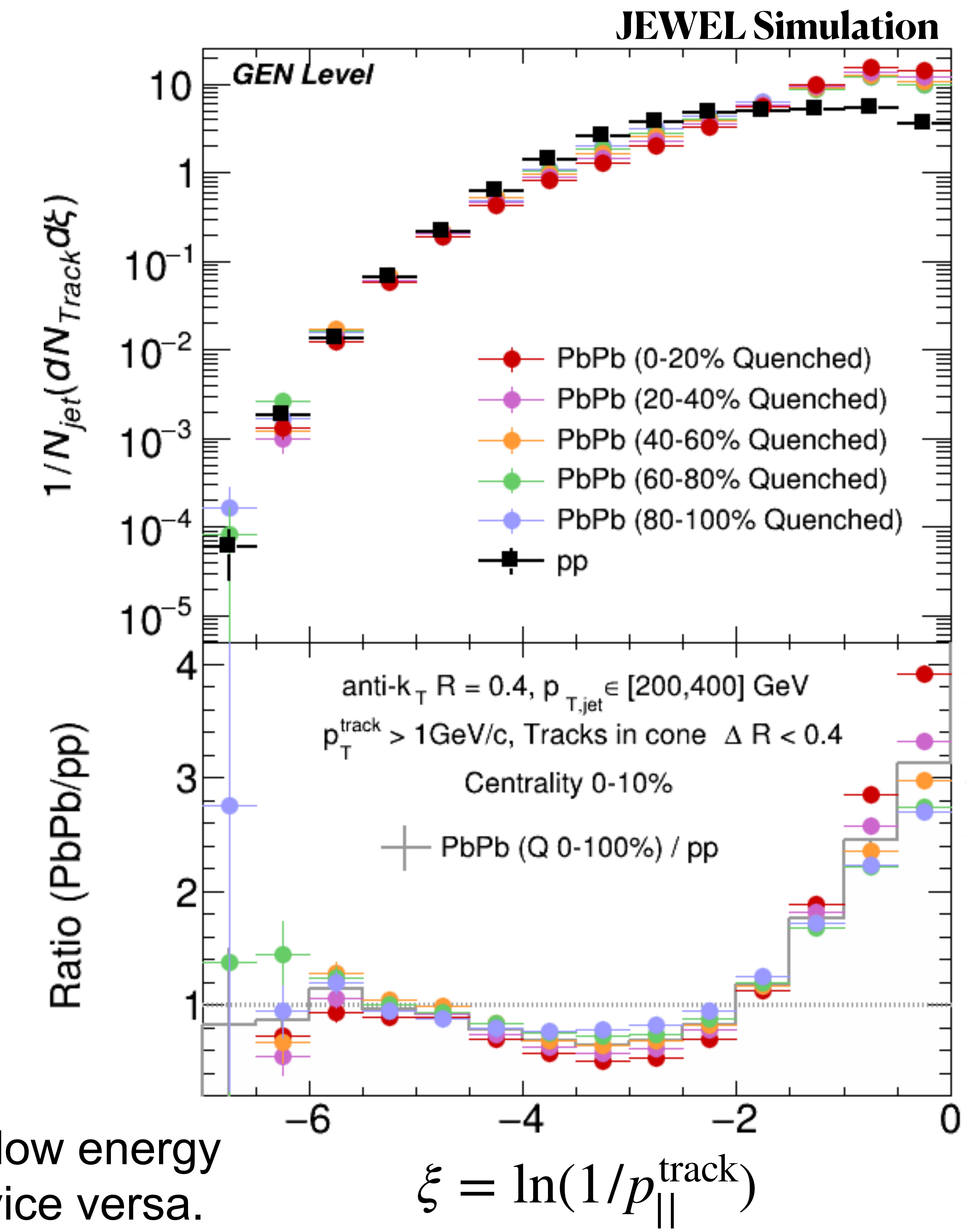


Jet fragmentation functions are modified to different levels and ordered according to the ML quenching classification.



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NN predicts that strongly quenched jets have more soft tracks than weakly quenched jets

Detector Effects on the Training

We use DELPHES-3.5.0 Fast Simulation to get the CMS detector responses[1].

✓ Tracker (Tracking Efficiency and Momentum Smearing)

✓ ECal and HCal for energy smearing

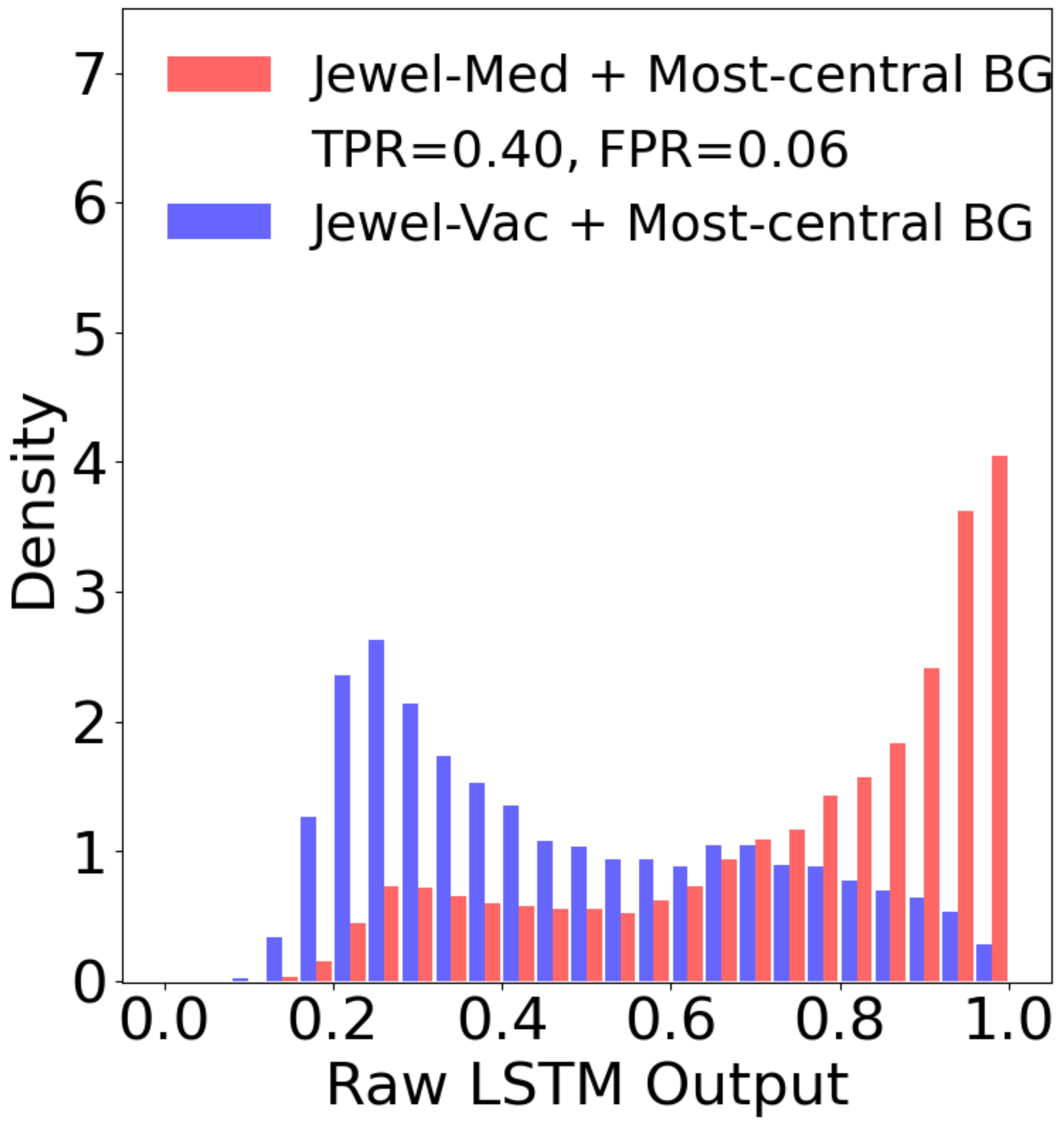
✓ Energy Flow algorithm corresponding to the Particle Flow algorithm in CMS

The RECO jet energy is corrected to the GEN level in our study.

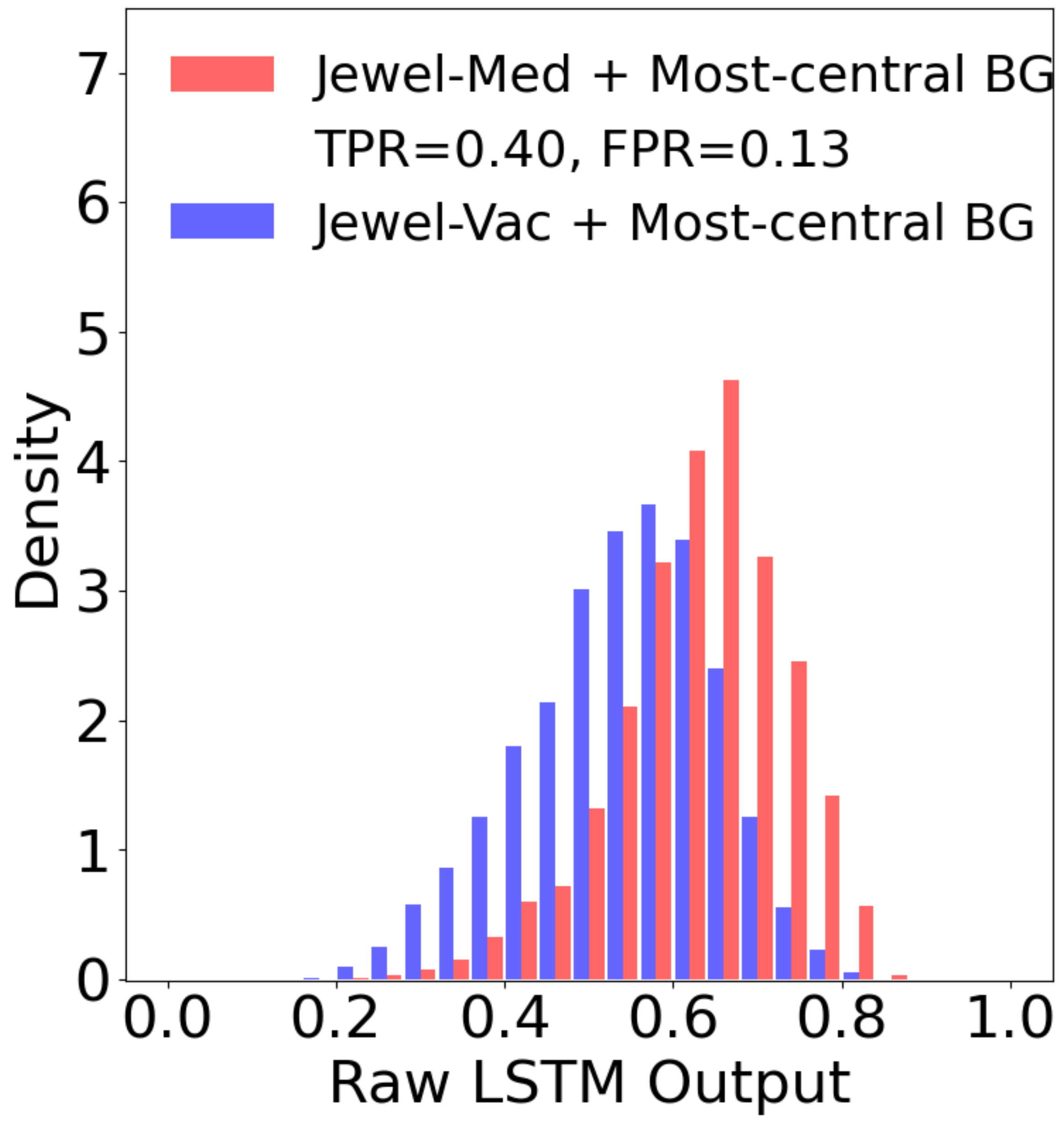
[1] https://github.com/delphes/delphes/blob/master/cards/delphes_card_CMS.tcl

