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

Machine Learning Application in Jet Quenching Analysis

Yilun Wu

Vanderbilt University

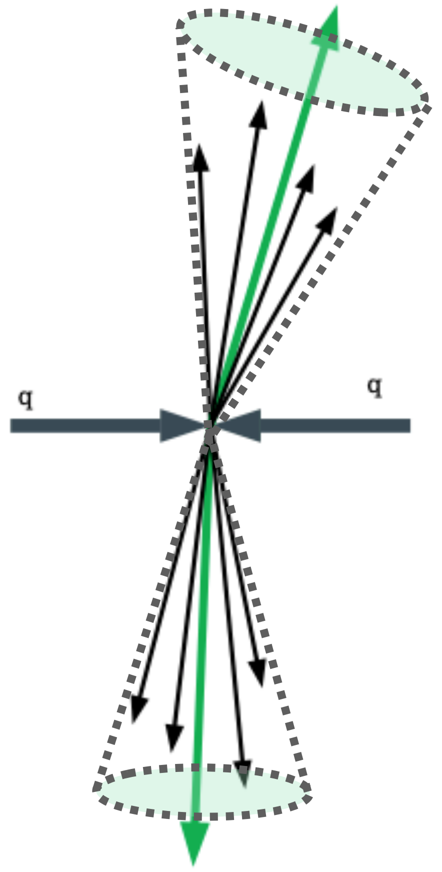
My Take Aways from the Workshop..

Jet-QGP interaction

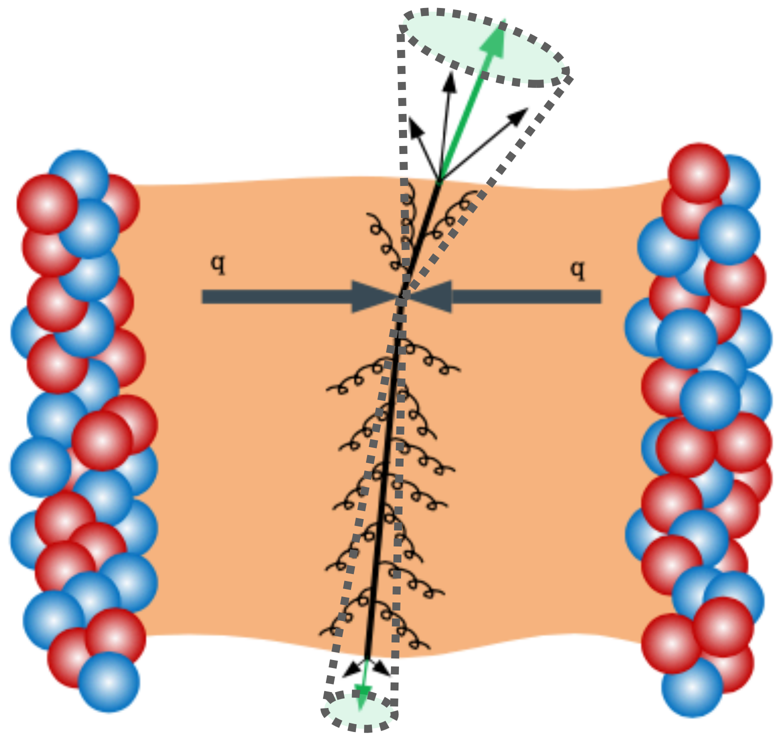
Elastic scattering,
Medium induced Radiation,
Medium Response...

What we measured

Jet loses energy as a whole
Internal structures of jets are modified
(Jet observable A, B, C, D...)



p+p
Vacuum jet



A+A
Quenched jet

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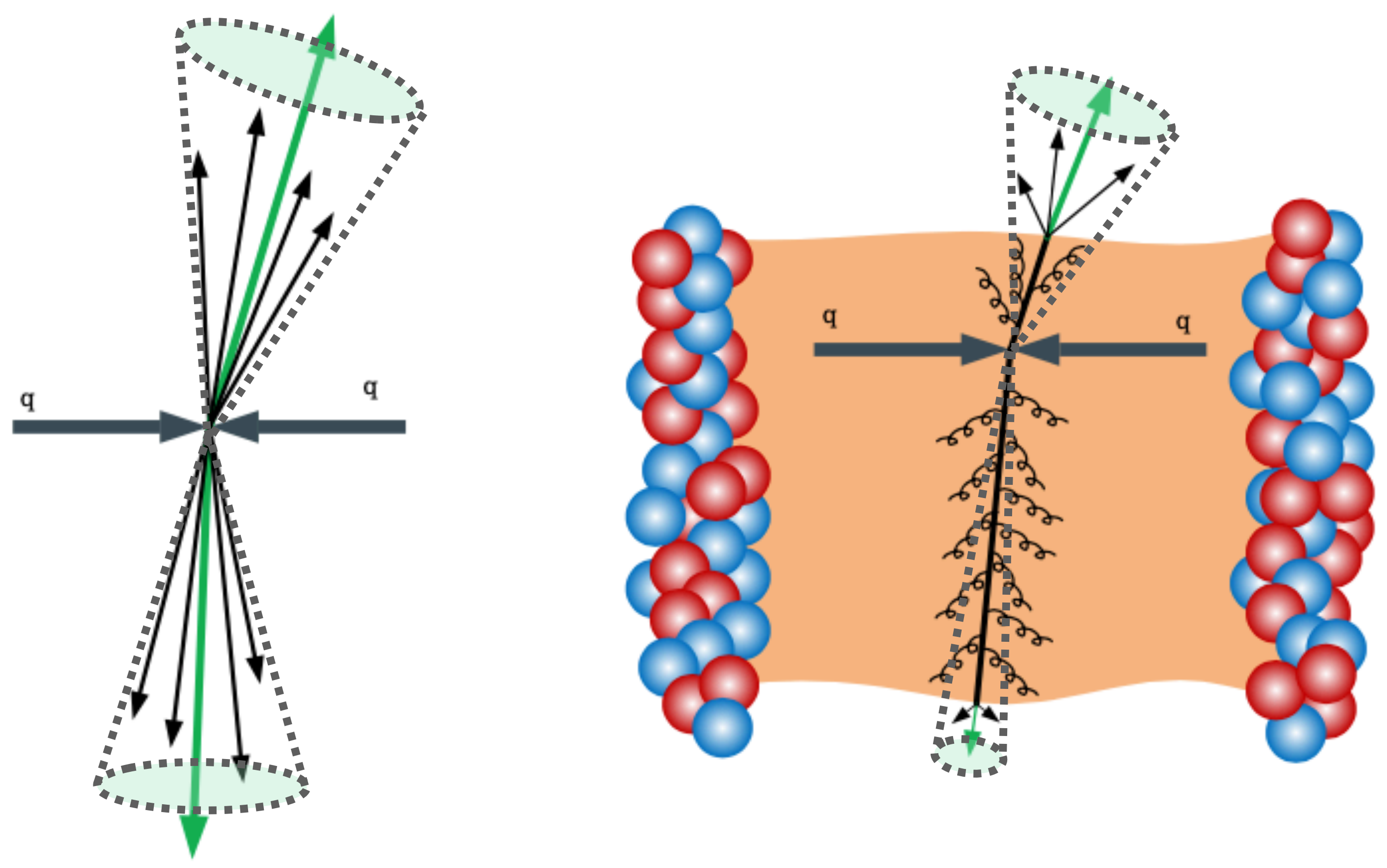

p+p
Vacuum jet

A+A
Quenched jet

For what we measured..

- ❖ Can they fully describe the jet quenching effect?
- ❖ Can we disentangle each jet-QGP interaction from the measurements?
- ❖ When we see modifications, are they from jet quenching, or non-quenching bias, or both?
- ❖ In addition, the surface effect… Many jets experience little quenching, thus diminishing the significance of the results.

For neural network trained from specific conditions..

- ❖ Can it be applied to a broader range? -physics interpretability

My Take Aways from the Workshop..

Jet-QGP interaction

Elastic scattering,
Medium induced Radiation,
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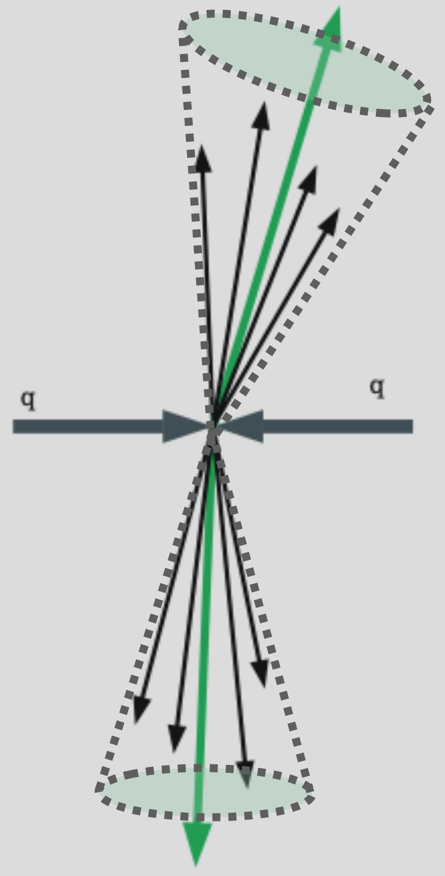
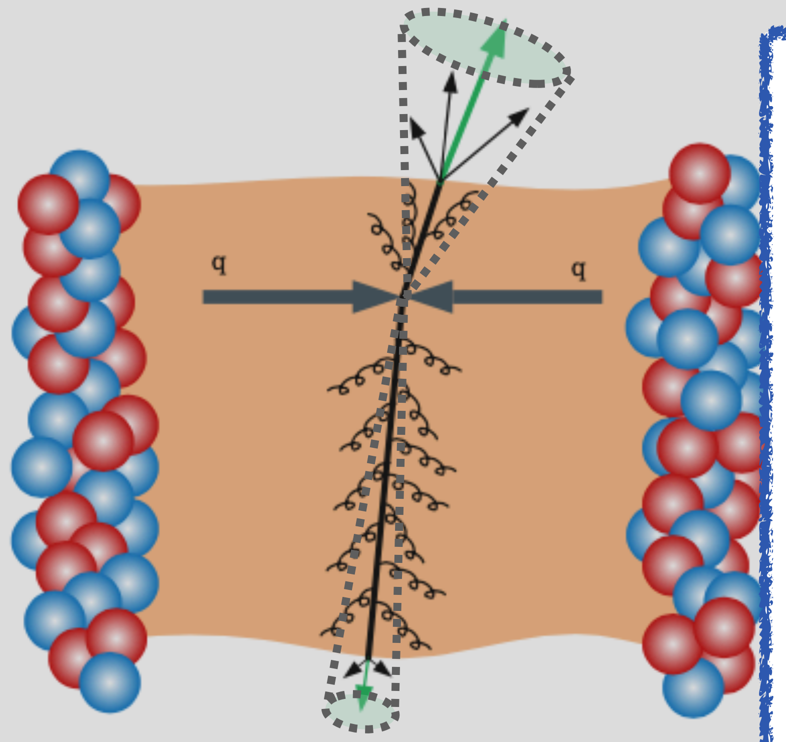


p+p
Vacuum jet



A+A
Quenched jet

For what we measured..

- ❖ ...et quenching effect?
- ...-QGP interaction from the ...
- ..., are they from jet quenching, or non-...
- ...ct... Many jets experience little quenching, thus diminishing the significance of the results.

My presentation today:

A trained neural network can identify jet quenching level on a **jet-by-jet basis**

For neural network trained from specific conditions..

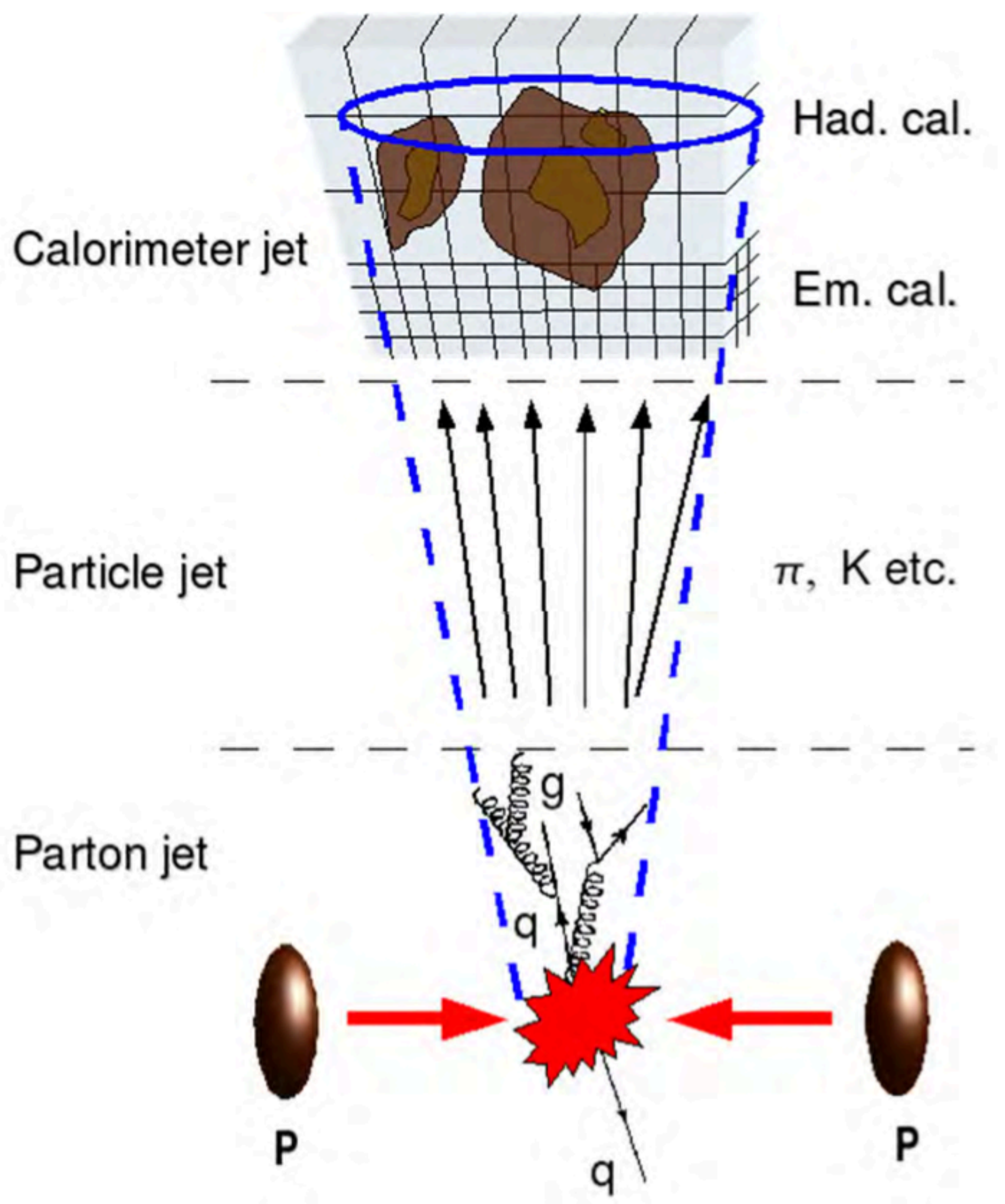
- ❖ Can it be applied to a broader range? -physics interpretability

Jet Quenching Study as a Binary Classification Problem in ML

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

Part of the previous works
- L. Apolinário, N.F. Castro, M. C. Romão, et al., JHEP11(2021)219
- YLD, D. Pablos and K. Tywoniuk, JHEP03(2021)206
- Y. S. Lai, J. Mulligan, M. Płoskoń, et al., JHEP10(2022)011
- U.S. Qureshi, R. Kunnawalkam Elayavalli, arXiv:2411.19389
- …

Different representations of jets



Input: Choose jet observables that signify the quenching effects

Global jet observable
Internal jet structures
Jet shape
Jet fragmentation function
Lund planes
Jet substructures
Jet constituents
…

Neural Network of Choice:

CNN, RNN, DNN, Transformer…

Binary Classification & Supervised Learning

Quenched jets: 1
Unquenched jets:0

Output:

Quenching level prediction

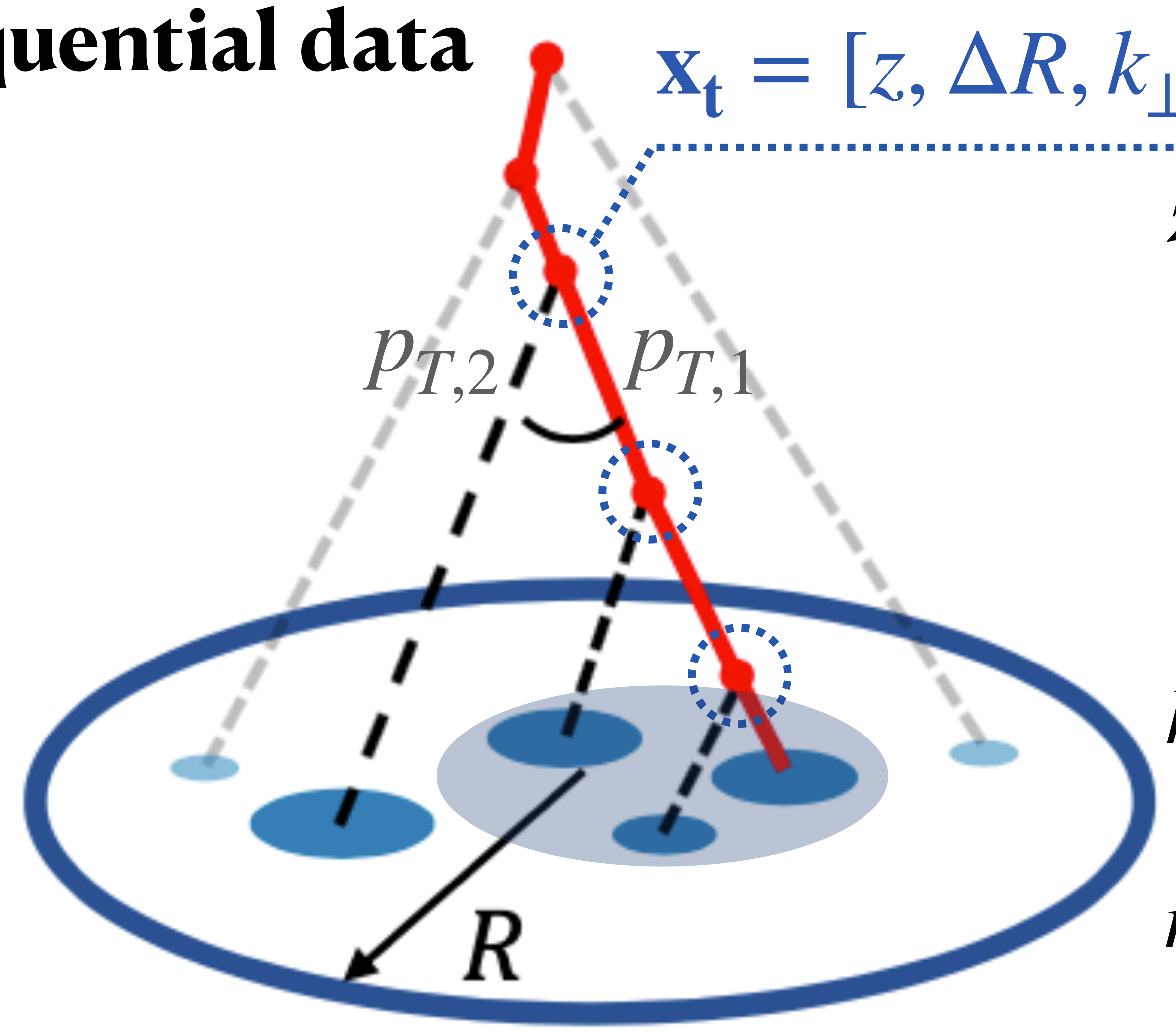
From 0 to 1

Jet Quenching Study as a Binary Classification Problem in ML

Our input to ML: Jet substructures

- We reconstruct jets in to a binary tree by soft drop
- Define jet substructures on each splitting point
- Following the hardest branch, they form sequential data, as input of NN

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

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

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

Neural Network of Choice:

Long Short-Term Memory Neural Network (LSTM)

Binary Classification & Supervised Learning

Quenched jets: 1
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From 0 to 1

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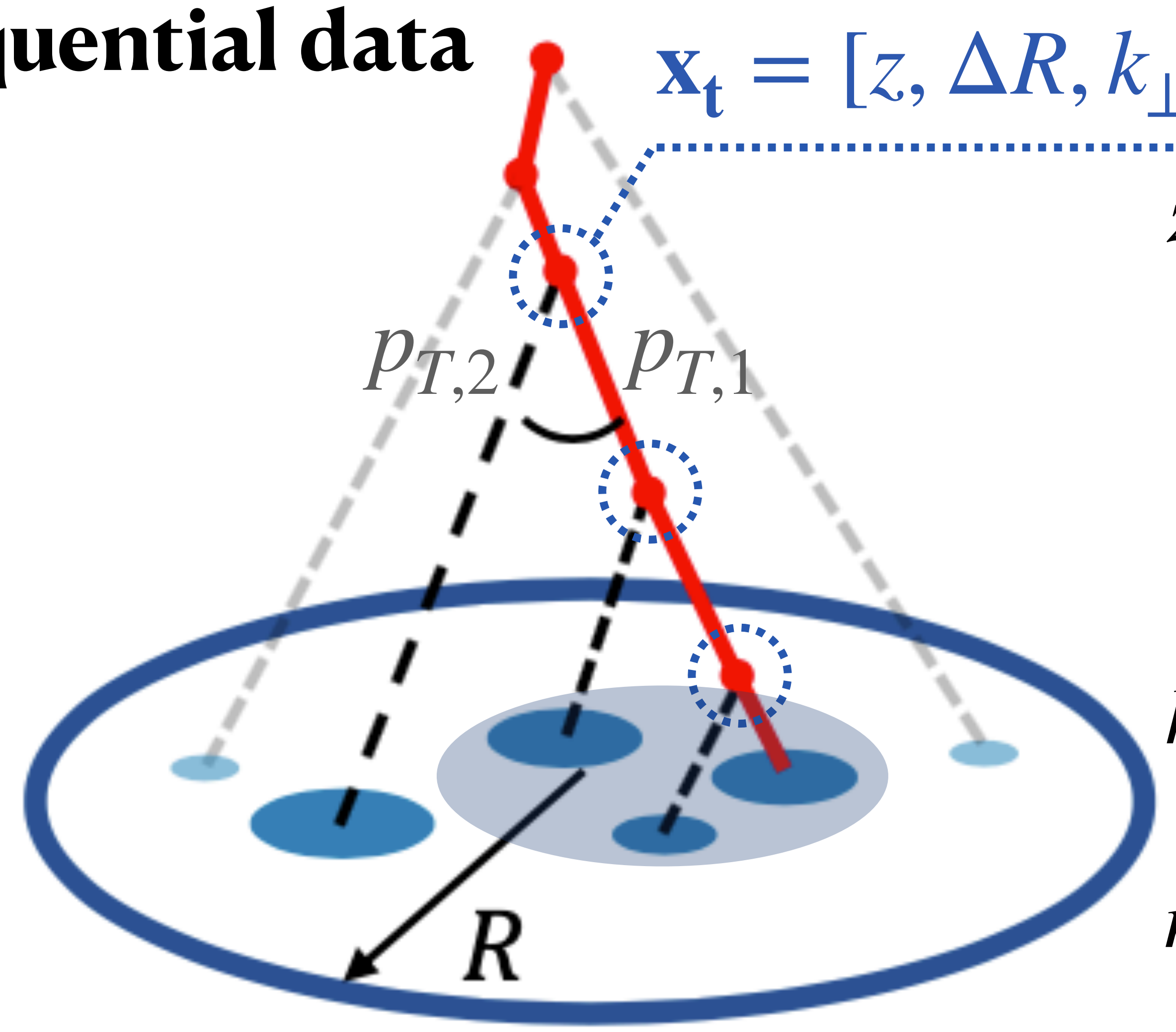
Sequential data



