

Jet quenching with machine learning

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Could you introduce the machine learning applications in jet quenching?



Jet quenching refers to the phenomenon in high-energy nuclear collisions where high-energy particles known as jets lose energy as they traverse the hot and dense medium created by the collision. Machine learning has become increasingly important in jet quenching research, as it allows for the development of more efficient and accurate analysis techniques.



Here are some examples of machine learning applications in jet quenching:

1. Jet classification: Machine learning algorithms can be used to classify different types of jets, such as quark jets or gluon jets. This is important because different types of jets behave differently in the quark-gluon plasma produced in heavy-ion collisions.
2. Jet substructure analysis: Machine learning can be used to analyze the substructure of jets, which can reveal information about the particles that produced the jet and the properties of the quark-gluon plasma. For example, jet substructure analysis can help distinguish between jets produced by a single high-energy particle and jets produced by multiple lower-energy particles.
3. Event-by-event fluctuation studies: Machine learning can be used to study event-by-event fluctuations in jet production, which can provide information about the properties of the quark-gluon plasma. For example, machine learning can be used to identify events where there is a higher probability of jet quenching occurring.
4. Anomaly detection: Machine learning can be used to identify rare or anomalous events in jet production. For example, machine learning can be used to identify events where the quark-gluon plasma is particularly hot or dense, or events where there is evidence of exotic particles or interactions.



Could you summarize some references on this topic?



Sure, here are some recent papers on the topic of machine learning applications in jet quenching:



1. "Jet physics in heavy-ion collisions at the LHC with machine learning" by Simone Amoroso et al. (arXiv:2101.03112). This review paper provides an overview of the state of the art in machine learning applications to jet physics in heavy-ion collisions.
2. "Machine learning for jet substructure with Recursive Soft Drop" by Luke de Oliveira et al. (arXiv:2010.15830). This paper presents a new machine learning technique for analyzing jet substructure called Recursive Soft Drop, which improves the accuracy of substructure analyses.
3. "Deep Learning for Jet Substructure at the Large Hadron Collider" by Andrew Larkoski et al. (arXiv:1709.04464). This paper provides an introduction to machine learning techniques for jet substructure analysis, and presents several case studies demonstrating the effectiveness of these techniques.
4. "Machine learning assisted jet quenching analysis" by Xiaojian Bai et al. (arXiv:2009.14460). This paper presents a machine learning assisted analysis method for jet quenching experiments, which improves the sensitivity of the analysis and reduces the impact of systematic uncertainties.
5. "Uncovering the Dynamics of Jet Quenching with Machine Learning" by Minho Kim et al. (arXiv:2007.00060). This paper applies machine learning techniques to identify correlations between jet properties and the properties of the quark-gluon plasma produced in heavy-ion collisions, providing new insights into the dynamics of jet quenching.



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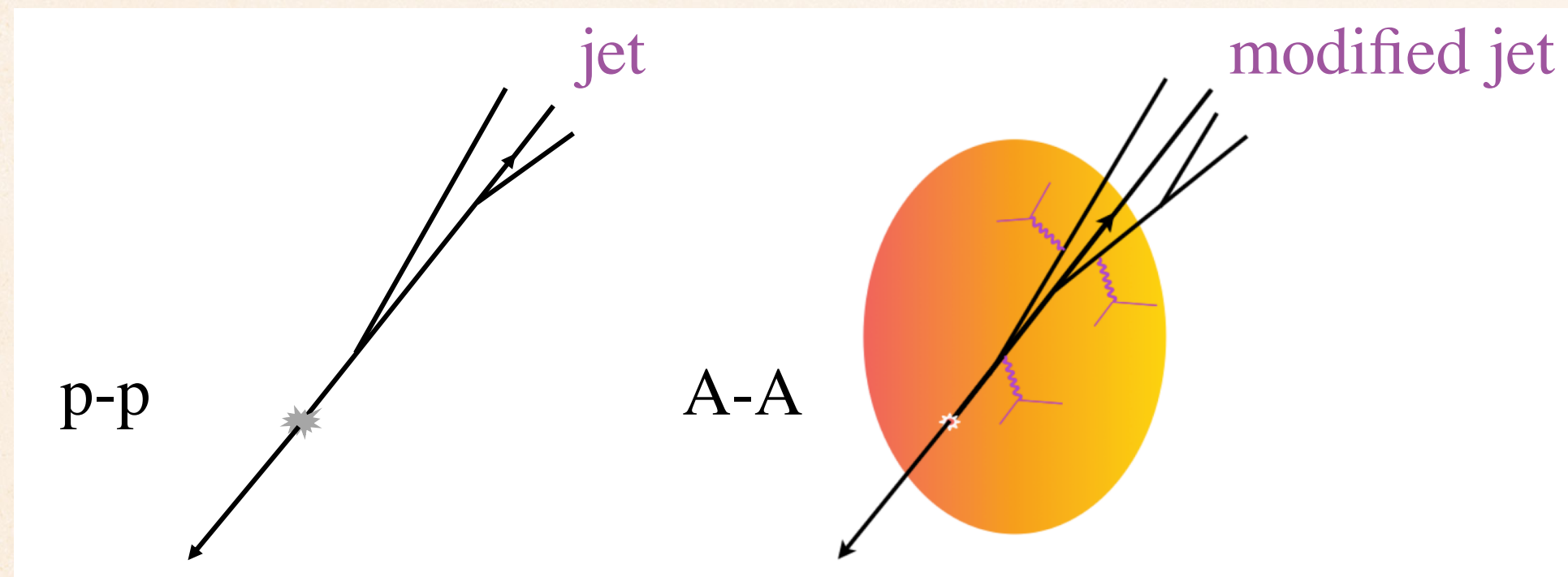
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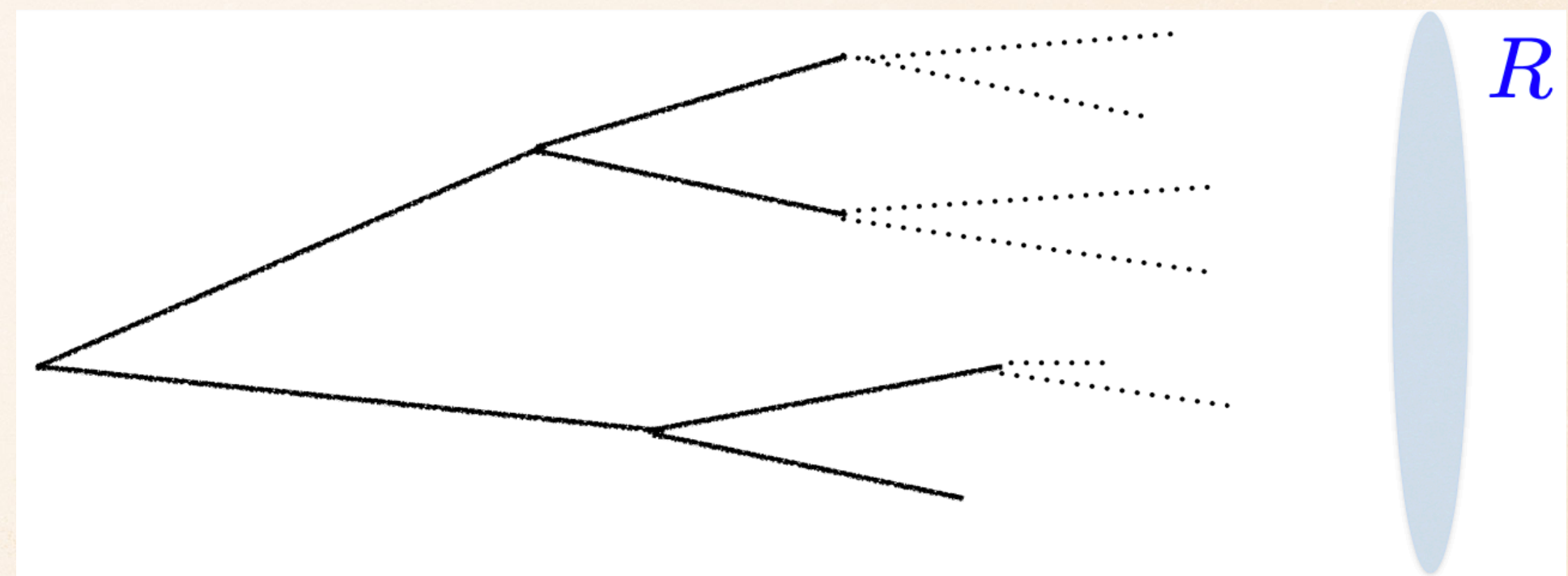
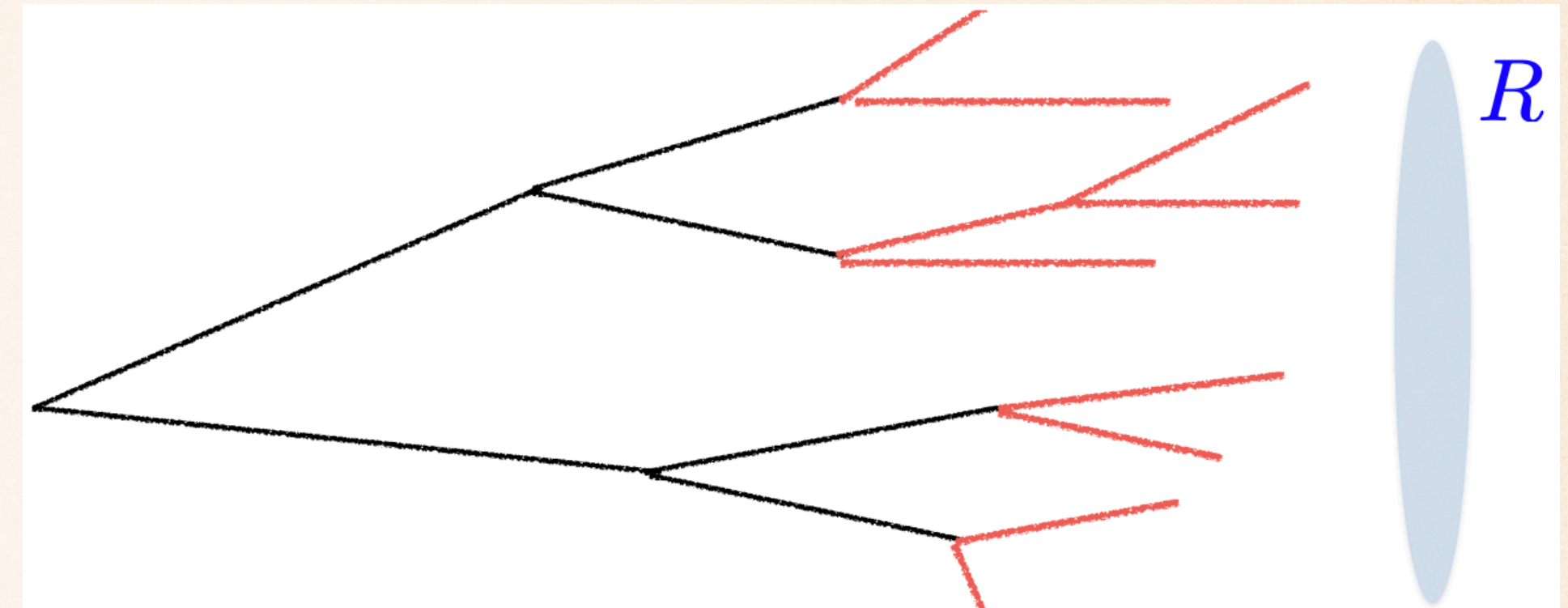
None exists!!

QGP and Jet Modifications



By J. Brewer

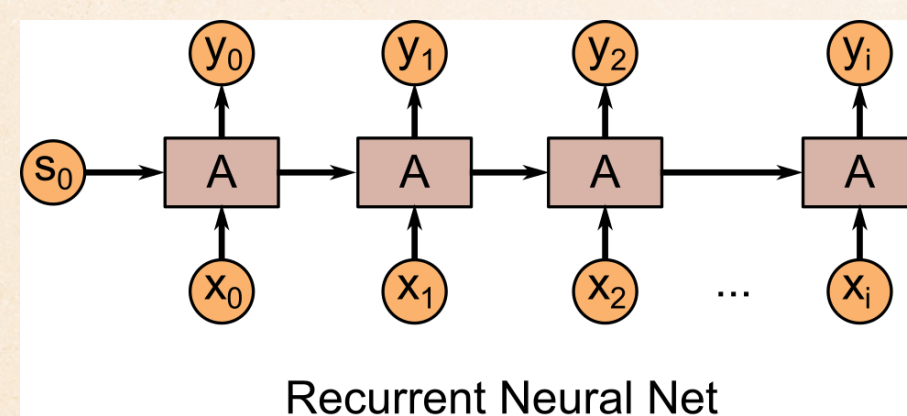
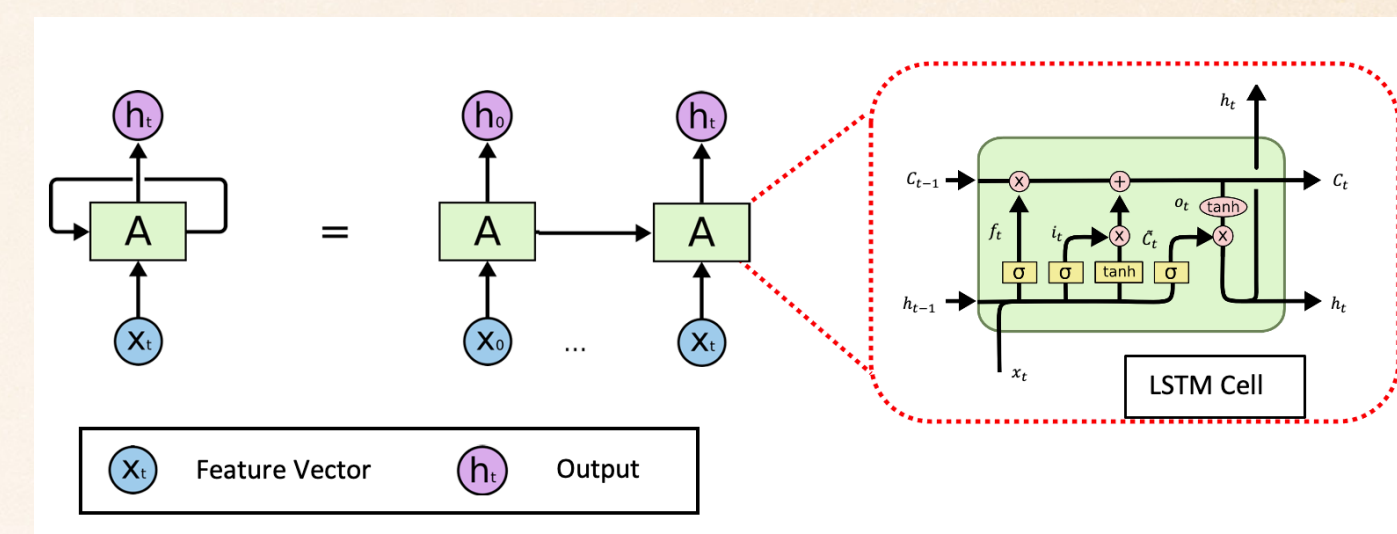
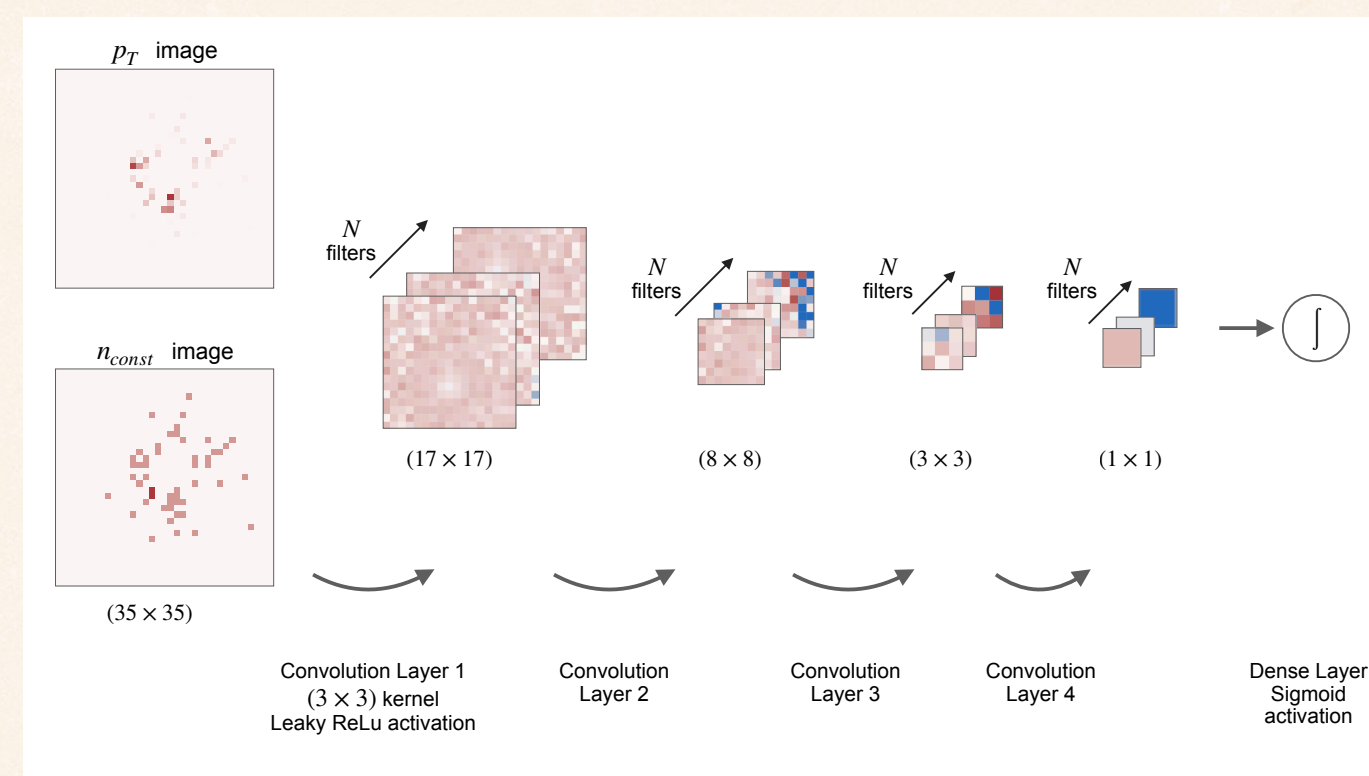
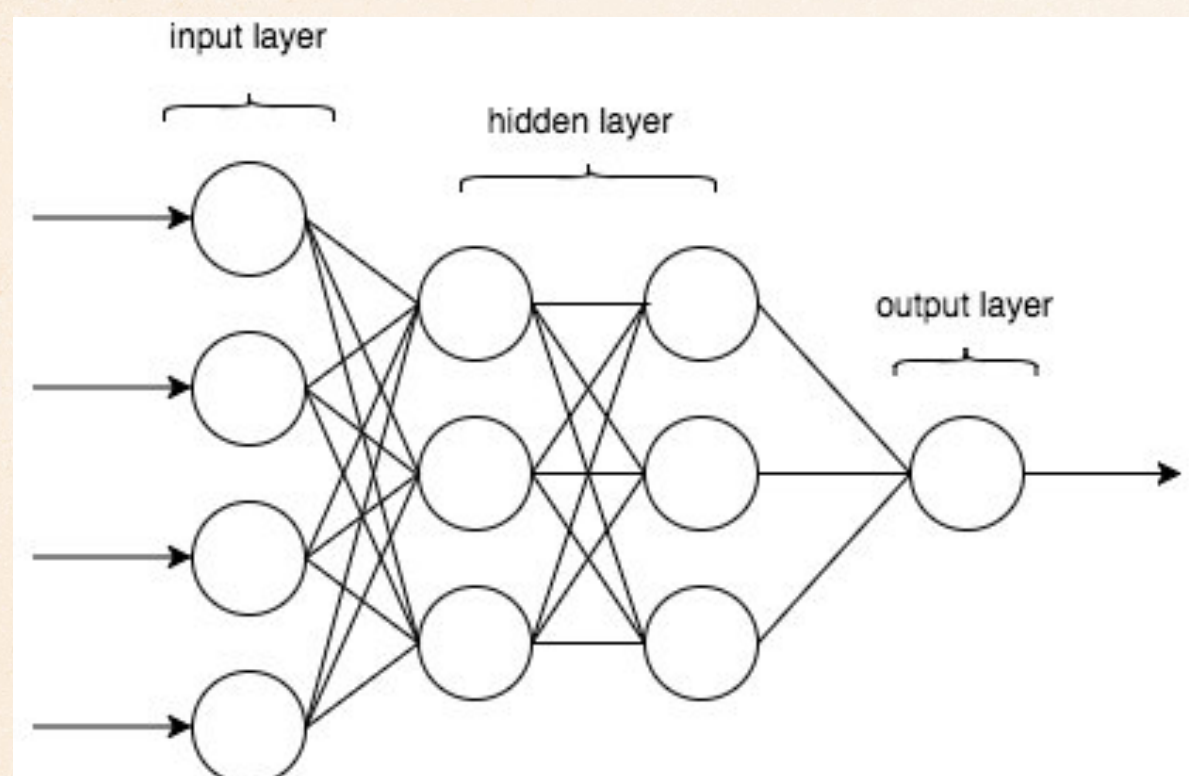
- ◆ Jets are powerful probes to QGP
 - QGP: AA collisions at \sqrt{s} with different centralities
 - Jets (dijets, γ/Z -jets): initiator's flavor, energy, position, direction and jet substructures developed at early stages
 - Jet-medium interactions
- ◆ Towards more precise probes & jet tomography with ML