Detector Effects: ROC curve and Binary Classification

GEN Level jet training



Detector effects smear the differences between medium jets and vacuum jets

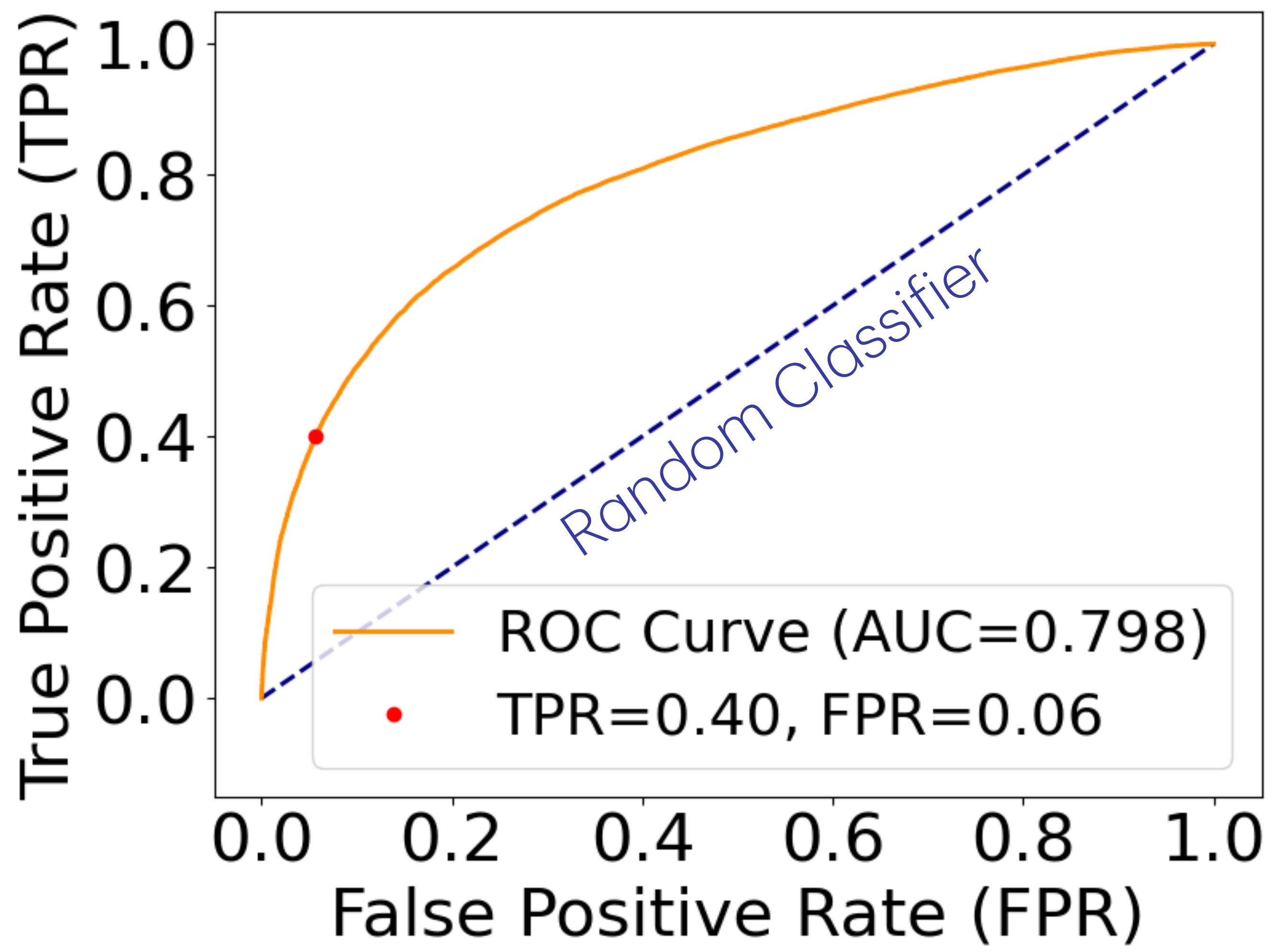


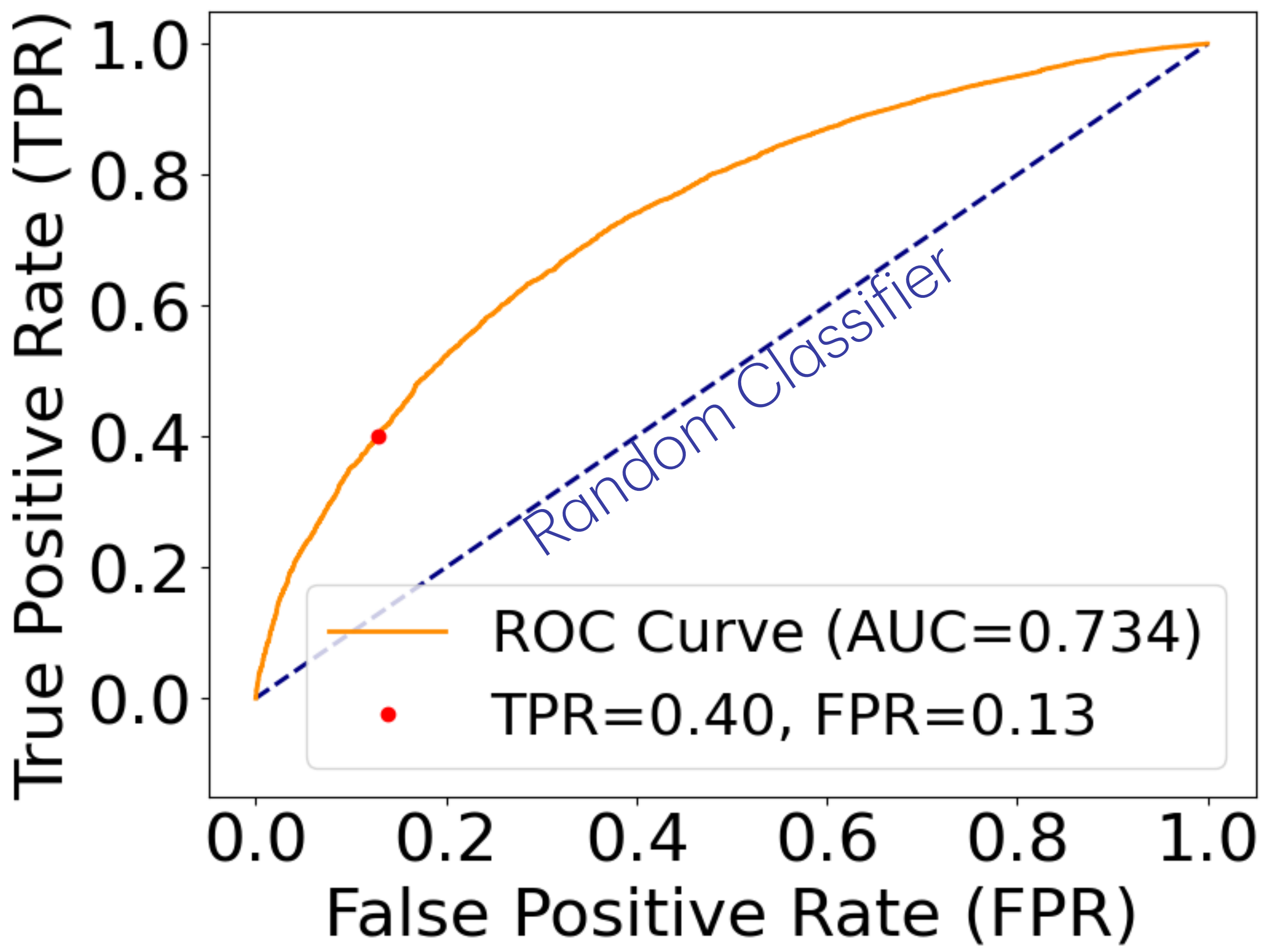
RECO jet training

EFlow Candidates from DELPHES:

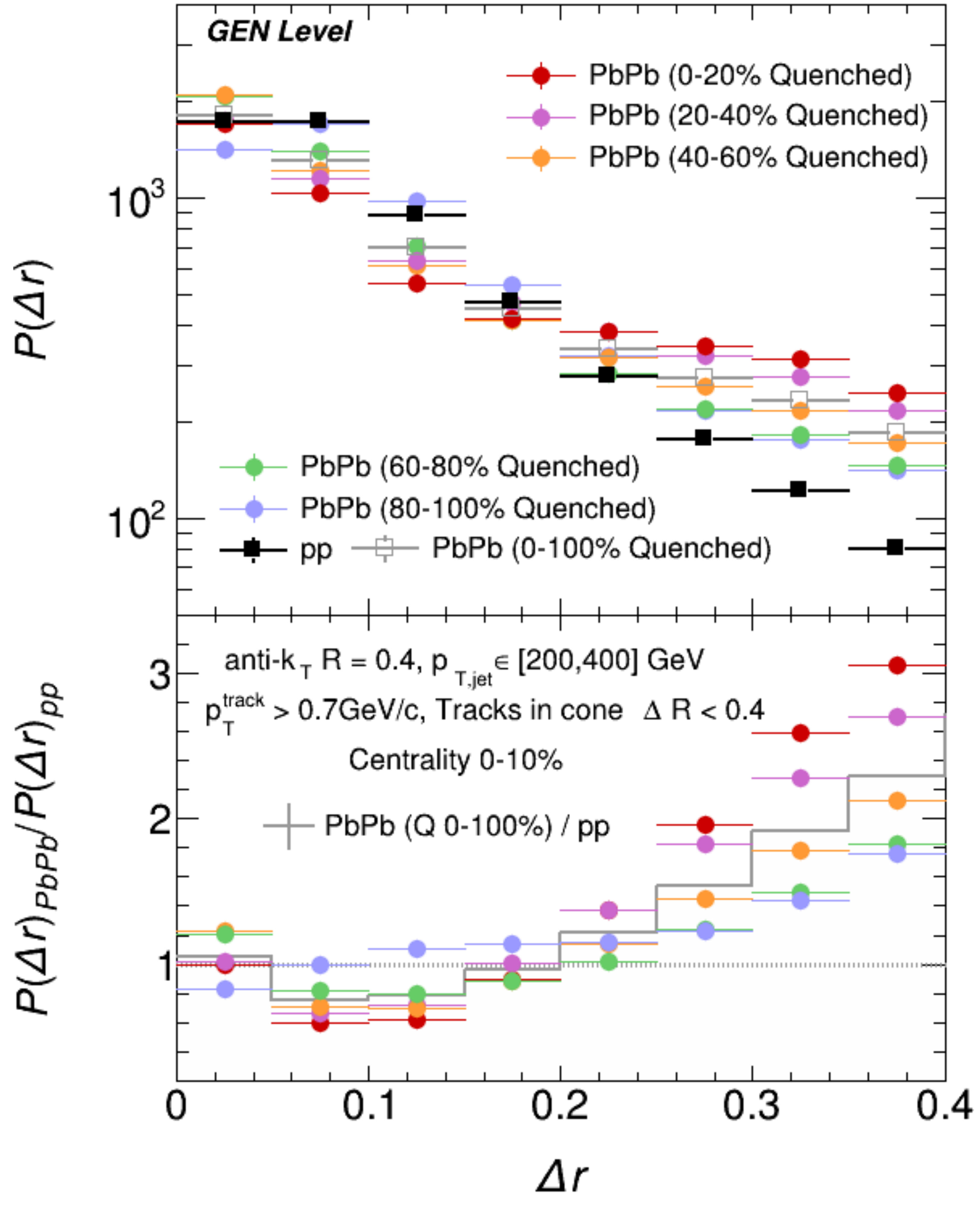
1) Combine the Tracker + Calorimeters

2) Comparable to CMS Particle Flow Candidates





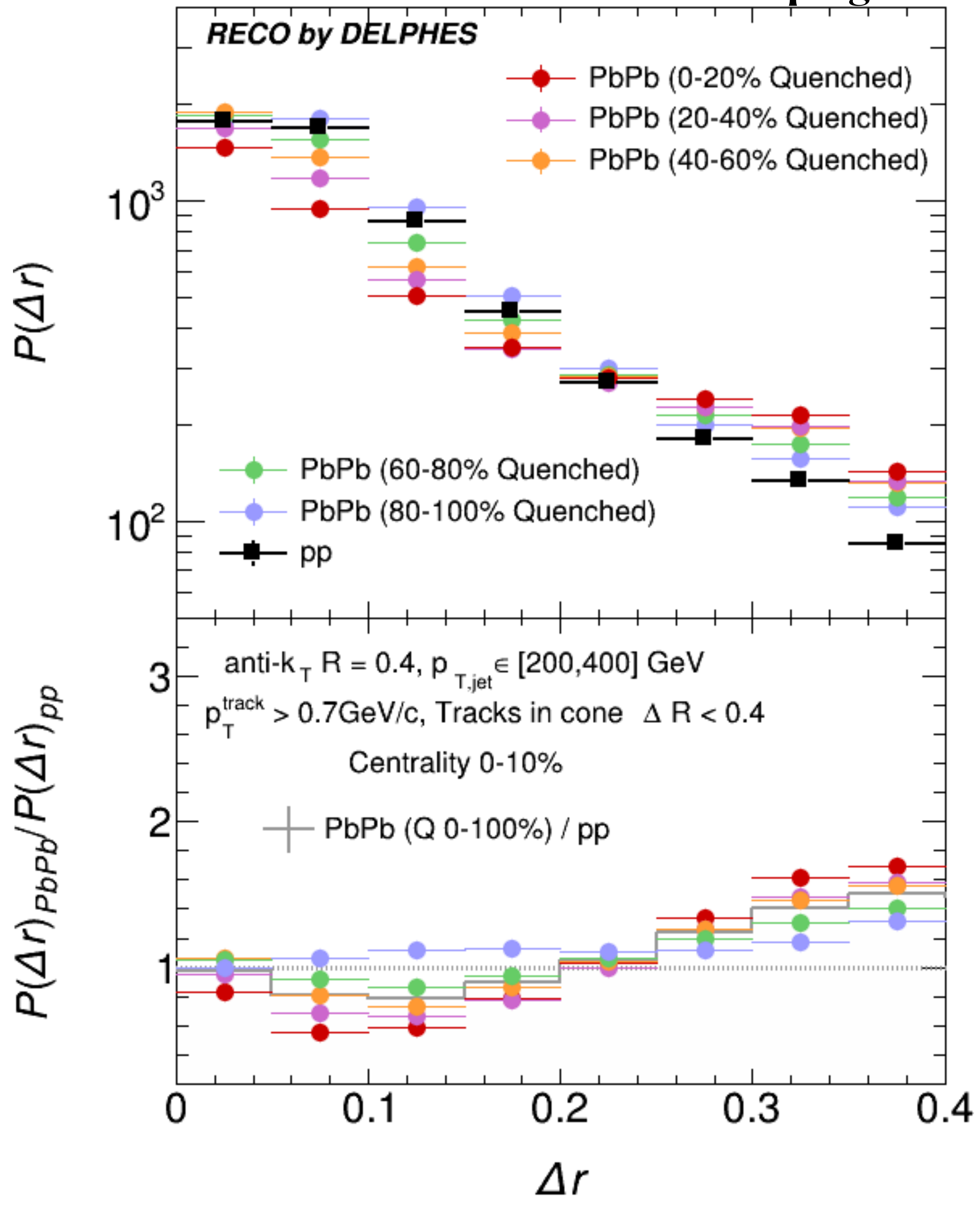
Detector Effects: Jet Shape



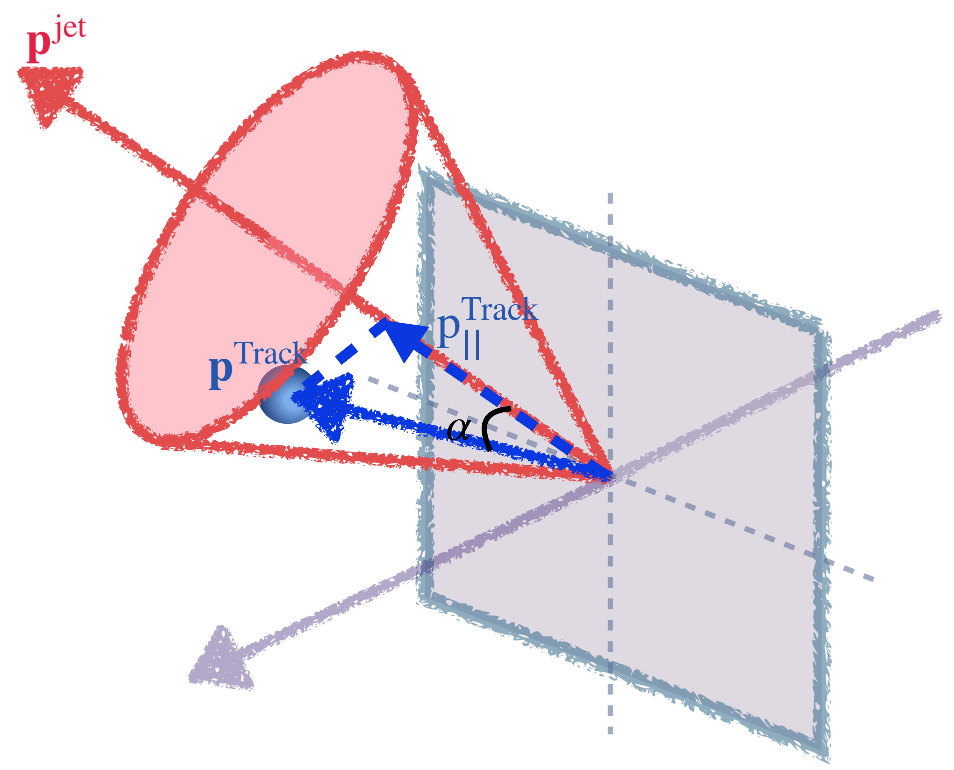
Detector effects smear the differences between jets with different quenching levels

but the order of the modifications predicted by NN is preserved.