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Jet substructures

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

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

- ❖ The binary tree structure matches to the evolving process of a jet from the initial parton fragmentation to final hadronization
- ❖ Records the history of how jet interact with the medium

Neural Network of Choice:

Long Short-Term Memory Neural Network (LSTM)

Binary Classification & Supervised Learning

Quenched jets: 1
Unquenched jets:0

Output:

Quenching level prediction

From 0 to 1

Thermal Bkg Effects are Considered in the Study

In data, we need to subtract uncorrelated background 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)

Embedding the simulated event with a uncorrelated background:

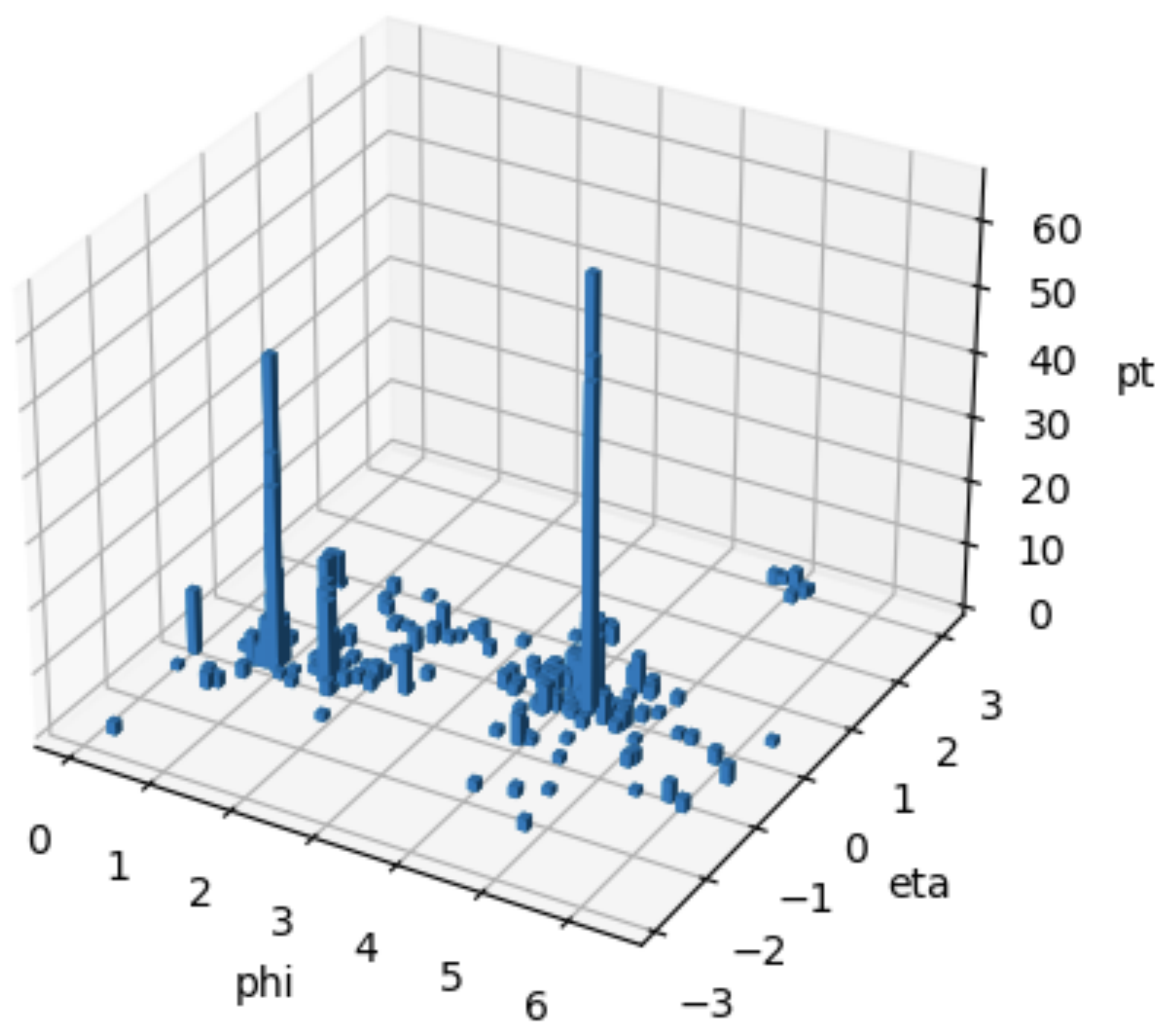
*Uncorr Bkg is simulated by the PYTHIA+ANGANTYR model

Background subtraction algorithm:

Event-wide Constituent Subtraction

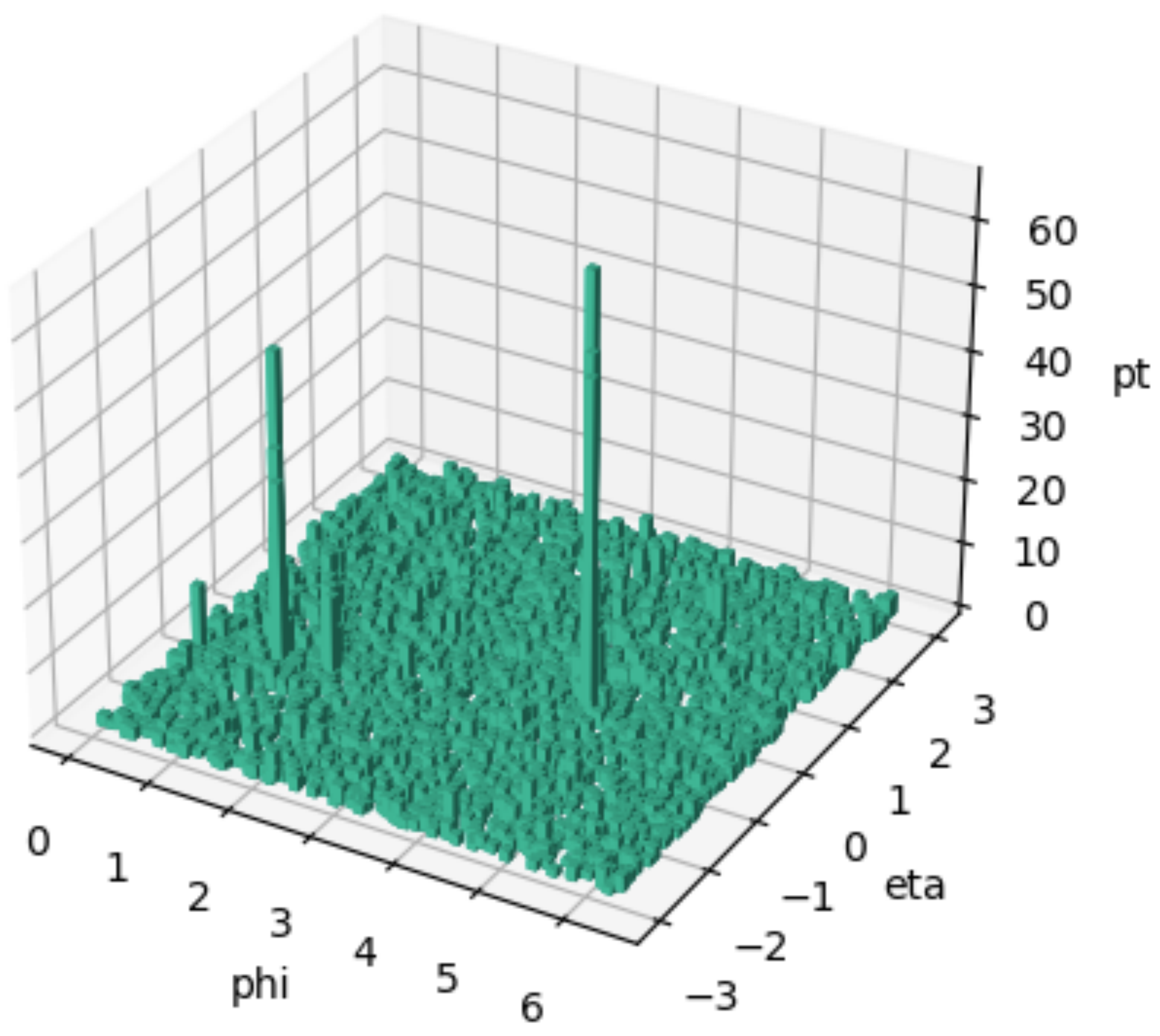
We use the jets reconstructed from the bkg-subtracted events for training.