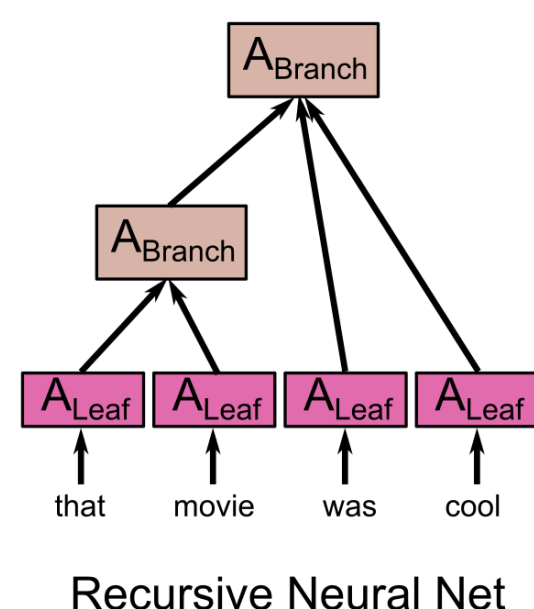
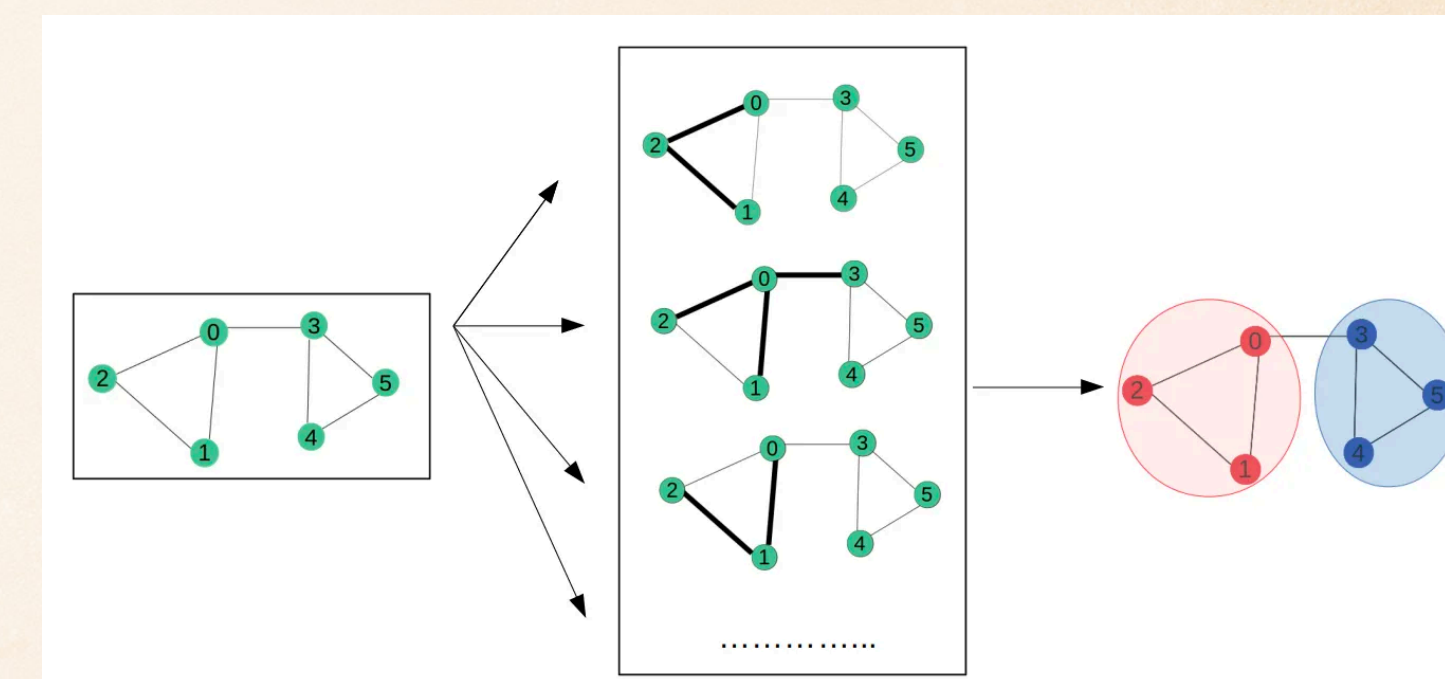
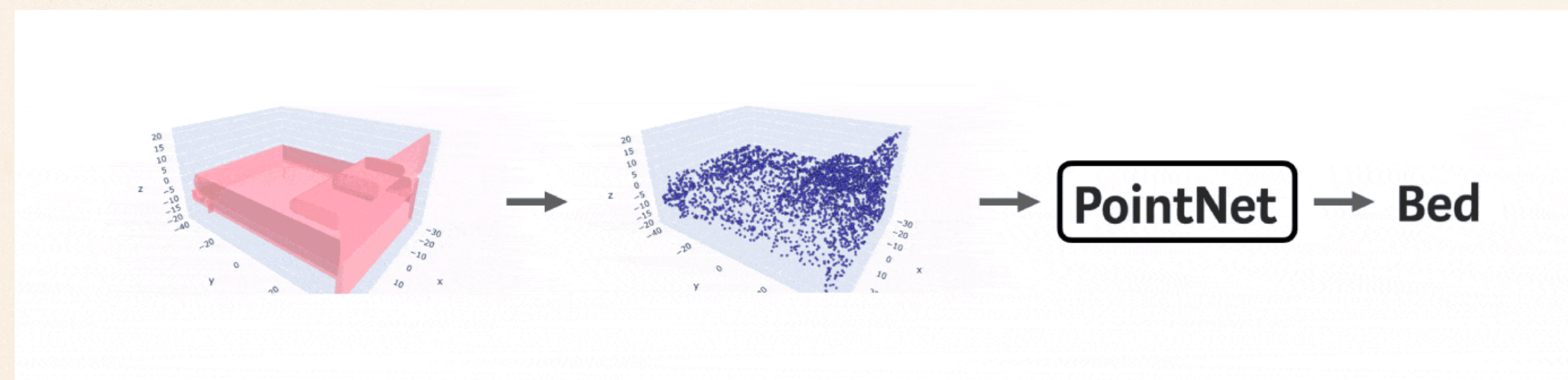
By D. Pablos

Hypethetical twin jets in vacuum/medium

Various ML tools for jets



Recurrent Neural Net



Recursive Neural Net

❖ Many tools suit a lot for jets

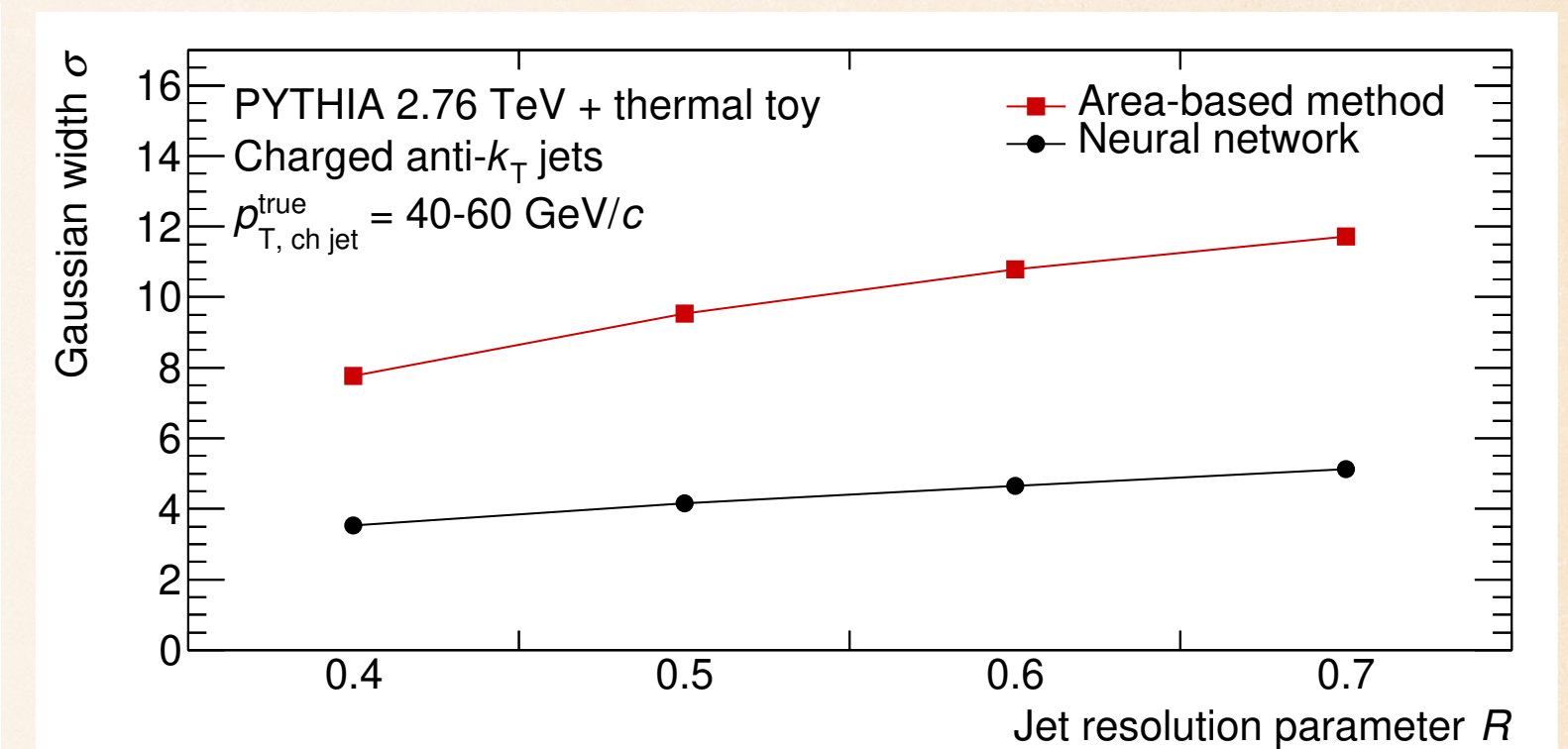
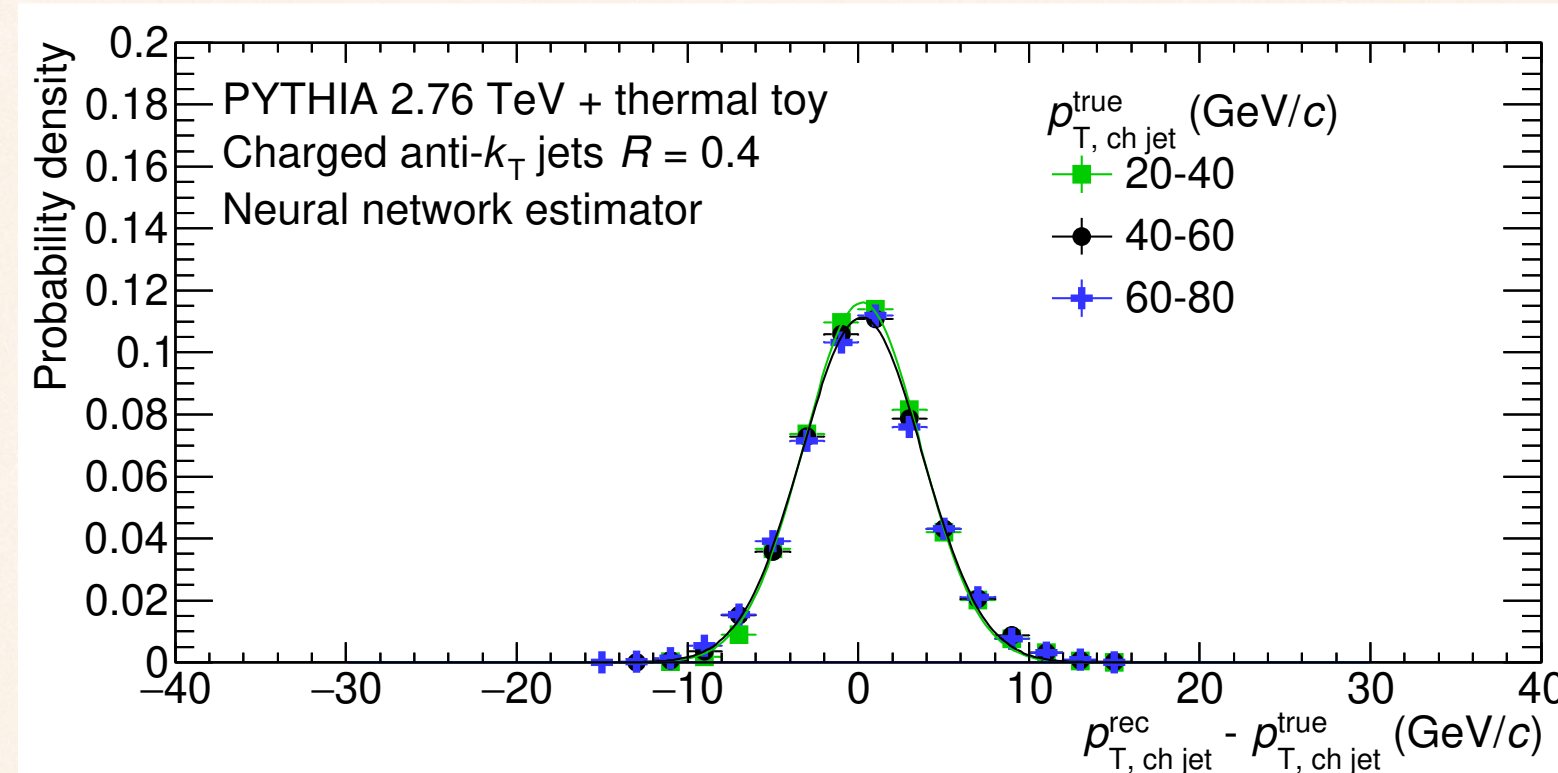
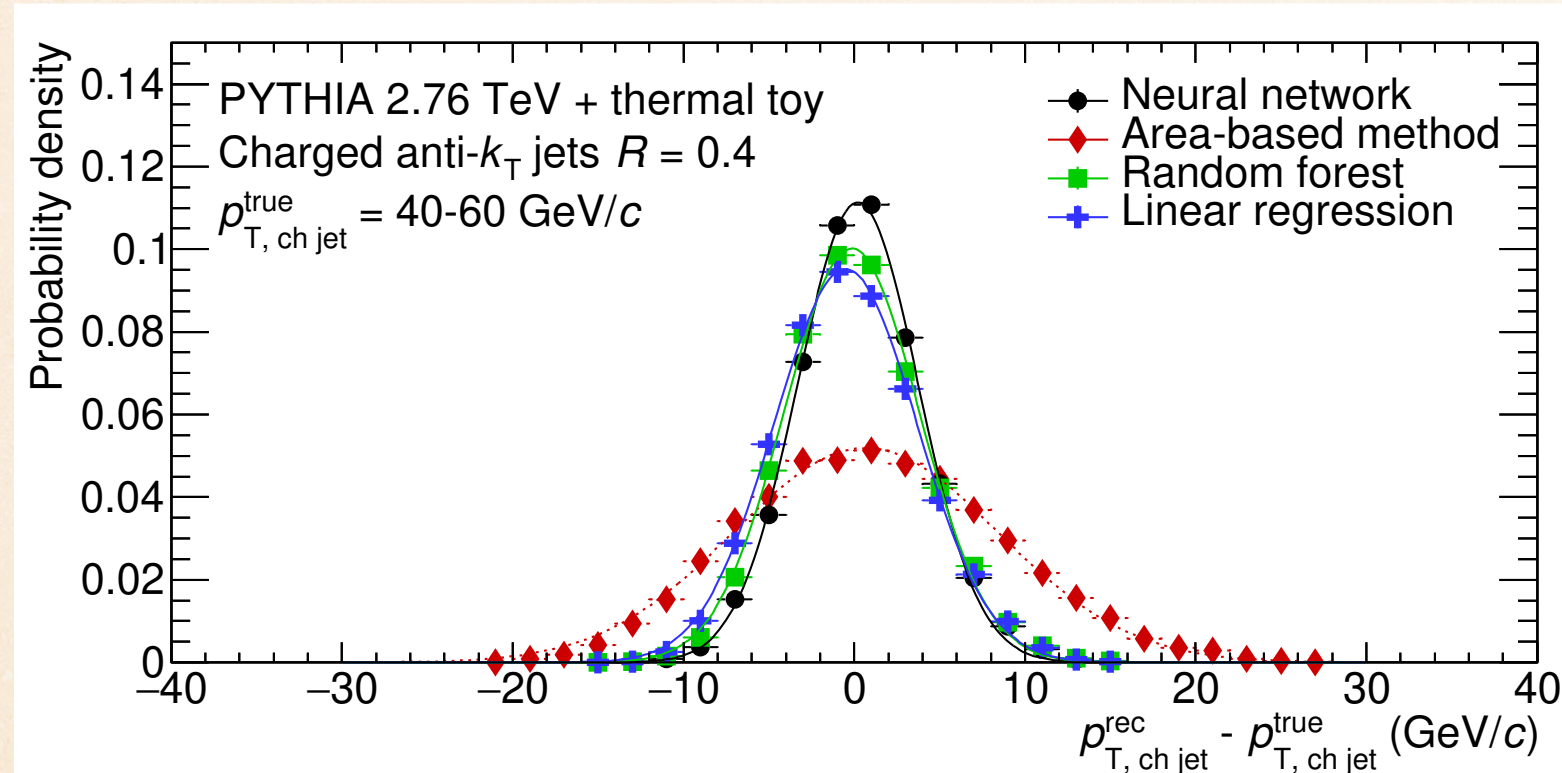
❖ A tremendous amount of applications in HEP [arXiv:2102.02770](https://arxiv.org/abs/2102.02770)