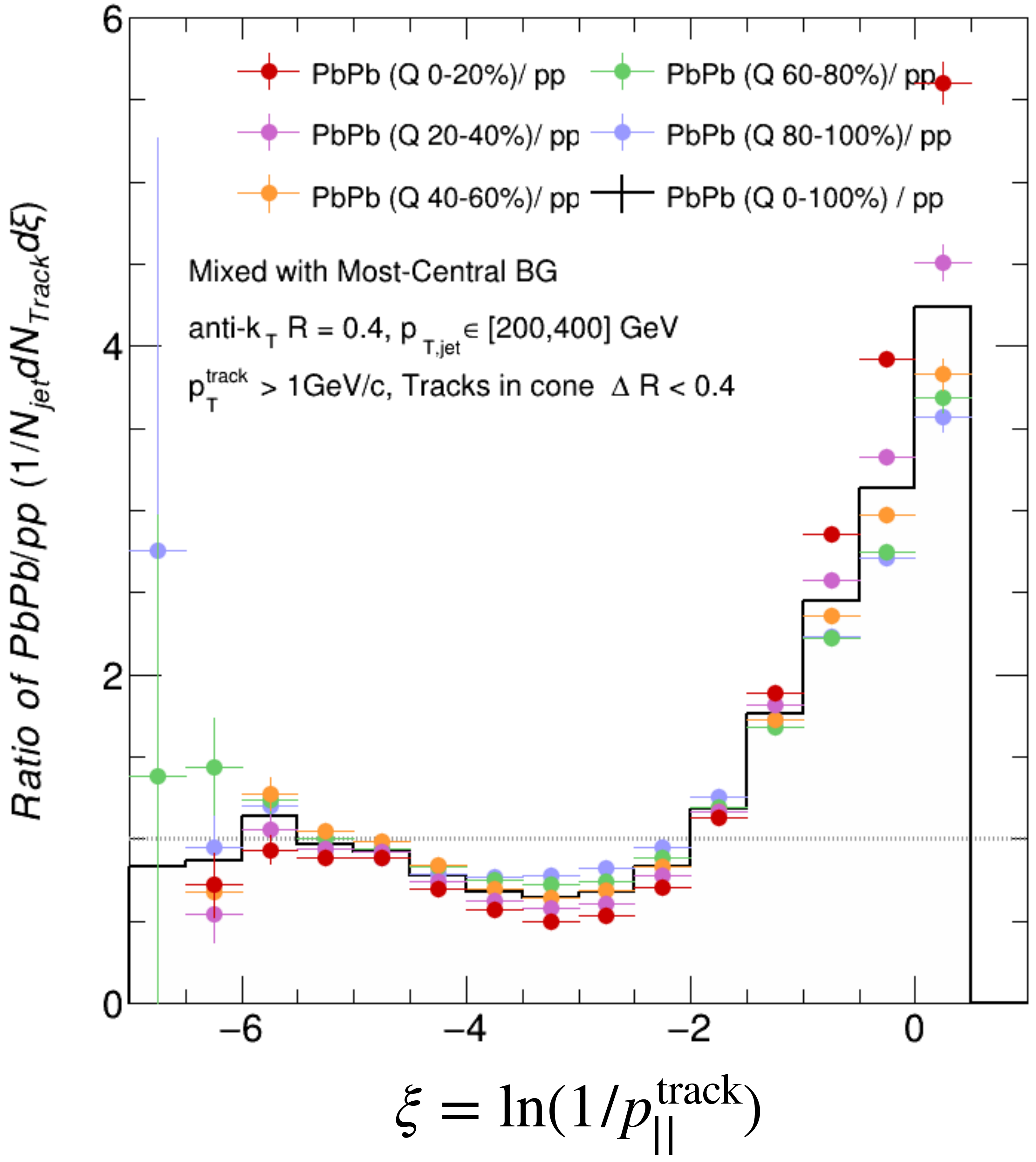
Work in progress



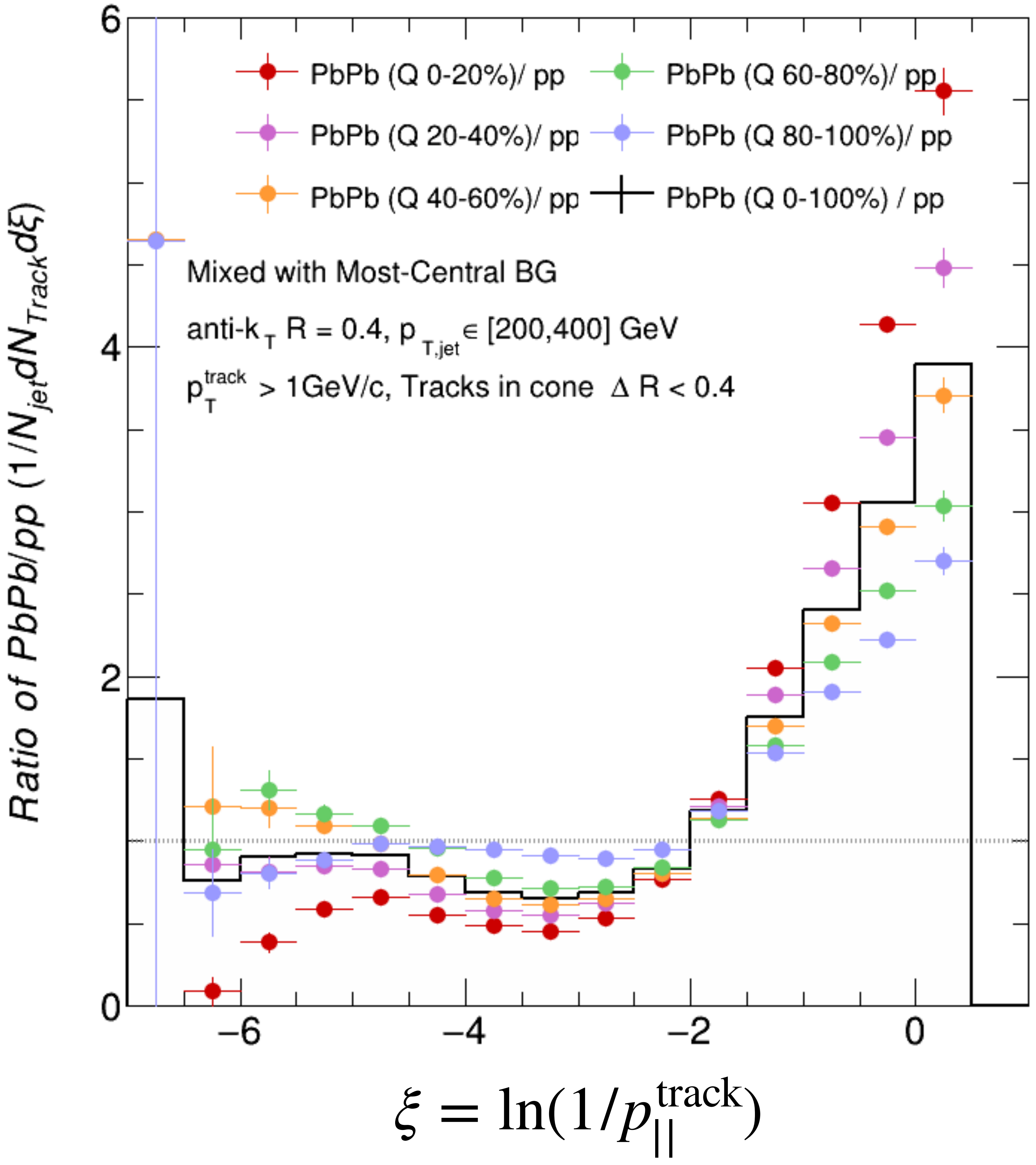
Detector Effects: Jet Fragmentation Function Ratio