0-10% Centrality

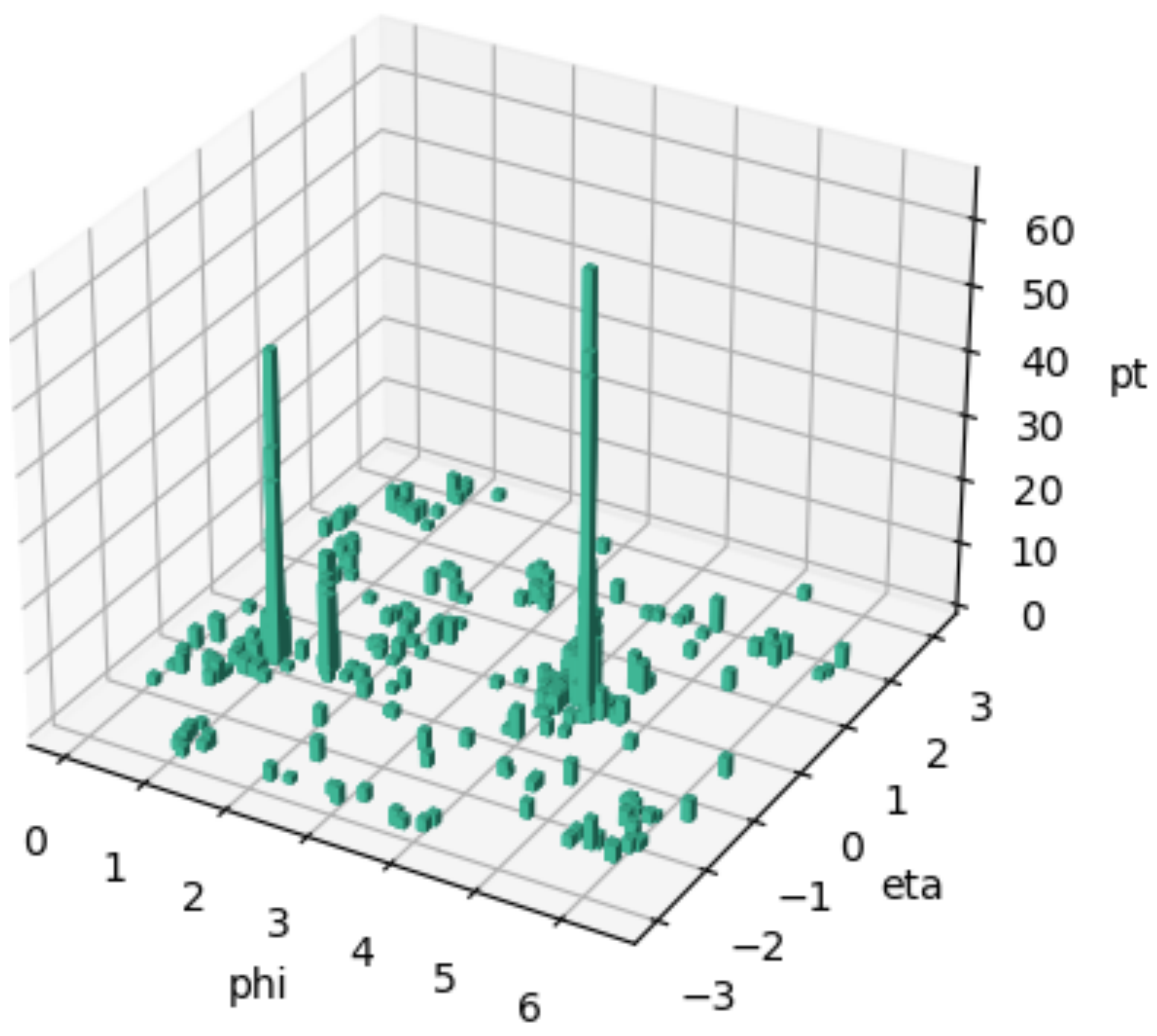


dijet hard event

+ uncorrelated bkg



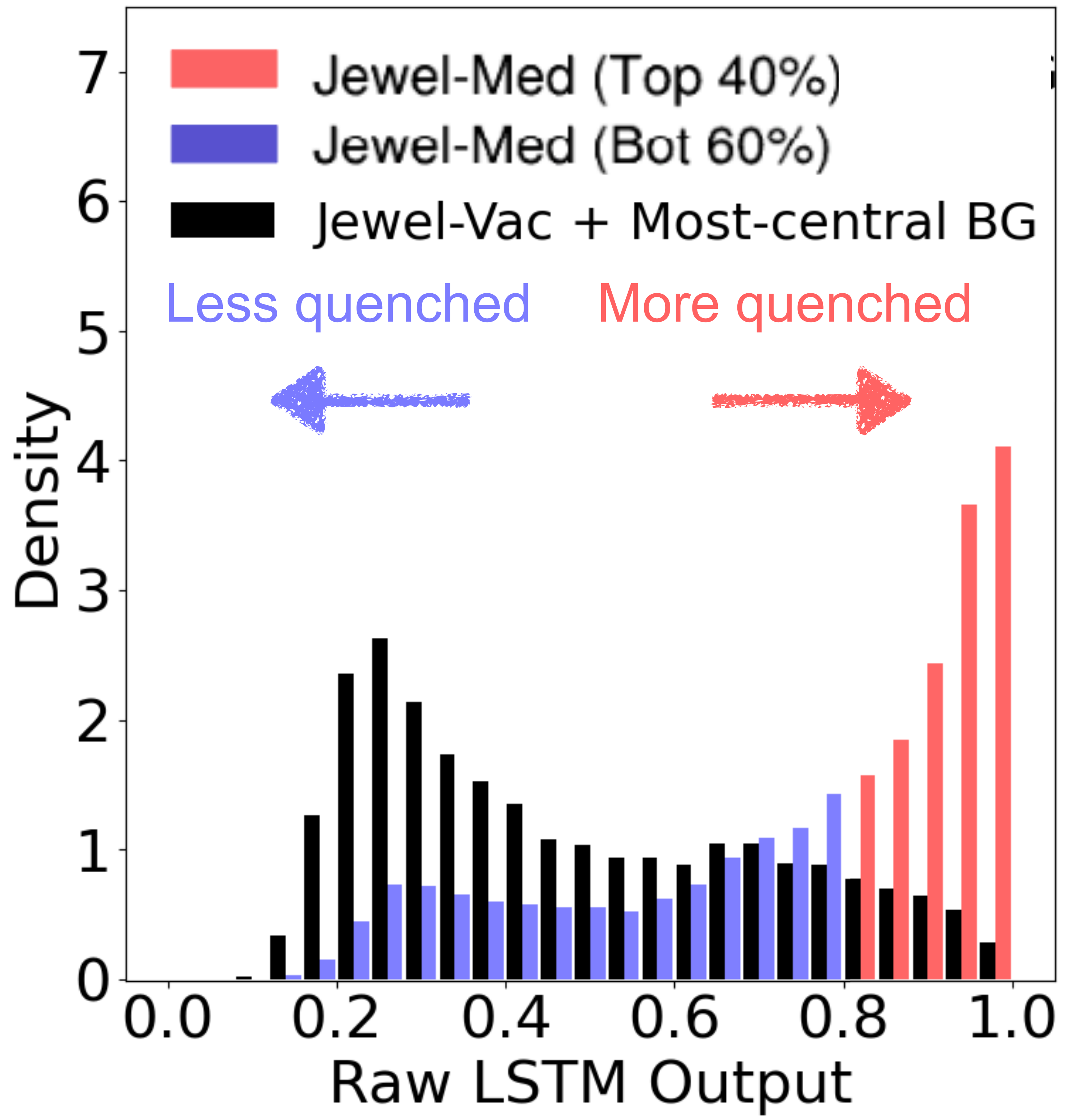
= mixed event

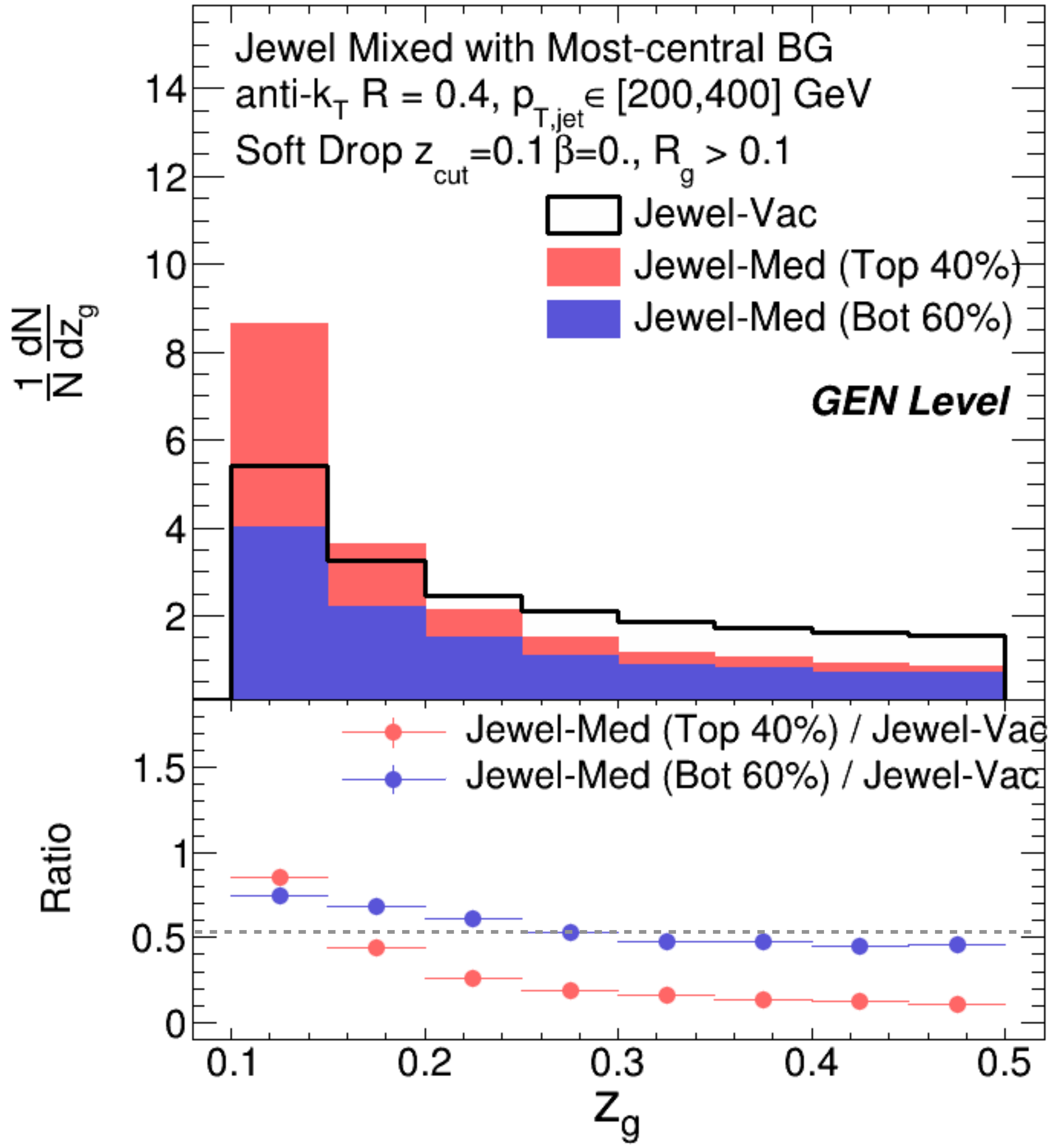


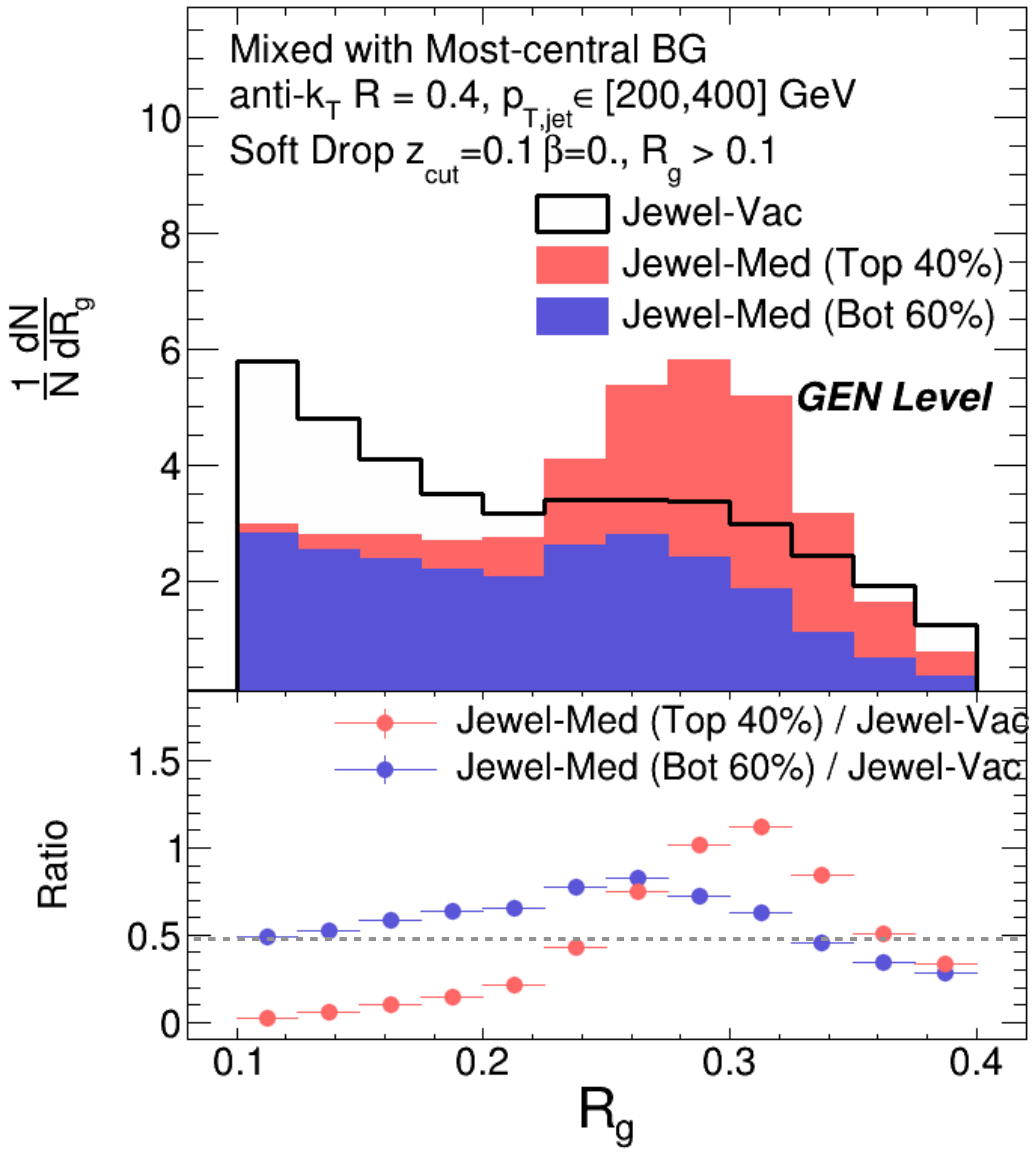
bkg-sub event

ML Classified Quenched Jets — Jet Substructures

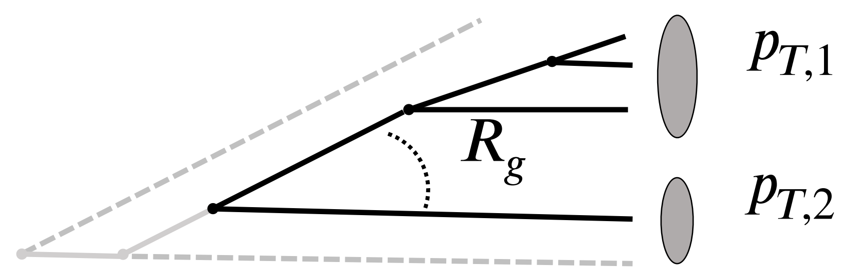
Paper: JHEP04(2023)140







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



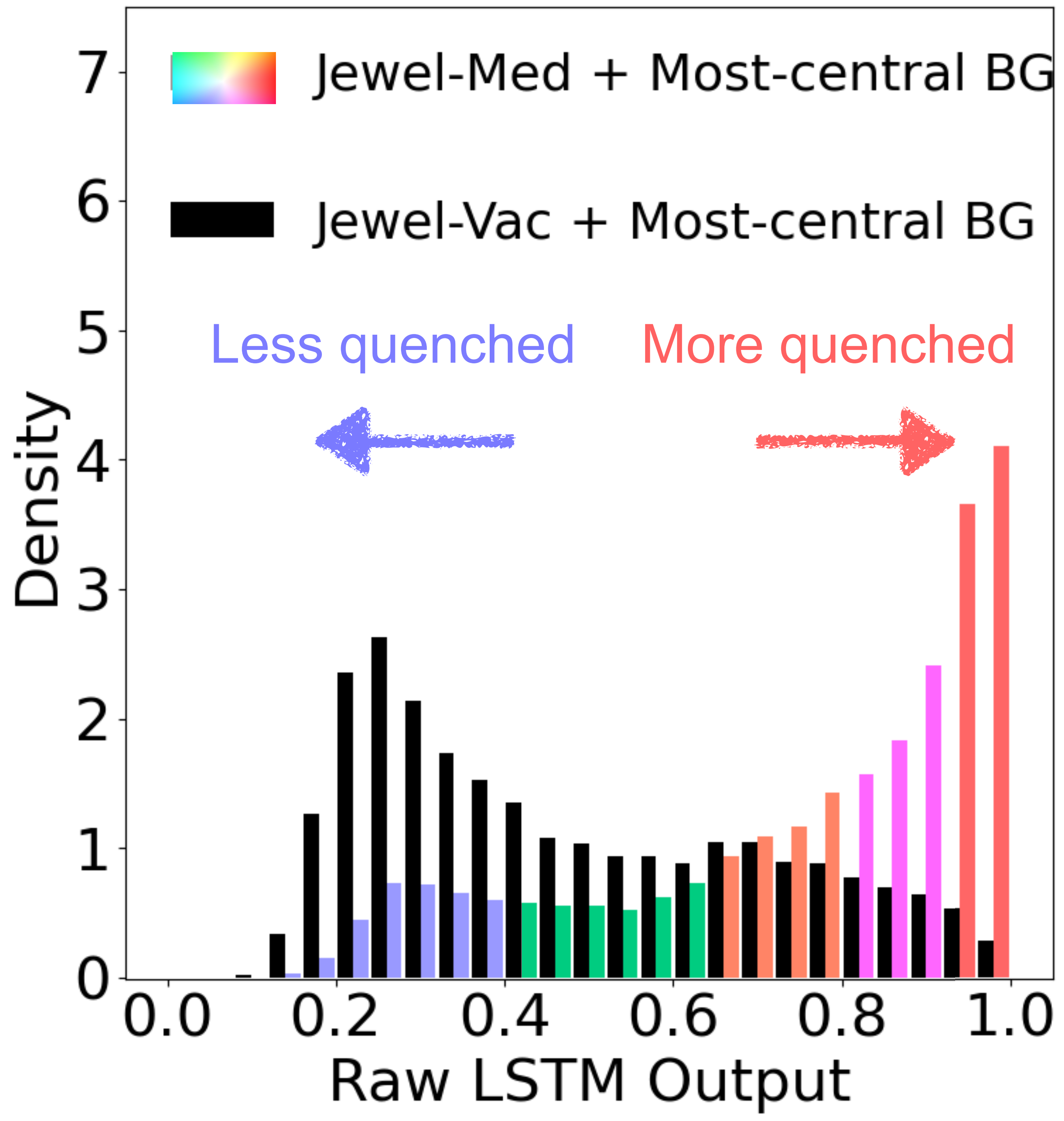
Quenchness: The LSTM output for each medium jet. If the value is closer to 1, then the jet is more quenched. And vice versa.

Neural network indeed learns from the jet-substructures. But does it "understand" the quenching features?

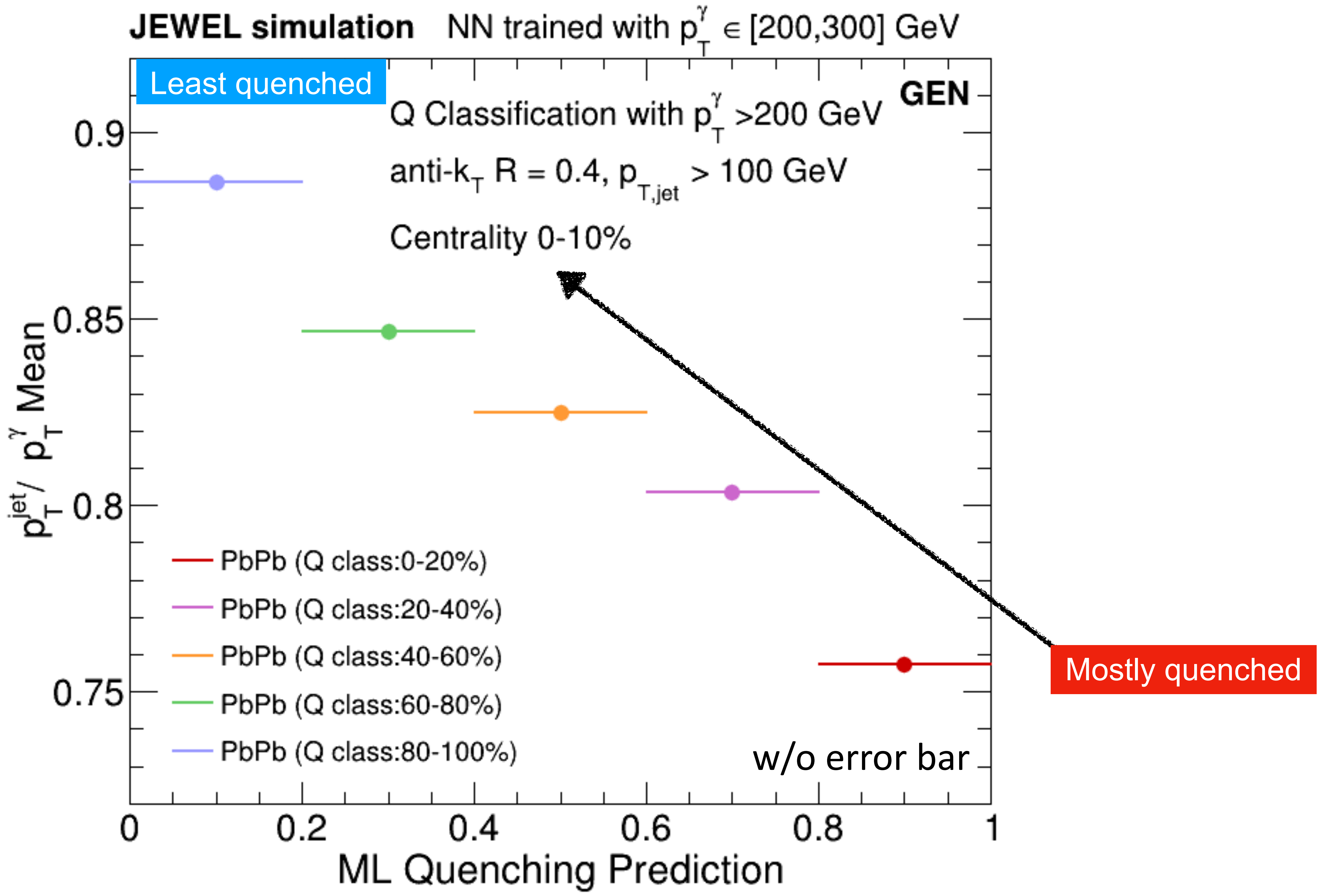
we can use the LSTM output to measure all kinds of jet observables that are unseen in the training.

ML Classified Quenched Jets — Photon-Jet Imbalance

Physics interpretability: ML output can be applied to observables not part of the training.



PbPb jets (Jewel-Med)

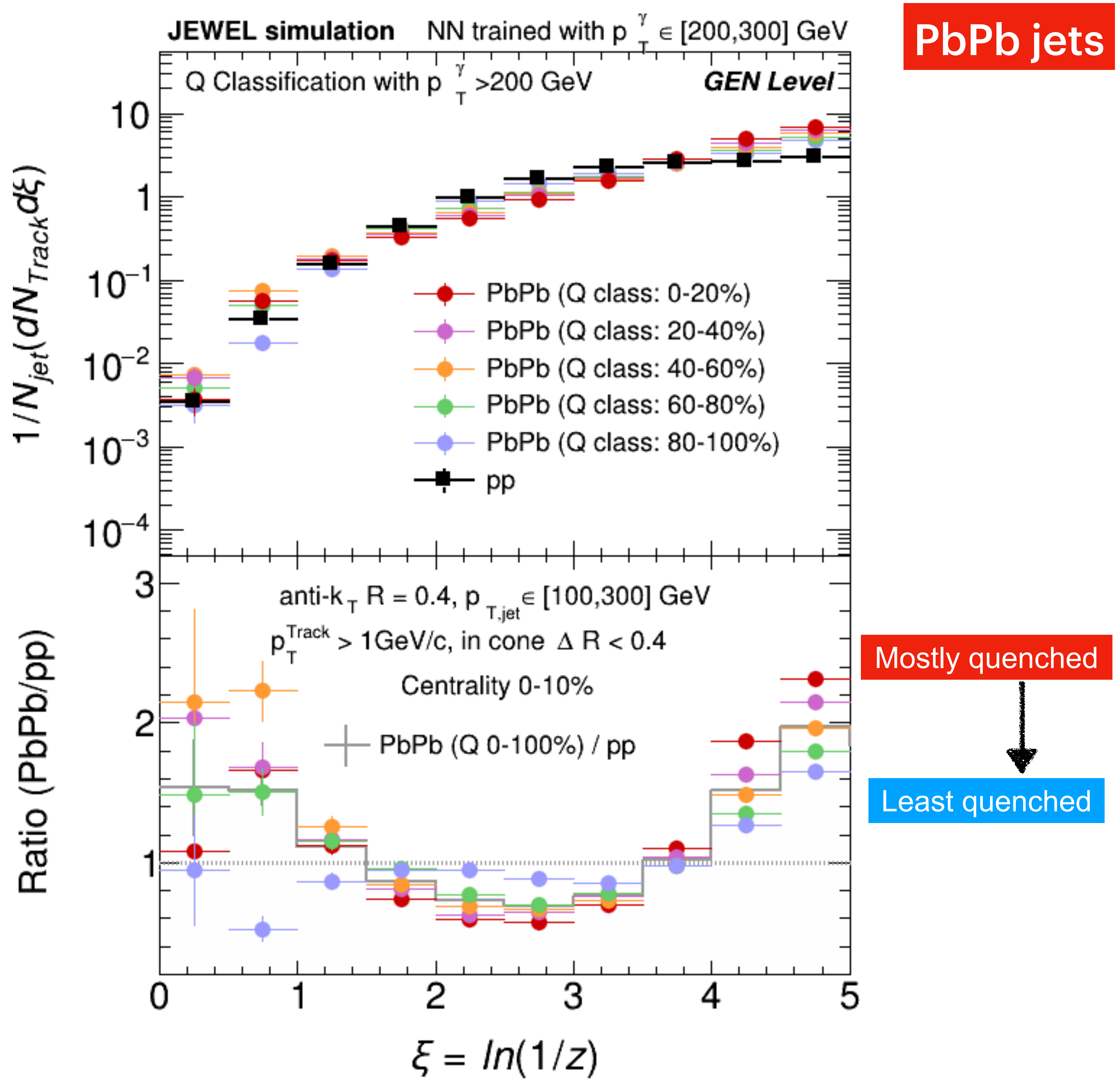


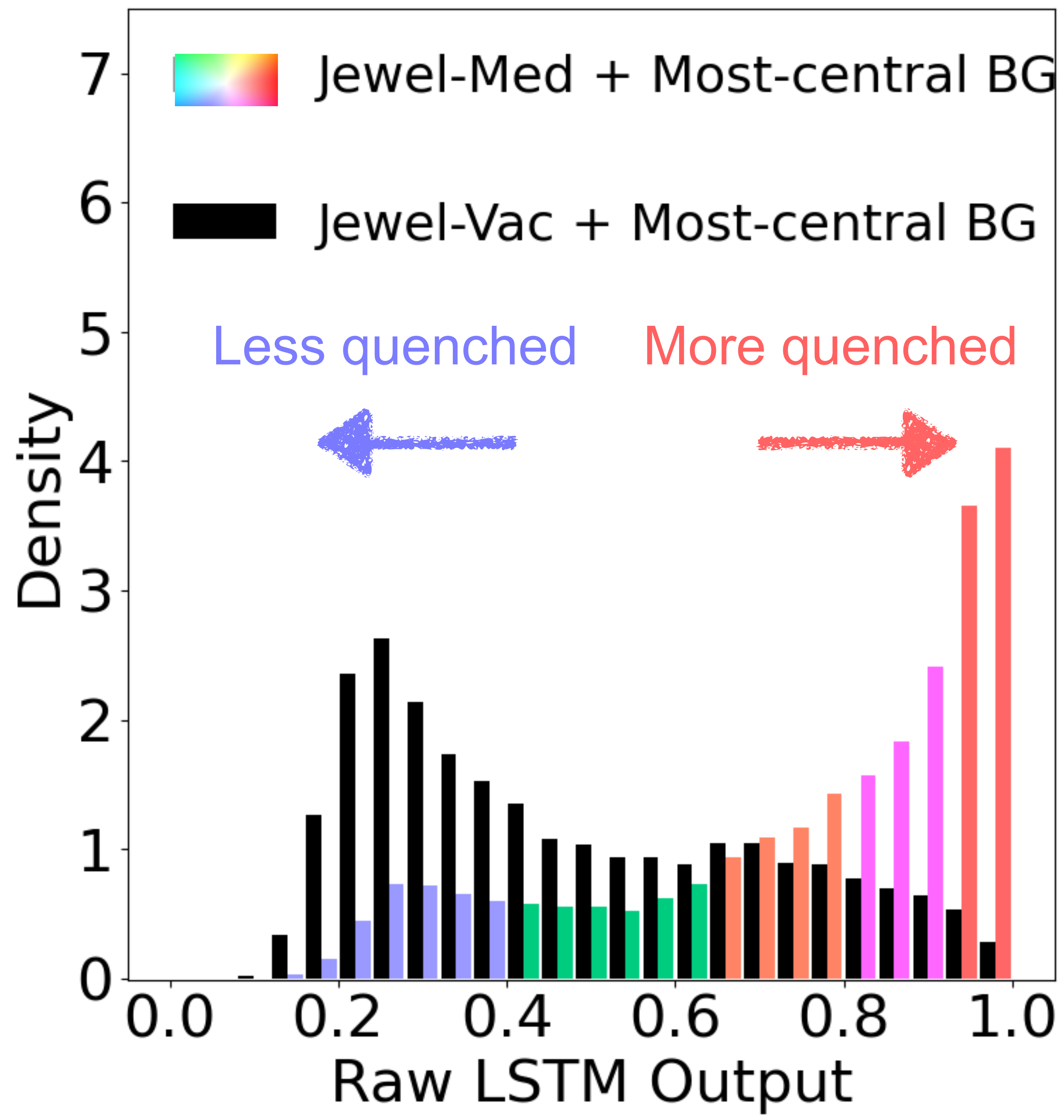
Quenchness: The LSTM output for each medium jet. If the value is closer to 1, then the jet is more quenched. And vice versa.

- **Jet energy loss is correlated with the ML output**
- **ML is able to get the key features of jet quenching**

ML Classified Quenched Jets — Fragmentation Function

Physics interpretability: ML output can be applied to observables not part of the training.

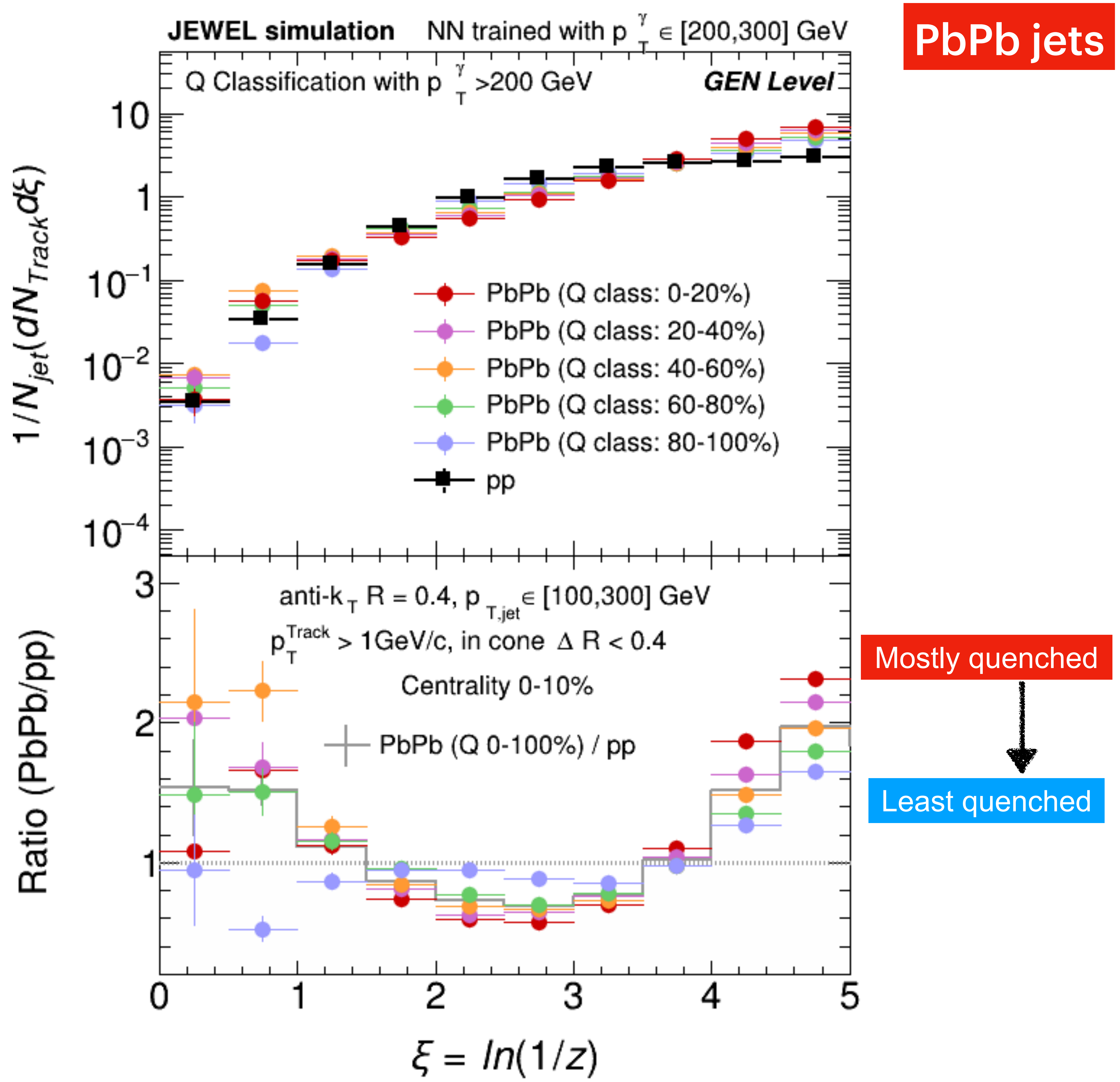


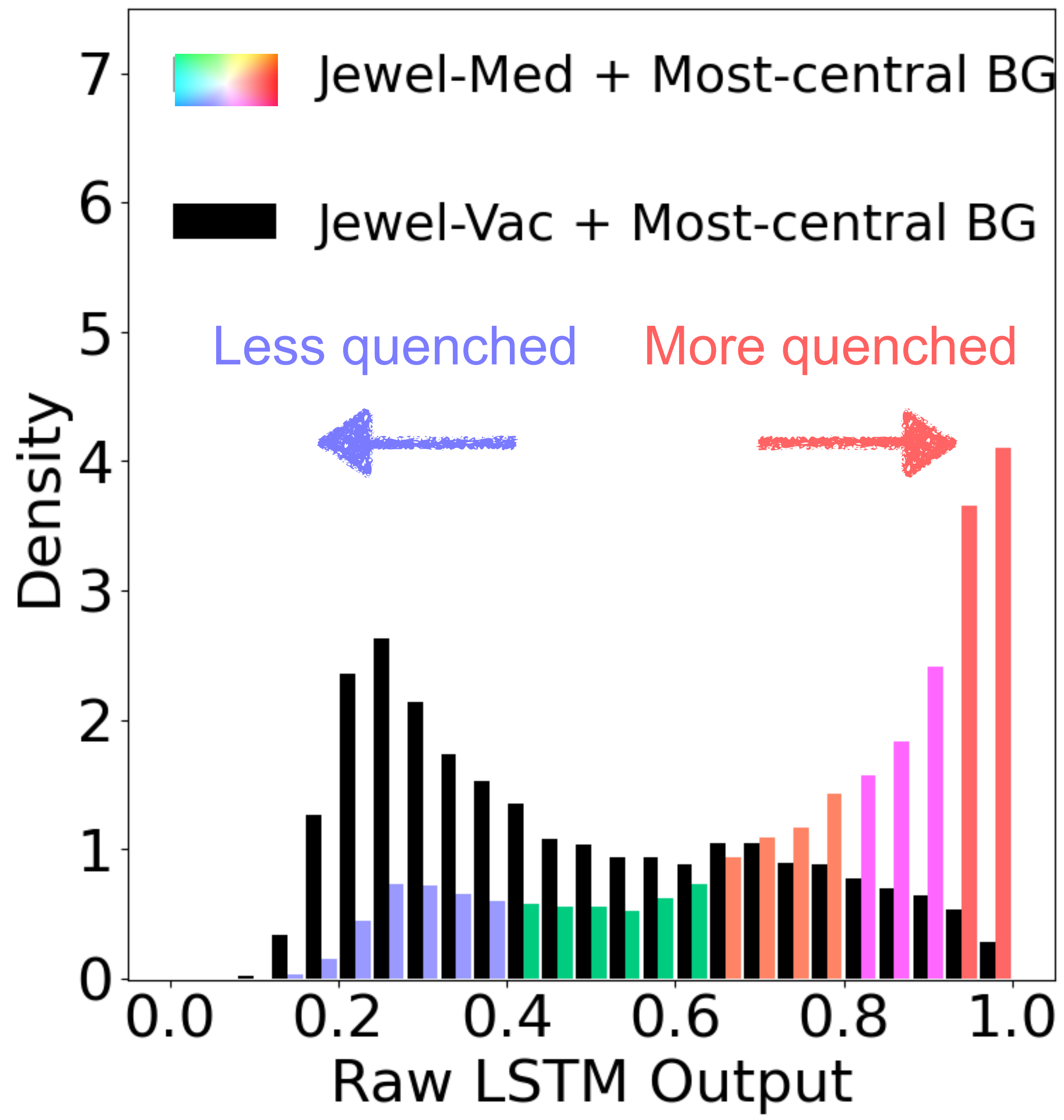


Jet fragmentation functions are modified to different levels based on their quenching levels by ML classification.

ML Classified Quenched Jets — Fragmentation Function

Physics interpretability: ML output can be applied to observables not part of the training.