Outline

- ❖ Jet Momentum Reconstruction
- ❖ Classification of Quark/Gluon Jets
- ❖ Classification of Quenched Jets
- ❖ Prediction of Jet Energy Loss
- ❖ Prediction of Jet Production Positions

Jet Momentum Reconstruction

R. Haake and C. Loizides, PHYS. REV. C 99, 064904 (2019)



$$p_{T, \text{ch jet}}^{\text{rec}} = p_{T, \text{ch jet}}^{\text{raw}} - \rho A$$

$$p_{T, \text{ch jet}}^{\text{true}} = p_{T, \text{ch jet}}^{\text{raw}} \cdot \frac{\sum_i p_{T, \text{const } i}^{\text{PYTHIA}}}{\sum_i p_{T, \text{const } i}}$$

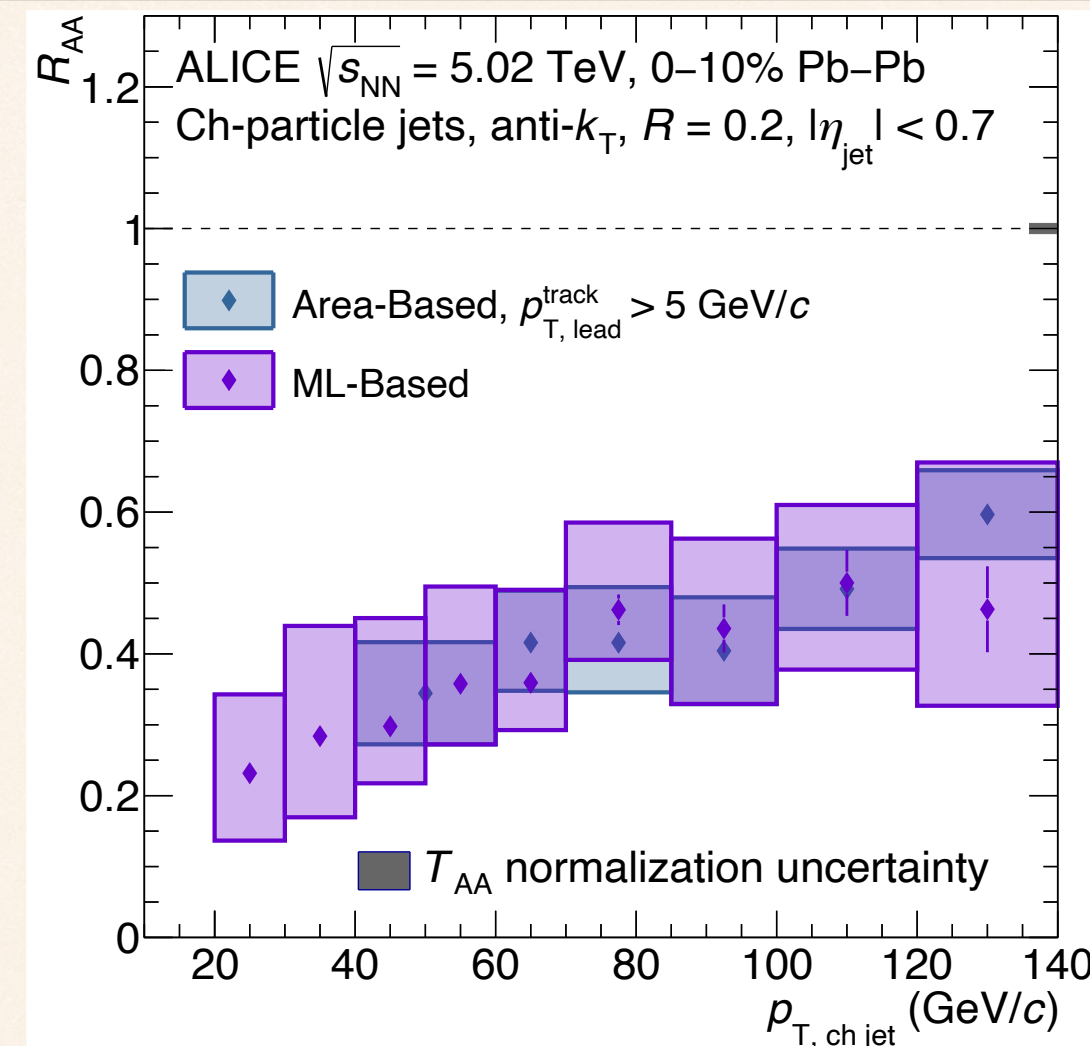
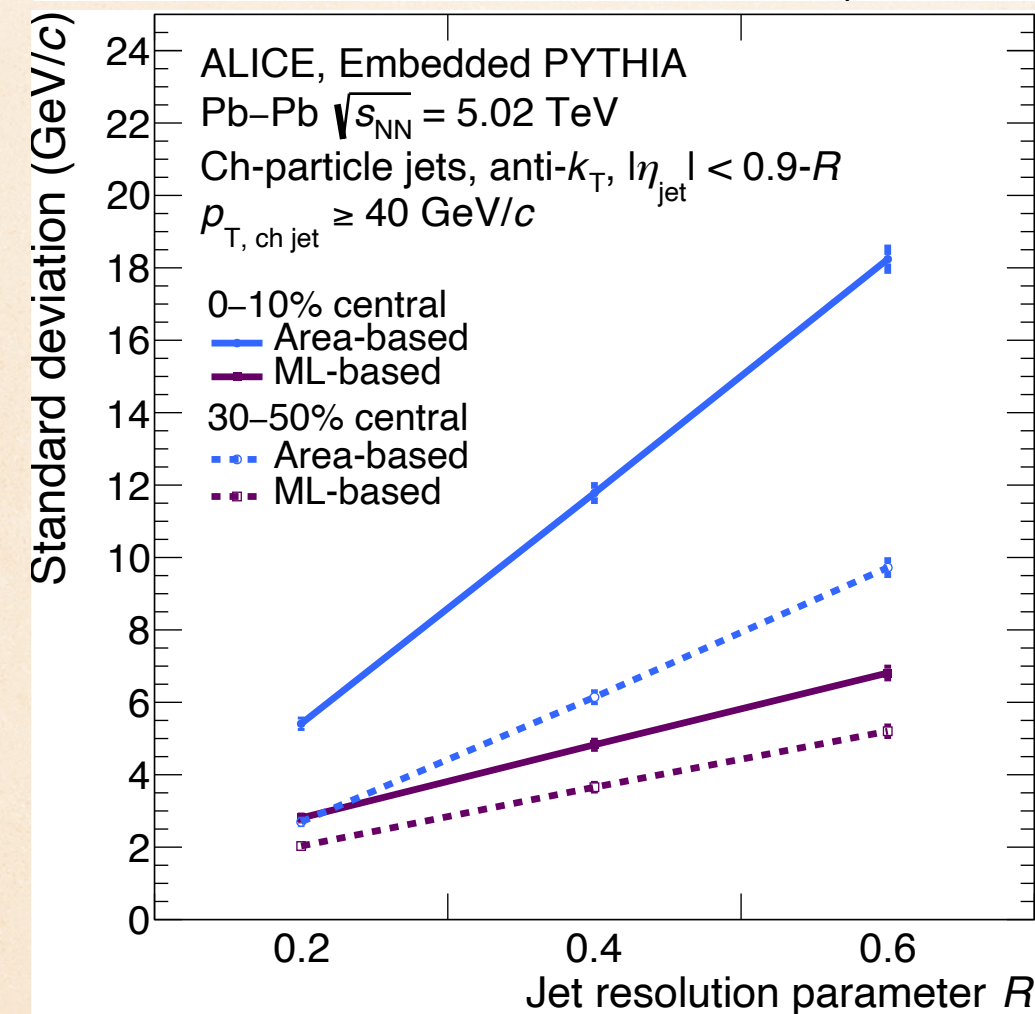
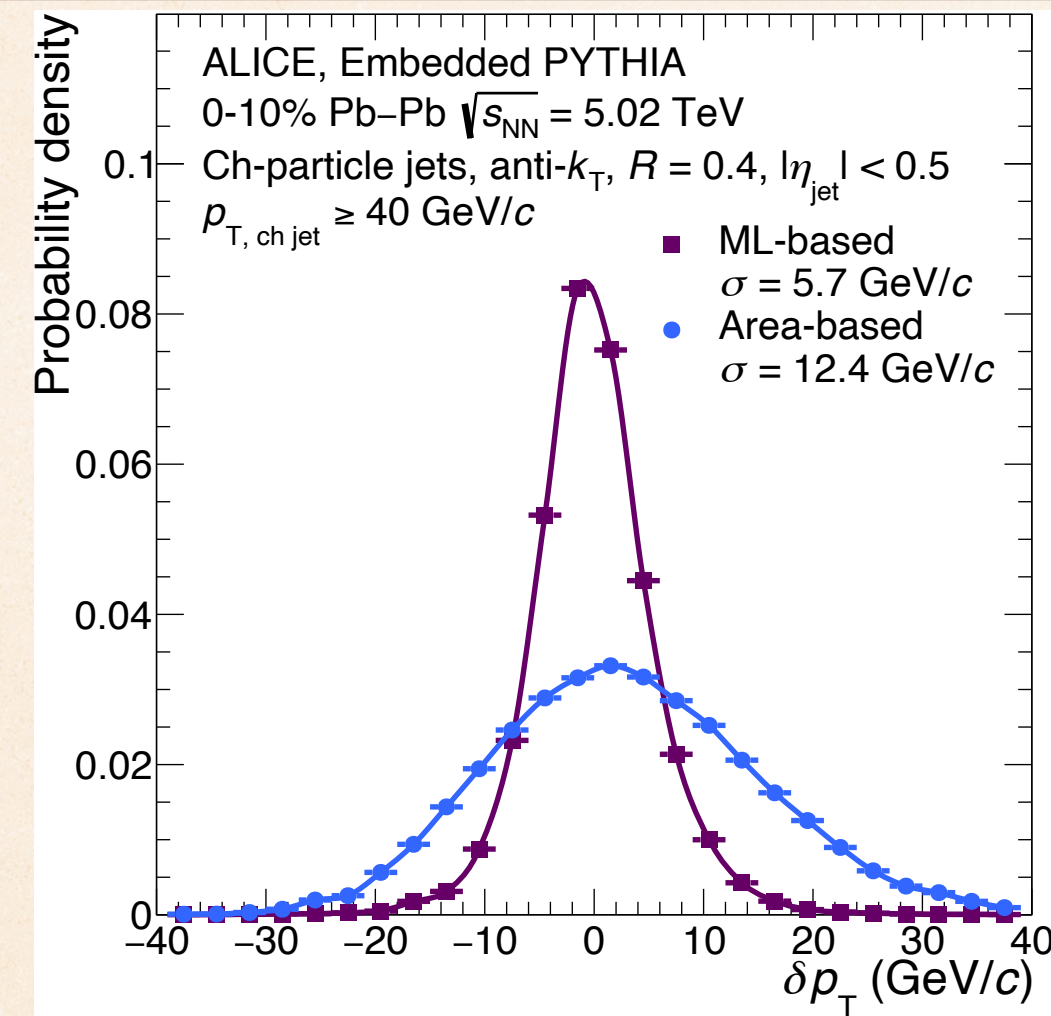
- ❖ **Pythia** jets embedded in a toy thermal model
- ❖ Linear Regression, Random Forest (decision trees), Neural Network
- ❖ Enable low- p_T large- R jet measurements

In order to find a suitable combination of input parameters, the analysis was repeated for a large variety of parameter sets. The number of parameters used is kept small to avoid a dependence on data subtleties. Eventually, the following input parameters prove to be useful, discriminative features:

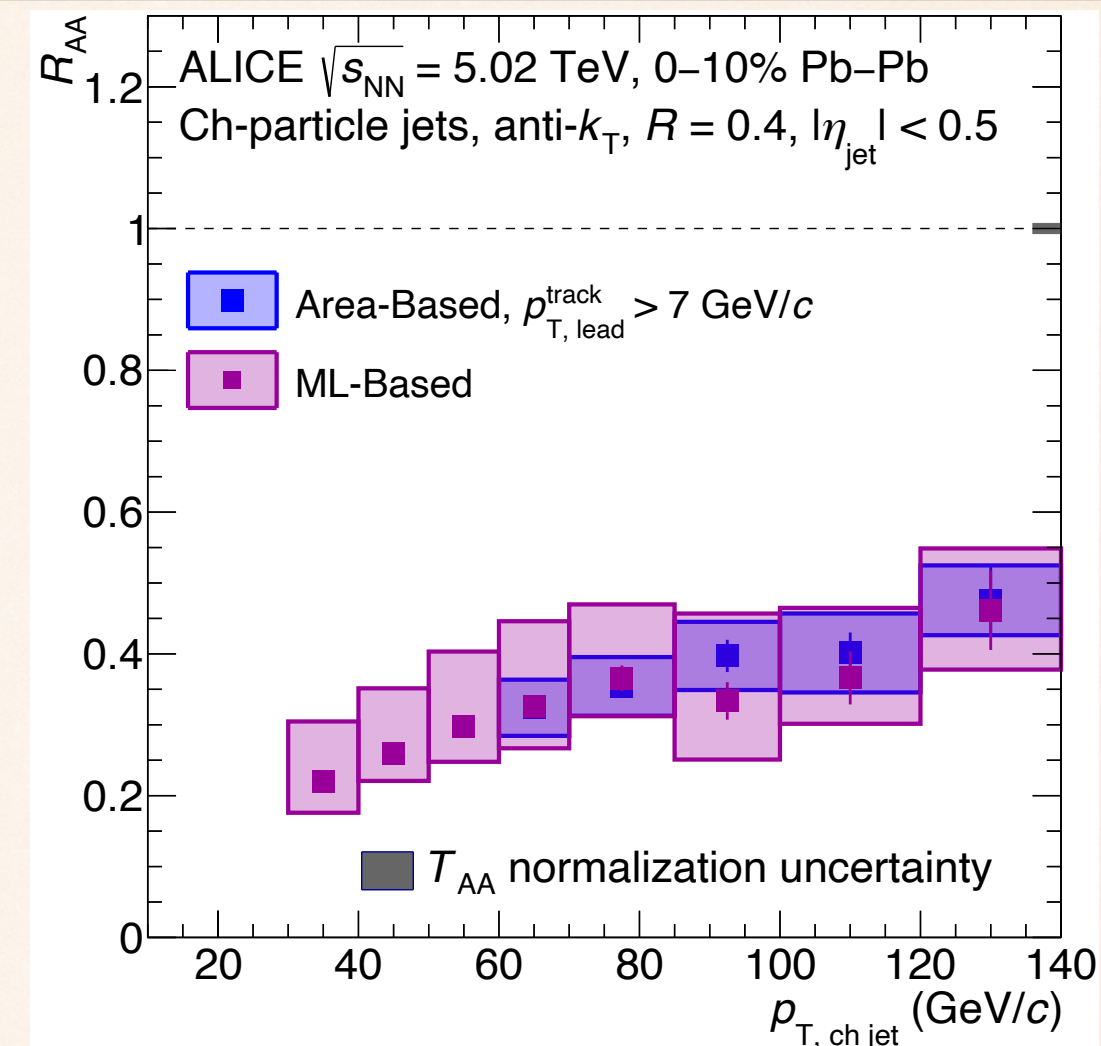
- (1) The uncorrected jet momentum as reconstructed by the jet finding algorithm,
- (2) **the jet transverse momentum, corrected by the established area-based method,**
- (3) several jet shape observables, namely jet mass, radial moment, momentum dispersion, and LeSub,
- (4) the number of constituents within the jet,
- (5) mean and median of all constituent transverse momenta,
- (6) the transverse momenta of the first ten leading, i.e., hardest, particles within the jet.