Generator Level JFF Ratio



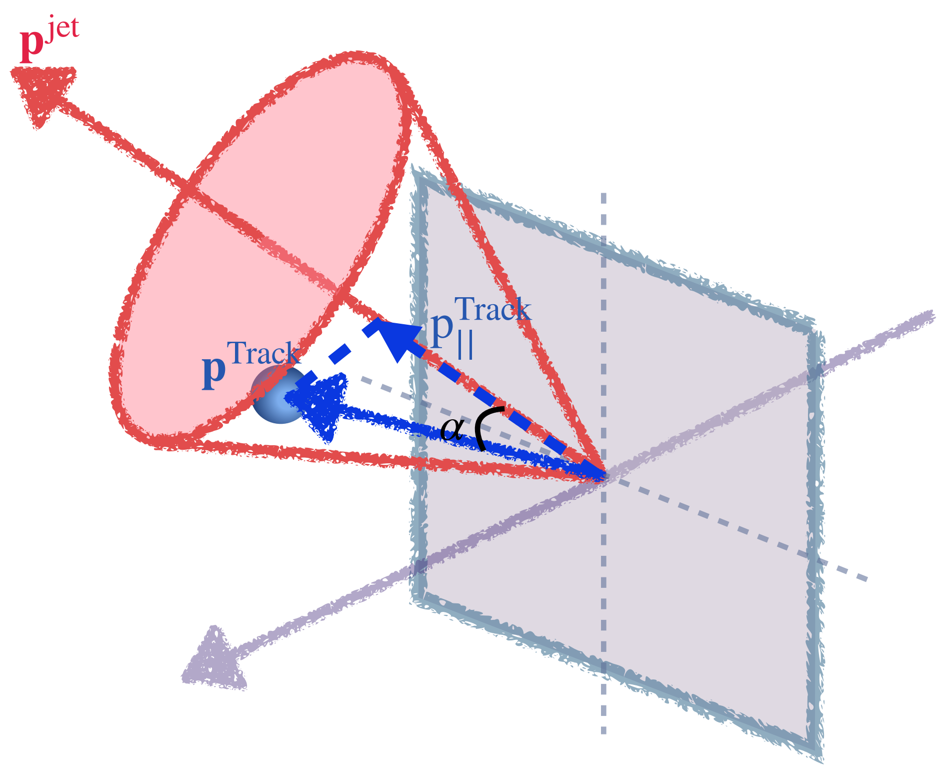
Toy Model for Detector Effects*



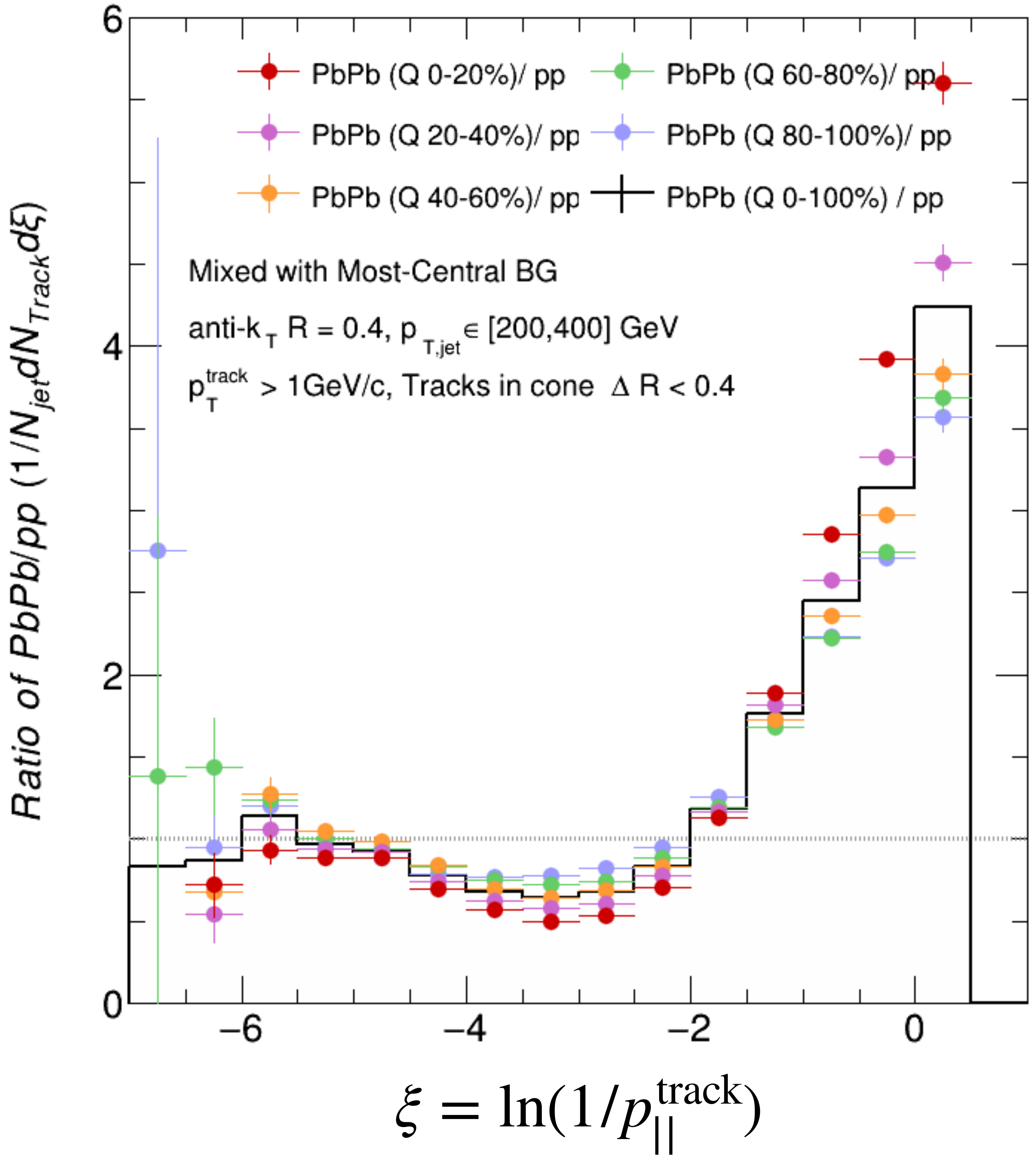
Work in progress

*** Particle acceptance rate for PbPb collision: 75%
pp collision: 85 %**

Detector Effects: Jet Fragmentation Function Ratio

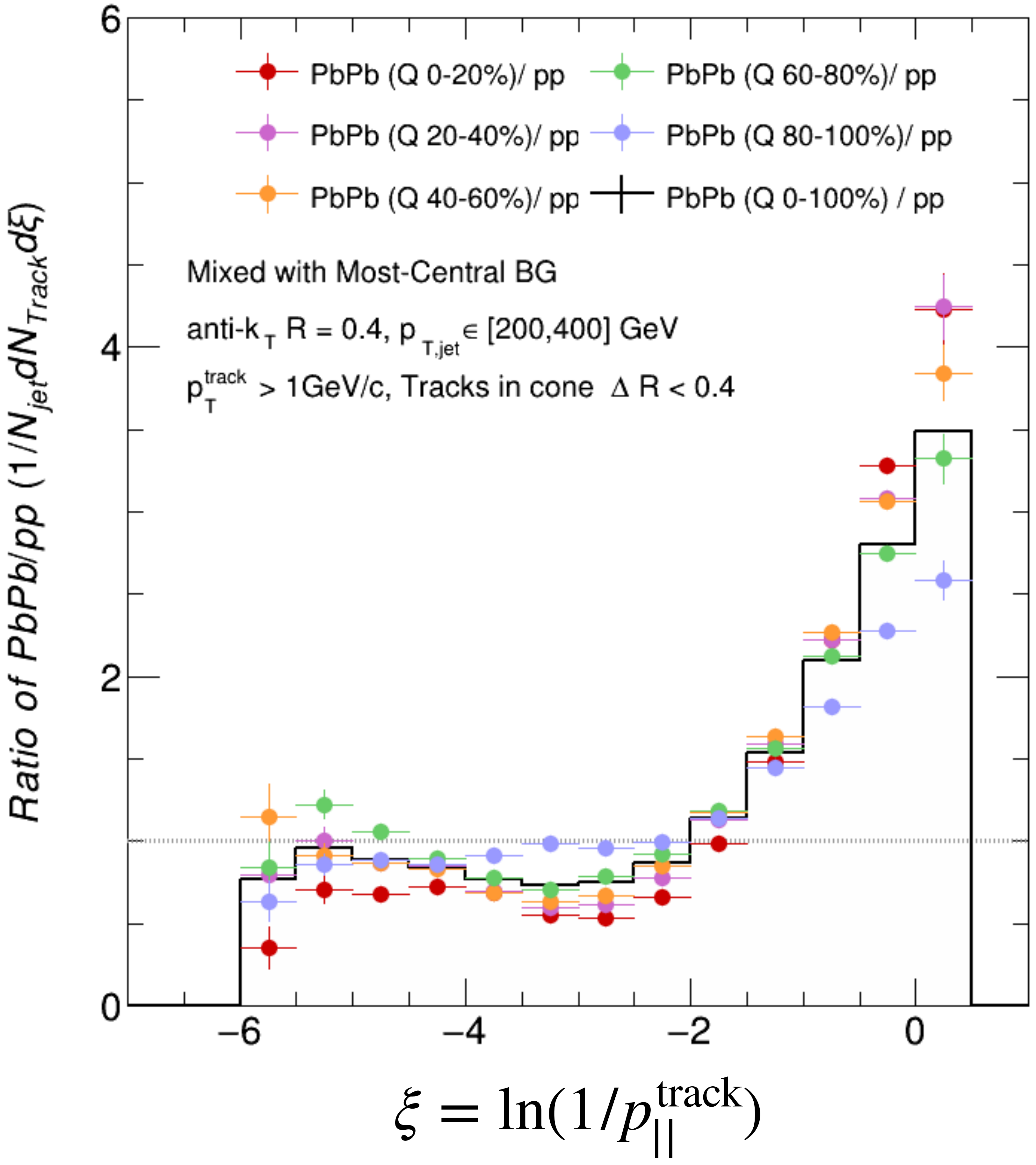


GEN Level JFF Ratio



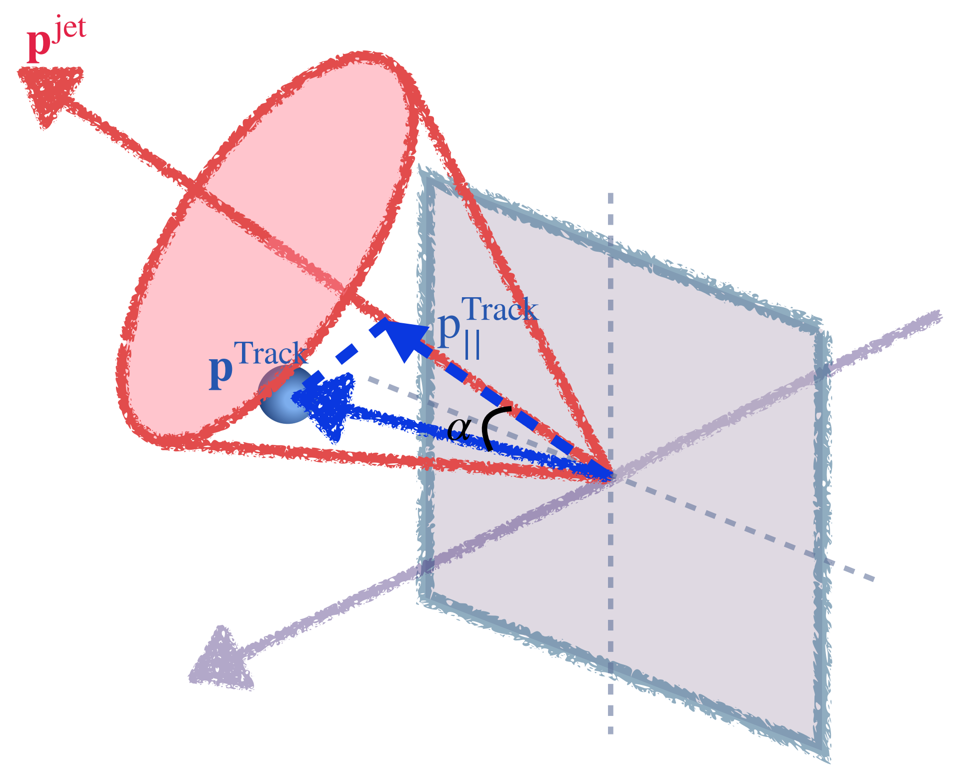
Tracks from DELPHES*

Work in progress

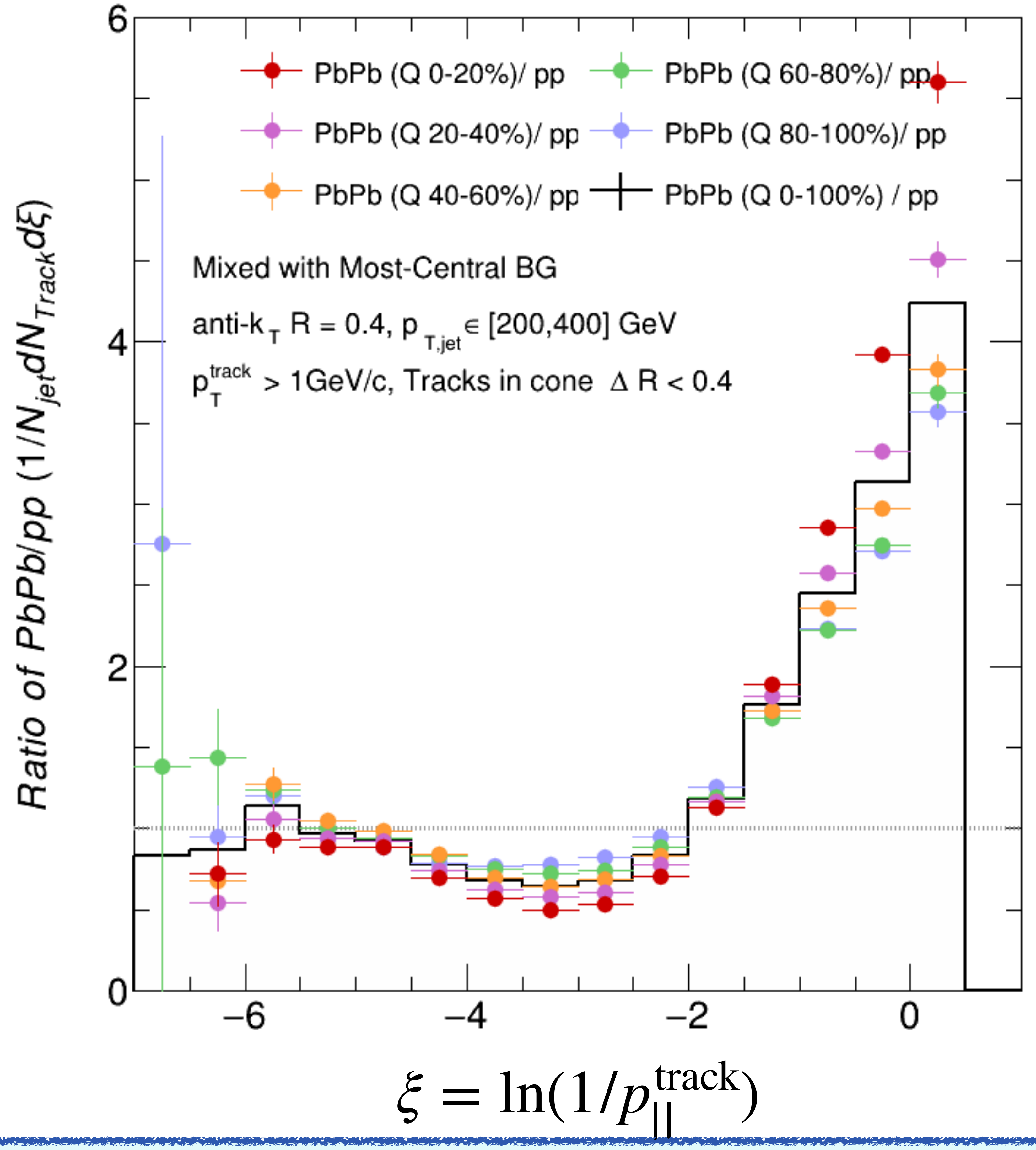


*** Tracking Efficiency & Momentum Smearing**

Detector Effects: Jet Fragmentation Function Ratio

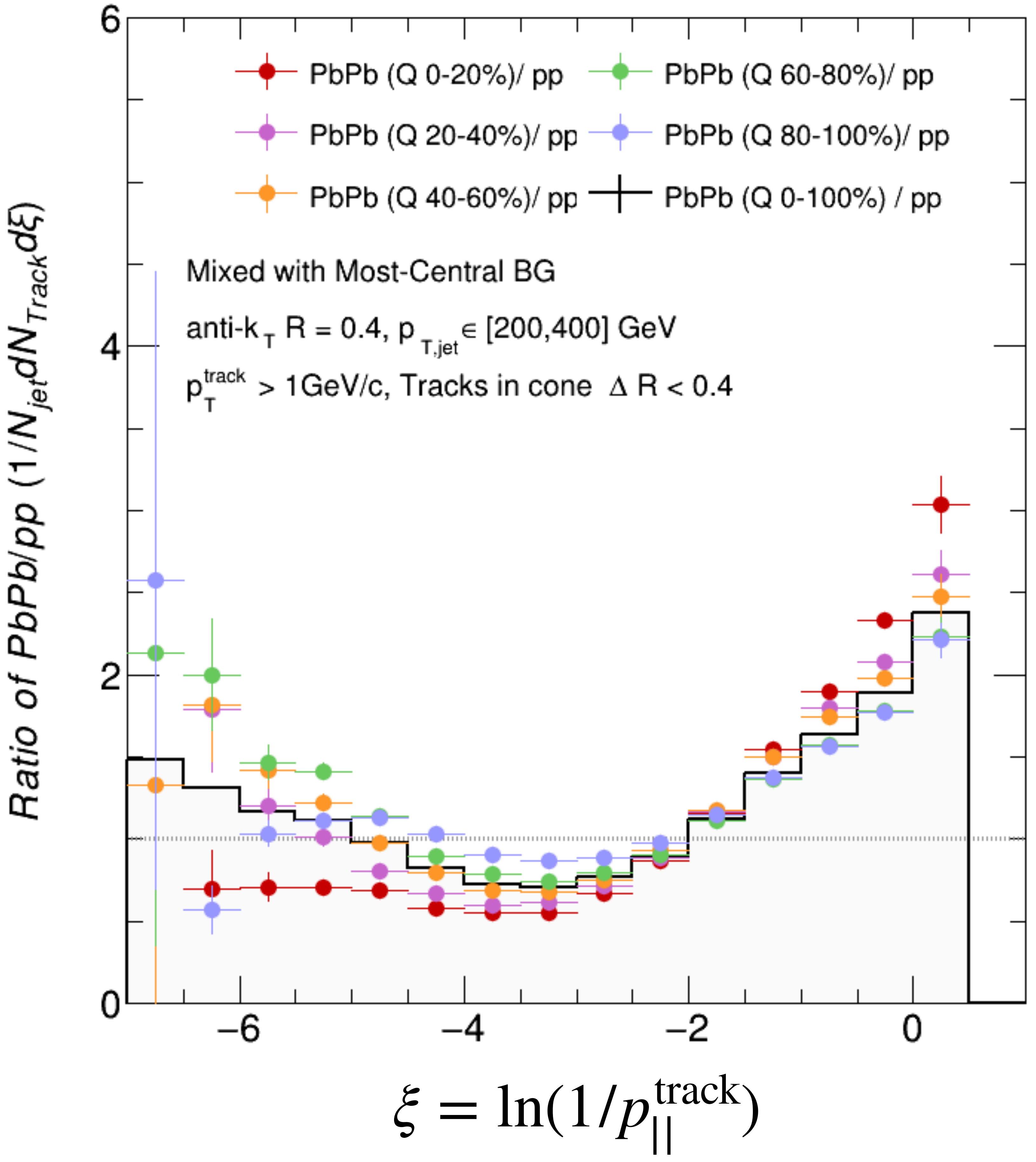


GEN Level JFF Ratio



EFlow Candidates from DELPHES*

Work in progress



Detector effects smear the differences between jets with different quenching levels, but the order of the modifications predicted by NN is preserved.

*** Combine the Tracker + Calorimeters; Approximation of CMS Particle Flow Candidates**

Summary and Outlook

NN can select jets that have strongly interacted with the matter.

✓ It has the potential to disentangle the complex jet quenching mechanisms.

✓ It is effective under the impact of thermal background and detector effects.

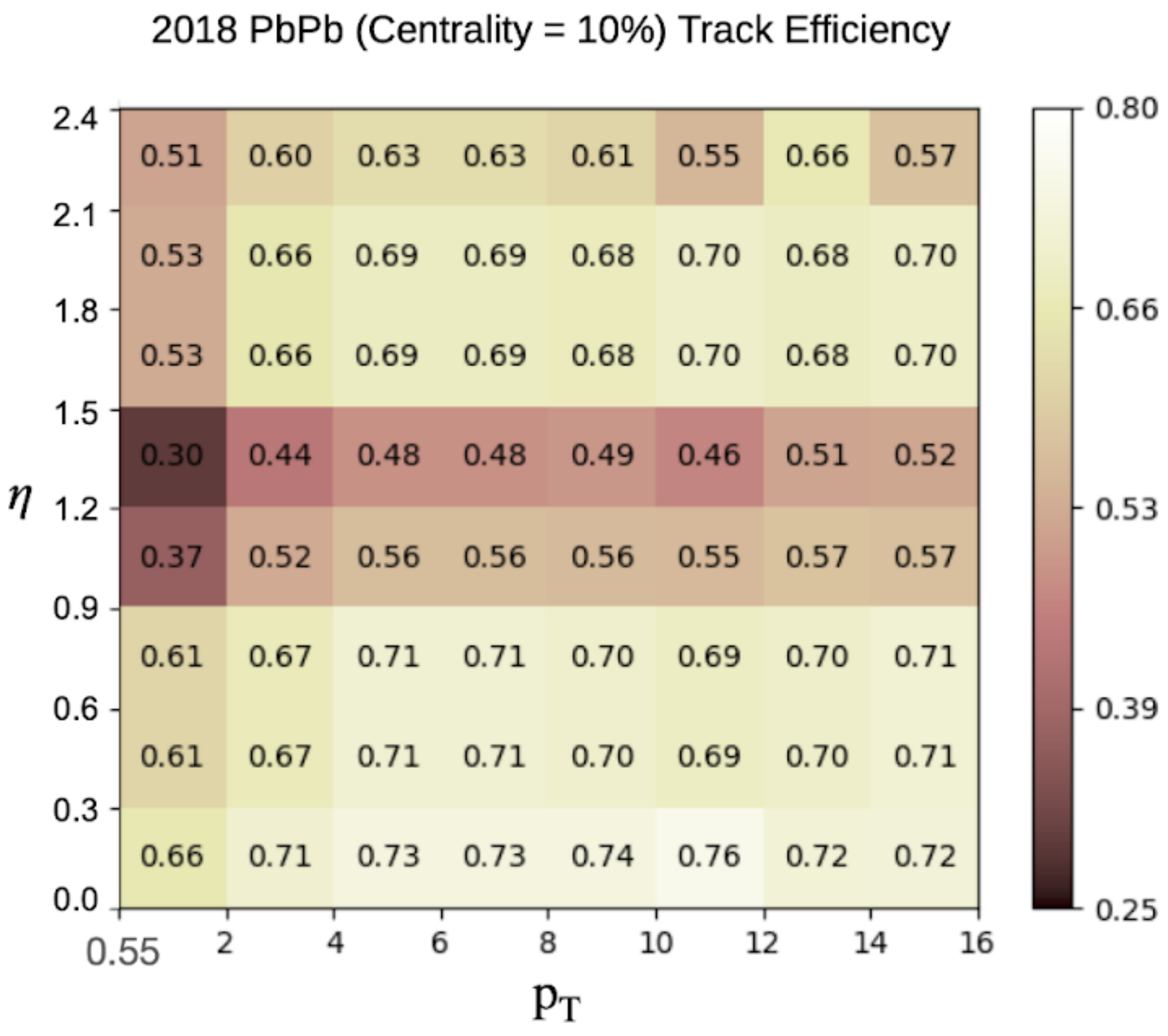
Simulation challenge: how to avoid training being model-dependent?