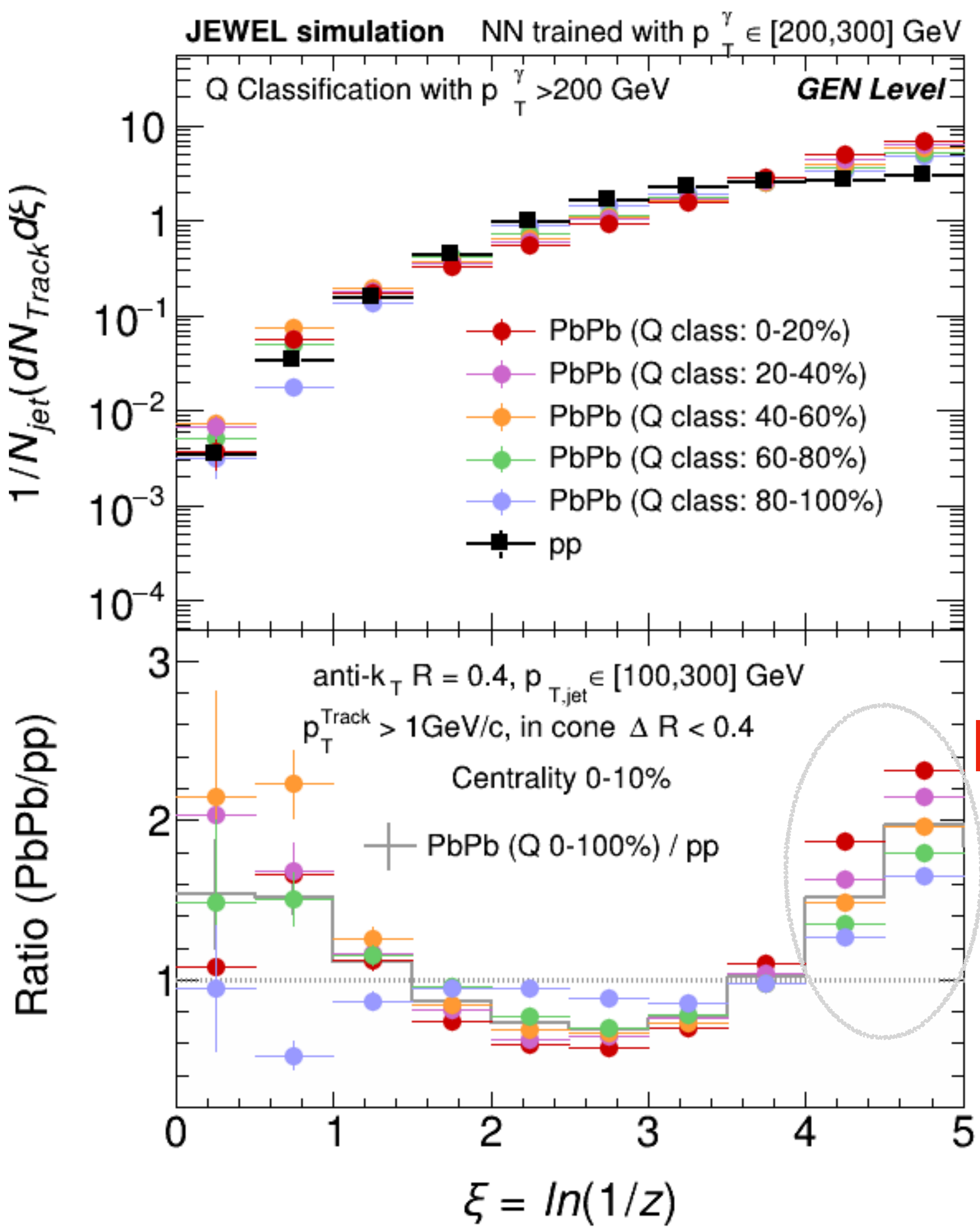




pp jets with a fake "quenching" prediction by the ML classifier?

ML Classified Quenched Jets — Fragmentation Function

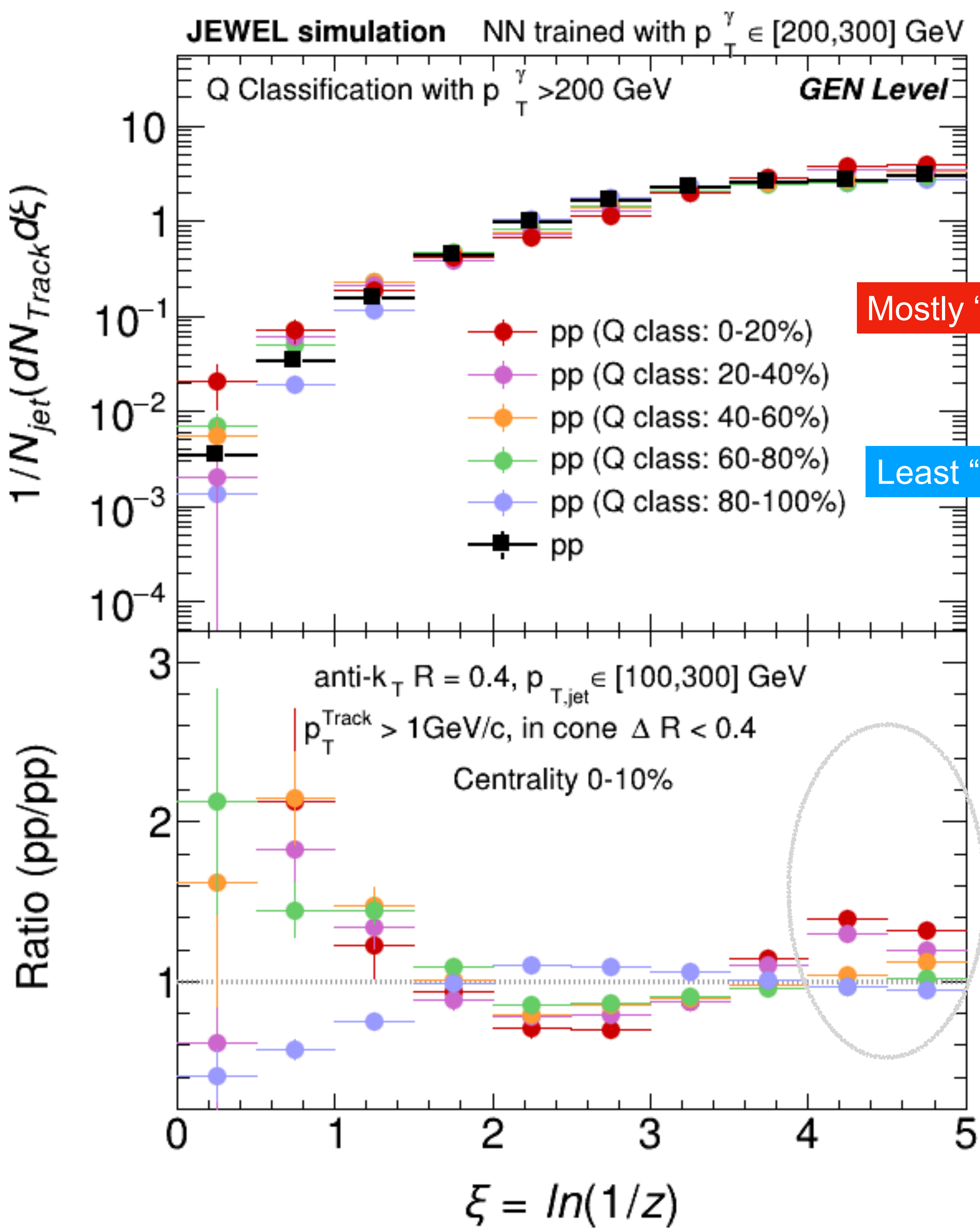
PbPb jets



Mostly quenched

Least quenched

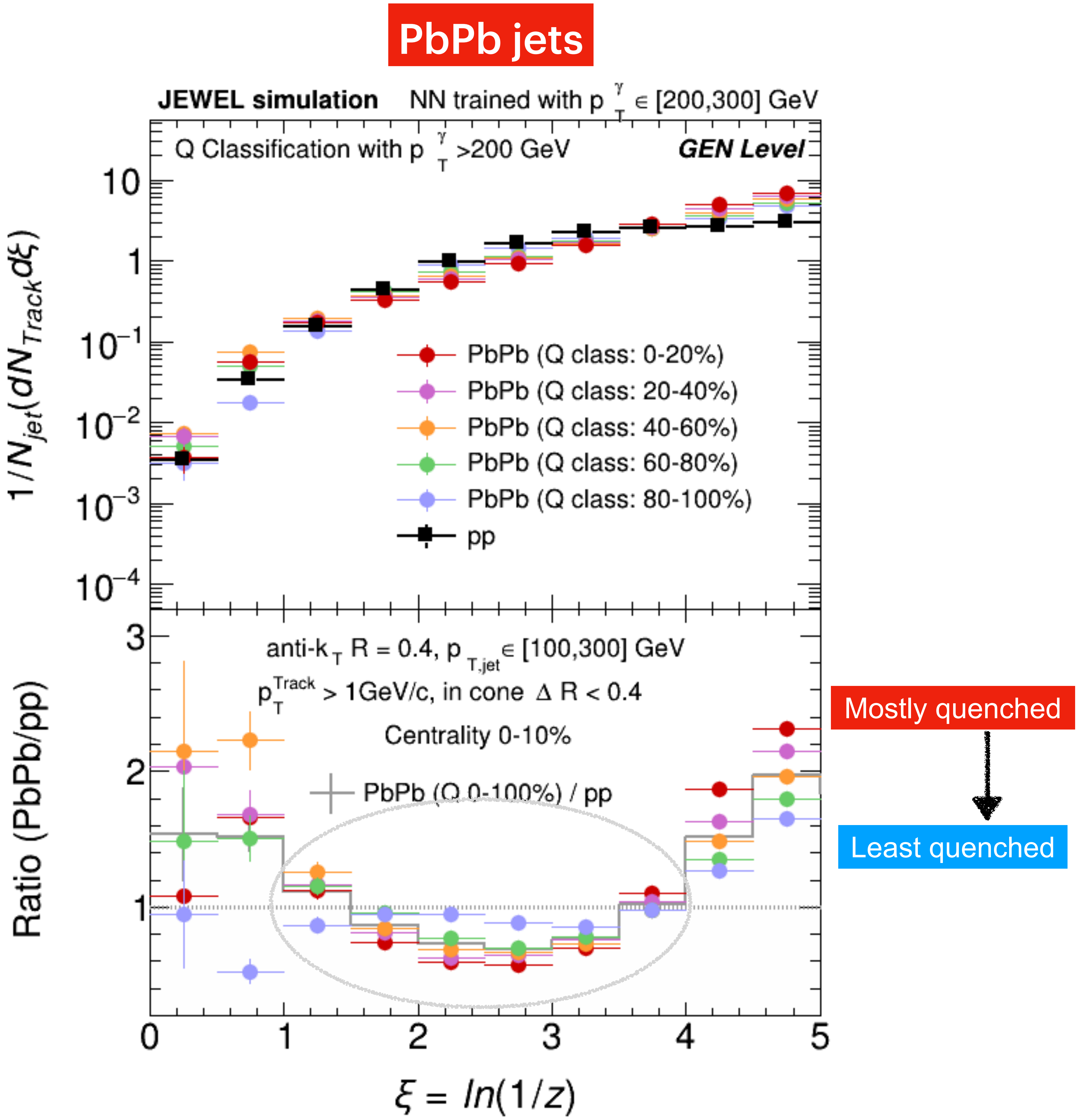
pp jets

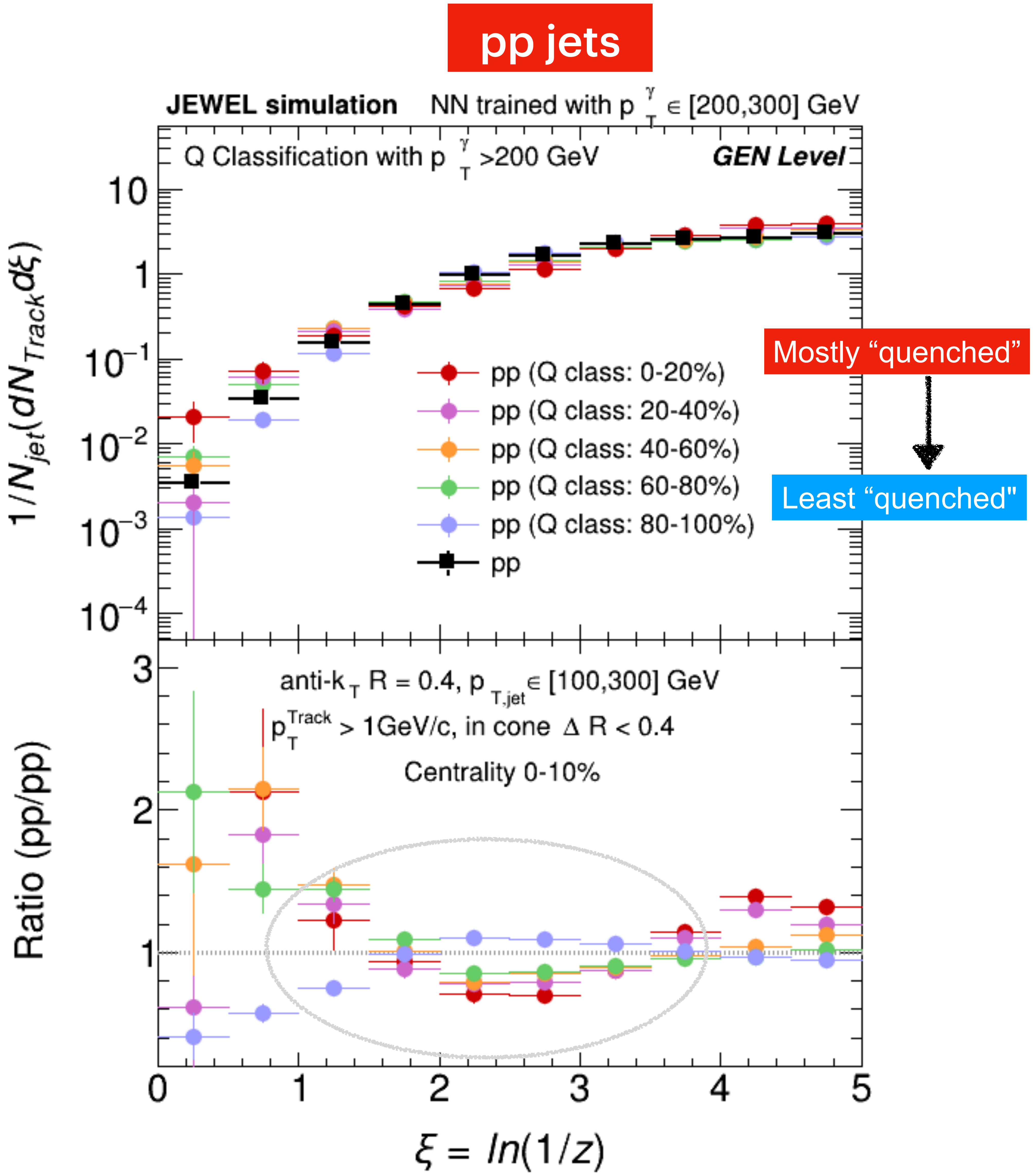


Mostly “quenched”

Least “quenched"

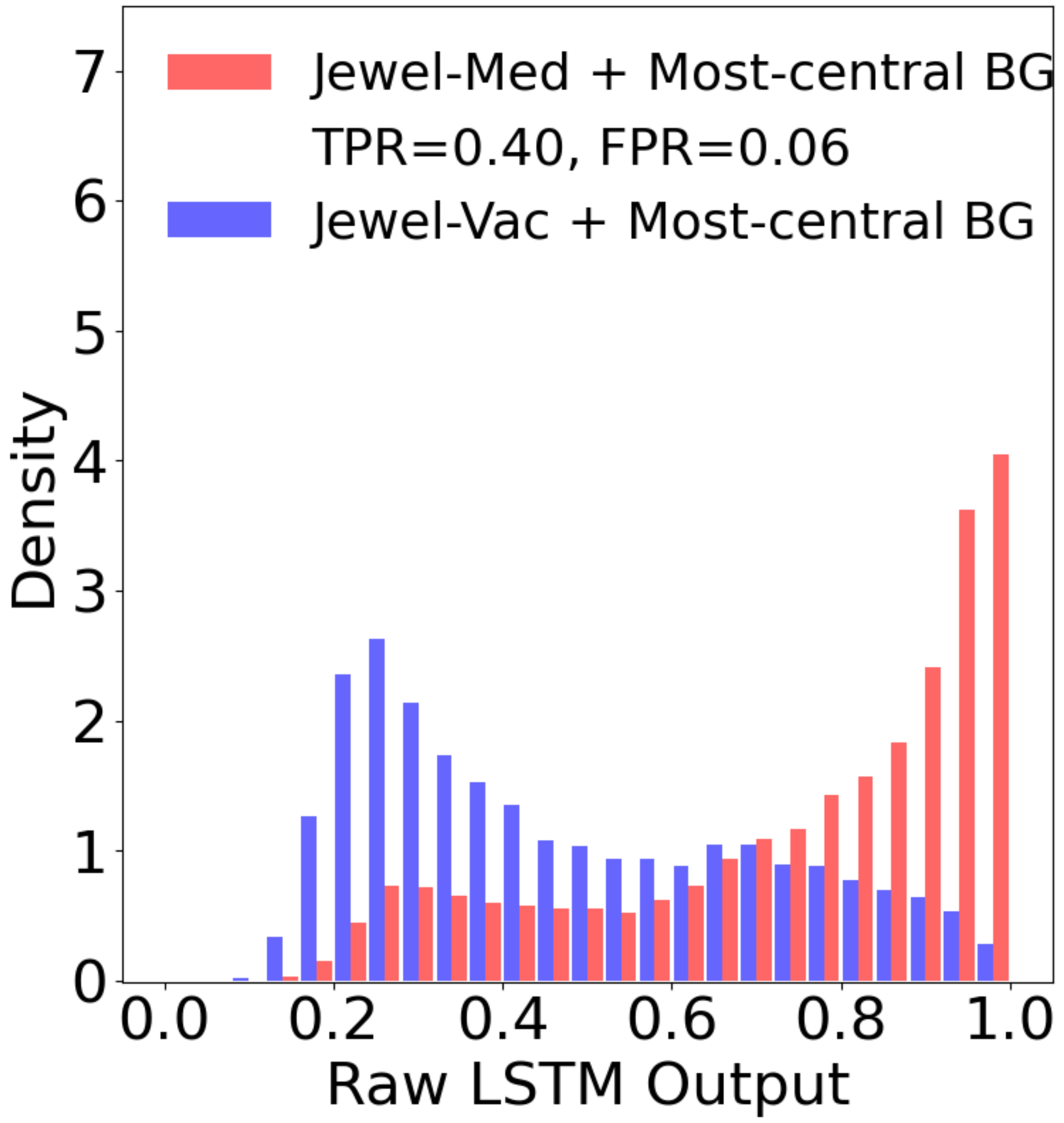
ML Classified Quenched Jets — Fragmentation Function