Jet Momentum Reconstruction in ALICE

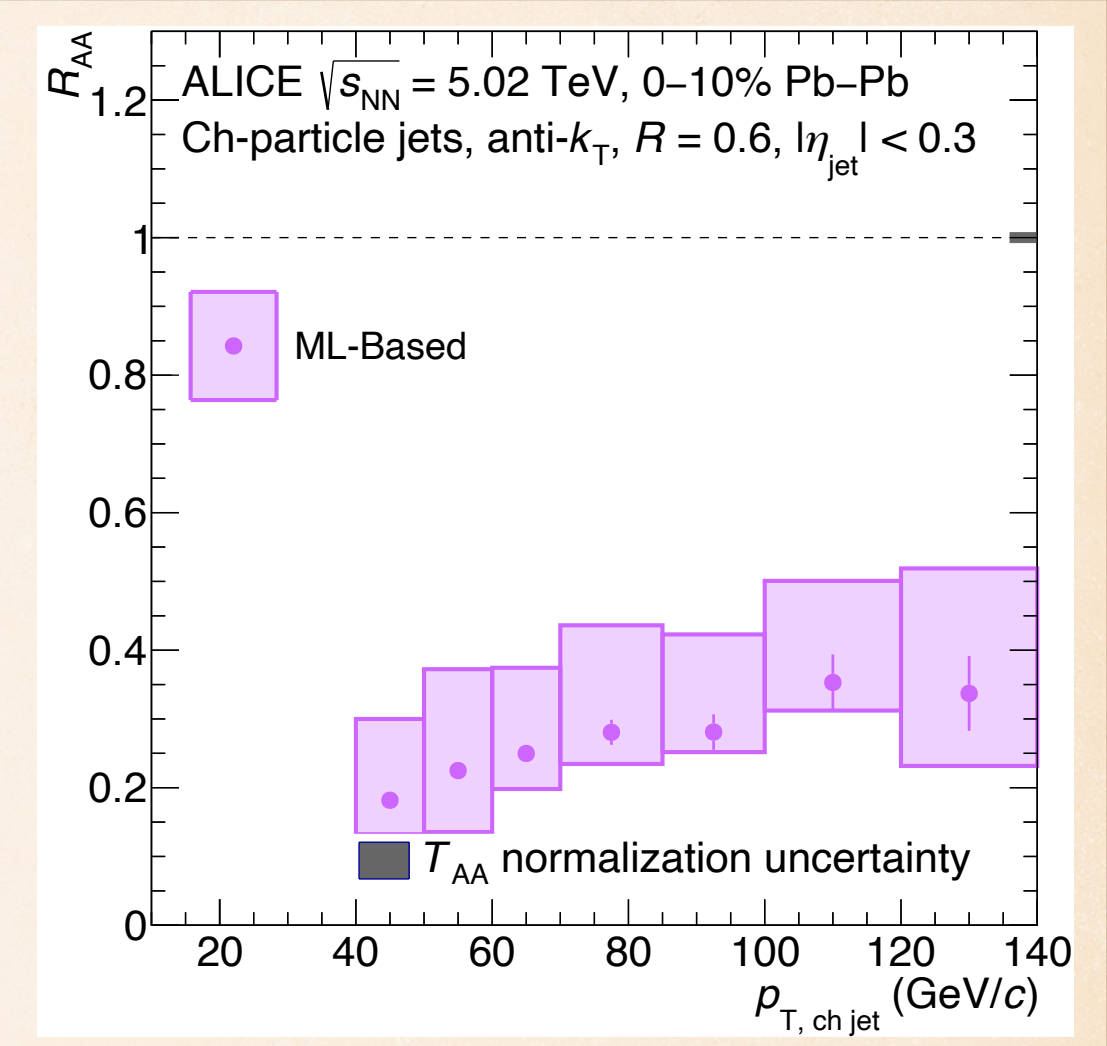
ALICE: arxiv.2303.00592



R=0.2



R=0.4

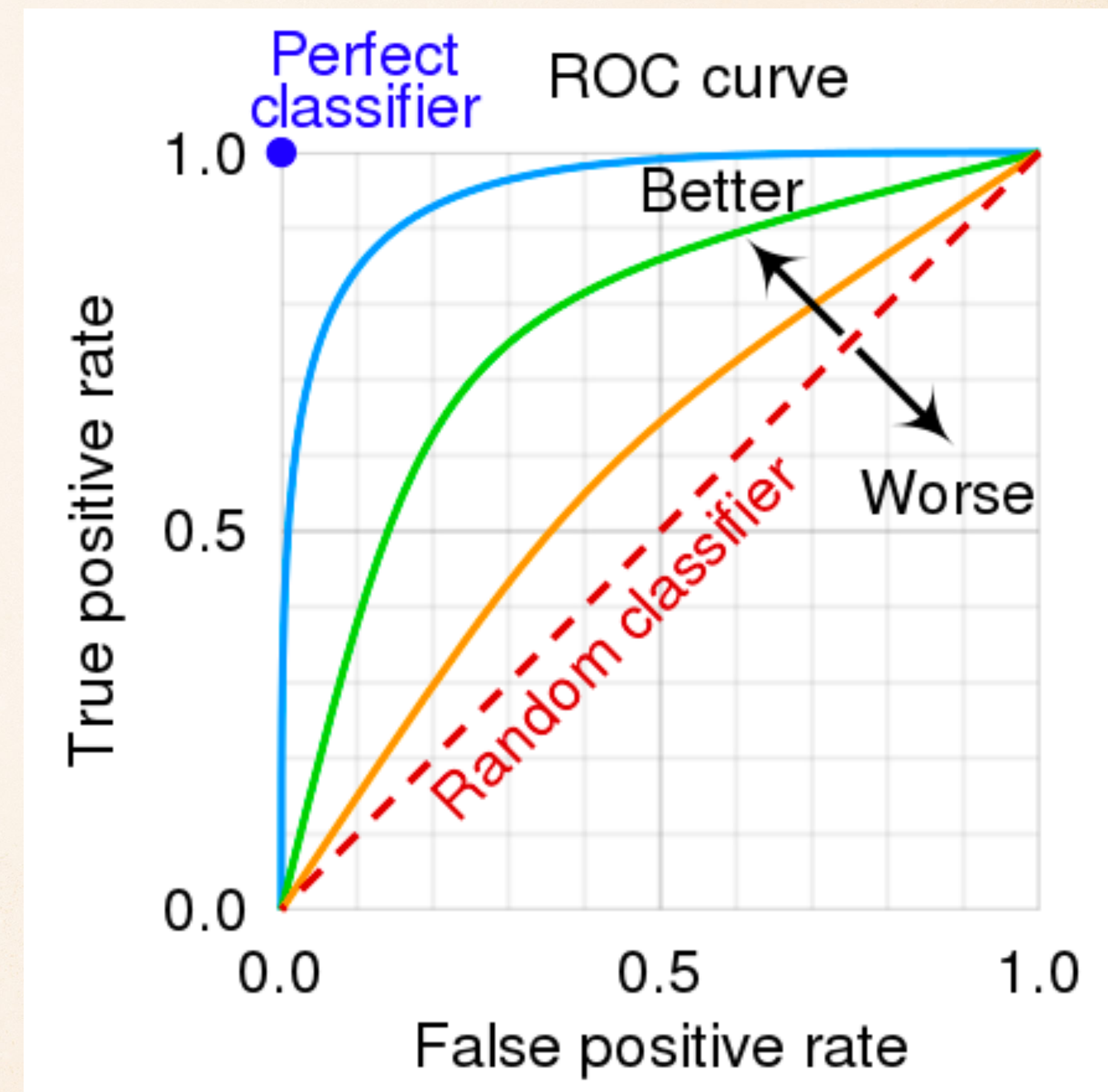
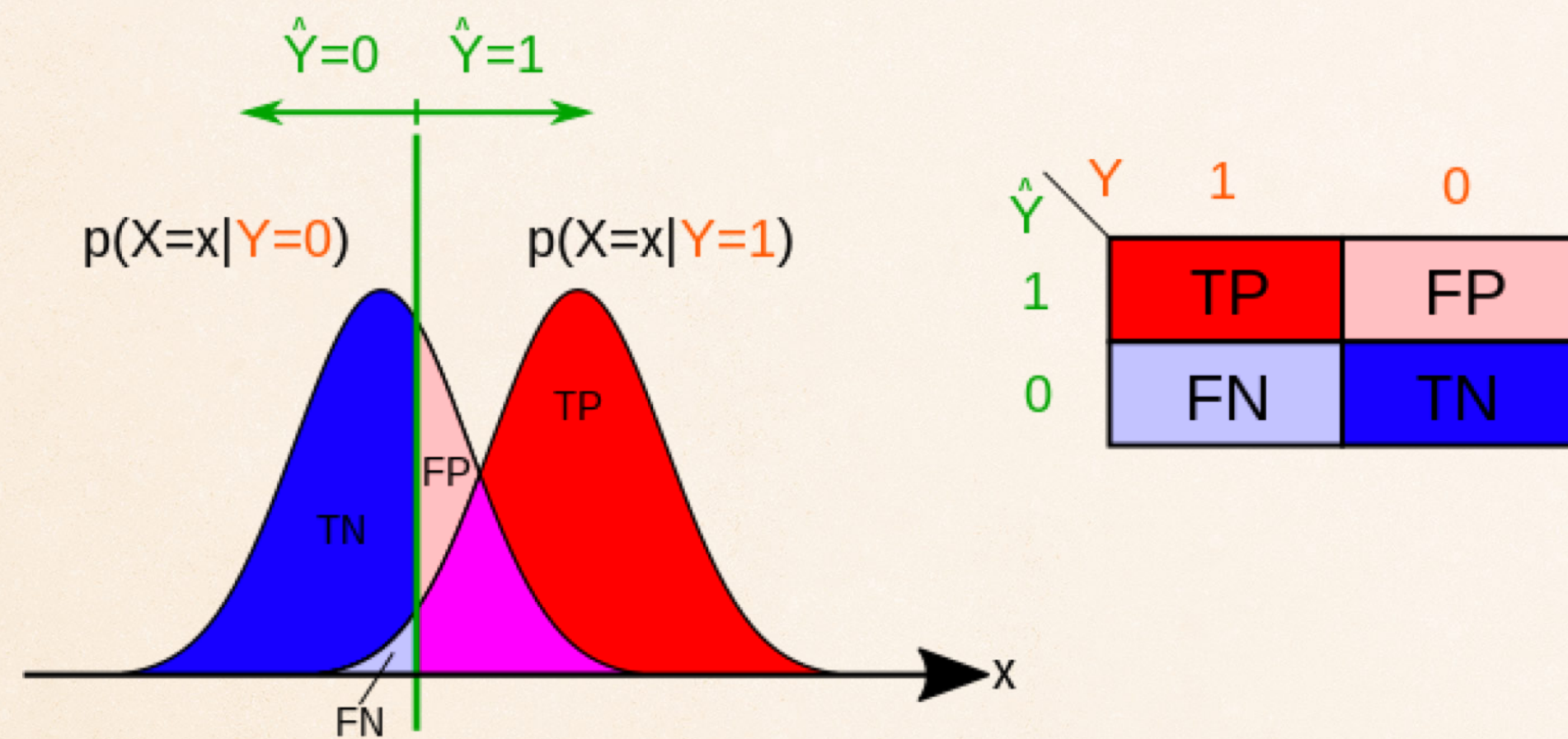


R=0.6

- ✦ Jet p_T correction with ML- VS. area-based approach in ALICE
- ✦ **More precise** jet p_T resolution with the ML-based method for **low- p_T jets at large R**
- ✦ However, this ML method could be biased by the **fragmentation pattern (Pythia-like jets for training)**