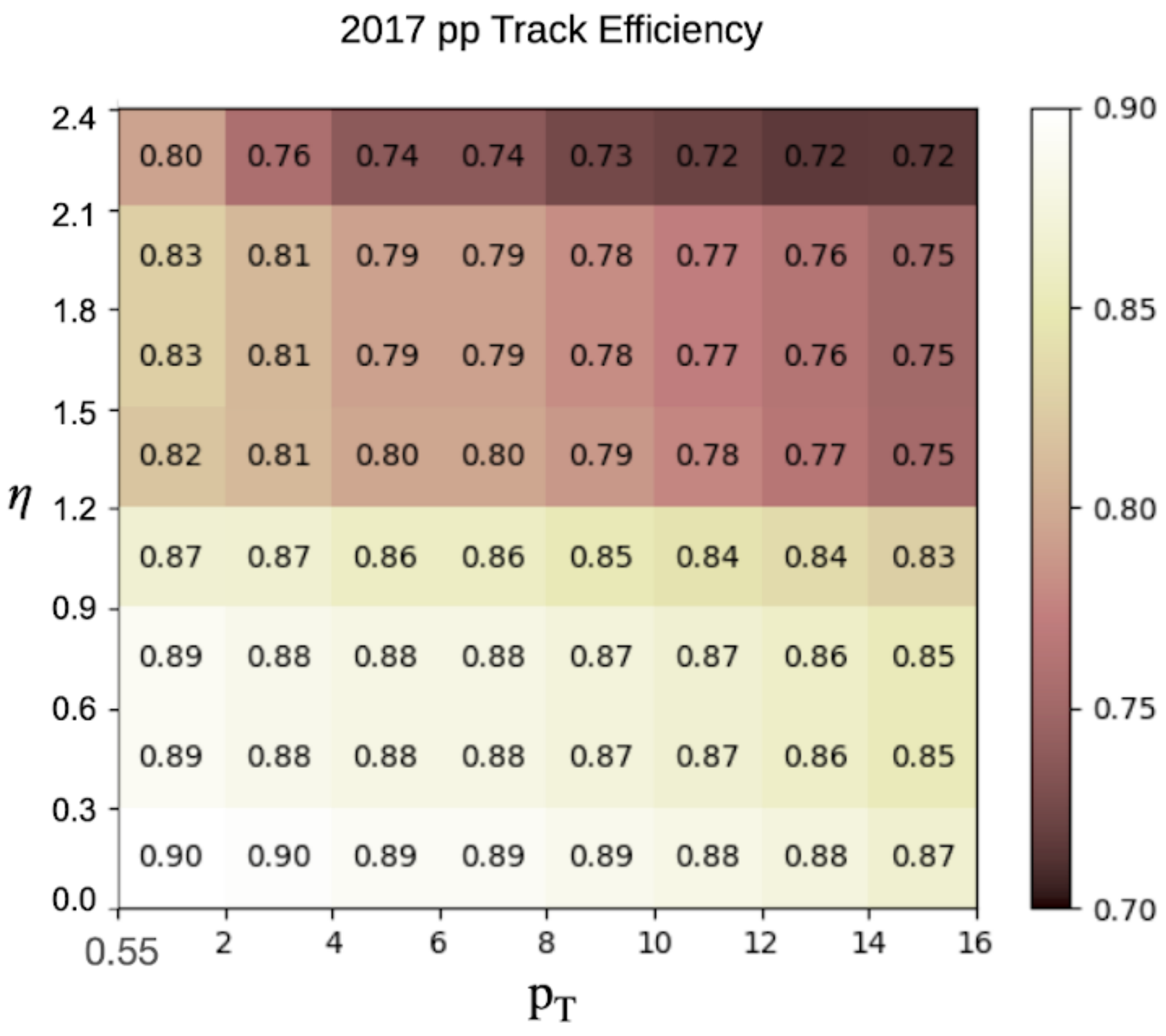
✓ Other MC event generator: JETSCAPE — *Savion Johnson Poster Session*

Apply ML to the di-jet, photon-jet CMS data analysis (ongoing): a different method to calibrate the jet energy loss using the photon energy.

Backups

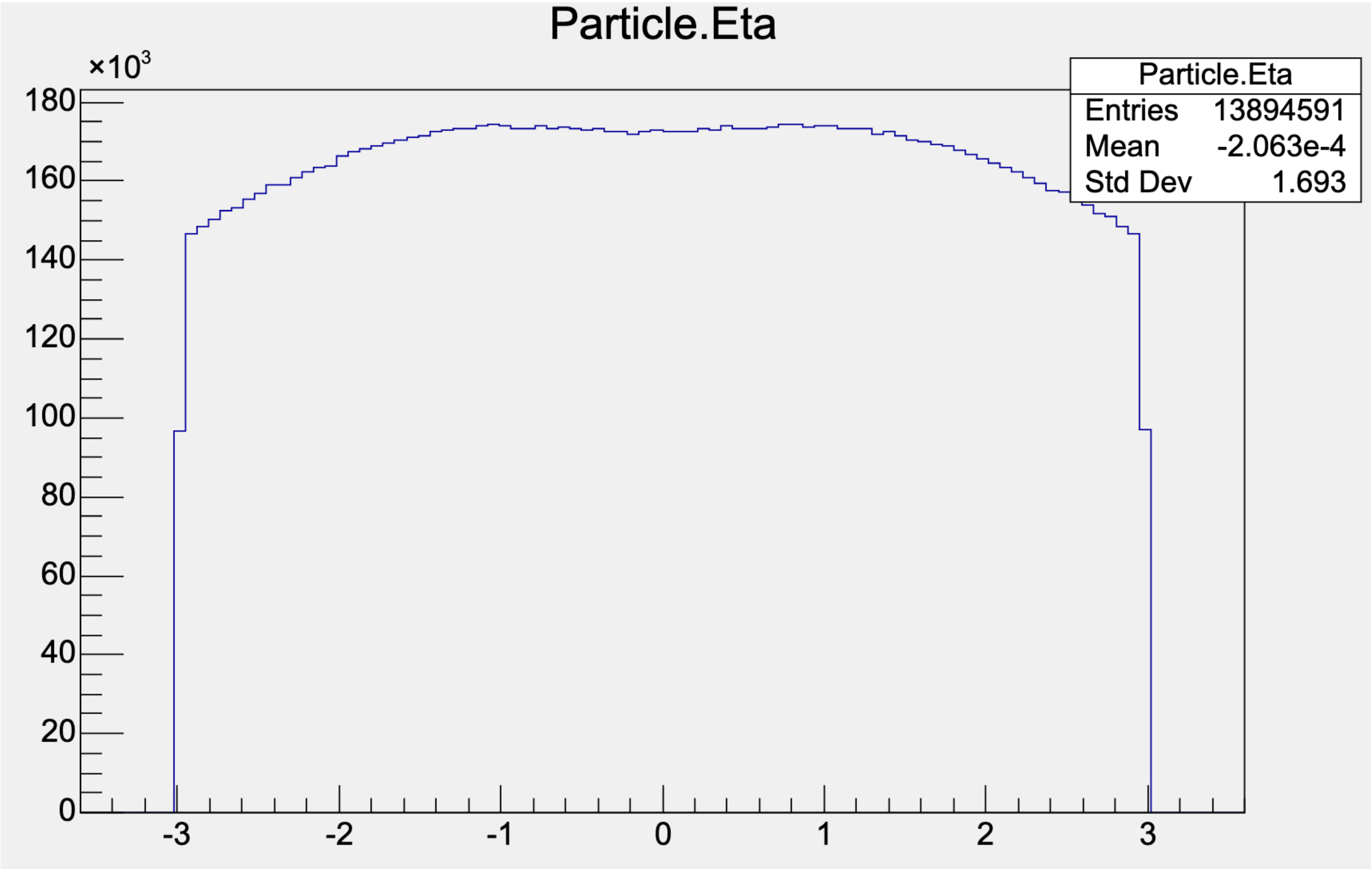
Efficiency Map for DELPHES





Thermal Bkg(Underlying Events) Simulation

https://github.com/YilunWuVanderbilt/PYTHIA-ANGANTYR-UEGenerator/



! cmnd file
! This file contains commands to be read in for a Pythia8 run.
! Angantyr is used to simulate the underlying events in heavy-ion collisions.

! 1) Settings that will be used in a main program.
Main:numberOfEvents = 20000 ! number of events to generate
Main:timesAllowErrors = 3 ! abort run after this many flawed events

! 3) Beam parameter settings. Values below agree with default ones.
Beams:idA = 1000822080
Beams:idB = 1000822080
Beams:frameType = 1
Beams:eCM = 5020. ! CM energy of collision

! 5a) Pick processes and kinematics cuts.
HardQCD:all = on
PhaseSpace:pTHatMax = 5. ! minimum pT of hard process
PhaseSpace:bias2Selection = on
PhaseSpace:bias2SelectionPow = 4
PhaseSpace:bias2SelectionRef = 100.

! 6) Other settings. Can be expanded as desired.
Random:setSeed = on
!Random:seed = 1

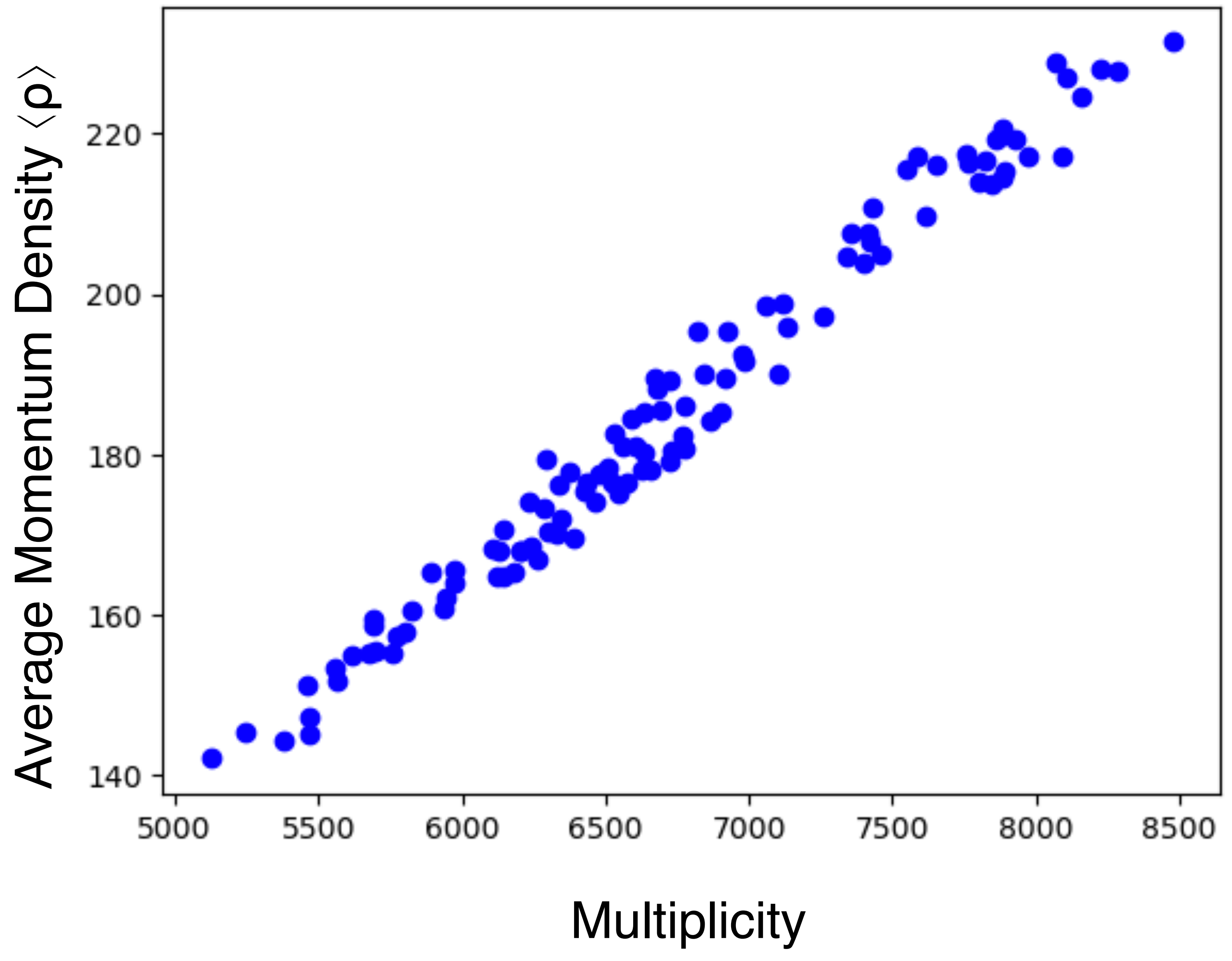
! 7) Initialize the Angantyr model to fit the total and semi-includive
! cross sections in Pythia within some tolerance.

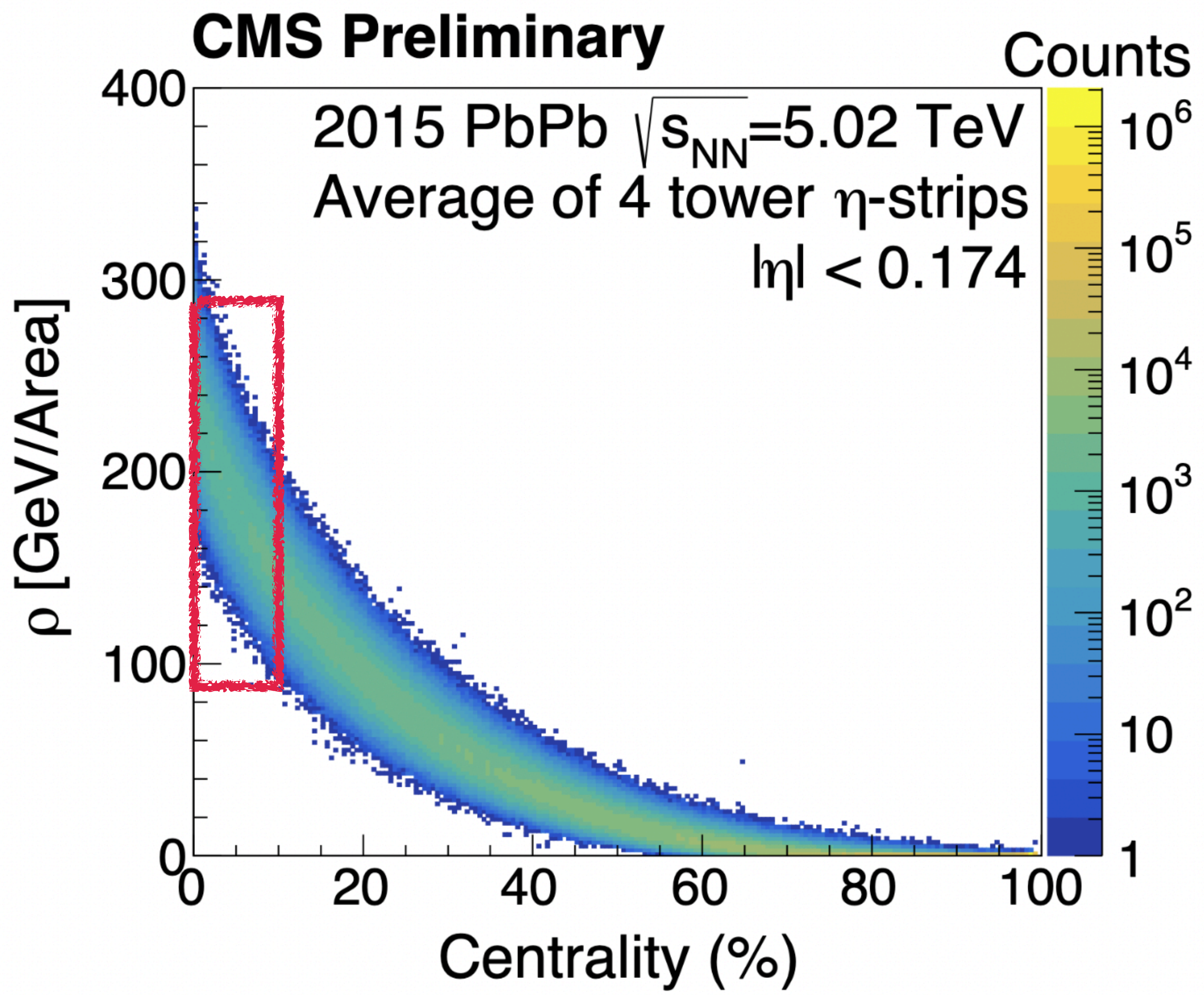
HeavyIon:SigFitErr = {0.02,0.02,0.1,0.05,0.05,0.0,0.1,0.0}
HeavyIon:SigFitDefPar = {17.24,2.15,0.33,0.0,0.0,0.0,0.0,0.0}
HeavyIon:SigFitNGen = 20