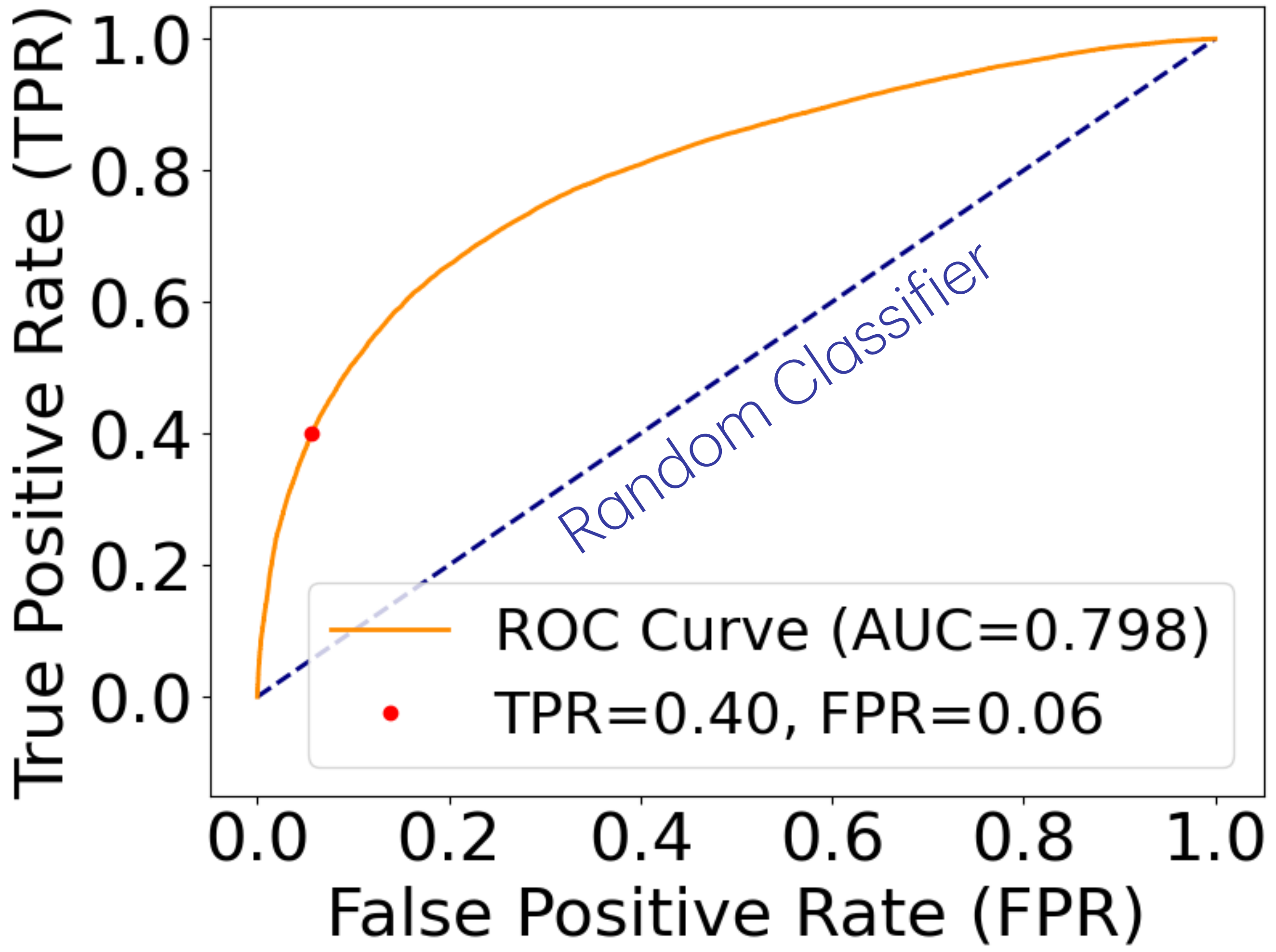




Detector Effects for ML Performance: ROC and Binary Classification

GEN Level jet training





Detector Effects for ML Performance: ROC and Binary Classification

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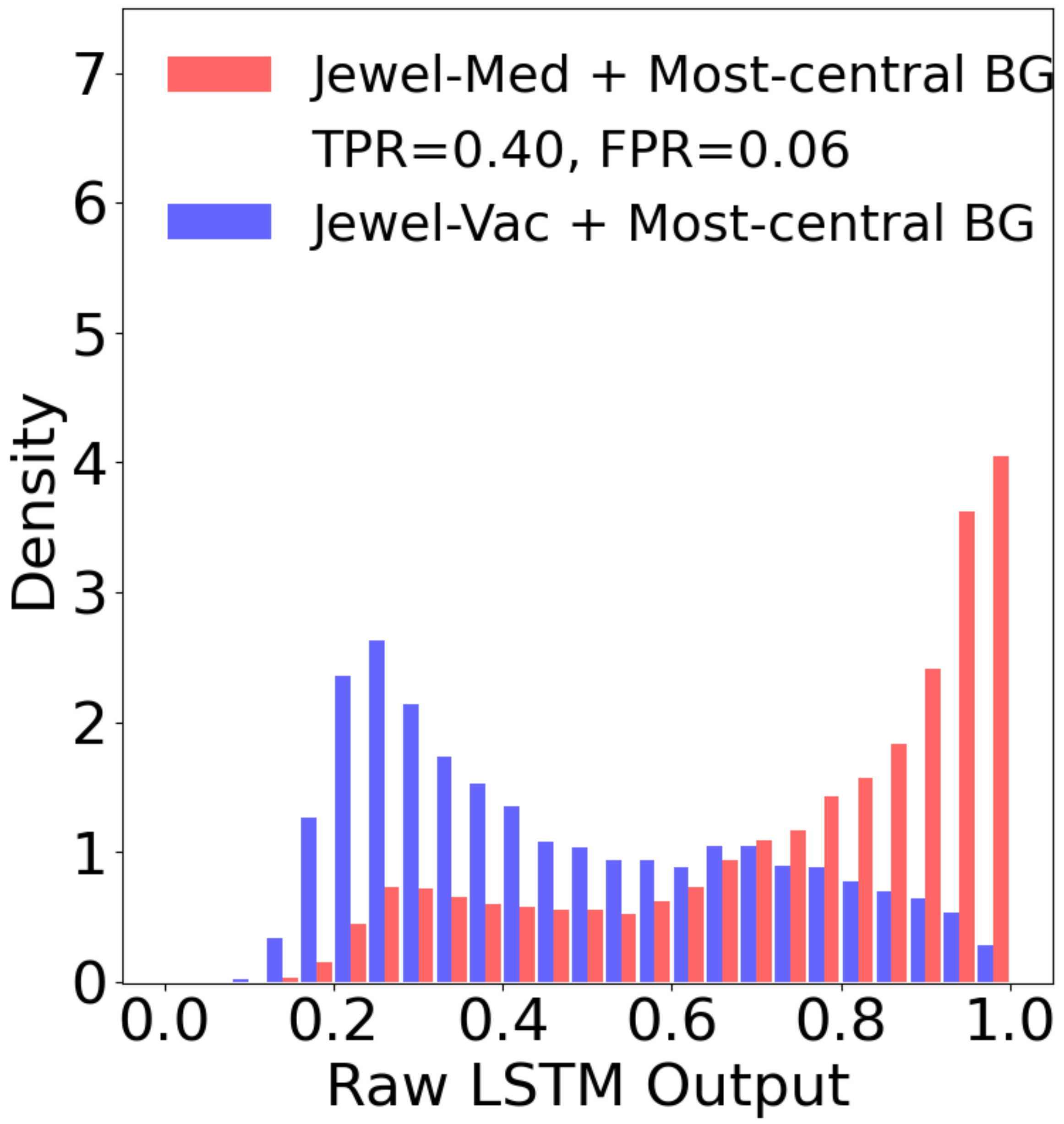
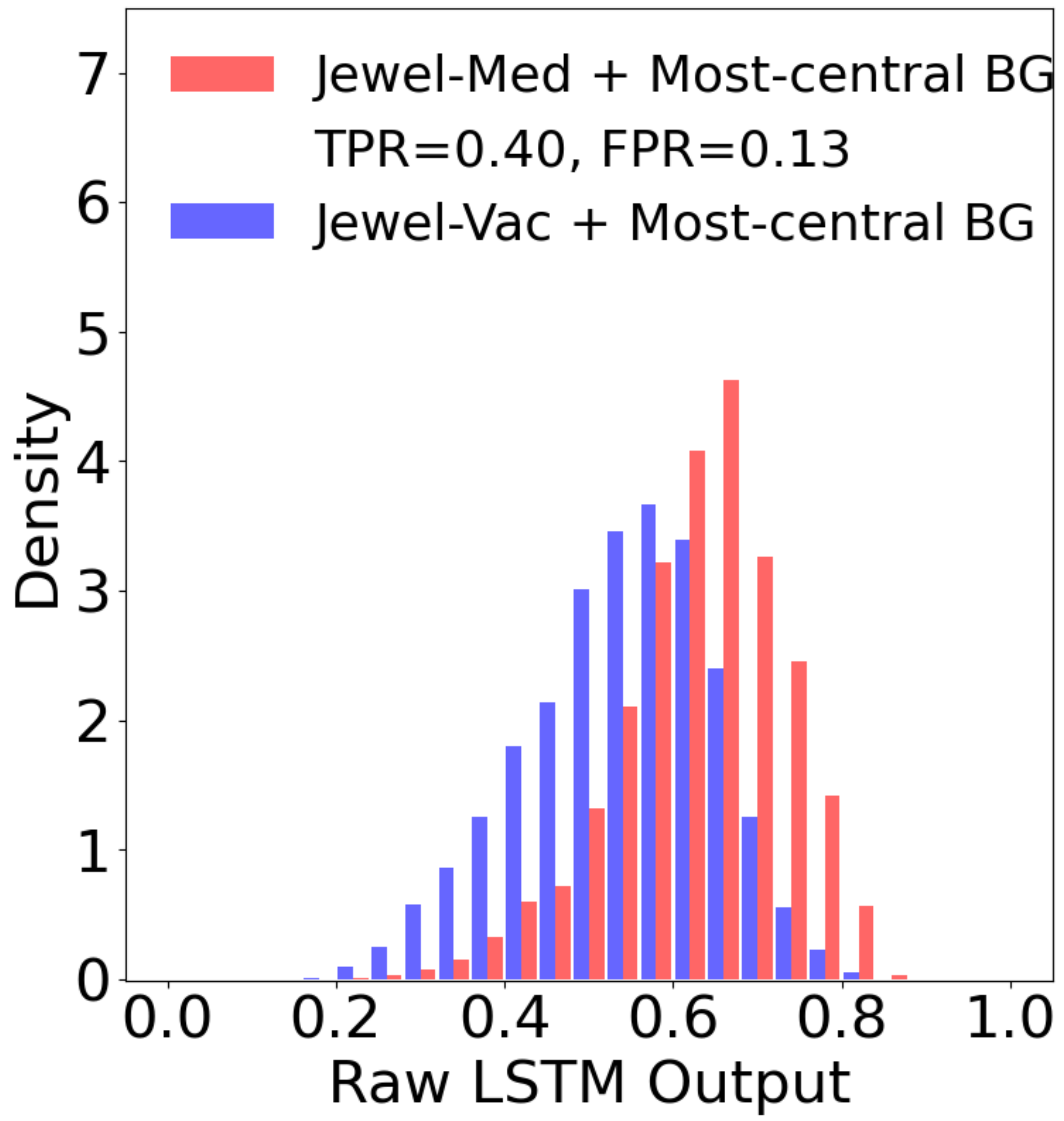


Detector effects smear the differences between medium jets and vacuum jets

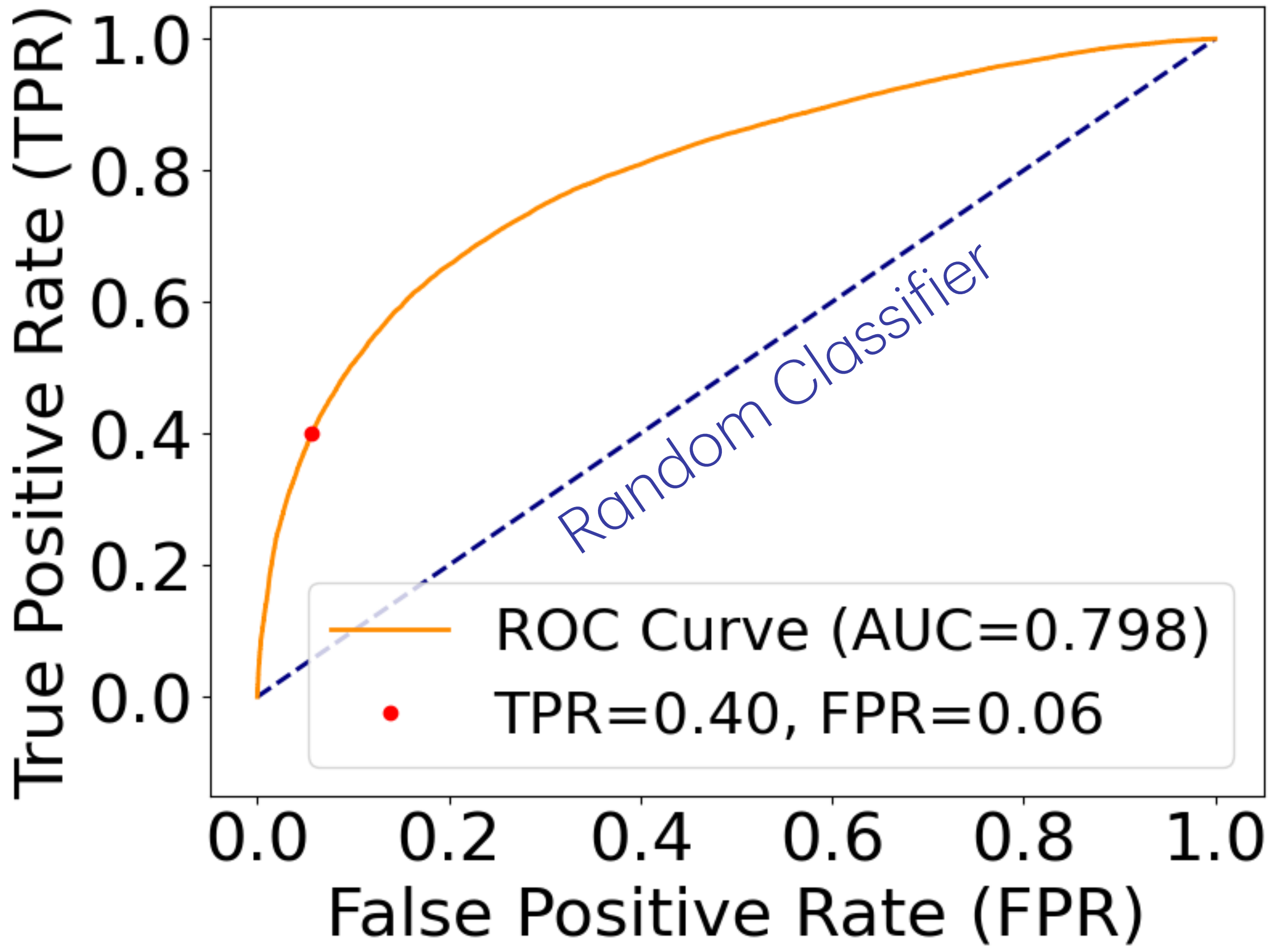


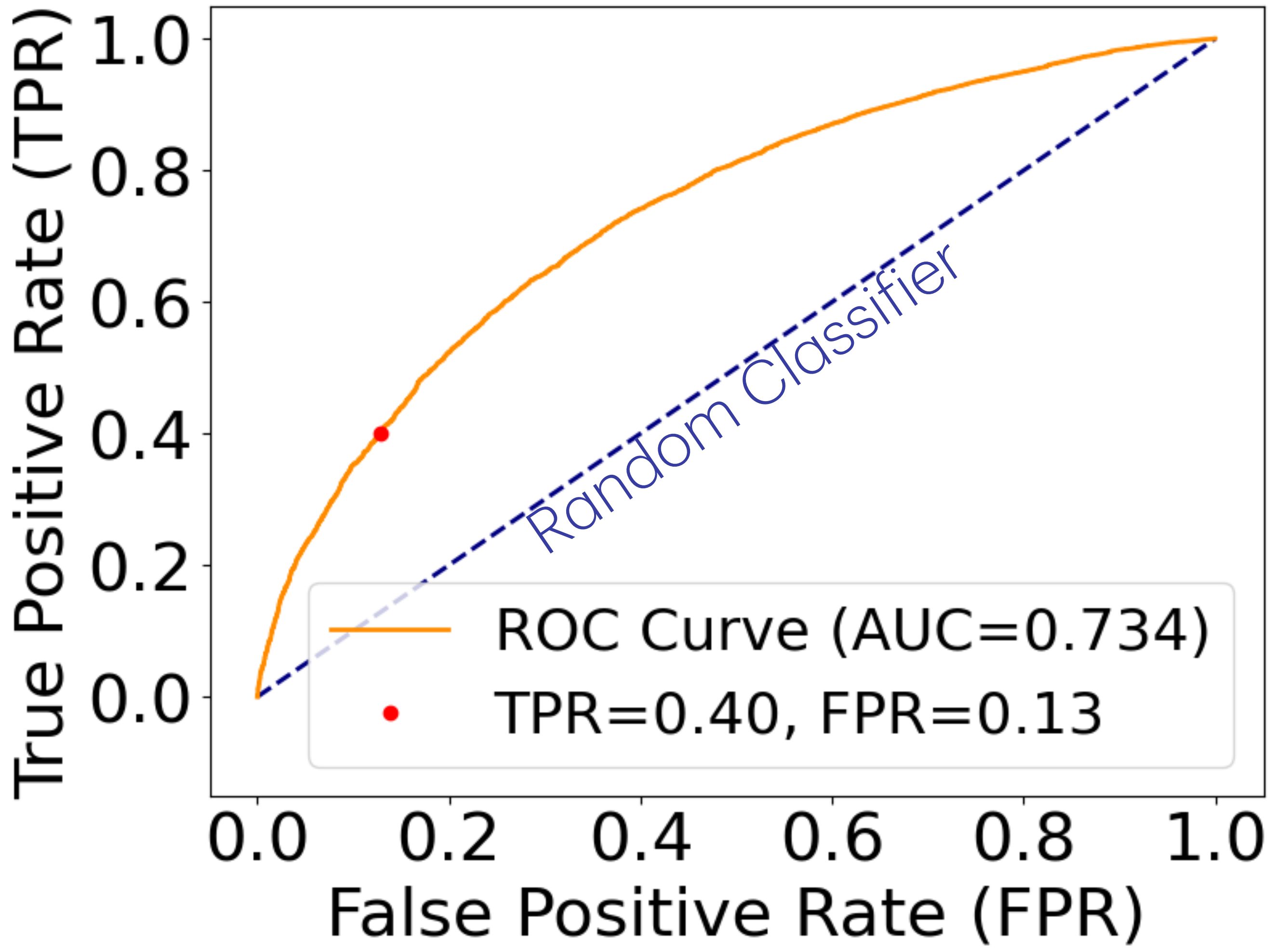
RECO jet training

EFlow Candidates from DELPHES:

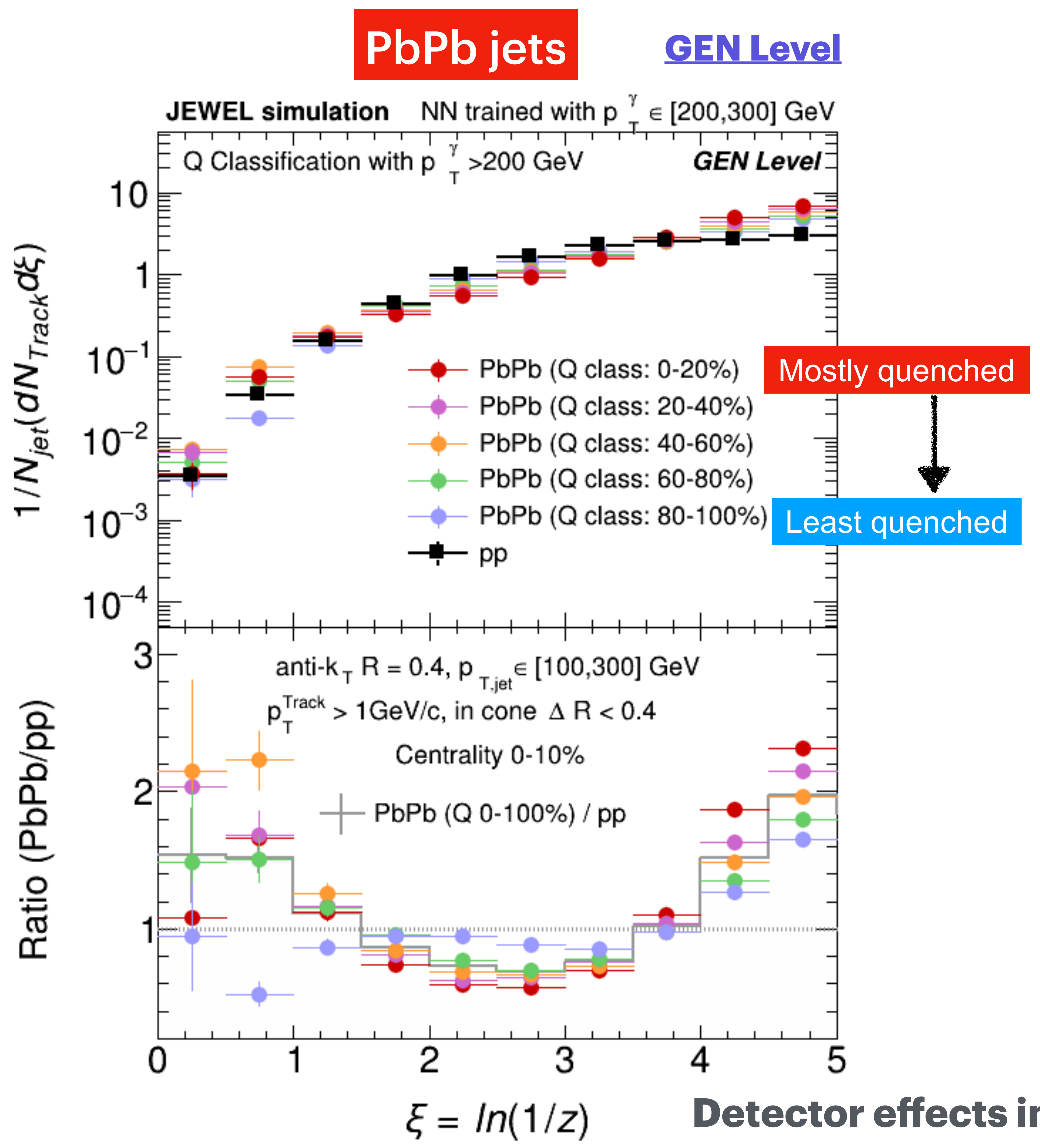
1) Combine the Tracker + Calorimeters

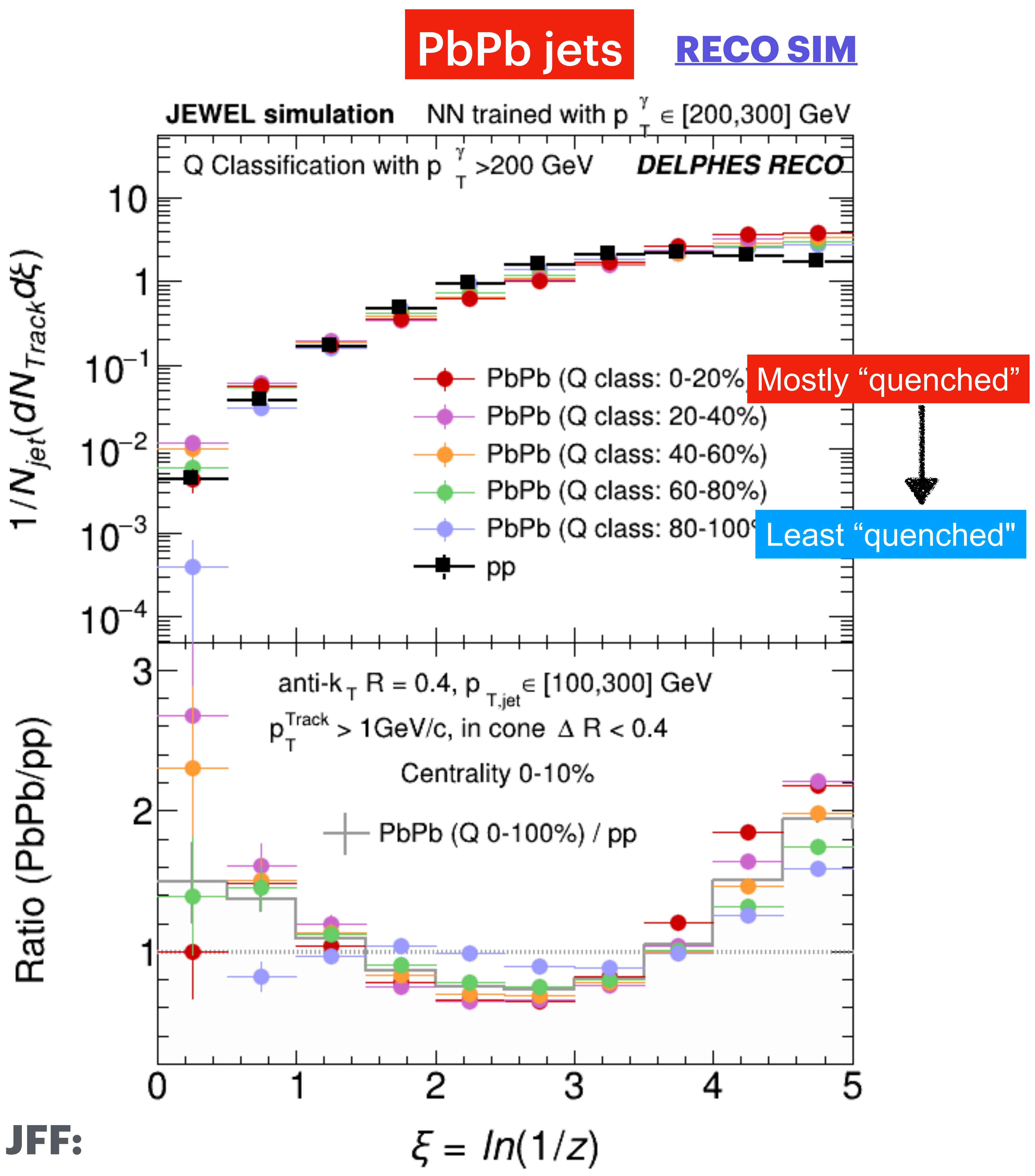
2) Comparable to CMS Particle Flow Candidates





Detector Effects for ML Performance: Fragmentation Function





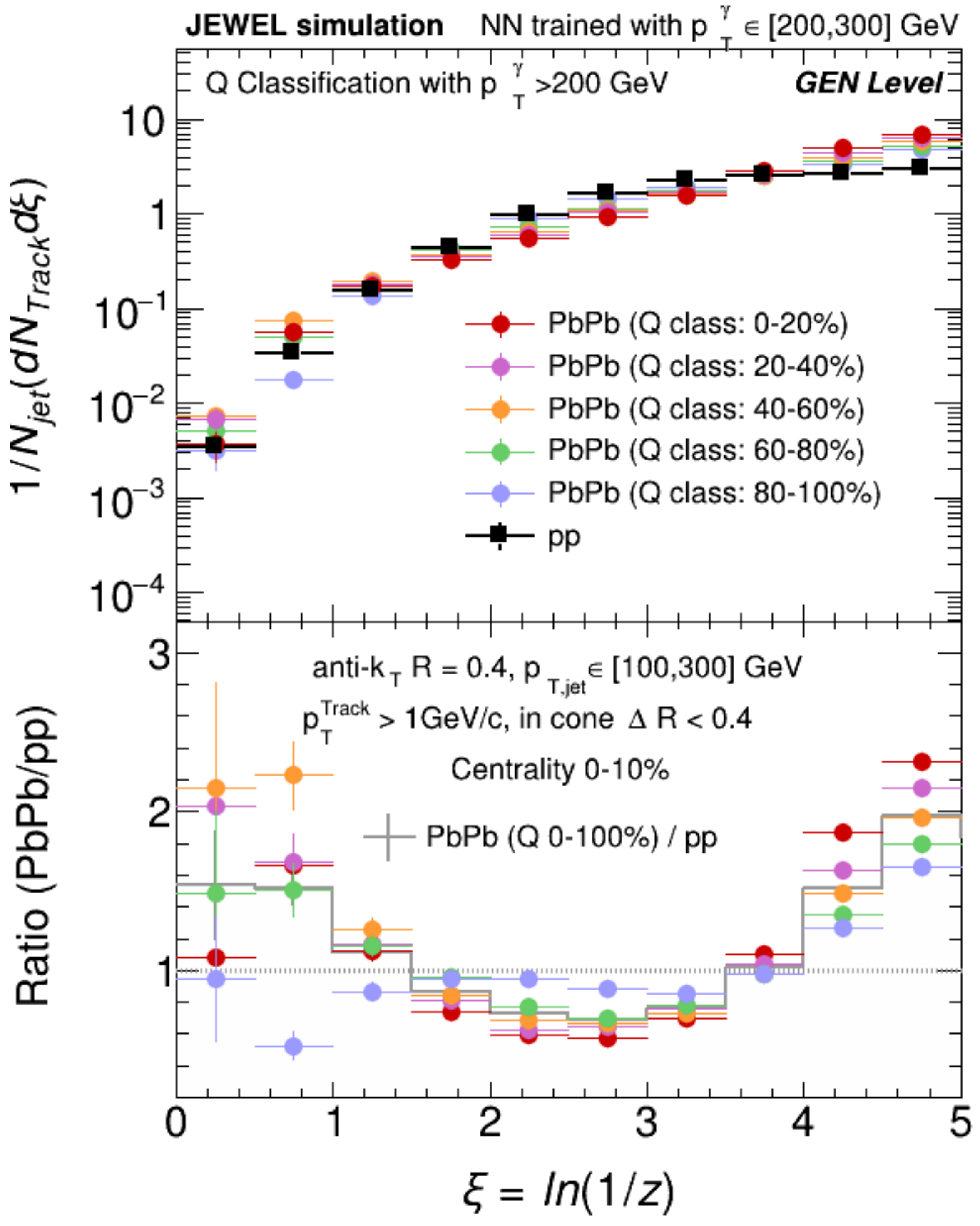
Detector effects impact on PbPb JFF:

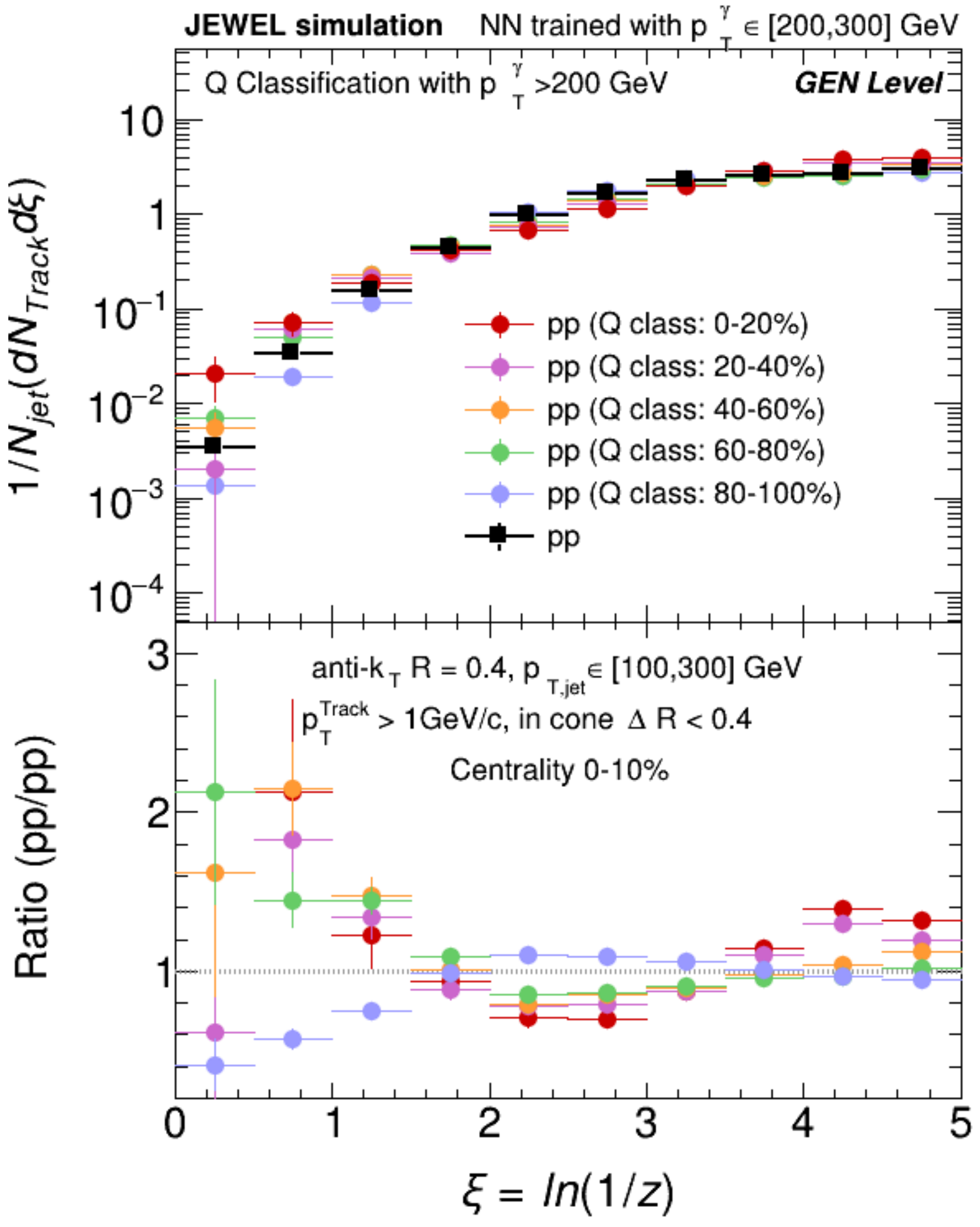
- the classification of quenching level gets closure for whole ξ region

Summary

LSTM can select jets with different quenching levels.

- ✓ It predicts correlation with the jet energy loss using photon-jet sample.
- ✓ It can be applied to **various jet observables**.
- ✓ It is effective under the impact of thermal background and detector effects —**doable in data!**