See talk by C. Platskas, 28 March, Tuesday, 9:00

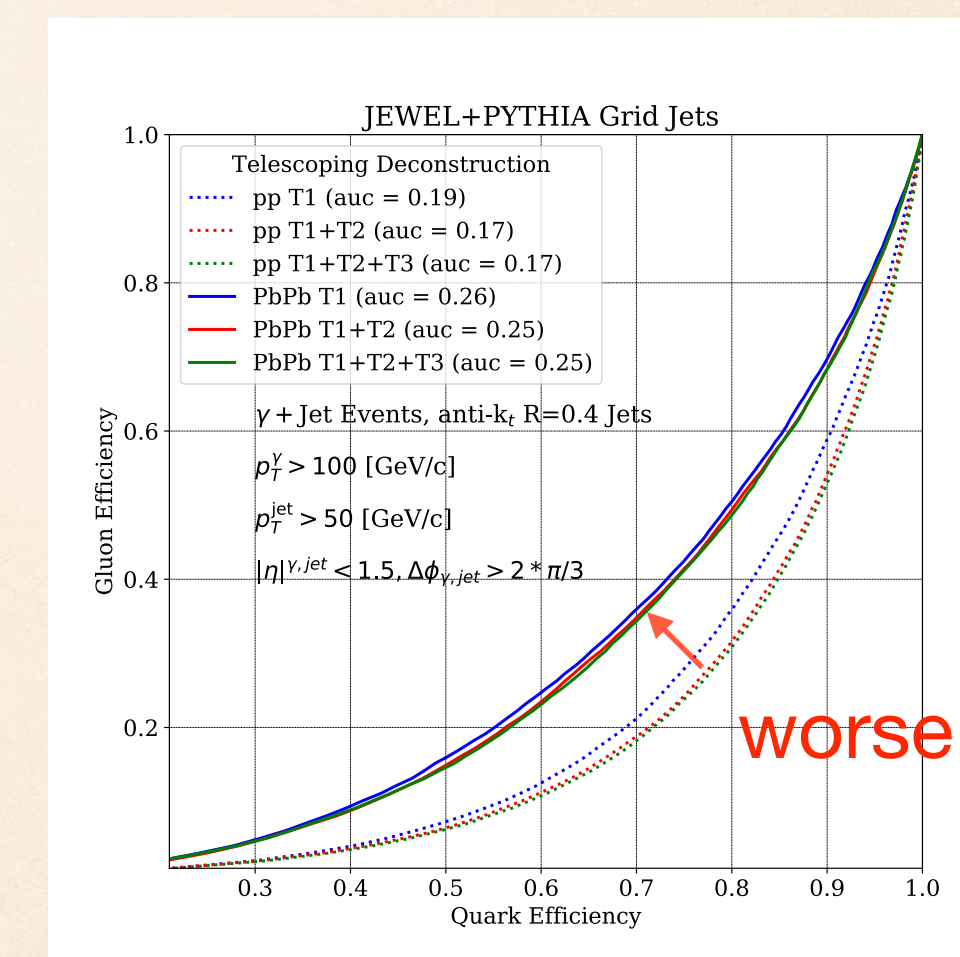
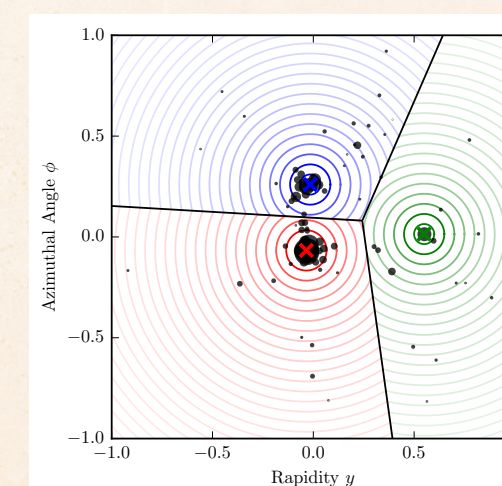
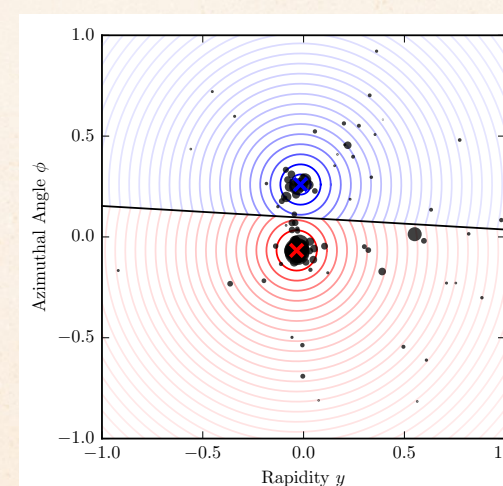
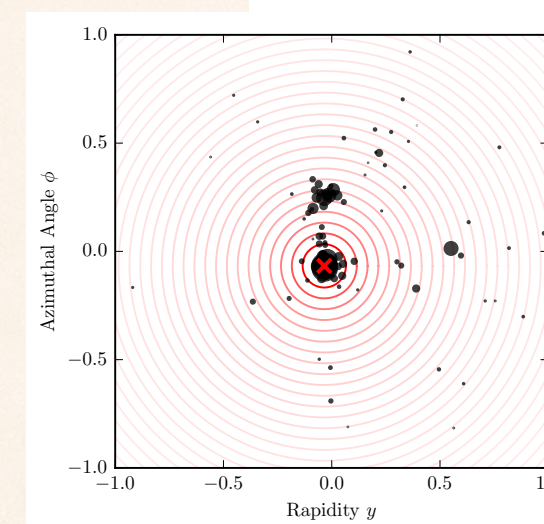
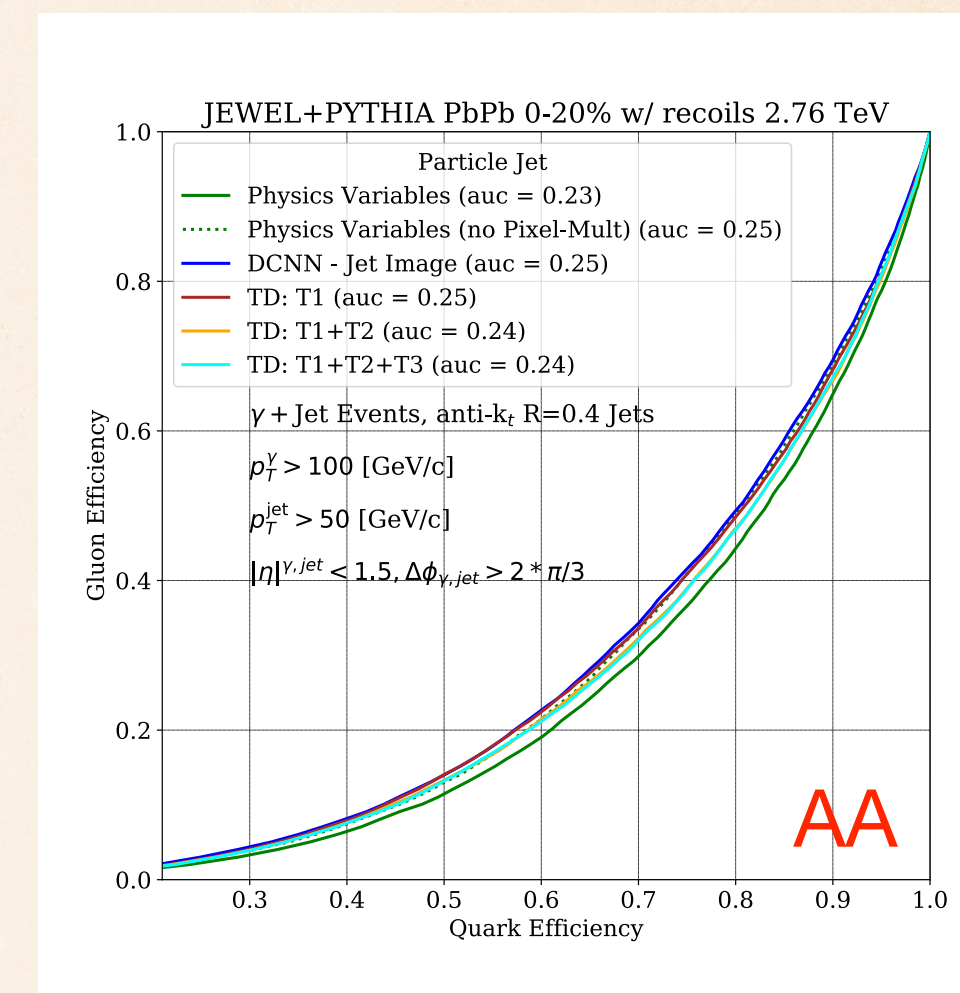
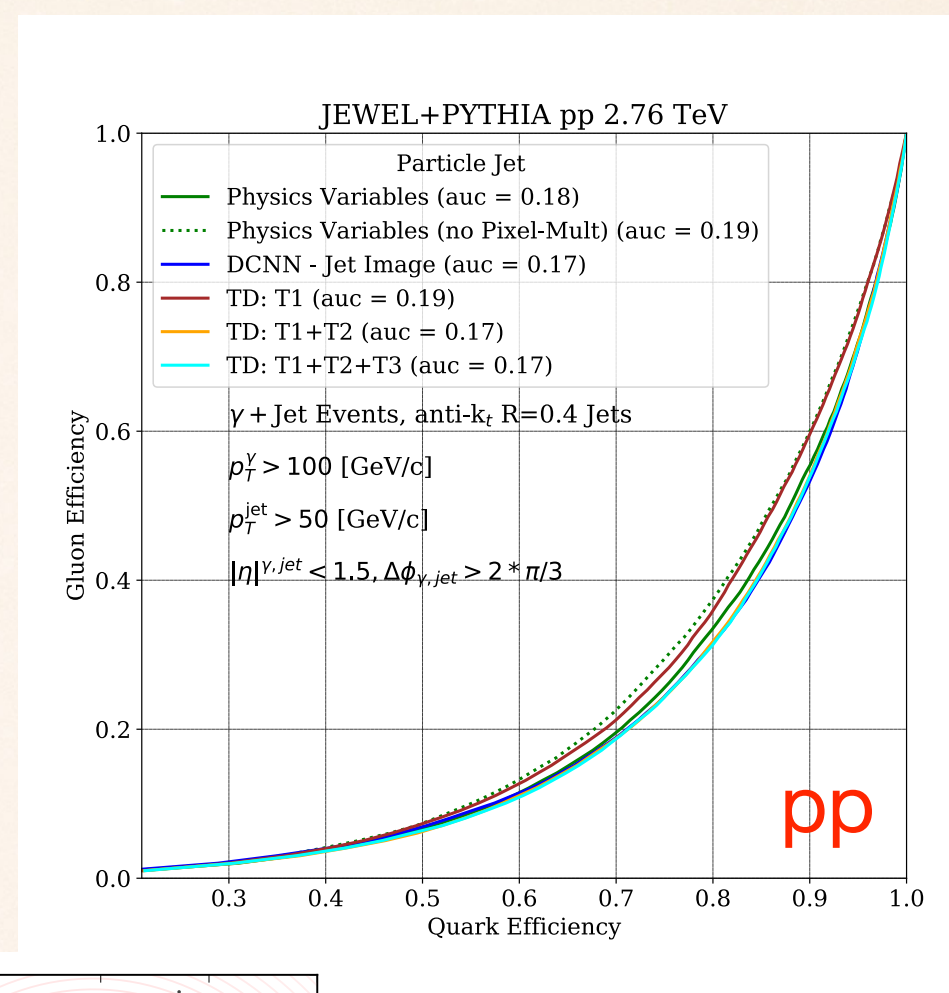
Reminder: Receiver operating characteristic (ROC) curve



Classification of Quark/Gluon Jets

Y.-T. Chien, R. K. Elayavalli, arXiv:1803.03589

- ❖ Jewel jets in pp and AA
- ❖ DNN with Jet mass, two radial moments including the girth, p_T^D , and the pixel multiplicity
- ❖ CNN on jet images (η, ϕ)
- ❖ DNN with **Telescoping deconstruction** framework exploiting subjet kinematics – p_T , mass
- ❖ “Quark gluon discrimination performance **worsens in heavy ion jets** due to significant **soft event activity** affecting the soft jet substructure”

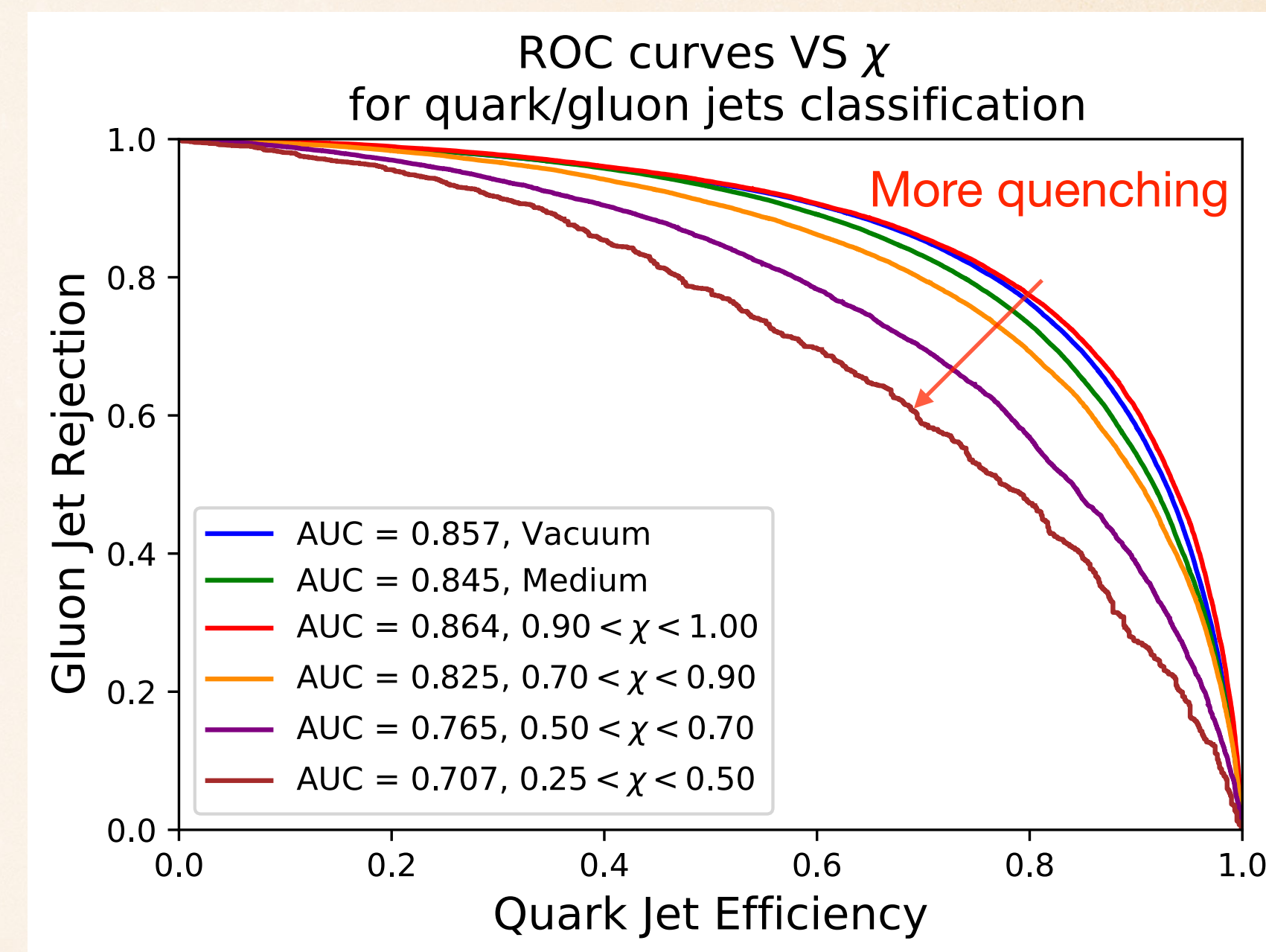
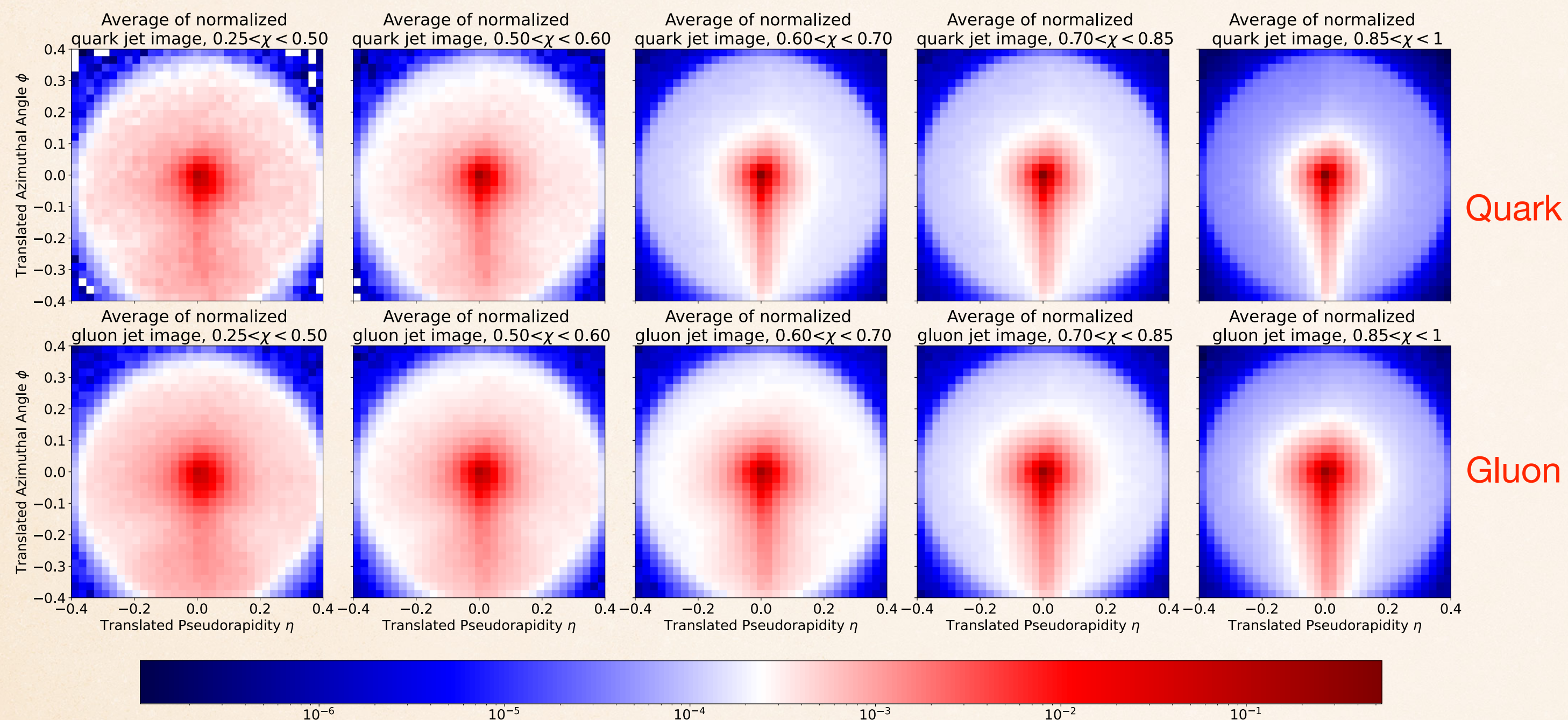