Thermal Bkg(Underlying Events) Simulation

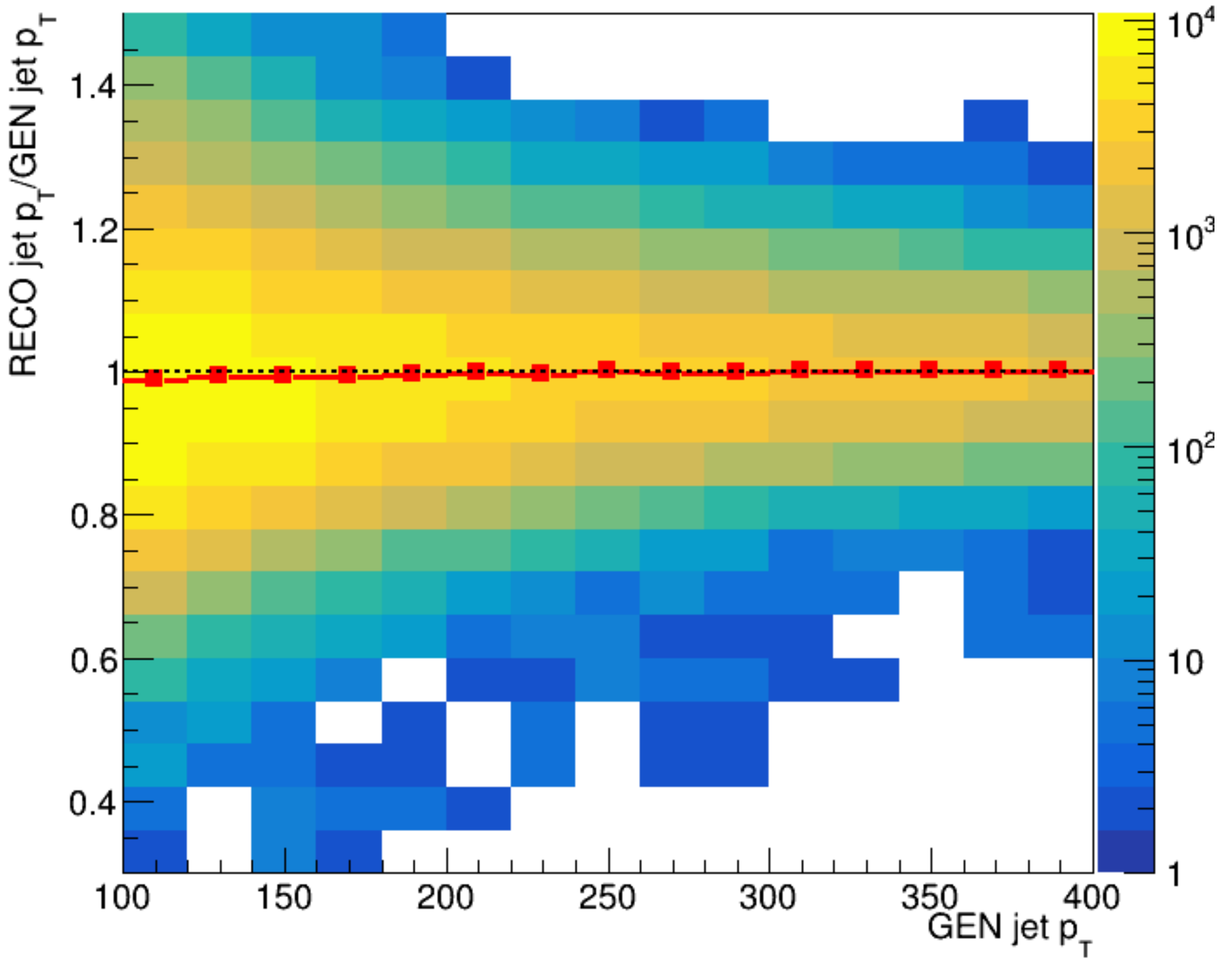
PYTHIA+ANGANTYR

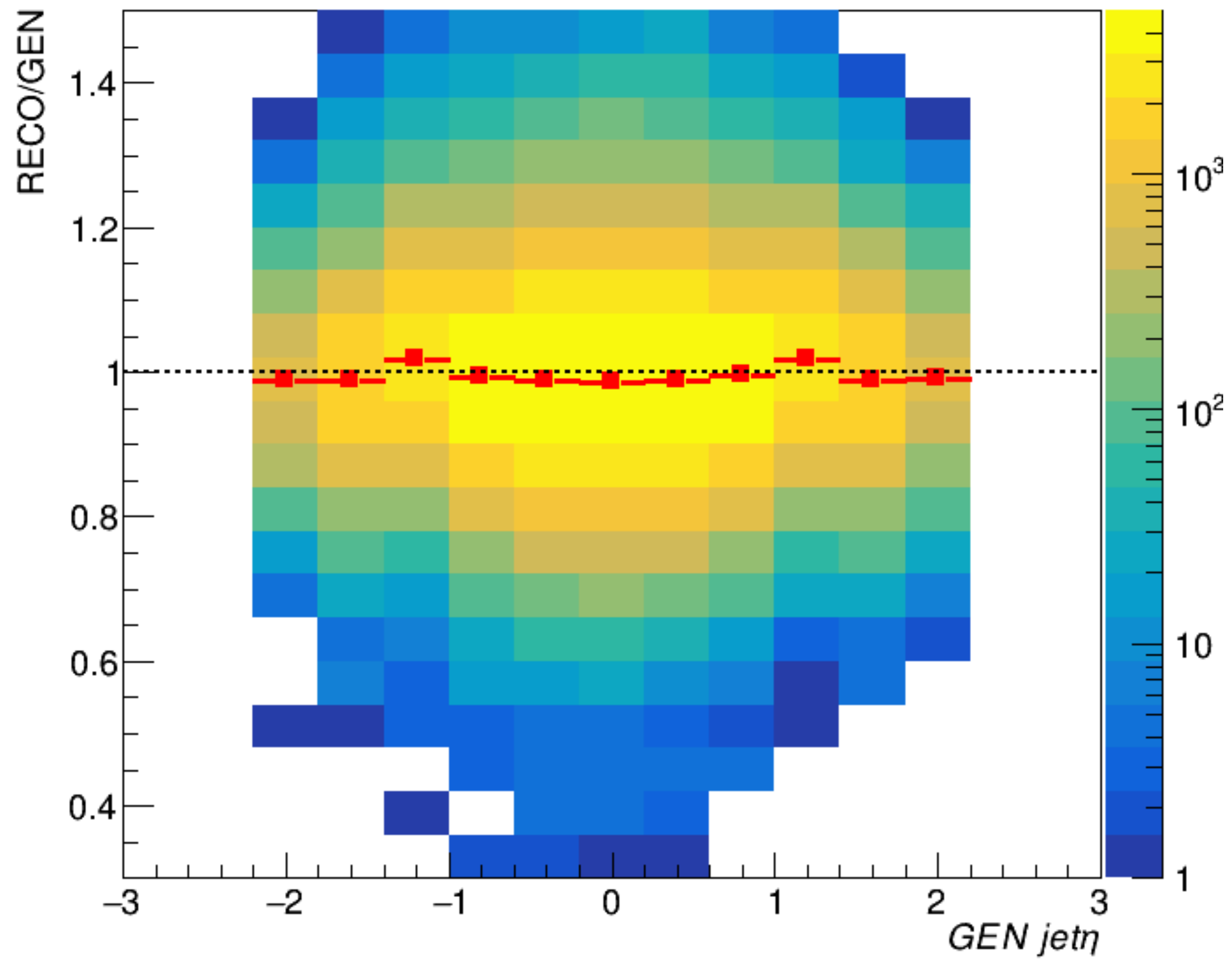
Centrality~0-10%

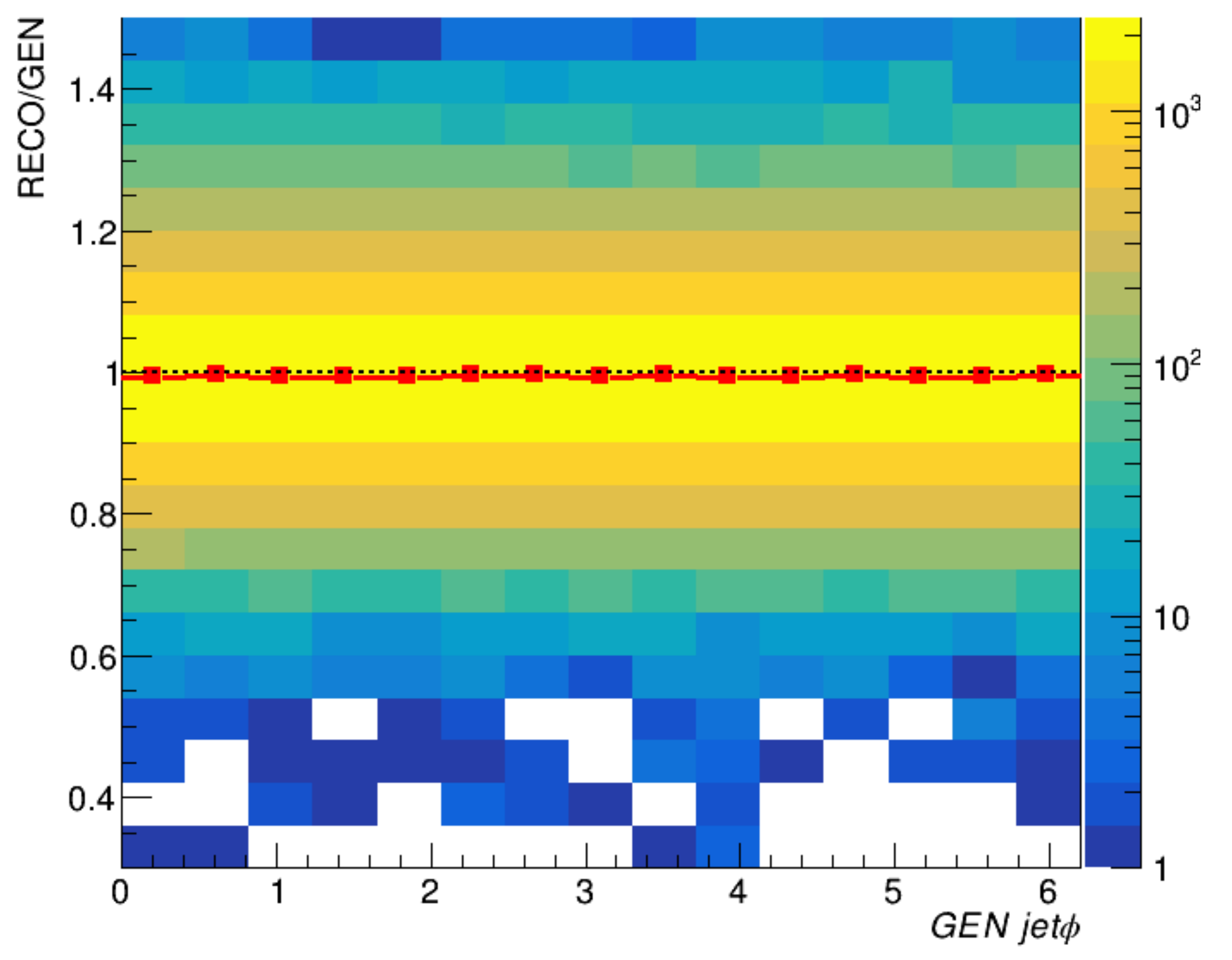


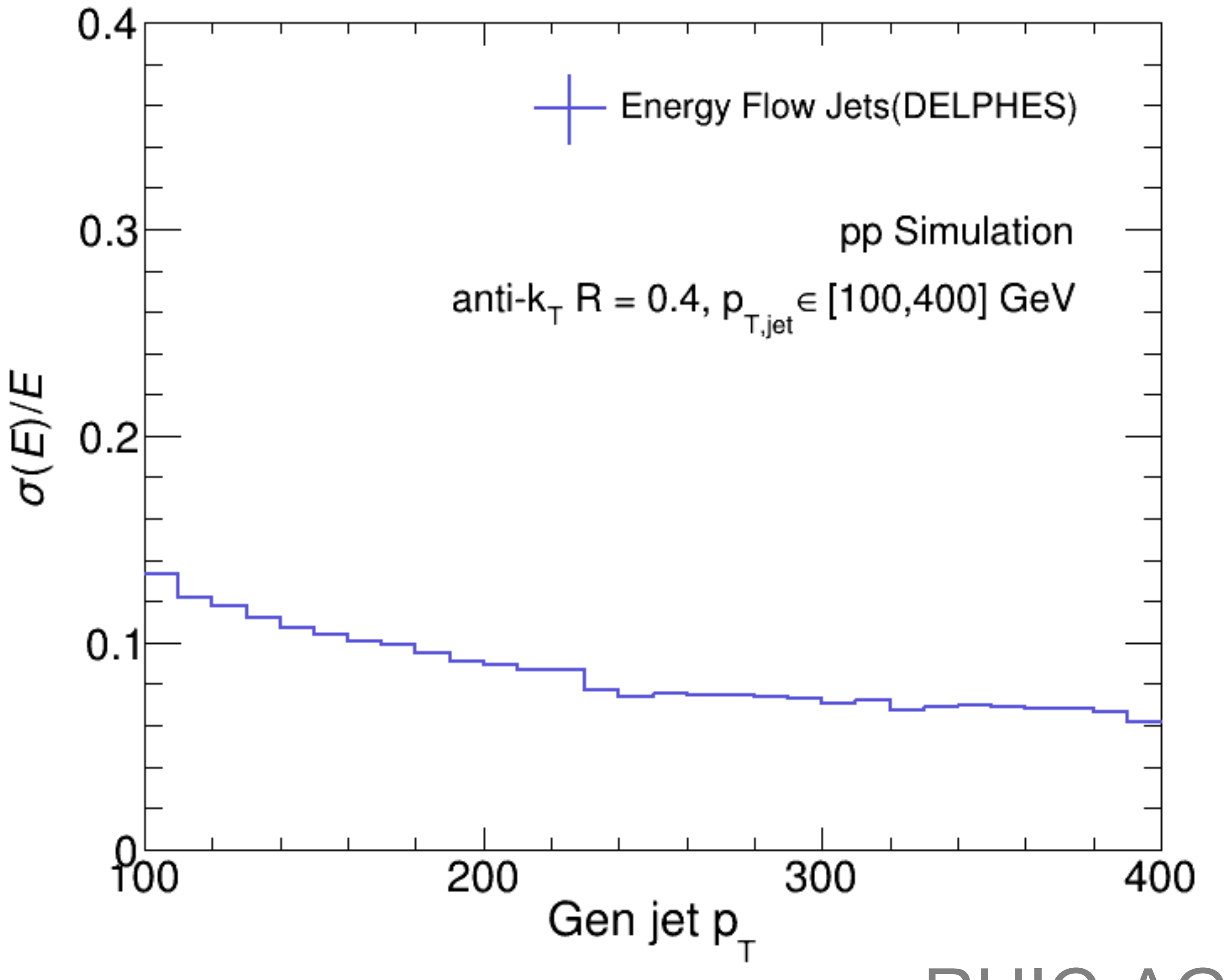


Jet Energy Scale-pp

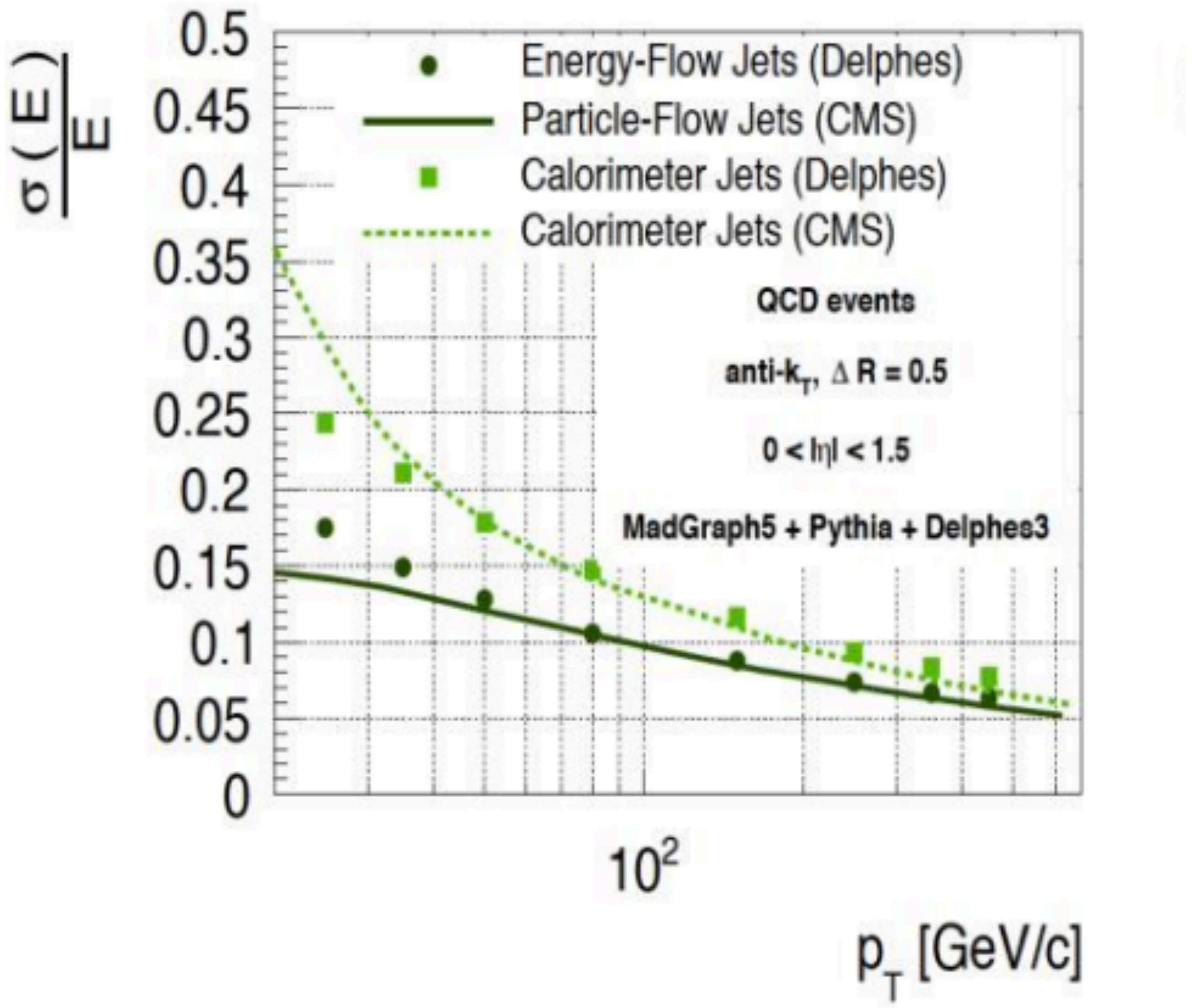




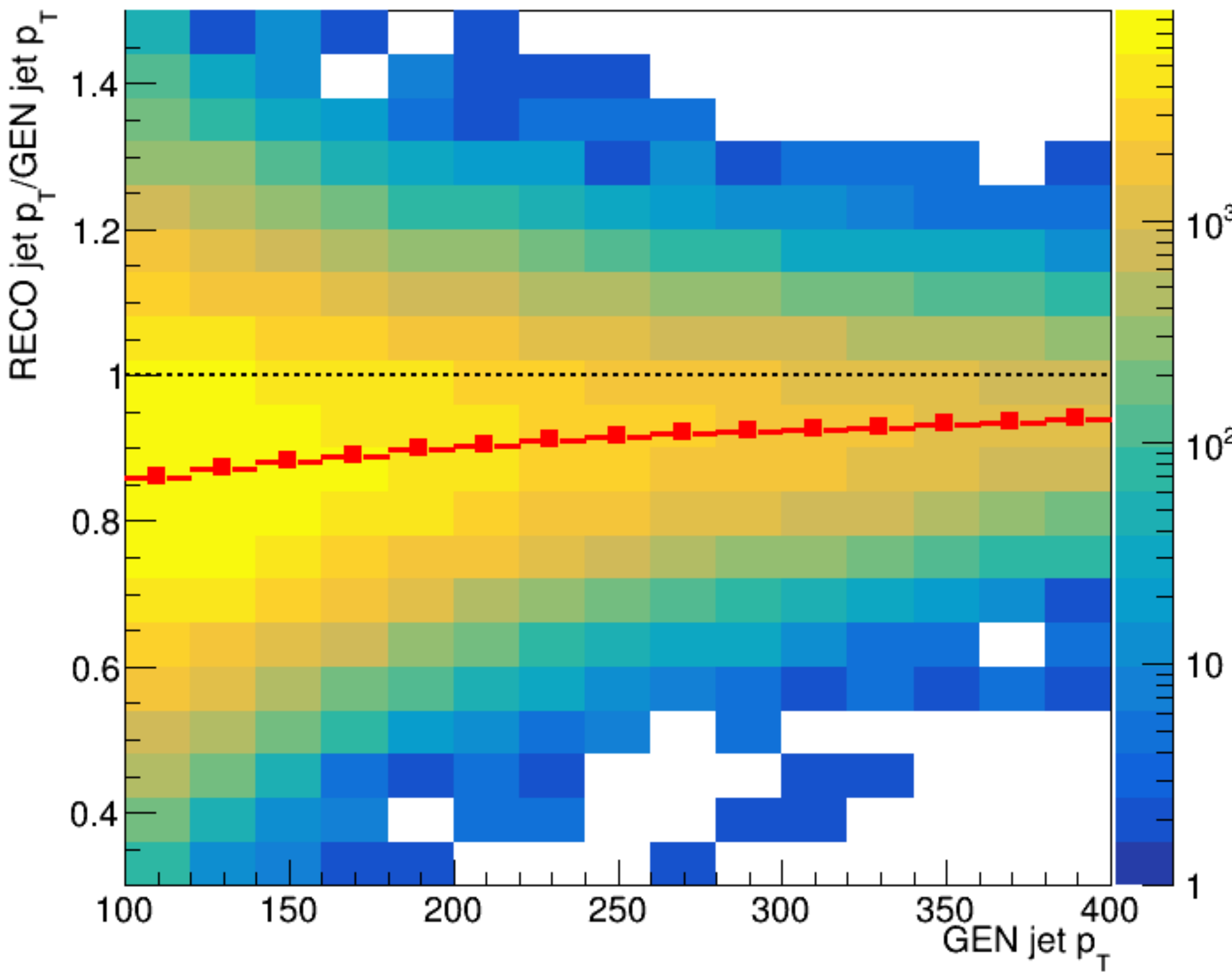


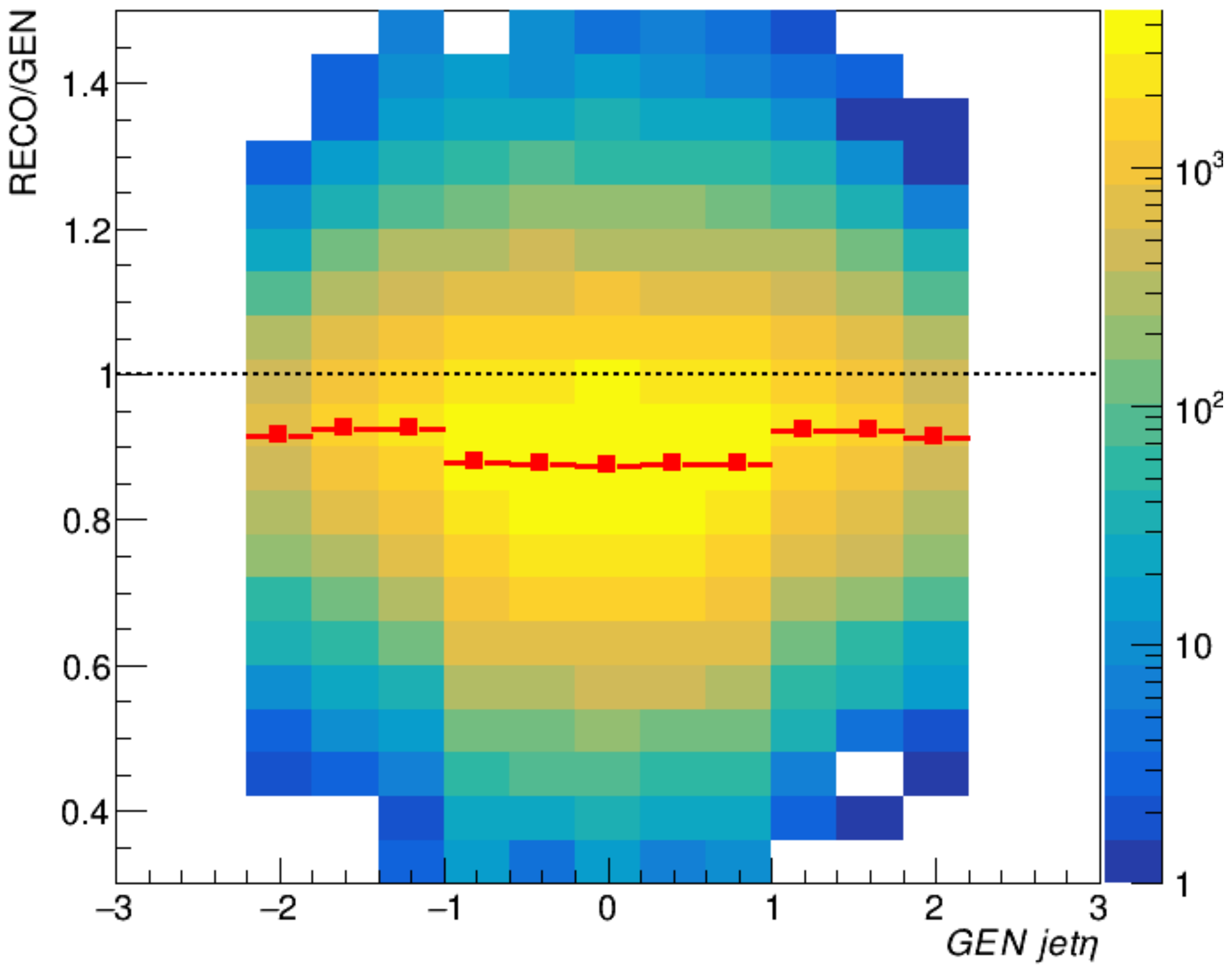


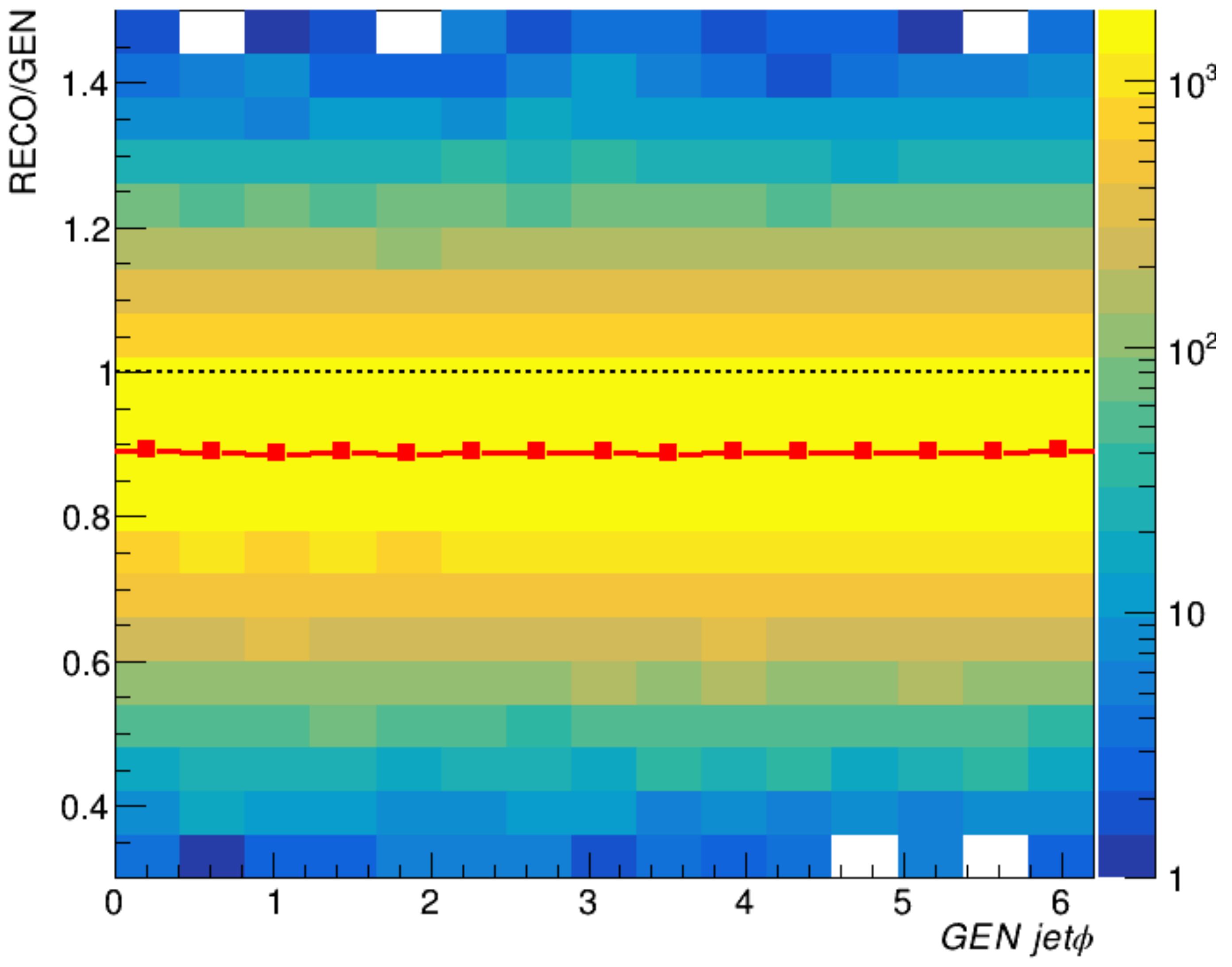
Jet energy resolution

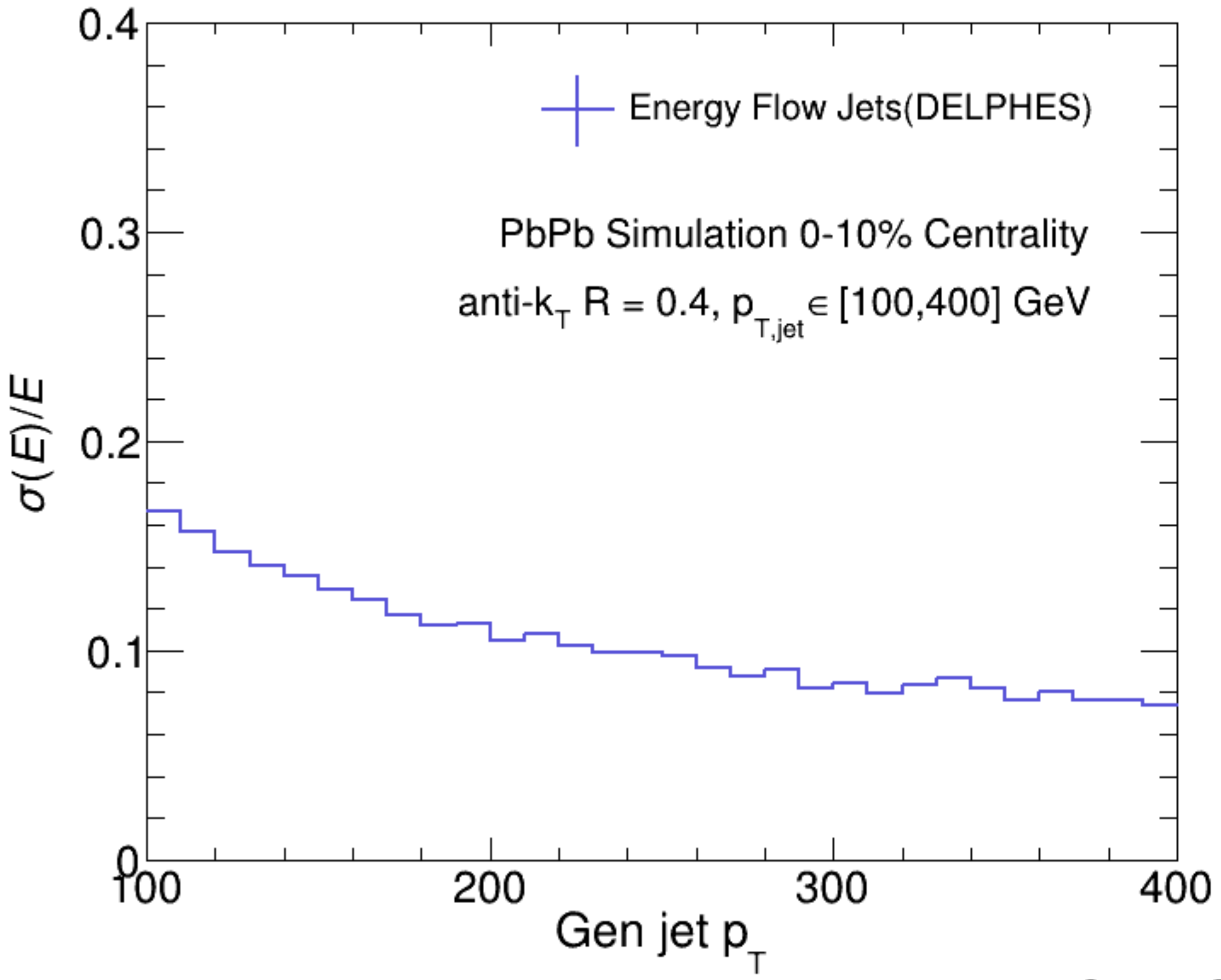


Jet Energy Scale-PbPb







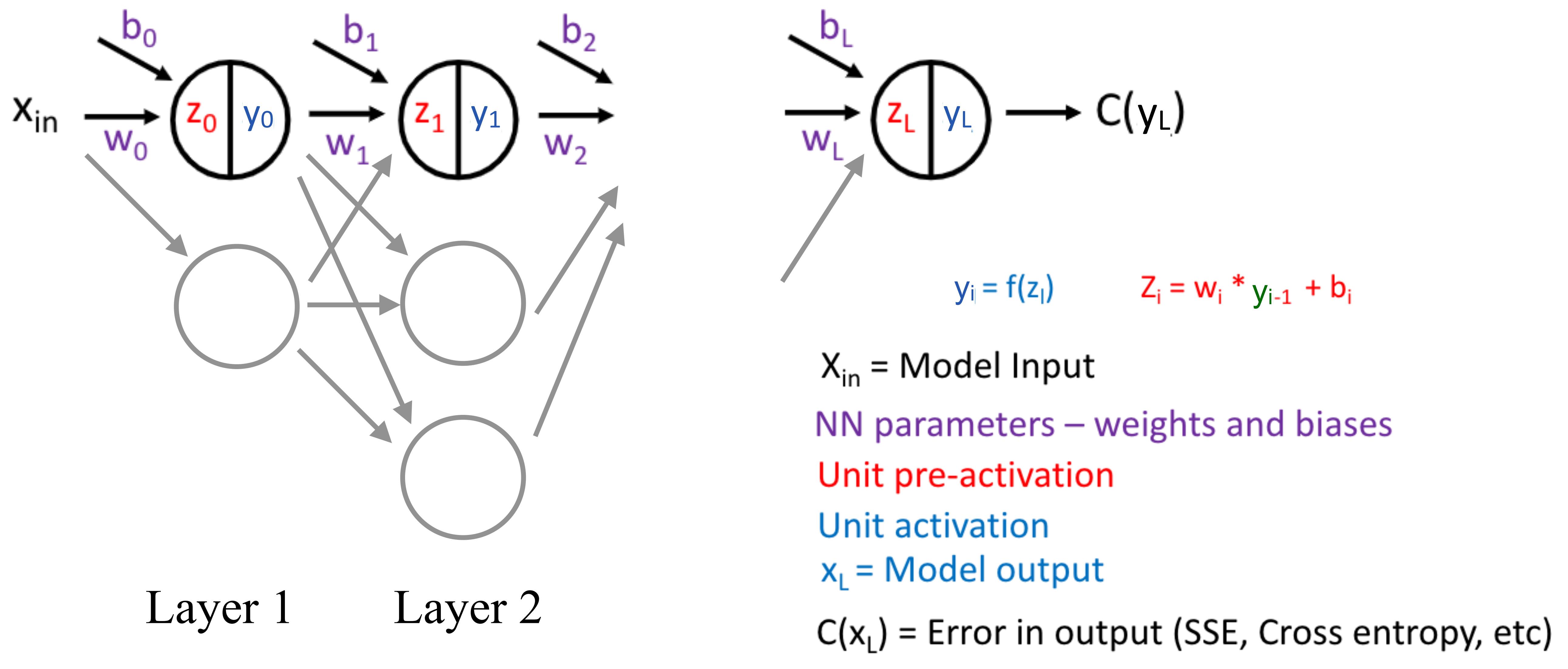


p_T Correction: $p_{T,jet} \times \sqrt{\frac{(A - B \cdot |\eta|)^2}{p_{T,jet}} + 1.0}$ (A = 7.0, B =1.2)

Neural Network and Feature Engineering

```
space = hp.choice('hyper_parameters',[
    {