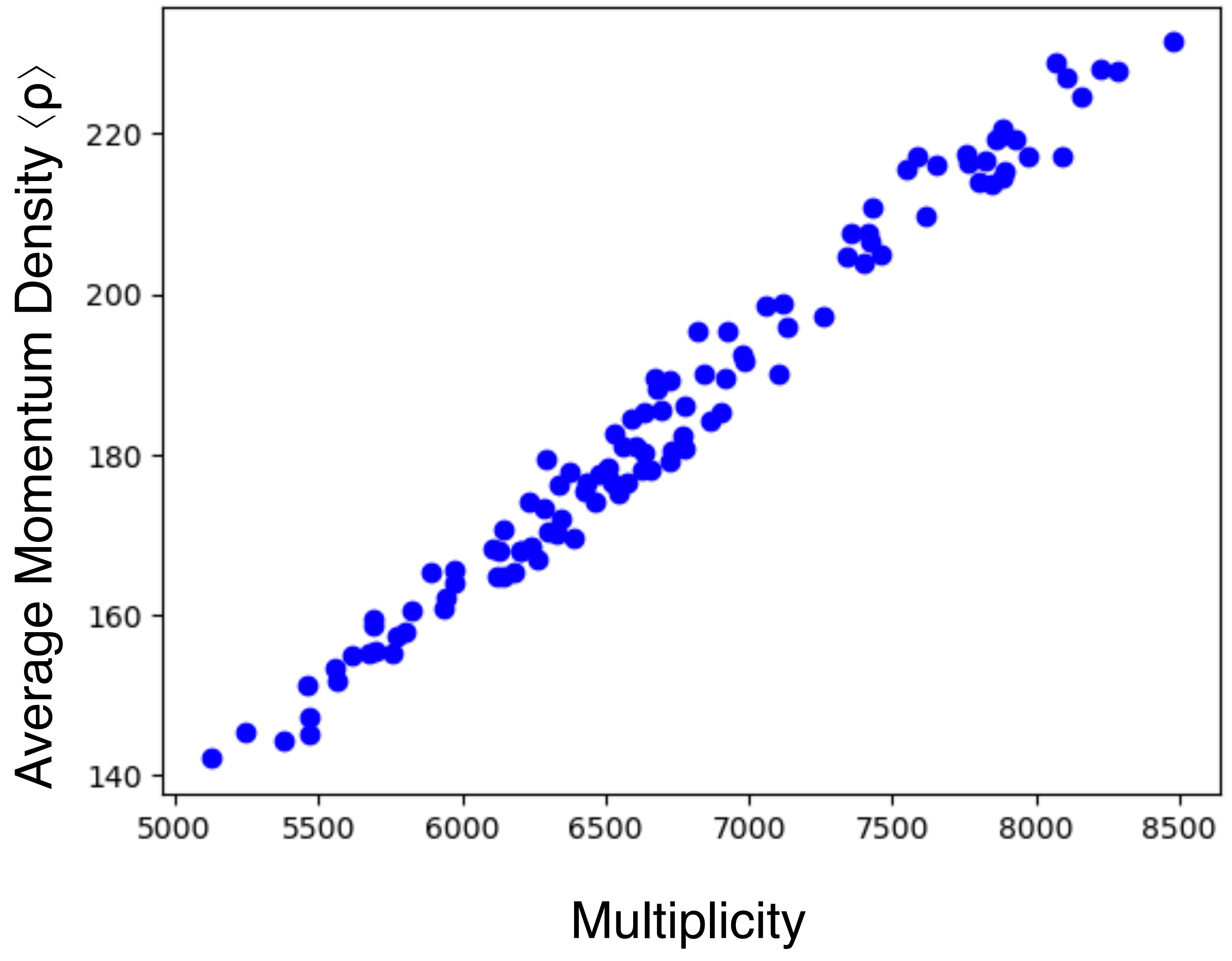


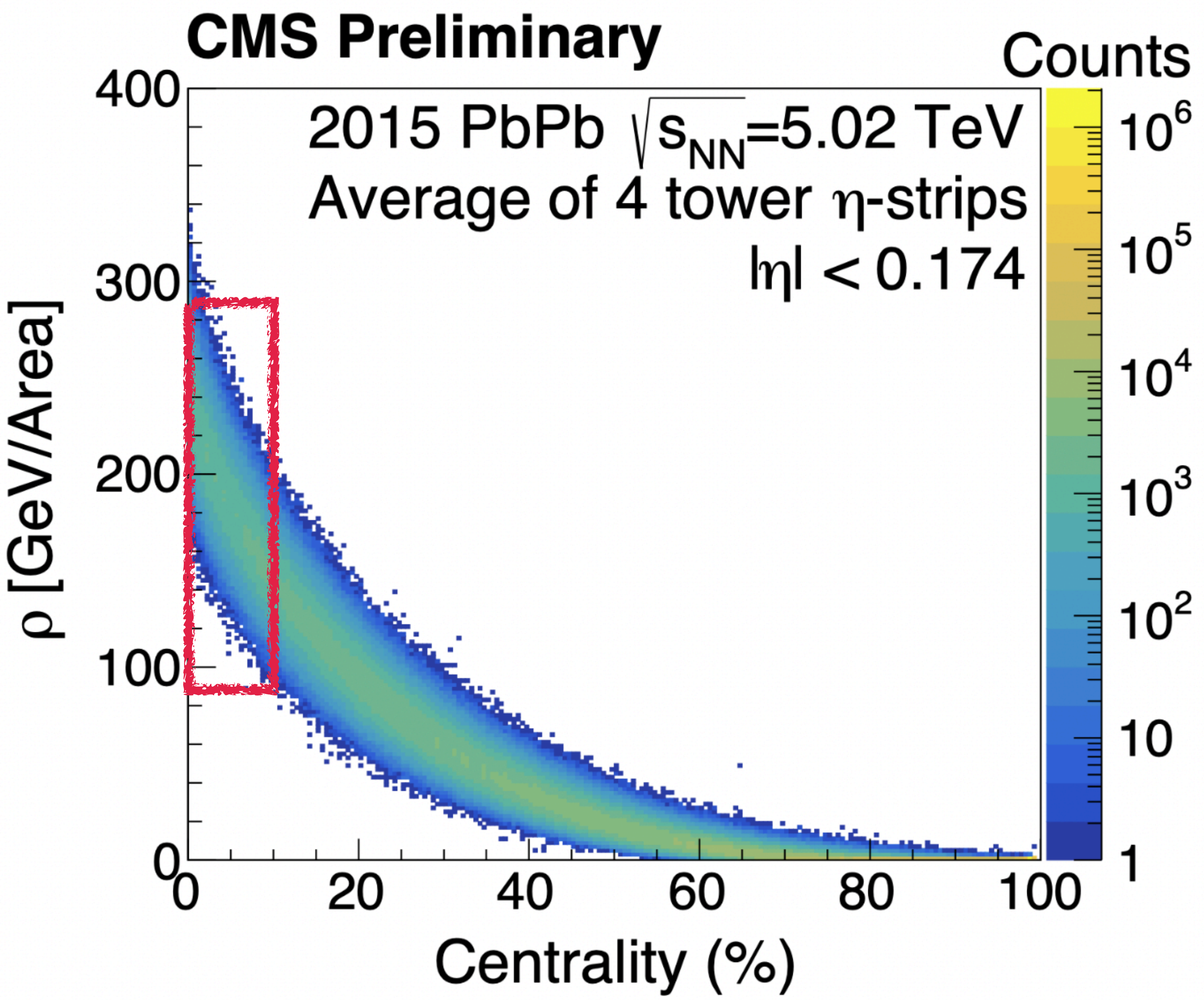
Backups

Thermal Bkg(Underlying Events) Simulation

PYTHIA+ANGANTYR

Centrality~0-10%

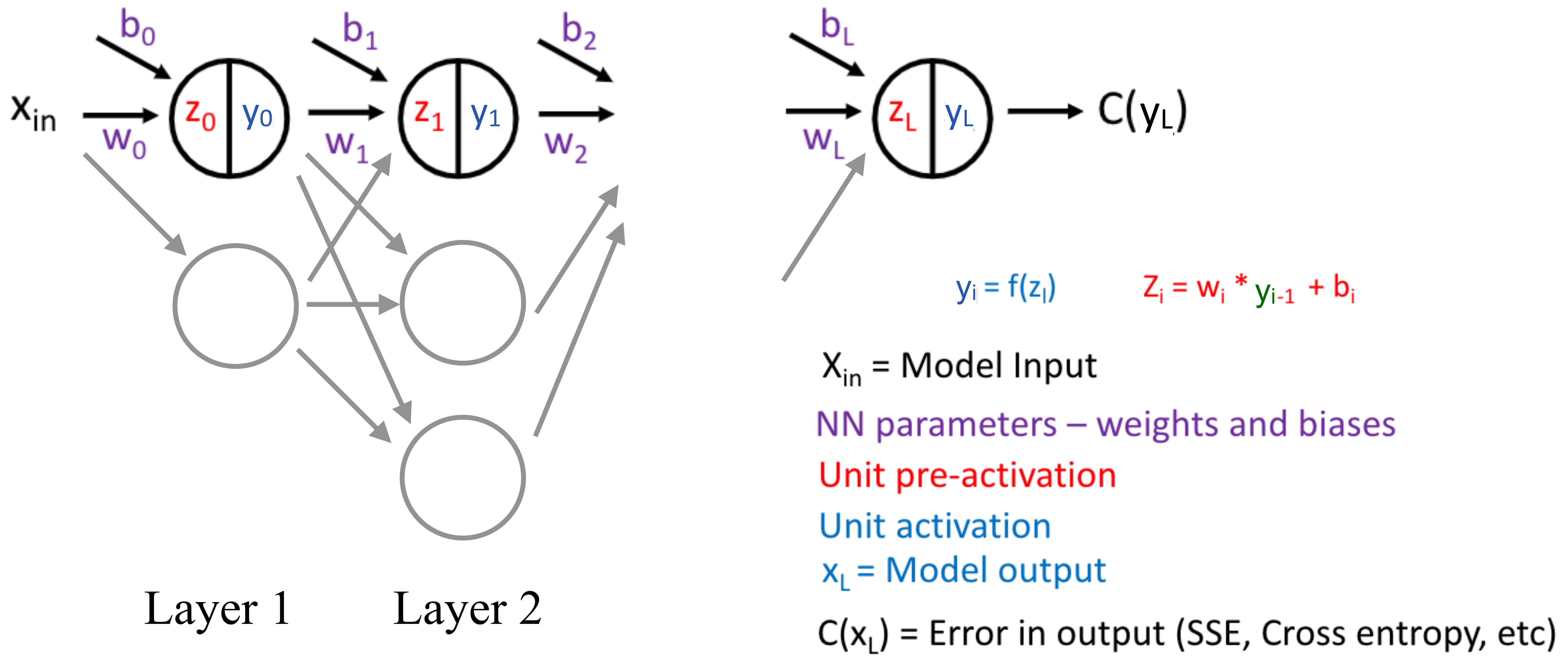




Neural Network and Feature Engineering

```
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

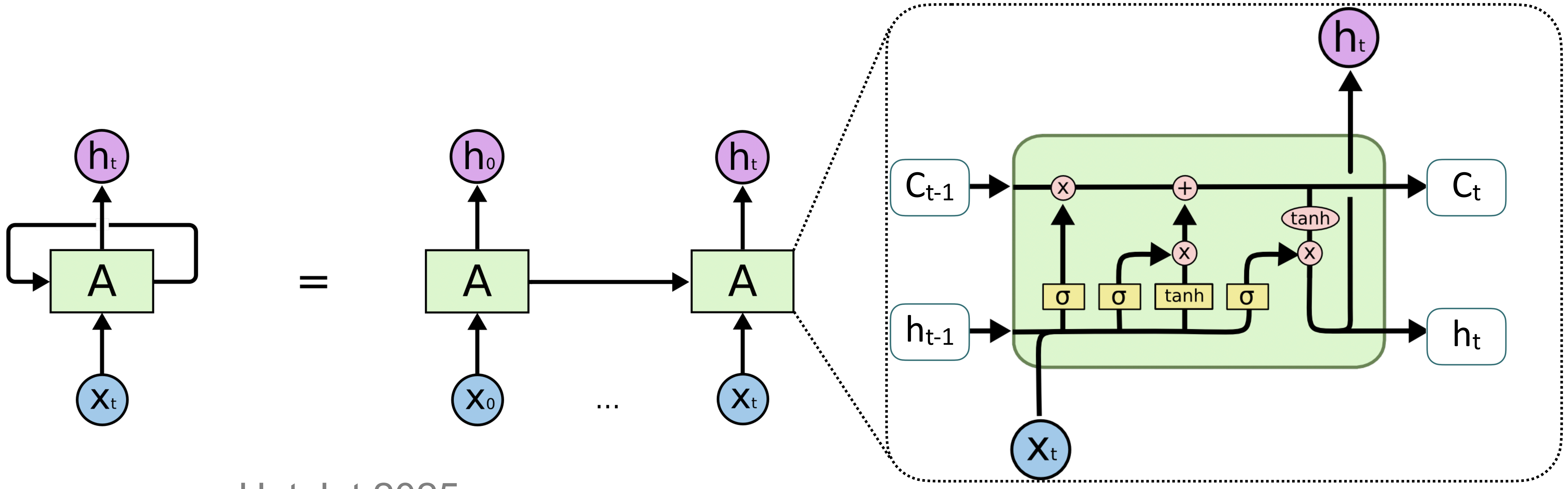


Fully Connected layers

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

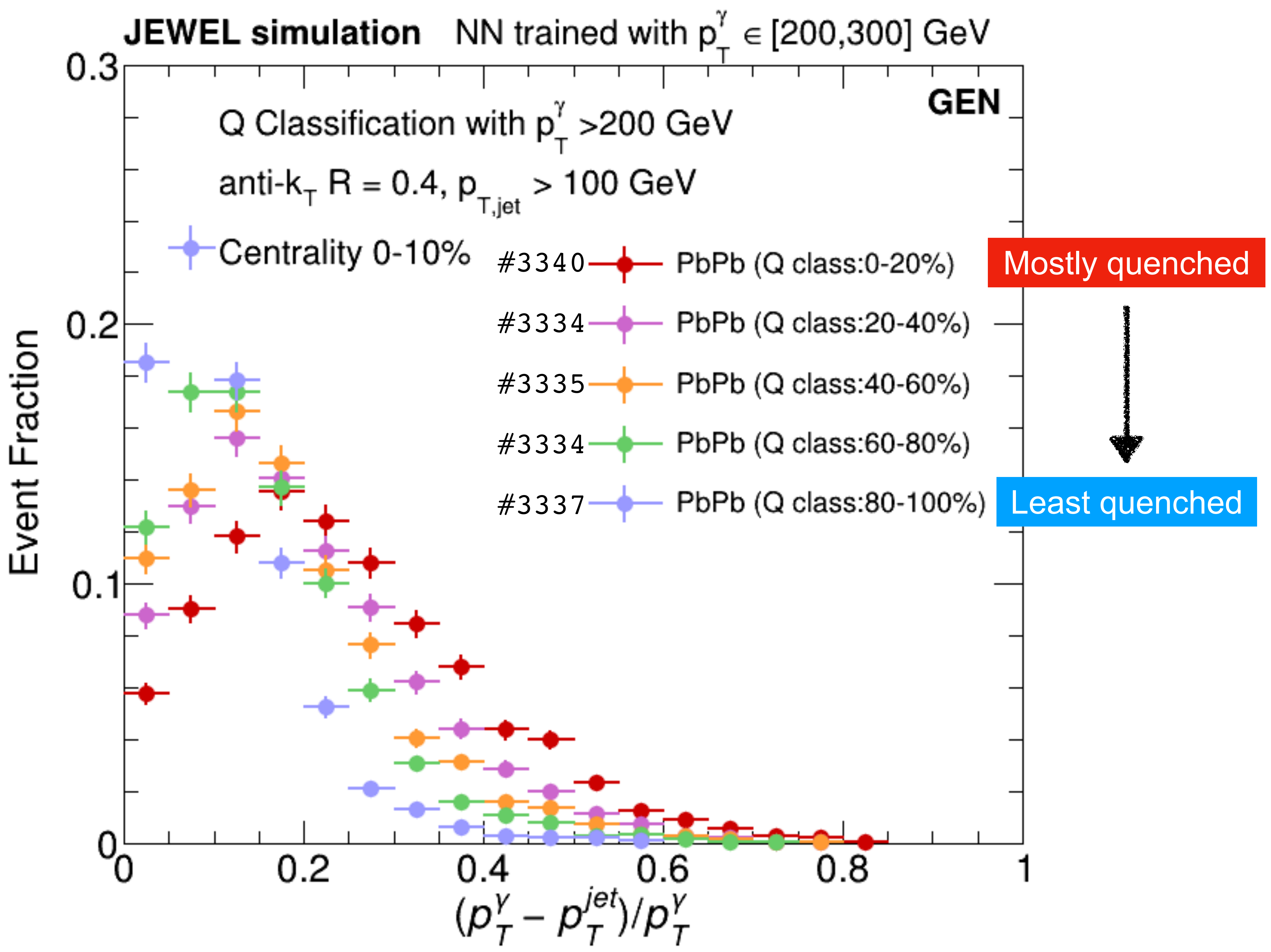
Both the input and output dimensions of the first full-connect layer are the hyper-parameters defining the architecture of the neural network.

**Paper:* *JHEP04(2023)140*

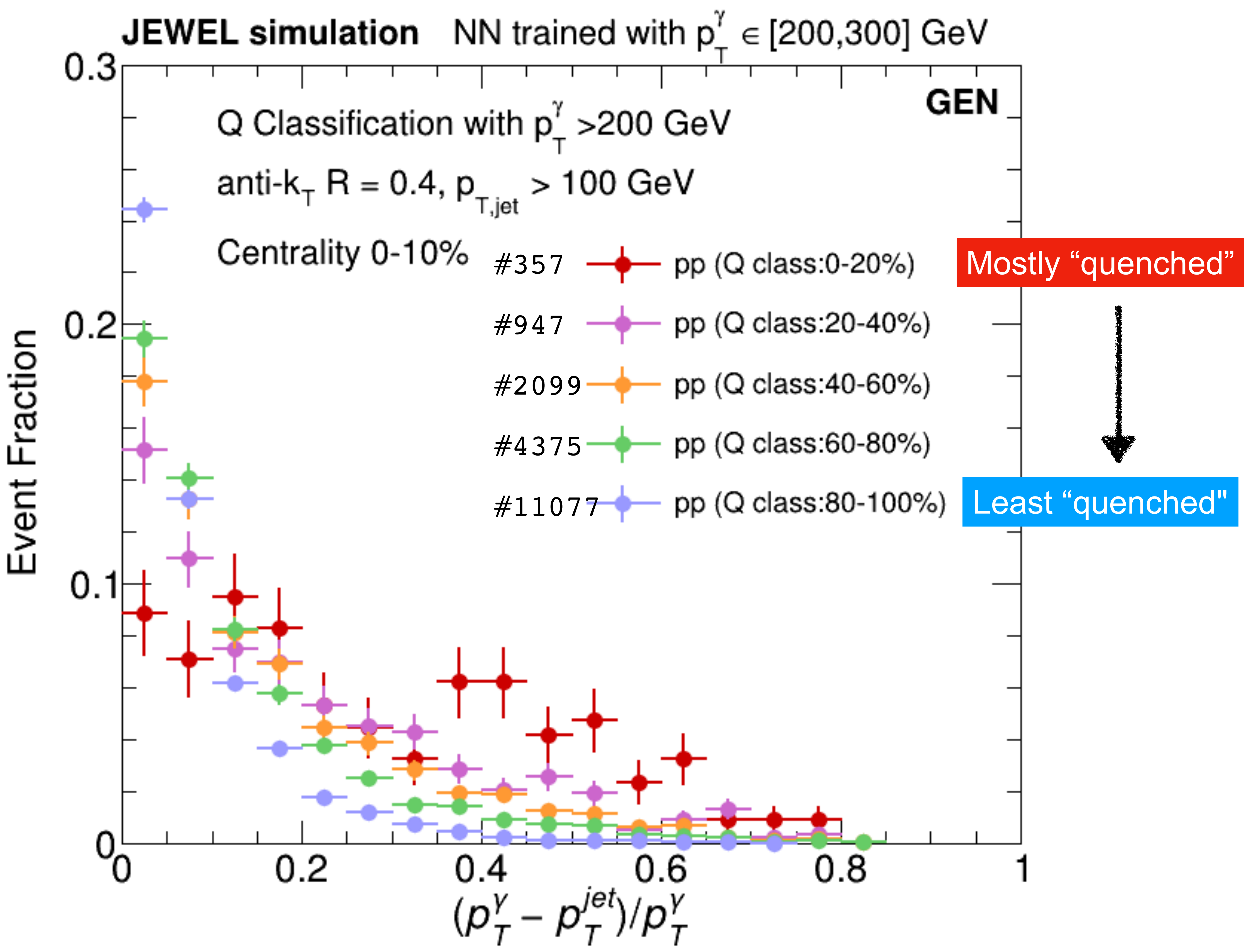


ML Classified Quenched Jets — Photon-Jet Imbalance

PbPb jets

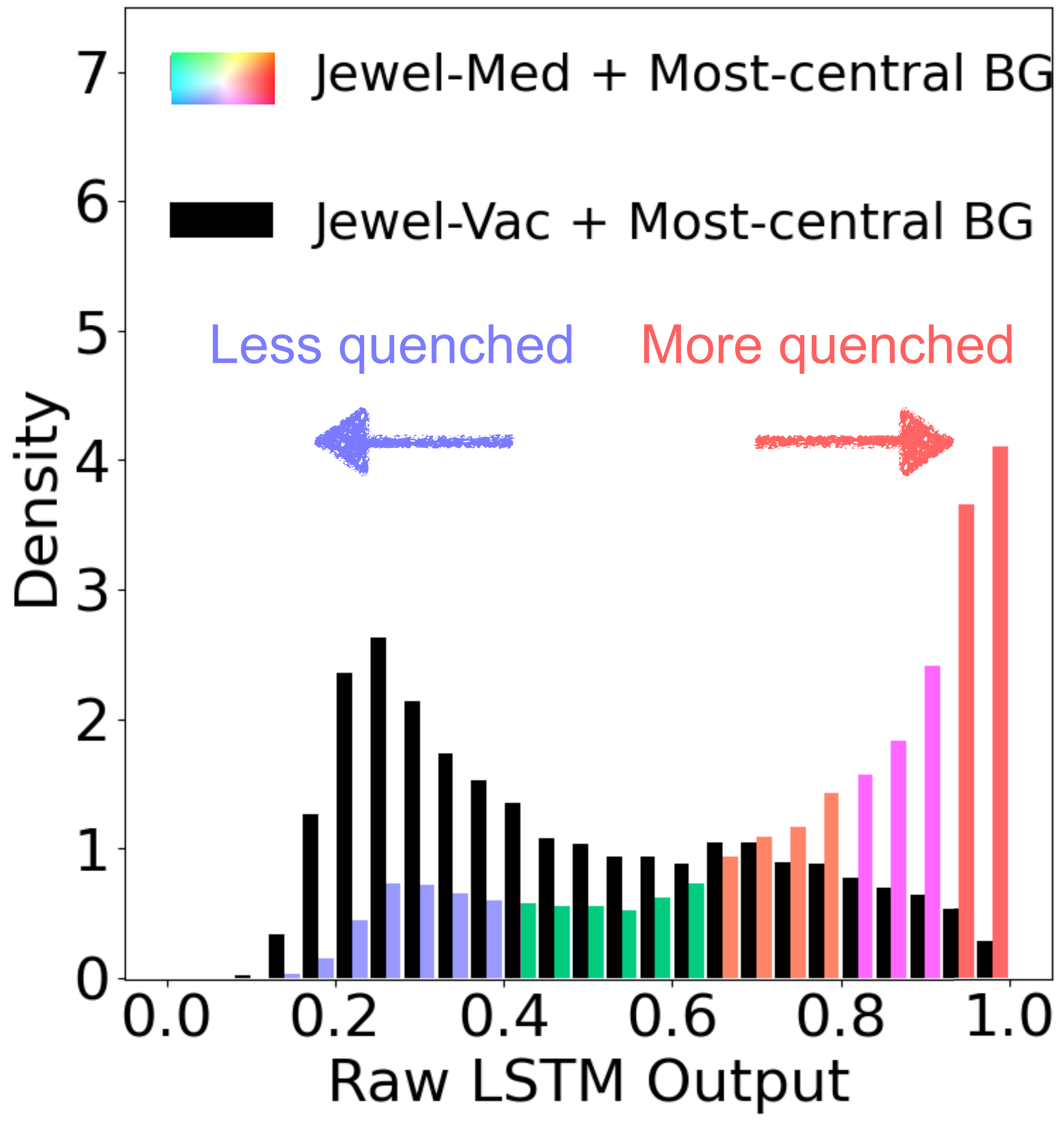


pp jets

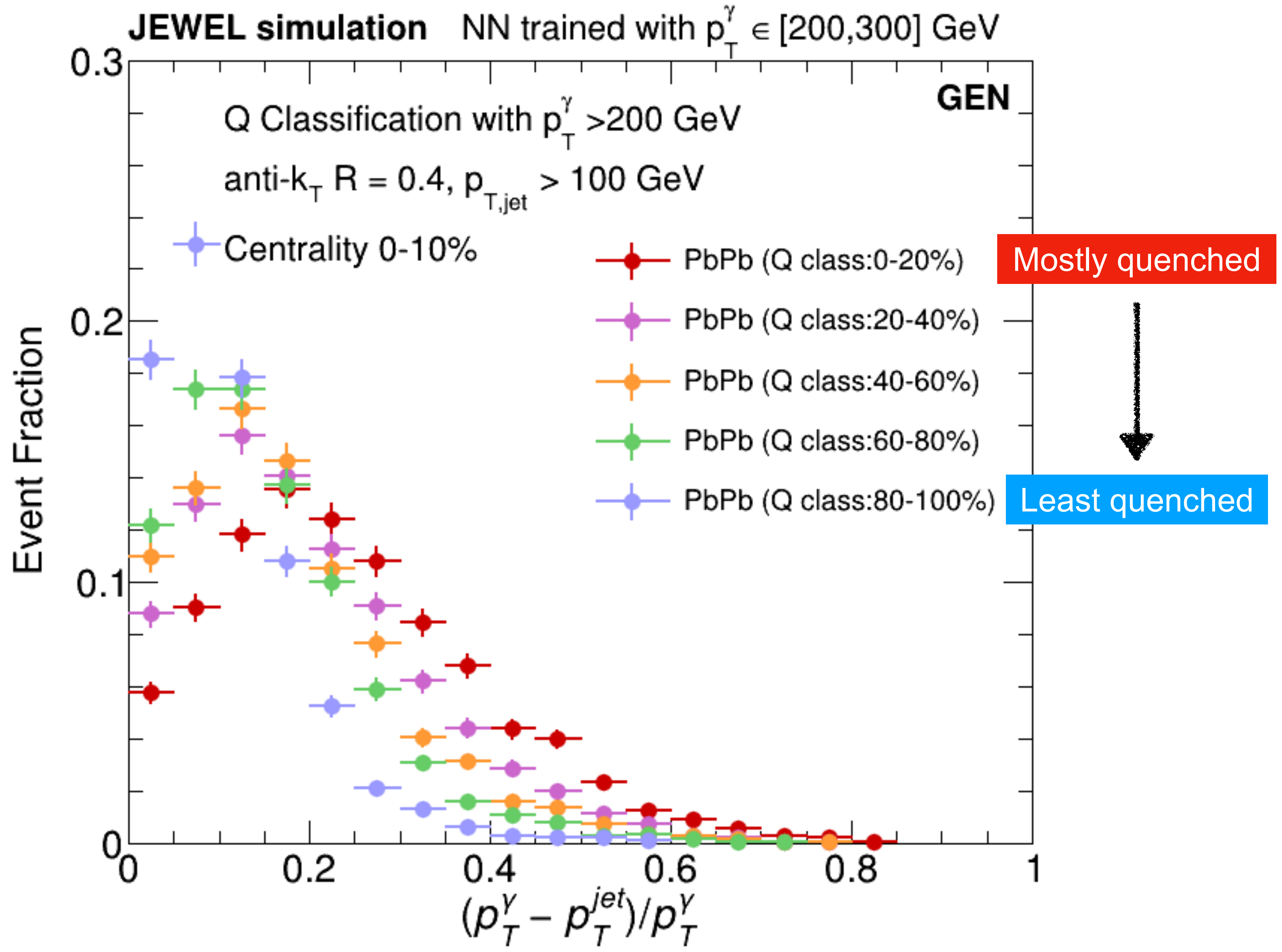


Why in pp jets there are jet with "energy loss"?
- Mismatch between photon and back-to back jet?
- Uncorrelated bkg fluctuation (pile-up simulation)?
- Does similar bias happen in PbPb when we study the quenching physics?

ML Classified Quenched Jets — Photon-Jet Imbalance



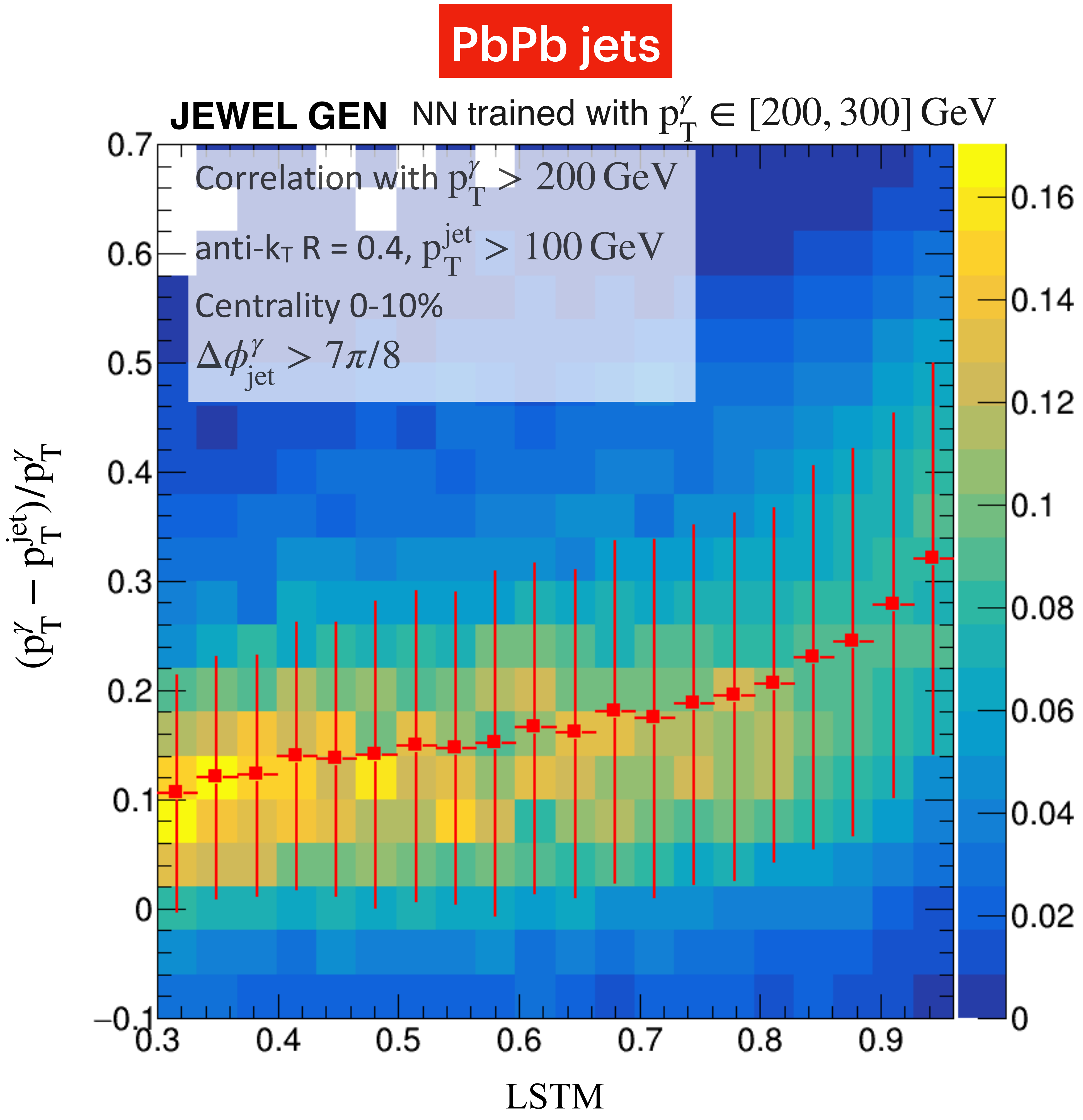
PbPb jets (Jewel-Med)

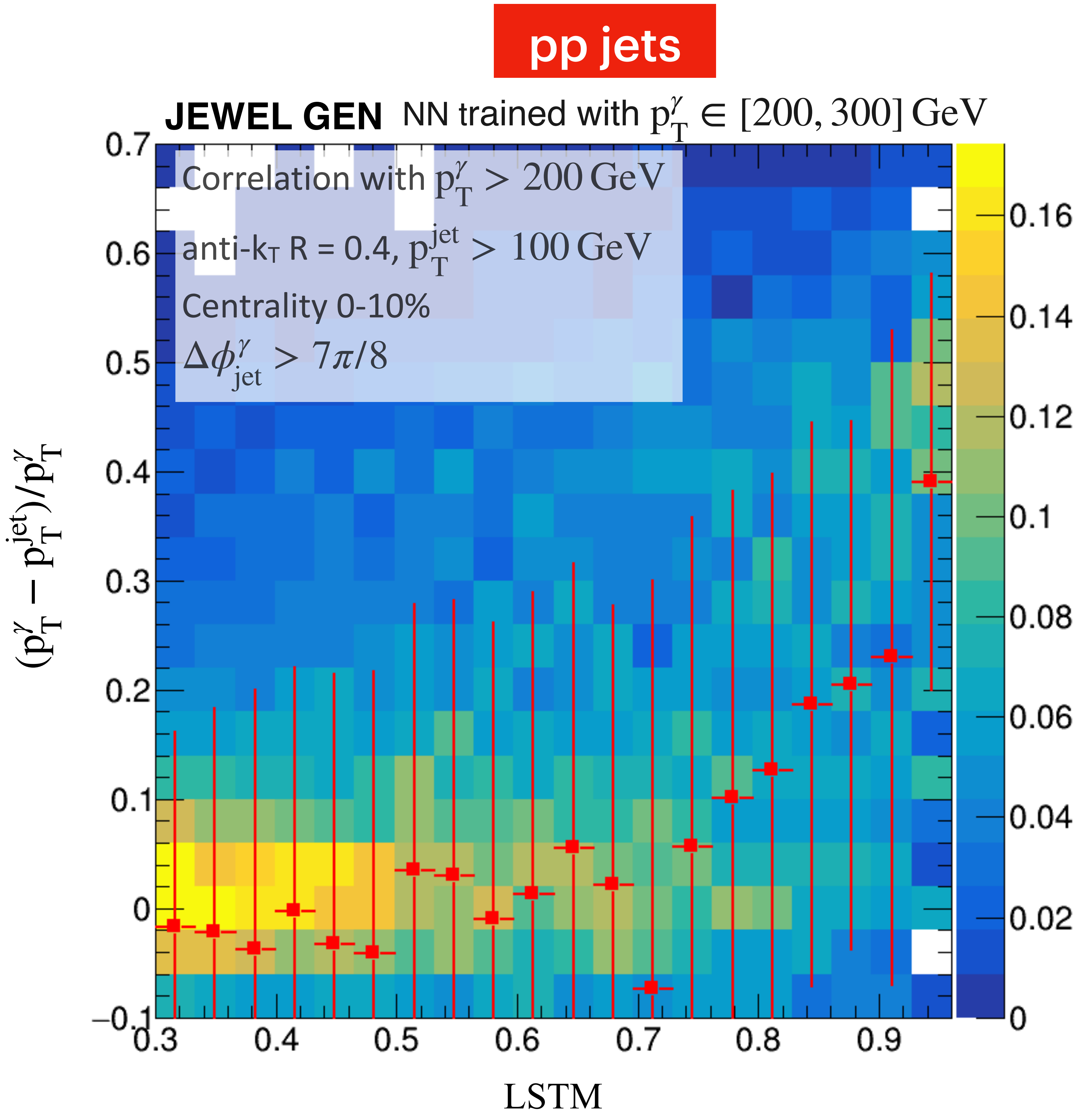


Quenchness: The LSTM output for each medium jet. If the value is closer to 1, then the jet is more quenched. And vice versa.

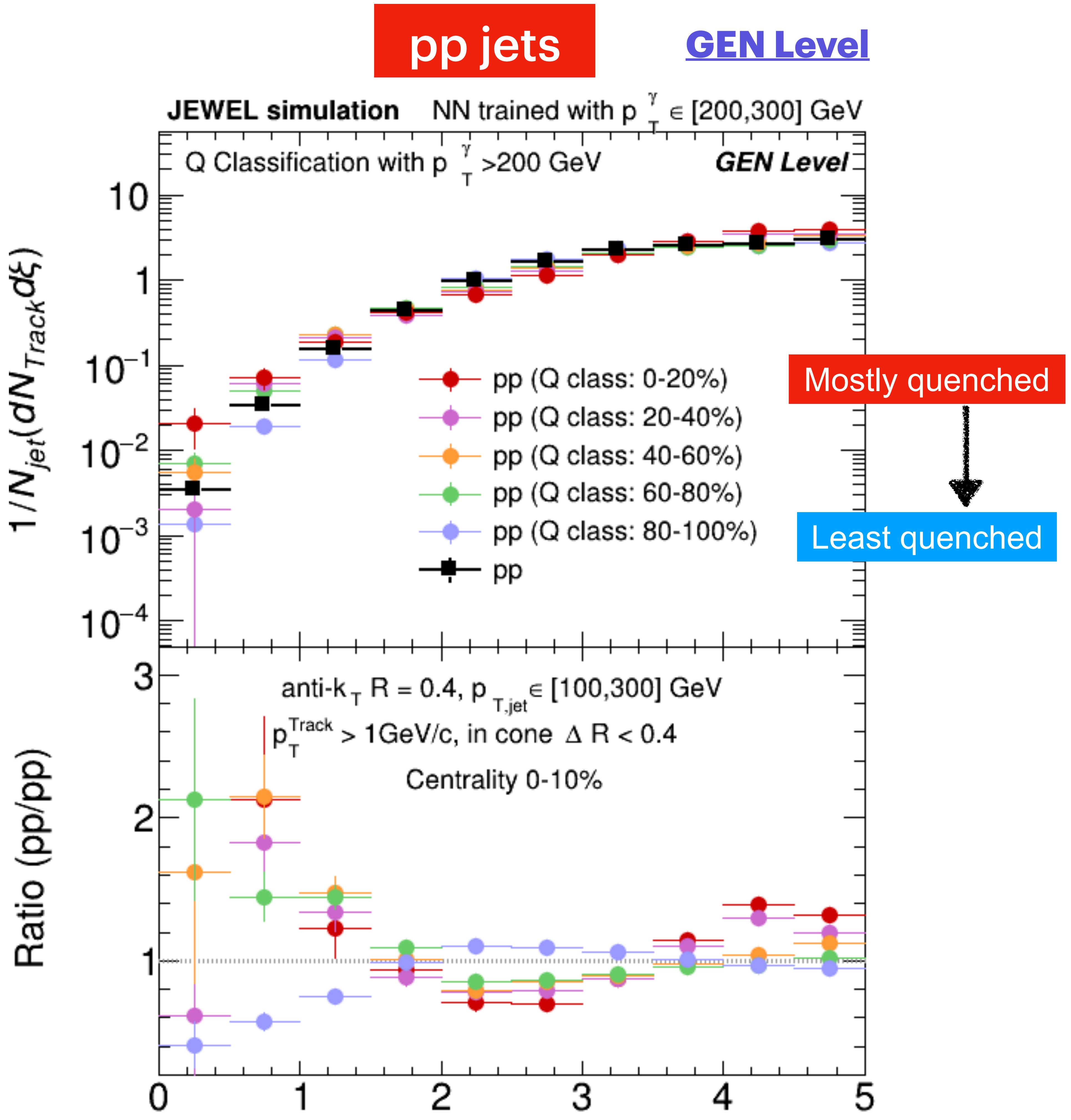
Jet energy loss is correlated with the machine learning output.

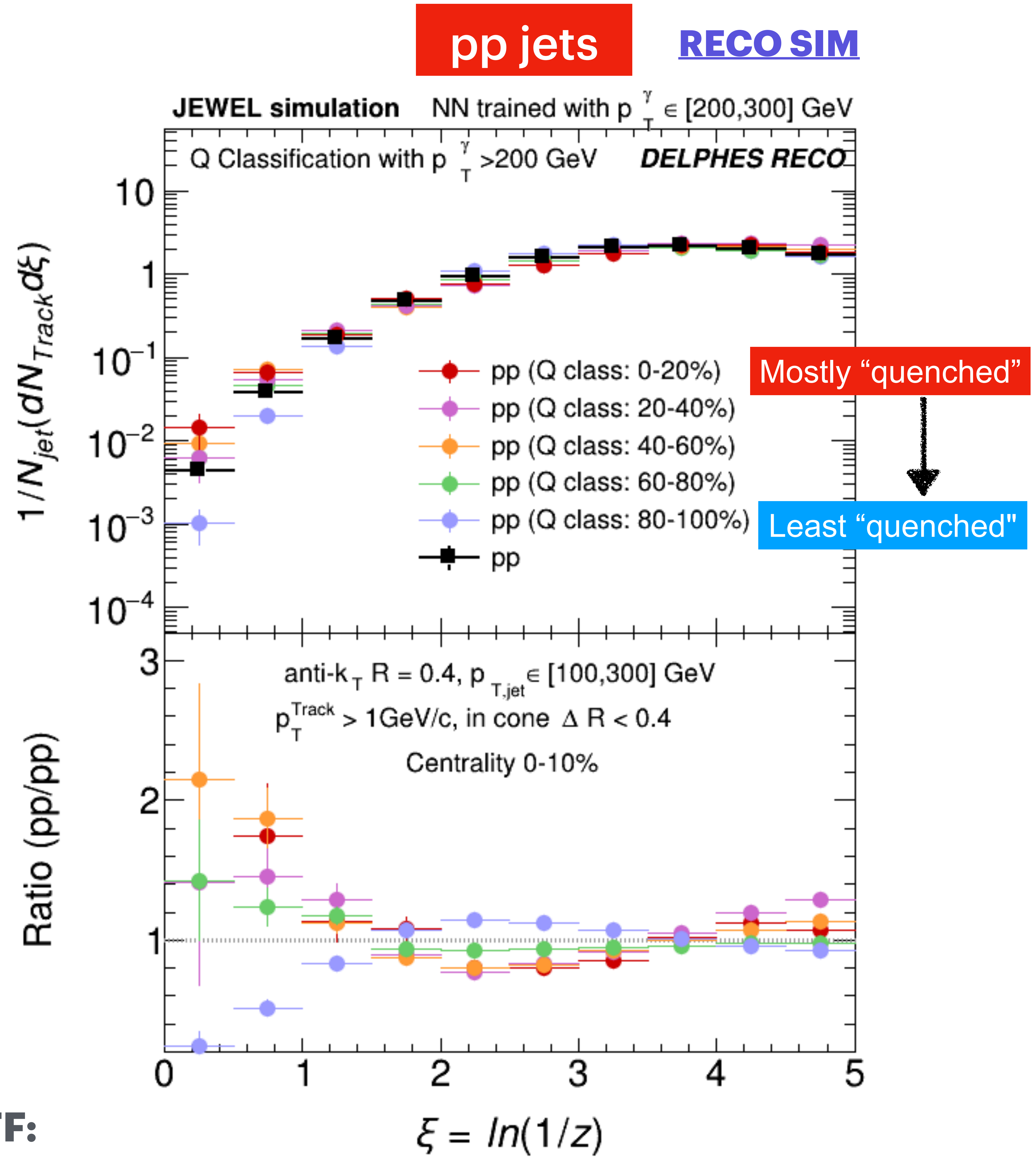