Classification of Quark/Gluon Jets

Hybrid model

More quenching

YLD, D. Pablos and K. Tywoniuk, PoS(PANIC2021)224

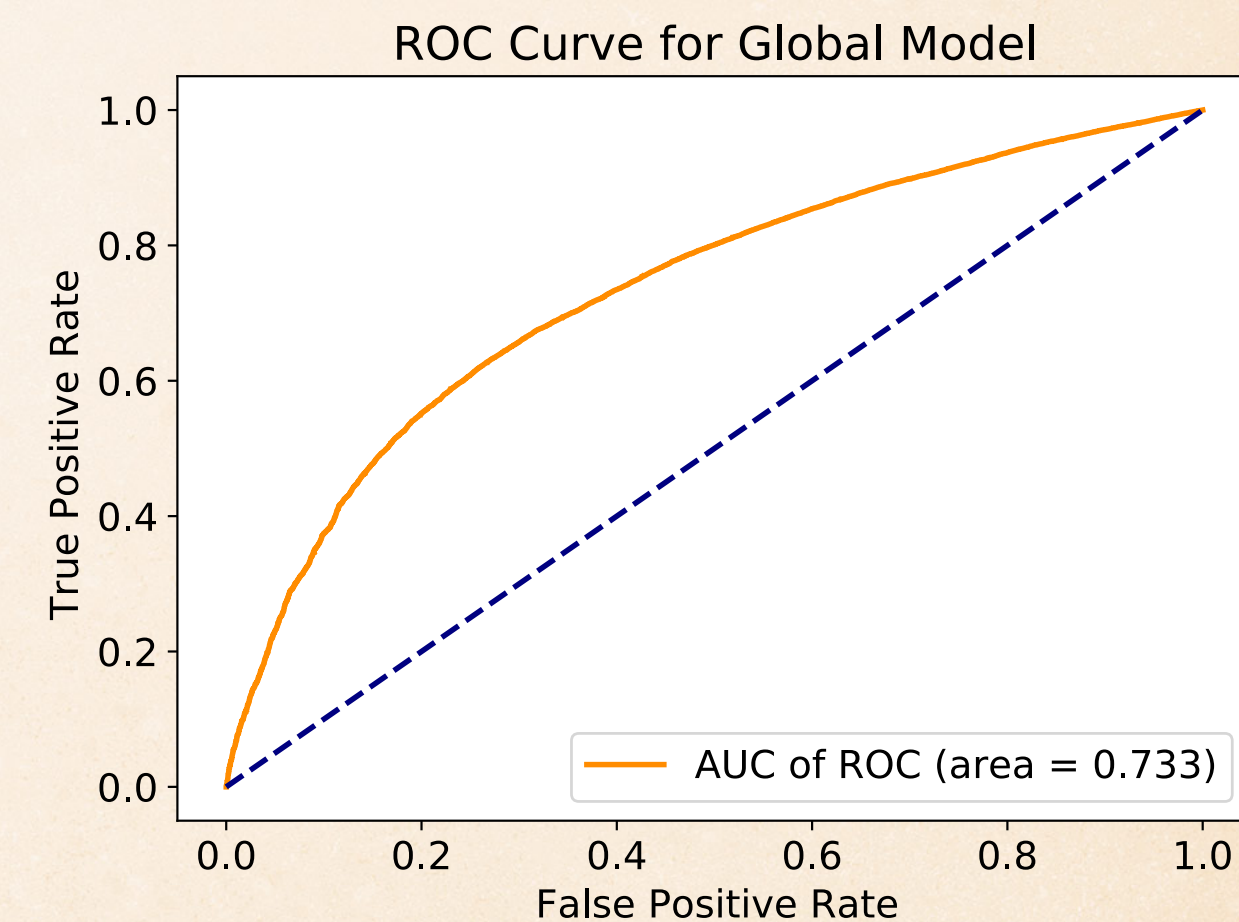
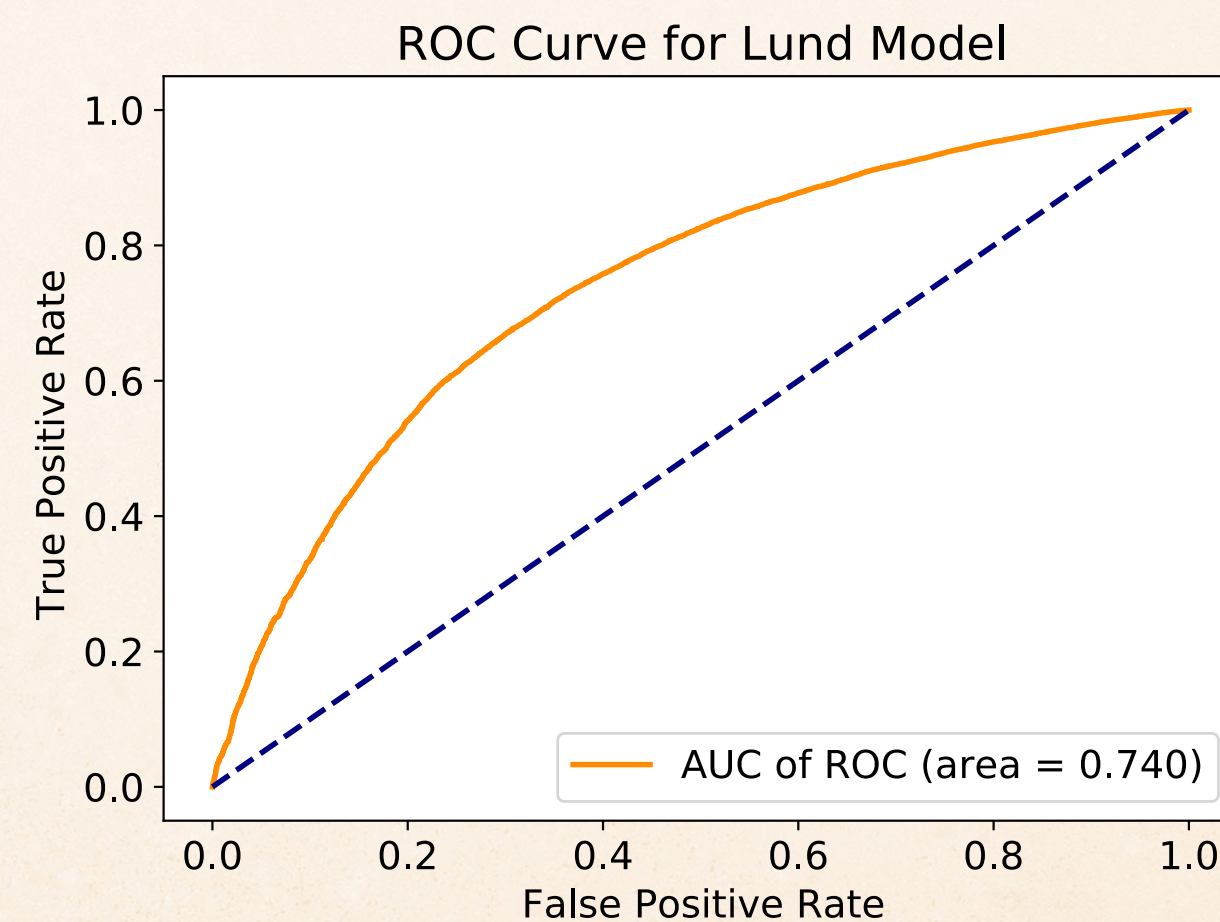
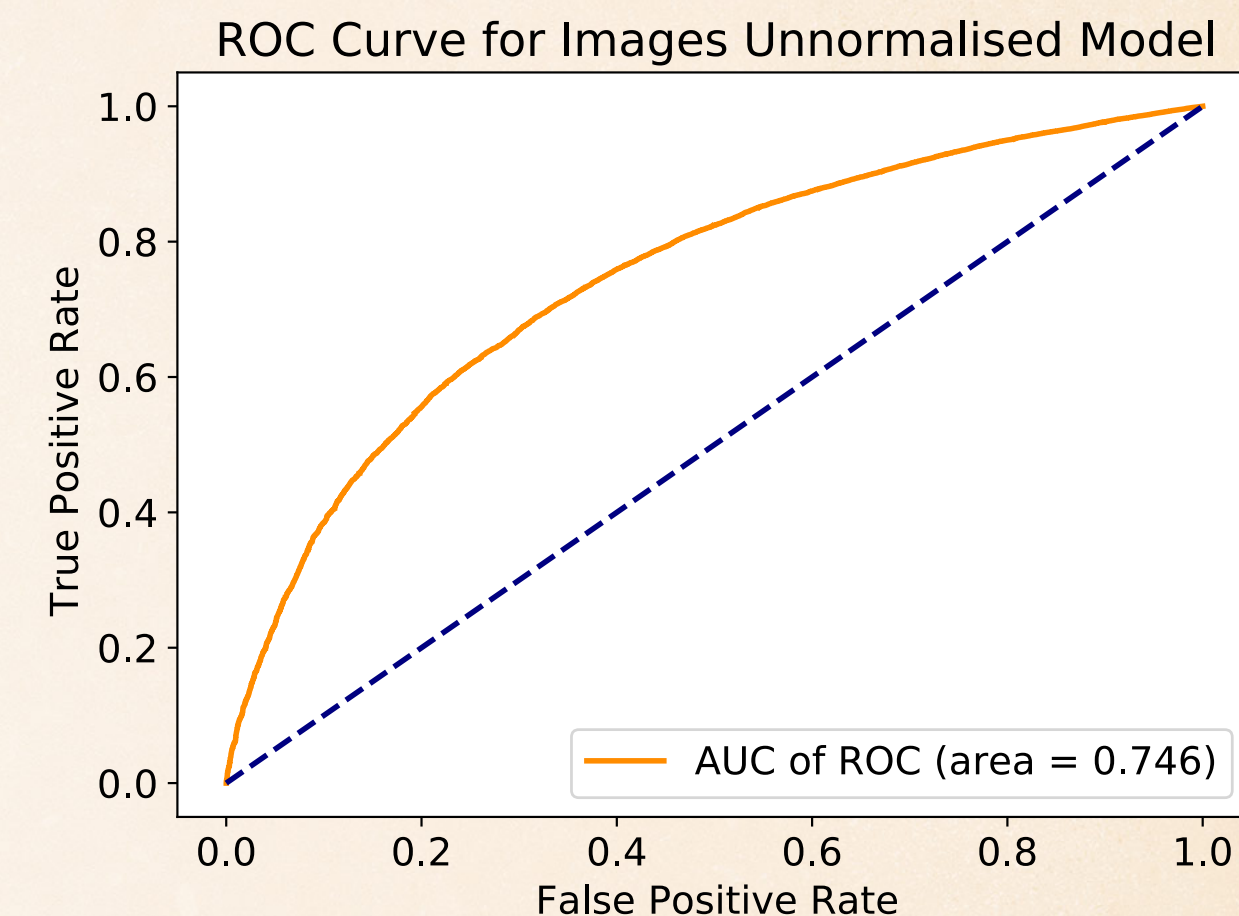
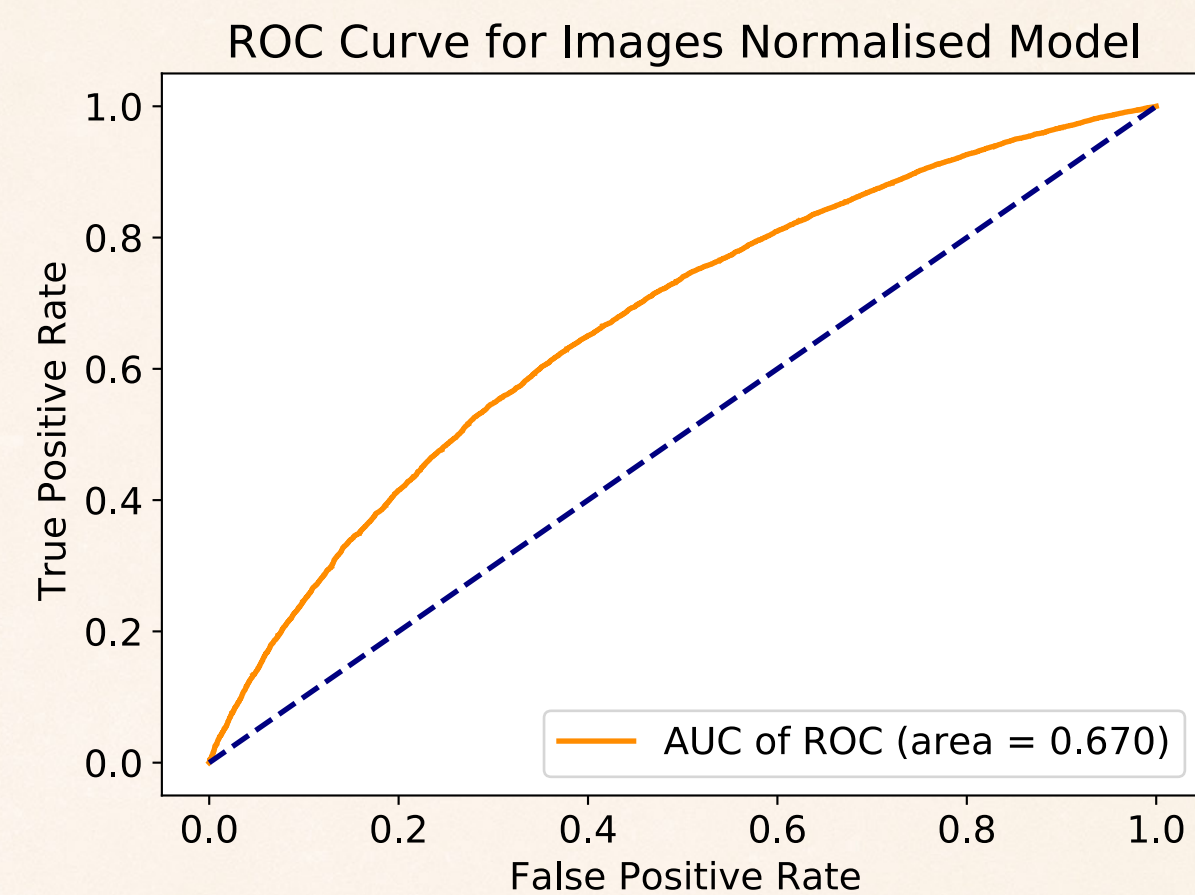


- Same qualitative characteristics: more soft particles at large angles within the jet cone
- The quenching smears the difference of substructures of quark/gluon jets
- The greater the energy loss is, the more difficult it is to classify

Classification of Quenched Jets

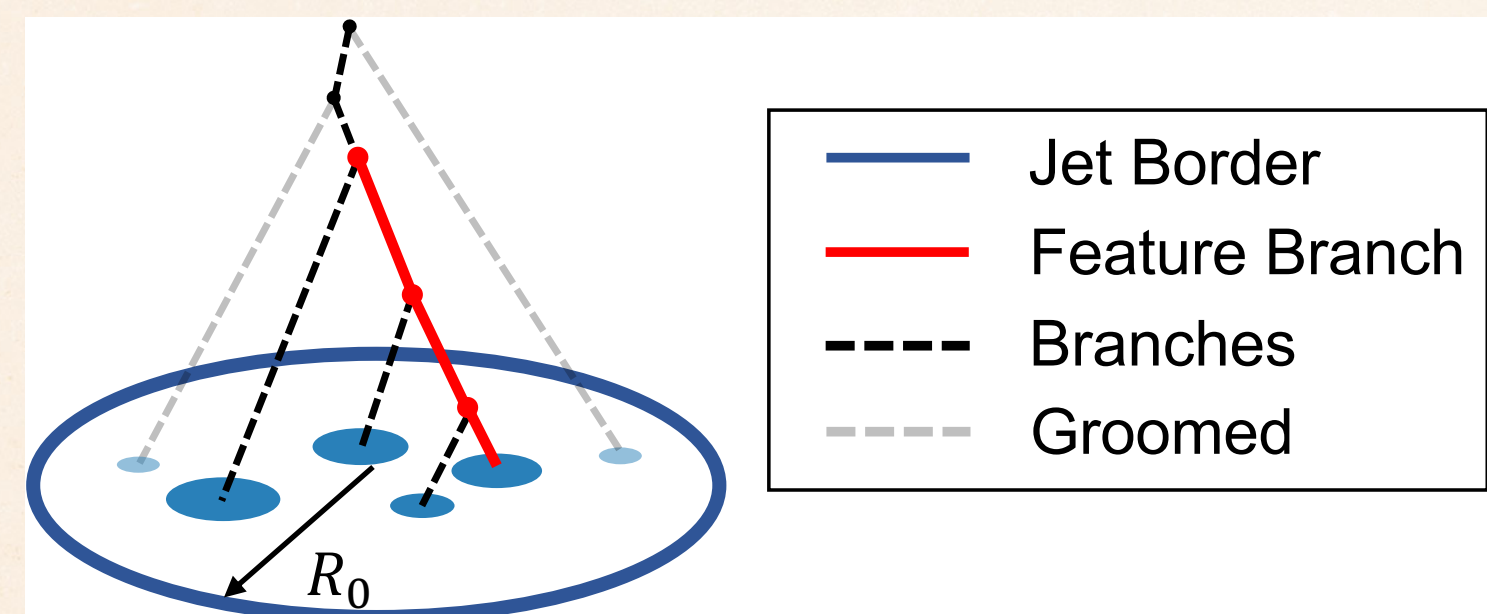
L. Apolinário, N.F. Castro, M. C. Romão, *et al.*, JHEP11(2021)219

- ❖ Jewel vacuum VS medium Z -jets
- ❖ CNN on jet image
- ❖ RNN on Lund
- ❖ DNN on global $(p_{T,jet}, n_{const})$
- ❖ Which observables contain most discriminating power?