        'size_batch': hp.quniform('size_batch', 2000, 10000, 1000),
        'num_epochs': hp.quniform('num_epochs', 30, 50, 5),
        'num_layers': hp.quniform('num_layers', 2, 4, 1),
        'Hidden_size 0': hp.quniform('hidden_size0', 8, 20, 2),
        'hidden_size1': hp.quniform('hidden_size1', 4, 8, 2),
        'learning_rate': hp.uniform('learning_rate', 0.01, 0.05),
        'decay_factor': hp.uniform('decay_factor', 0.9, 0.99),
        'loss_func' : hp.choice('loss_func', ['mse']),
    }
])
```

Hyper parameter space

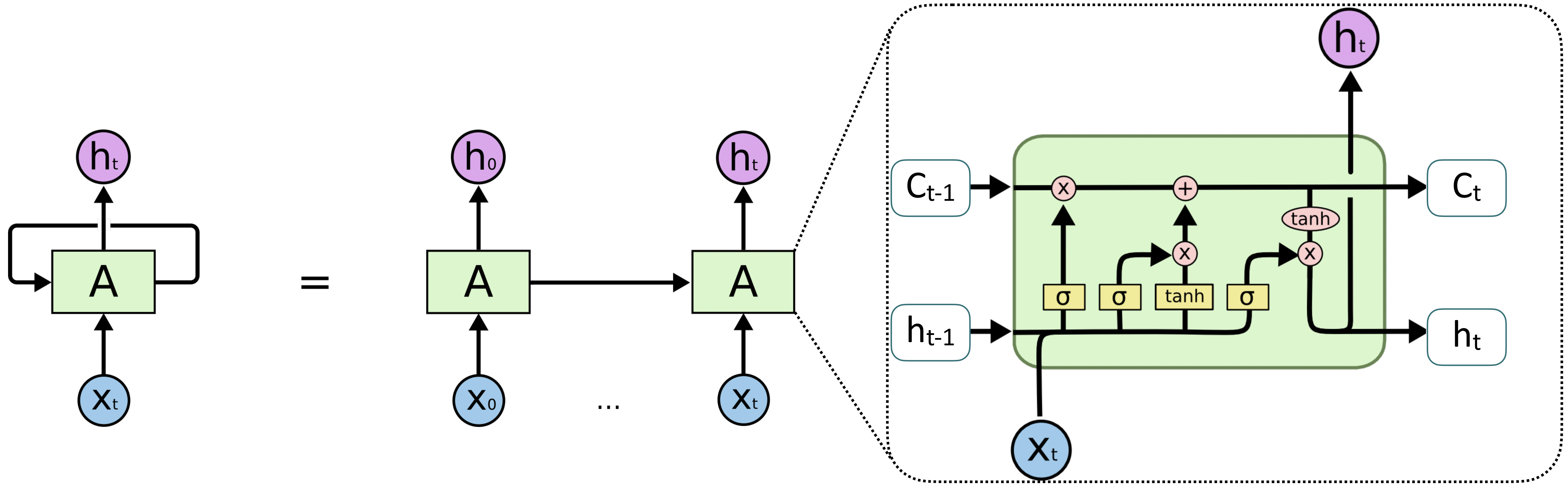


Fully Connected layers

Stacked LSTM layers + 2 full-connect layers. Output of the last step from the top LSTM layer is directed to two full-connect layers.