Correlation between Photon-Jet Imbalance and LSTM





Detector Effects for ML Performance: Fragmentation Function





Detector effects impact on pp JFF:

- the classification of quenching level breaks closure in large ξ region

Detector Effects for ML Performance: Photon-Jet Imbalance

PbPb jets

pp jets

GEN level jets

RECO level jets

DELPHES:
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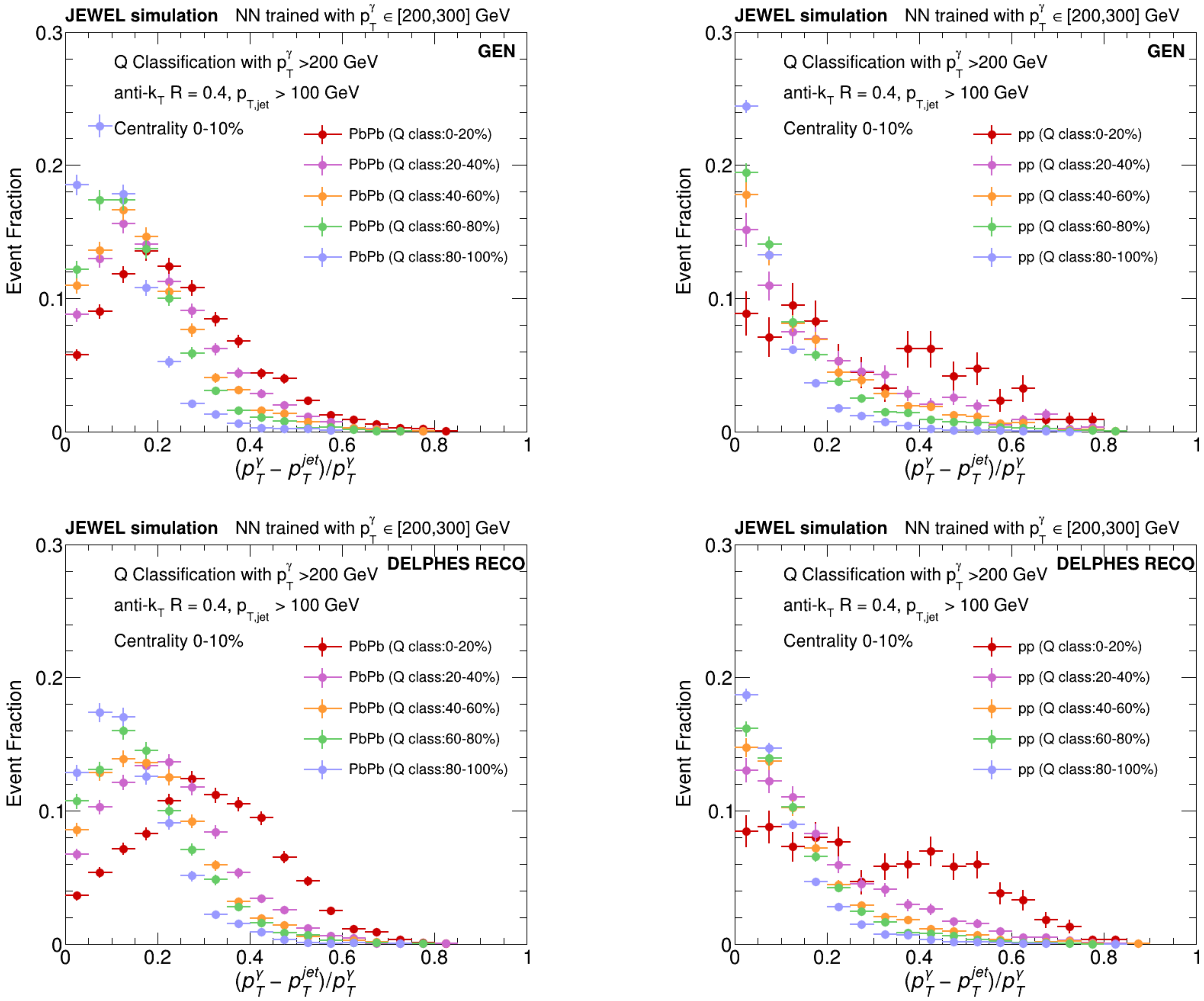
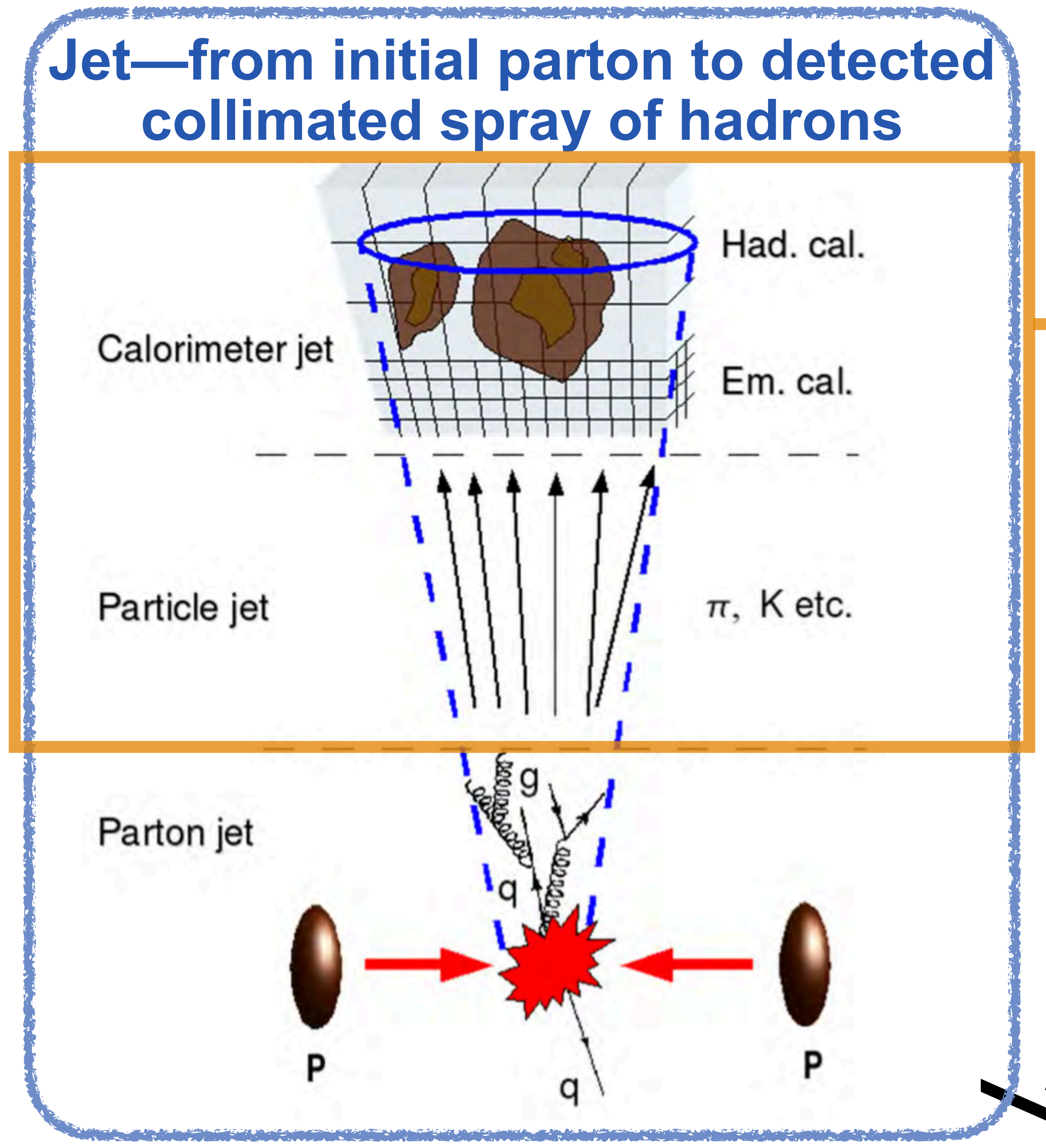
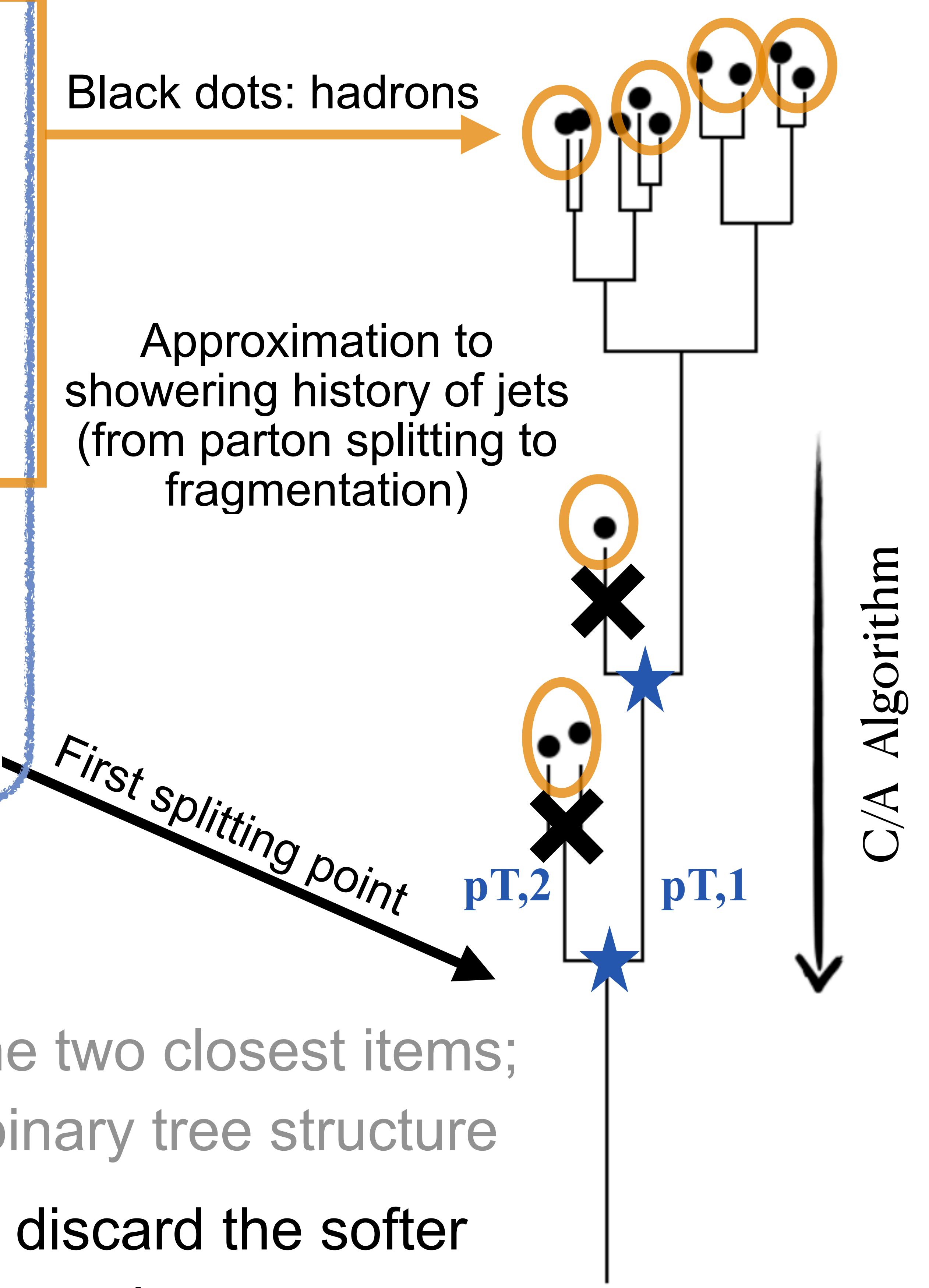


Work in progress:
Detector effects change the shape of distributions, but the ordering remains

Jet Substructures with Showering History as NN Input



Jet in a binary tree structure



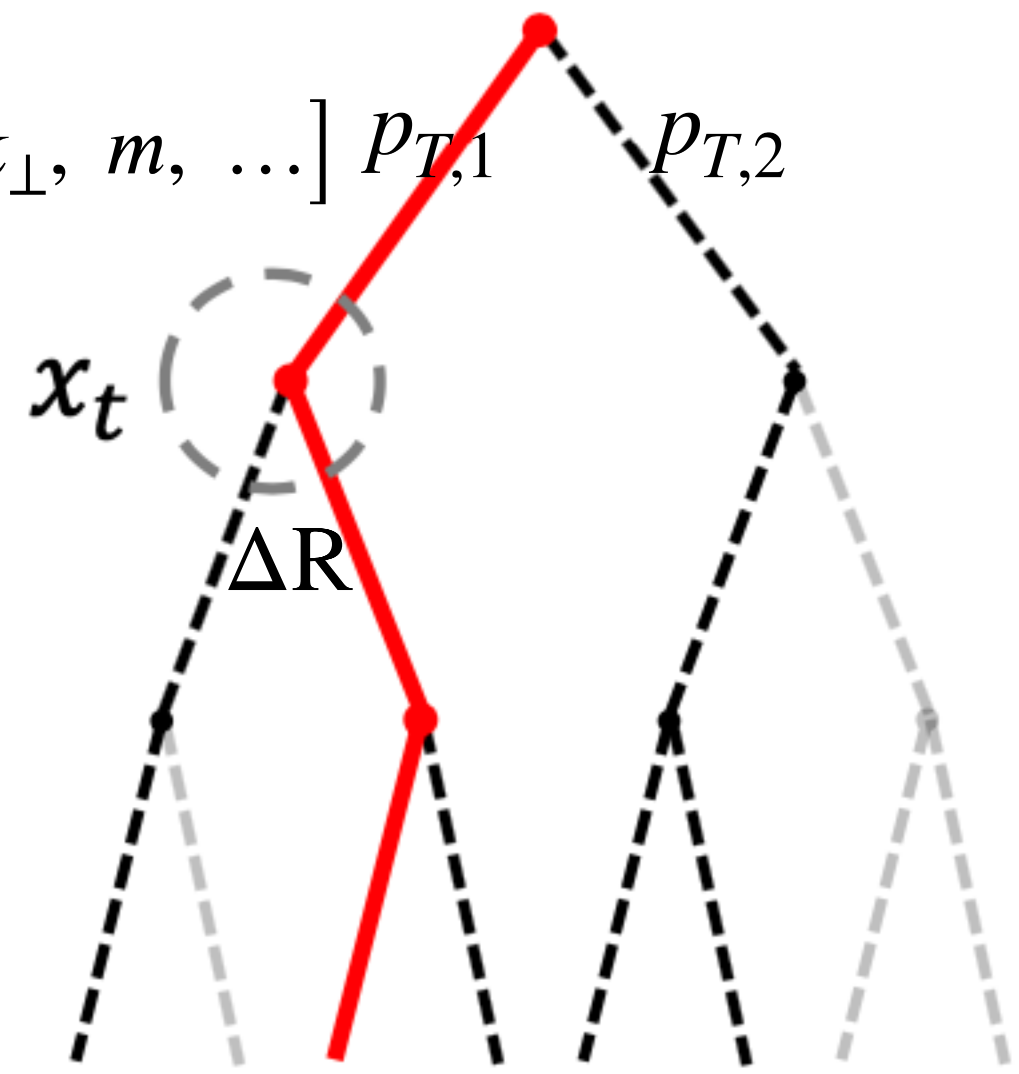
1st step: each time cluster the two closest items; eventually get the binary tree structure

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

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

Feature Engineering in this Study

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

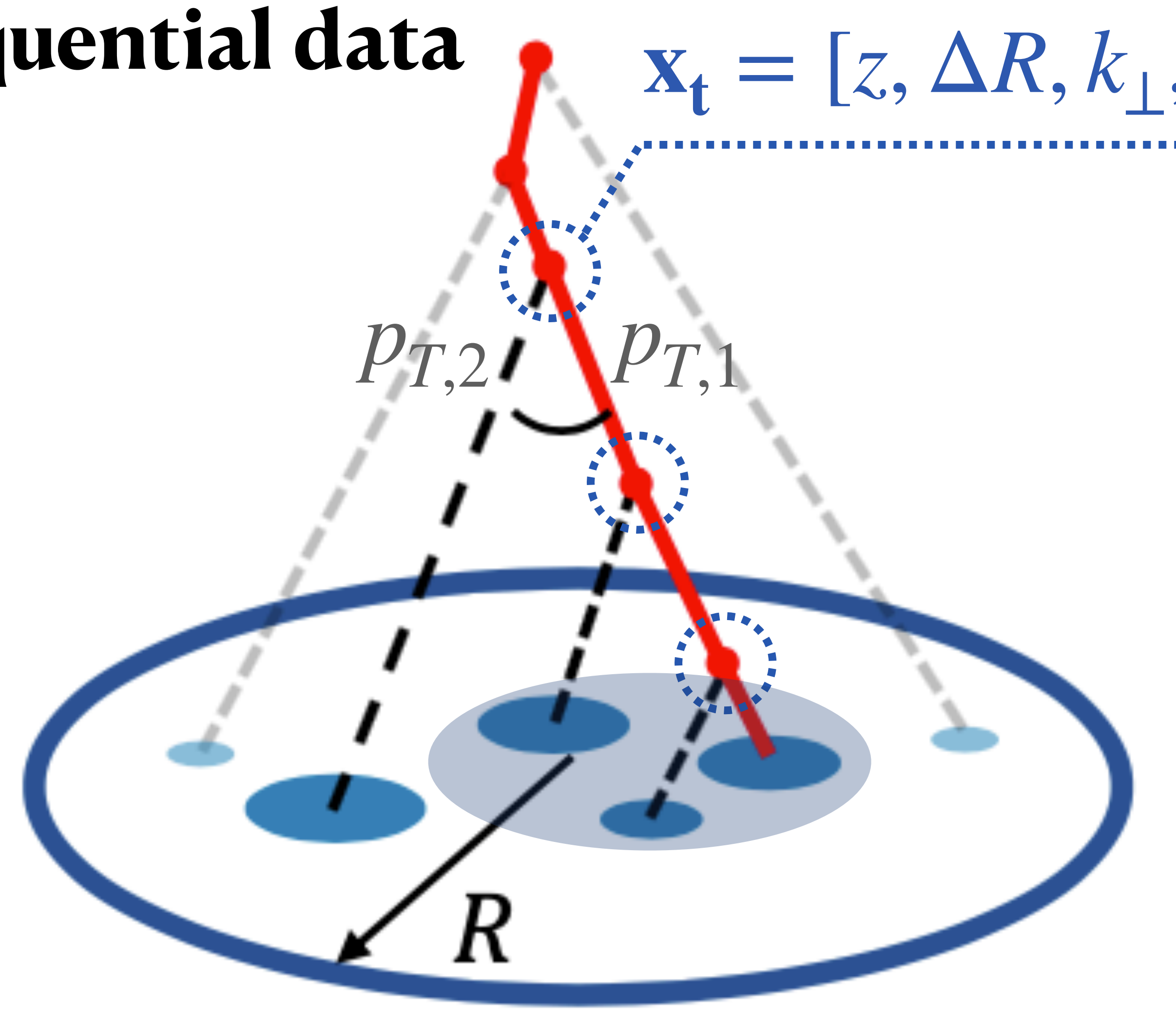
- **Jet substructure**

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

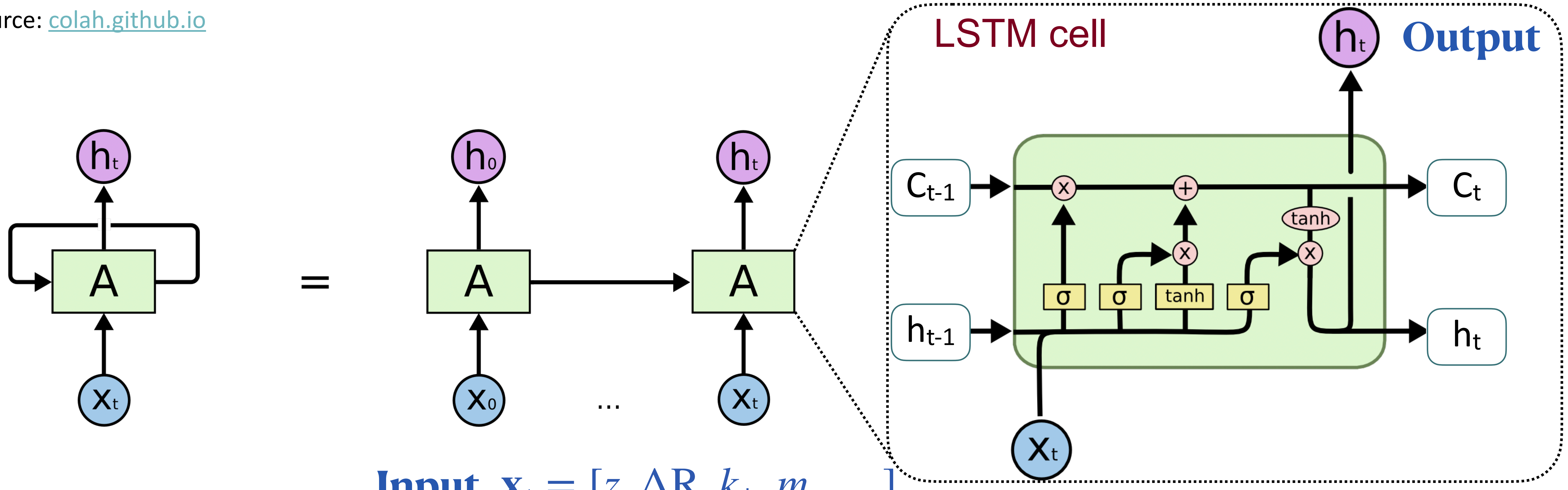
$$z = \frac{\min(p_{T,1},\ p_{T,2})}{p_{T,1} + p_{T,2}}$$ Shared momentum ratio

$$\Delta R = \sqrt{(\varphi_1 - \varphi_2)^2 + (\eta_1 - \eta_2)^2}$$ 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 $\mathbf{x_t} = [z, \Delta \mathrm{R}, k_\perp, m, \ldots]$