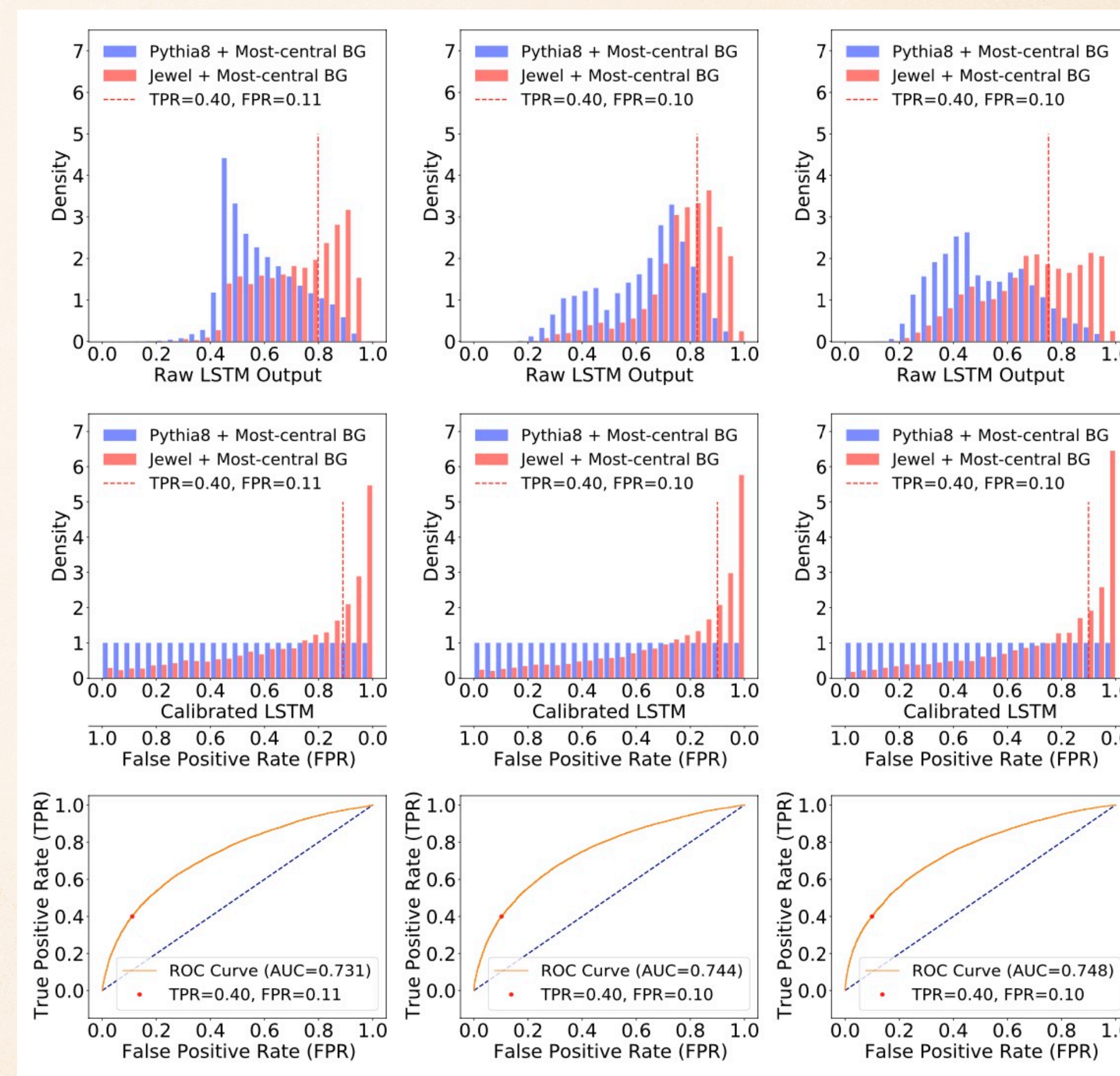


Identification of Quenched Jets

L. Liu, J. Velkovska, M. Verweij, arXiv:2206.01628



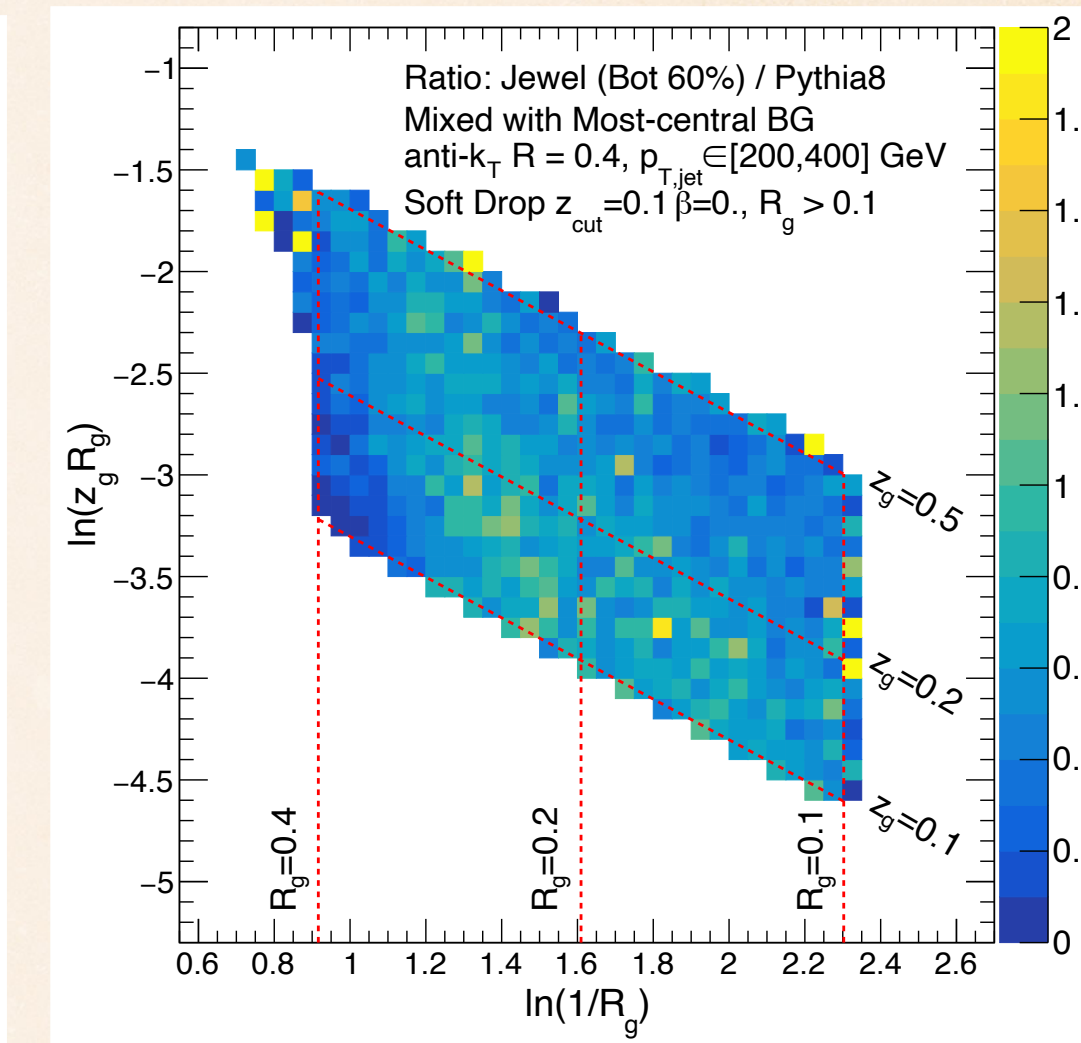
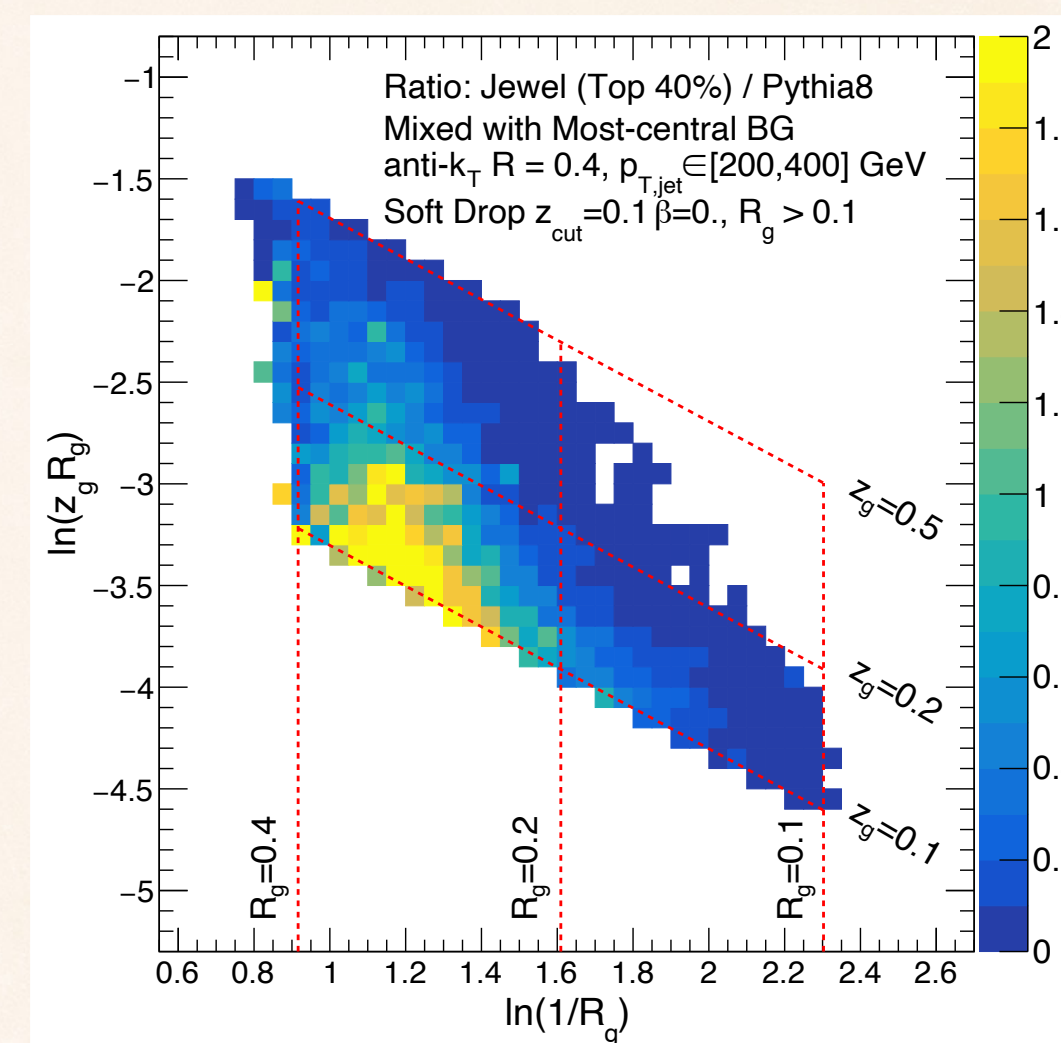
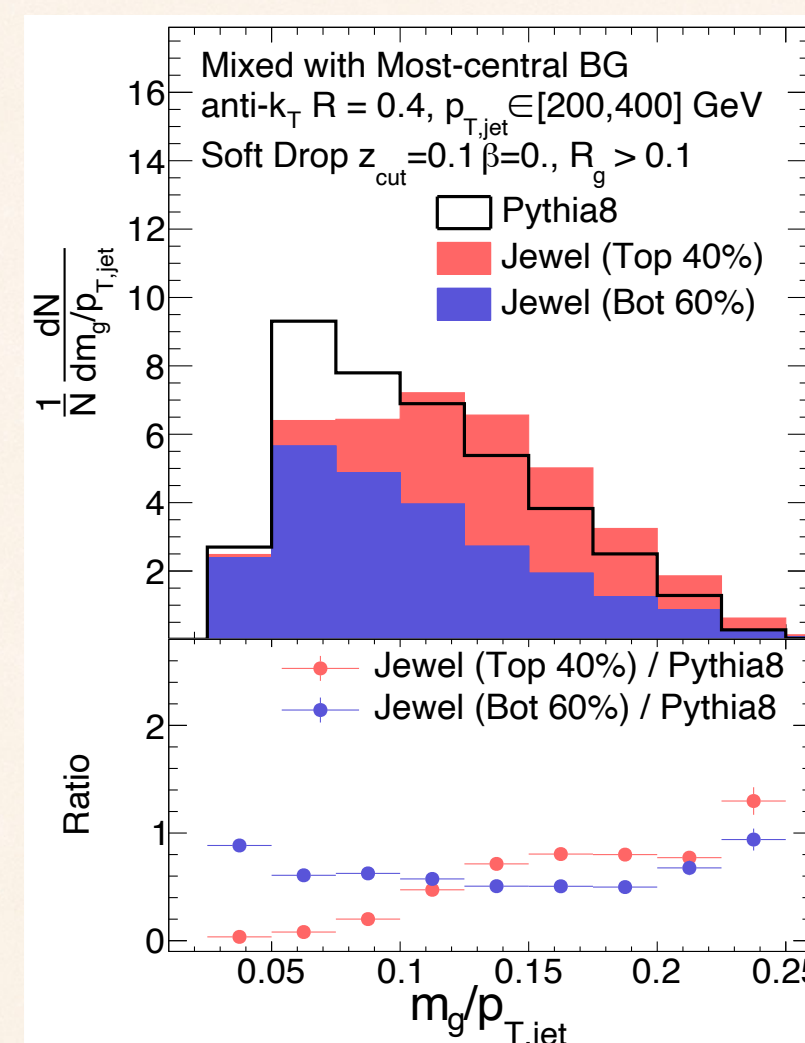
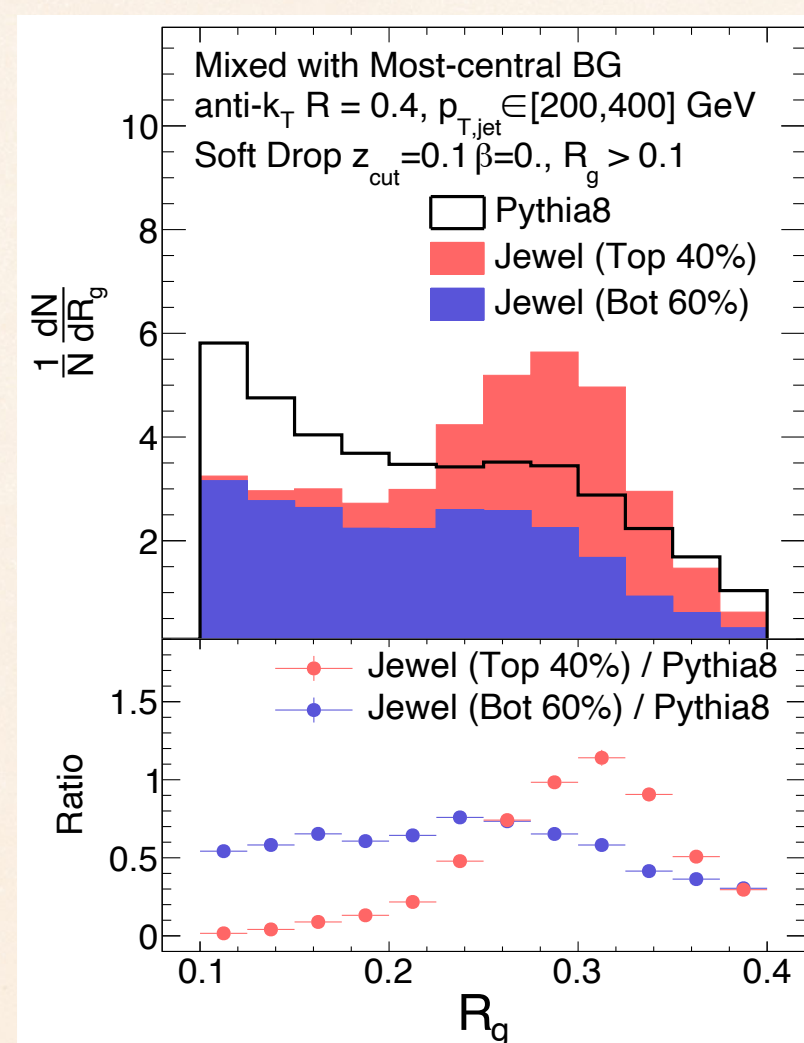
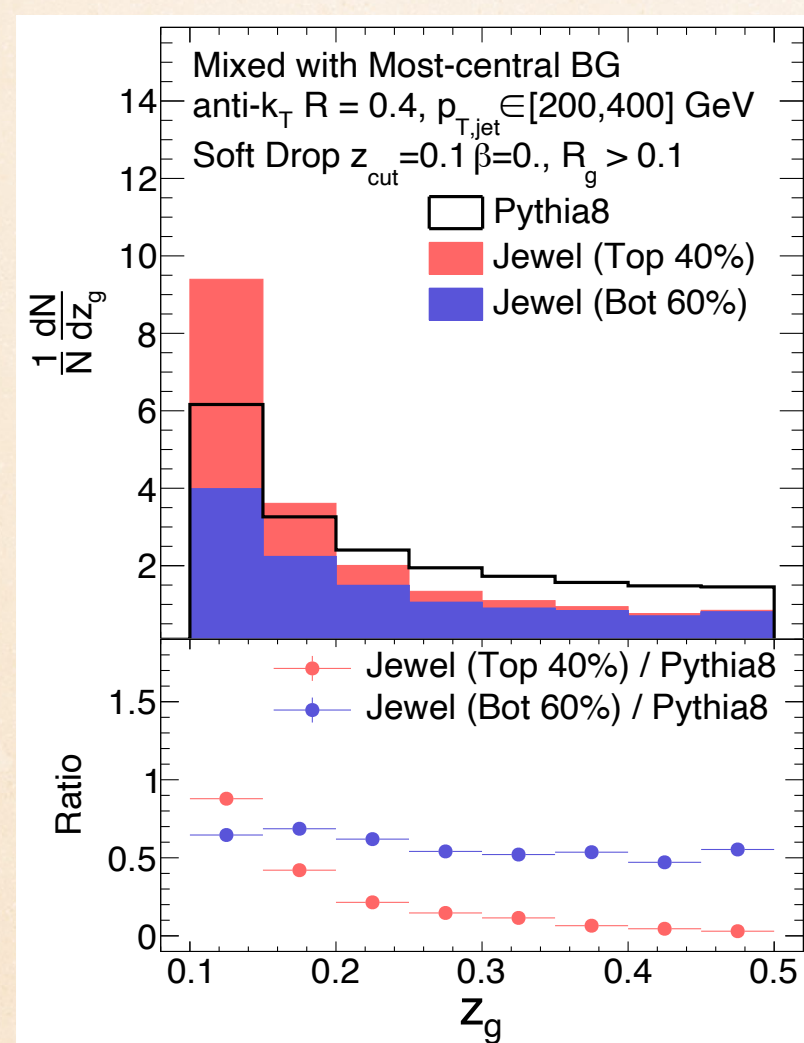
- ❖ JEWEL vs PYTHIA8
- ❖ Long short-term memory (LSTM) network on Lund primary branch
- ❖ Features: z , q , k_T ...
- ❖ **Calibration of LSTM output** is explored, claimed to be deterministic