Both the input and output dimensions of the first full-connect layer are the hyper-parameters defining the architecture of the neural network.

**Paper: JHEP04(2023)140*



Training+Validation

Select jets from dataset to form batches:
Non-quenched jets from Jewel-vacuum
Quenched jets (Medium jets) from Jewel

Mean square error (MSE) batch loss

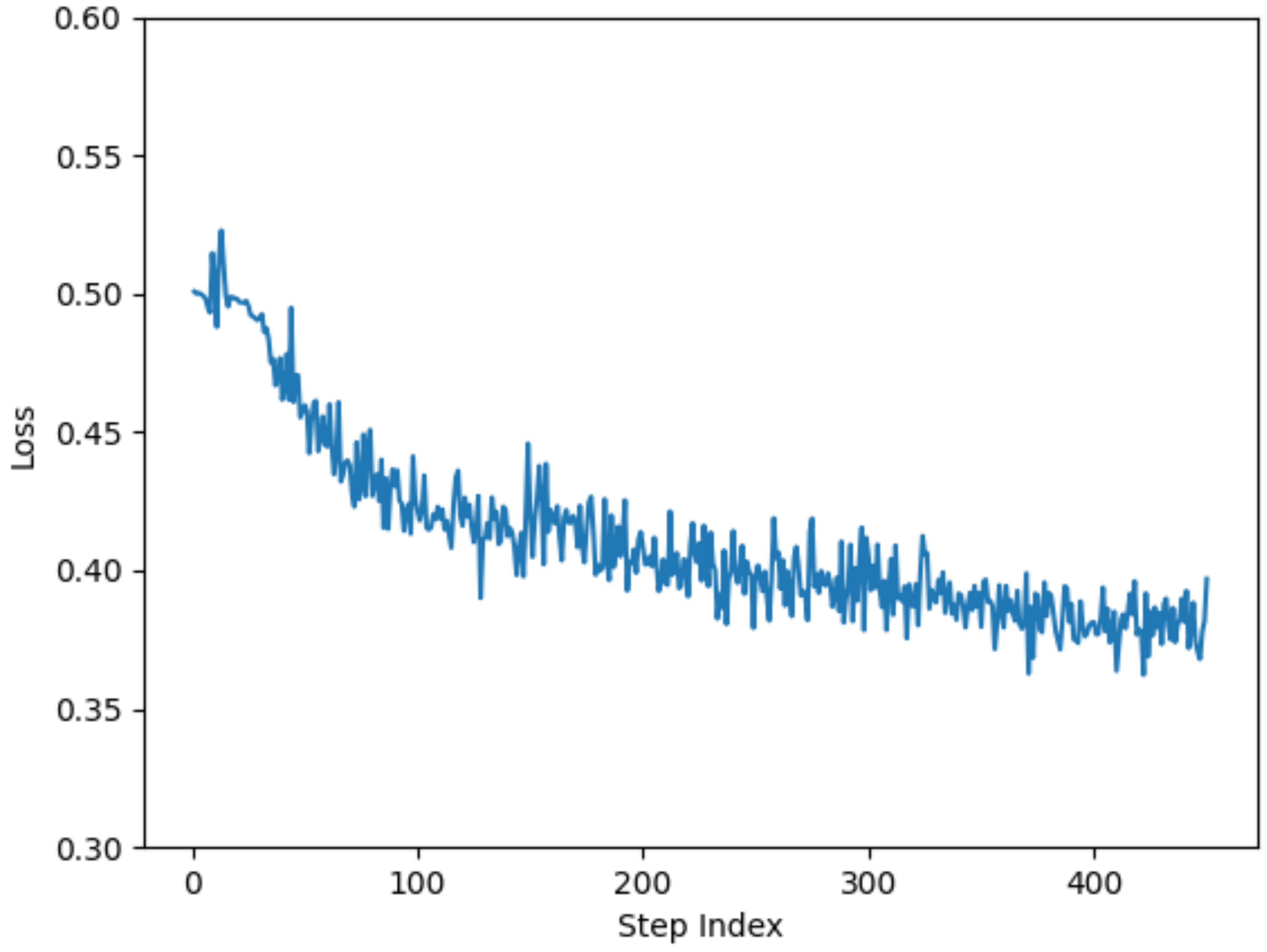
$$L = \frac{\sum_{batch} \omega_i * \left(x_i - y_i\right)^2}{\sum_{batch} \omega_i}$$

ω_i: event weight
x_i: predictive label
y_i: truth label

($\omega_i = 1$ for real experimental samples)

Input dataset:

No. of Jets	Training Set (w/wo cuts)	Validation Set (w/wo cuts)
	200k events	200k events
Non-quenched jets	**42535**/310332	**42272**/310276
Medium jets	**52954**/298675	**52967**/298876



Example of batch loss decreasing in the training