Poster by J. Velkovska and Y. Wu, 28 March, Tuesday, 18:15

Identification of Quenched Jets

L. Liu, J. Velkovska, M. Verweij, arXiv:2206.01628



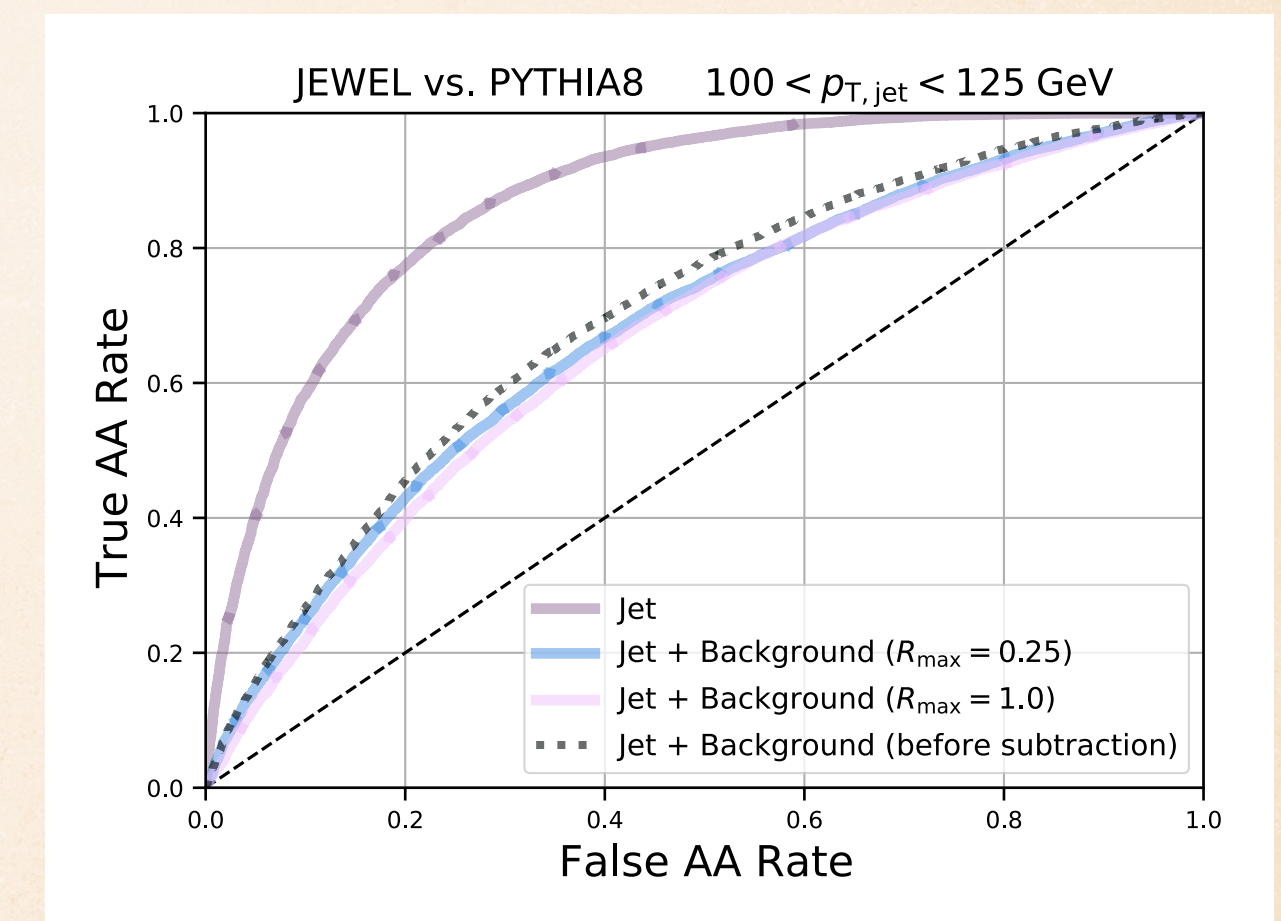
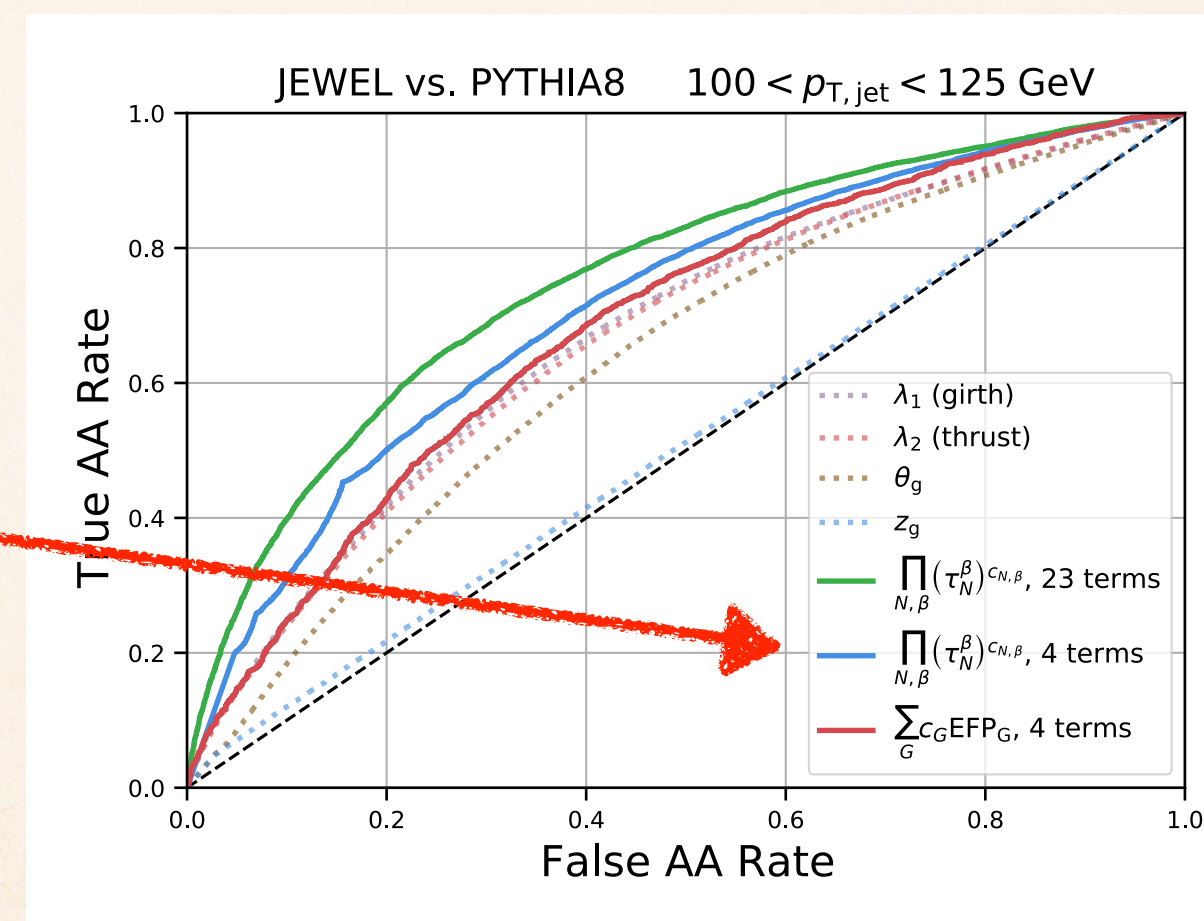
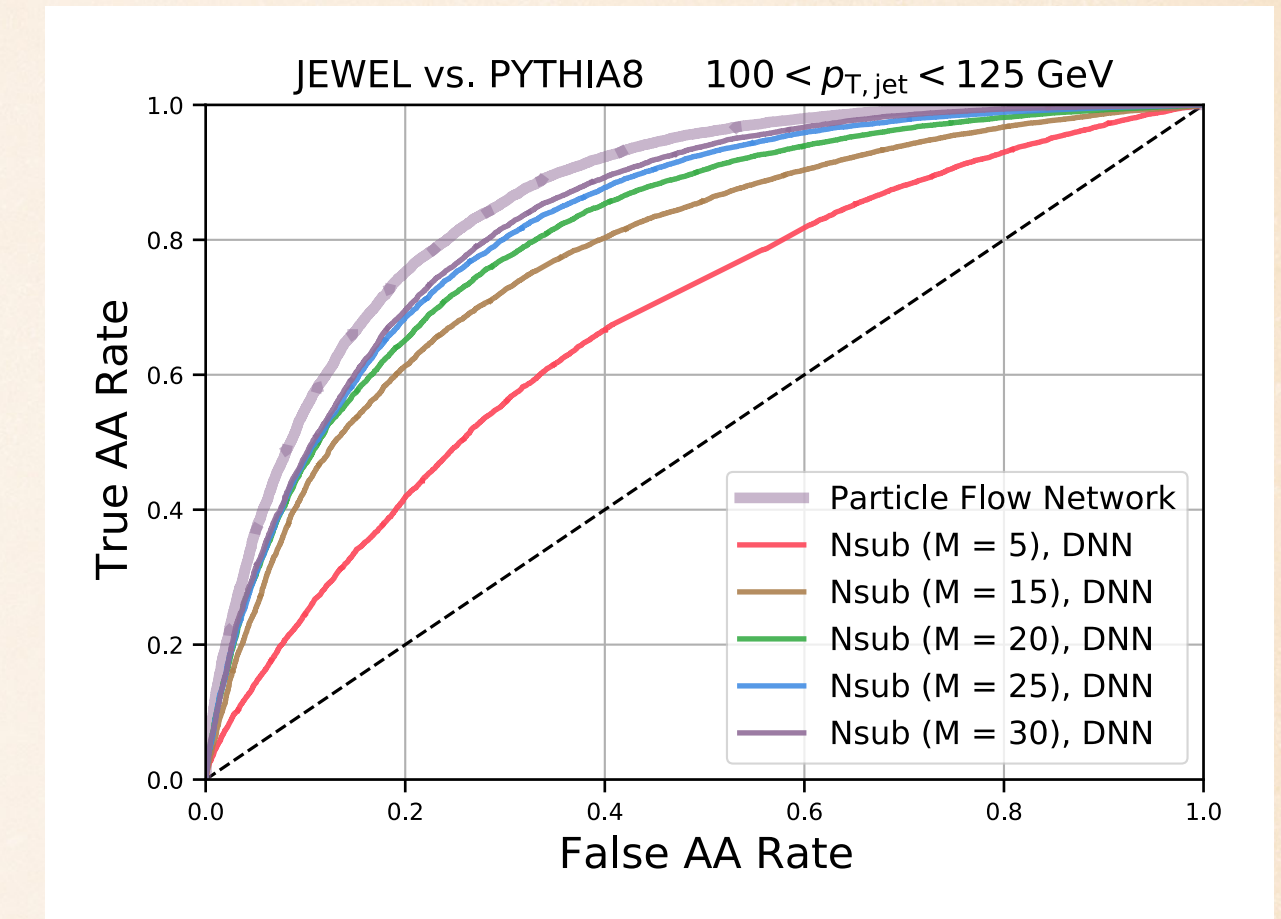
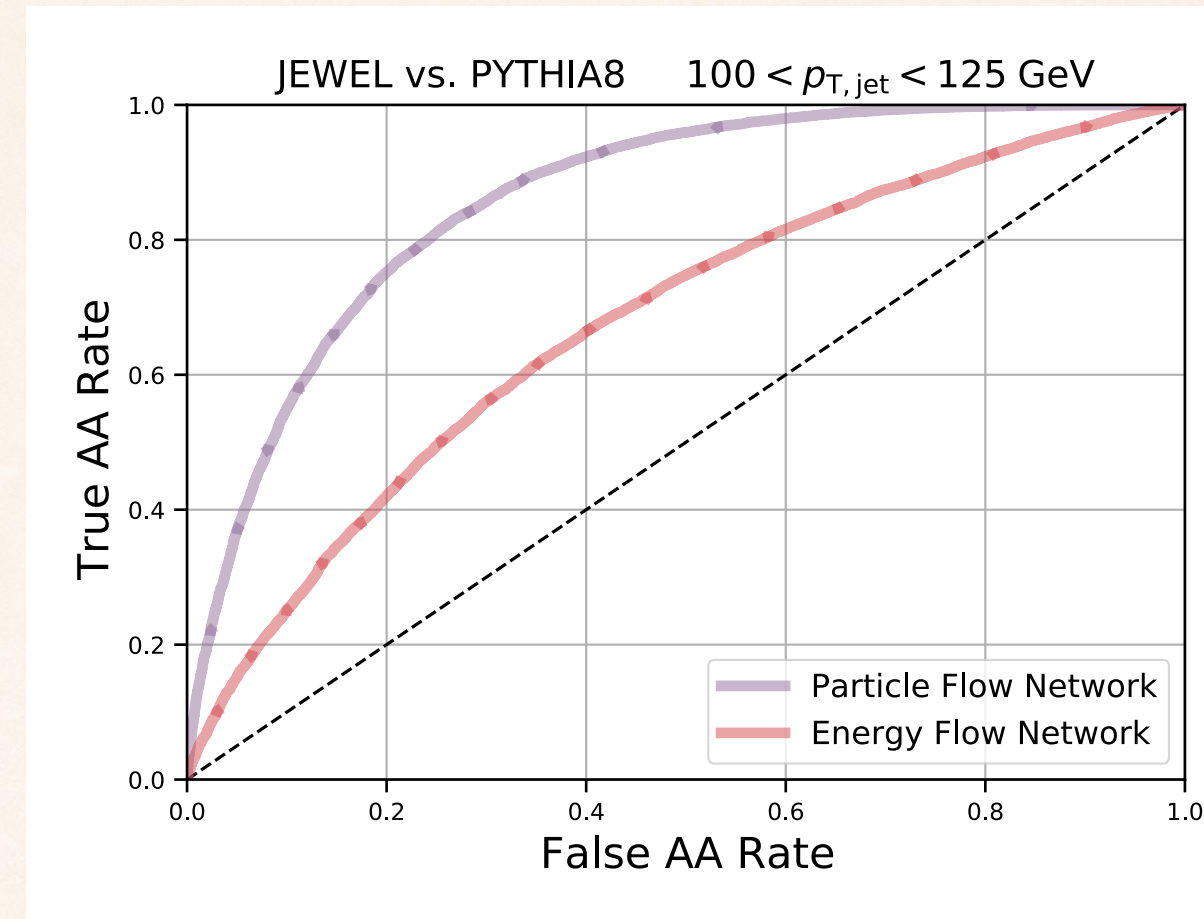
◆ Select Top 40% quenched jets to pronounce the quenching effects in observables and Lund plane

The information content of jet quenching and machine learning assisted observable design

Y. S. Lai, J. Mulligan, M. Płoskoń, *et al.*, JHEP10(2022)011

- ❖ JEWEL vs PYTHIA8
- ❖ IRC-unsafe information contains significant discriminating power
- ❖ Complete set of jet substructures — performance saturation: how many observables does one need to measure?
- ❖ Observables design
- ❖ Measure to background subtraction algorithm

$$\tau_N^{(\beta)} = \frac{1}{p_{T, \text{jet}}} \sum_{i \in \text{Jet}} p_{Ti} \min \{ R_{1i}^\beta, R_{2i}^\beta, \dots, R_{Ni}^\beta \}$$

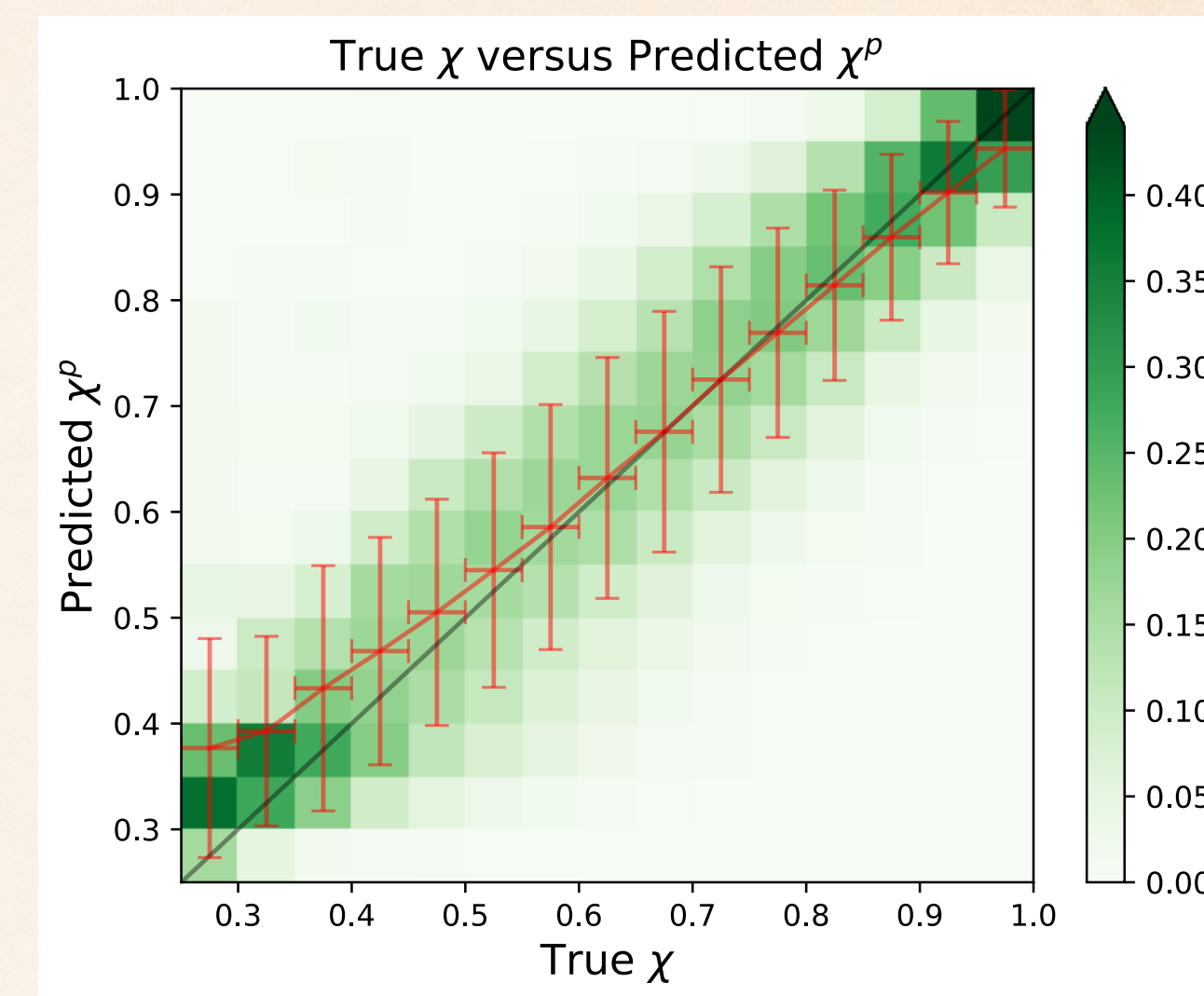
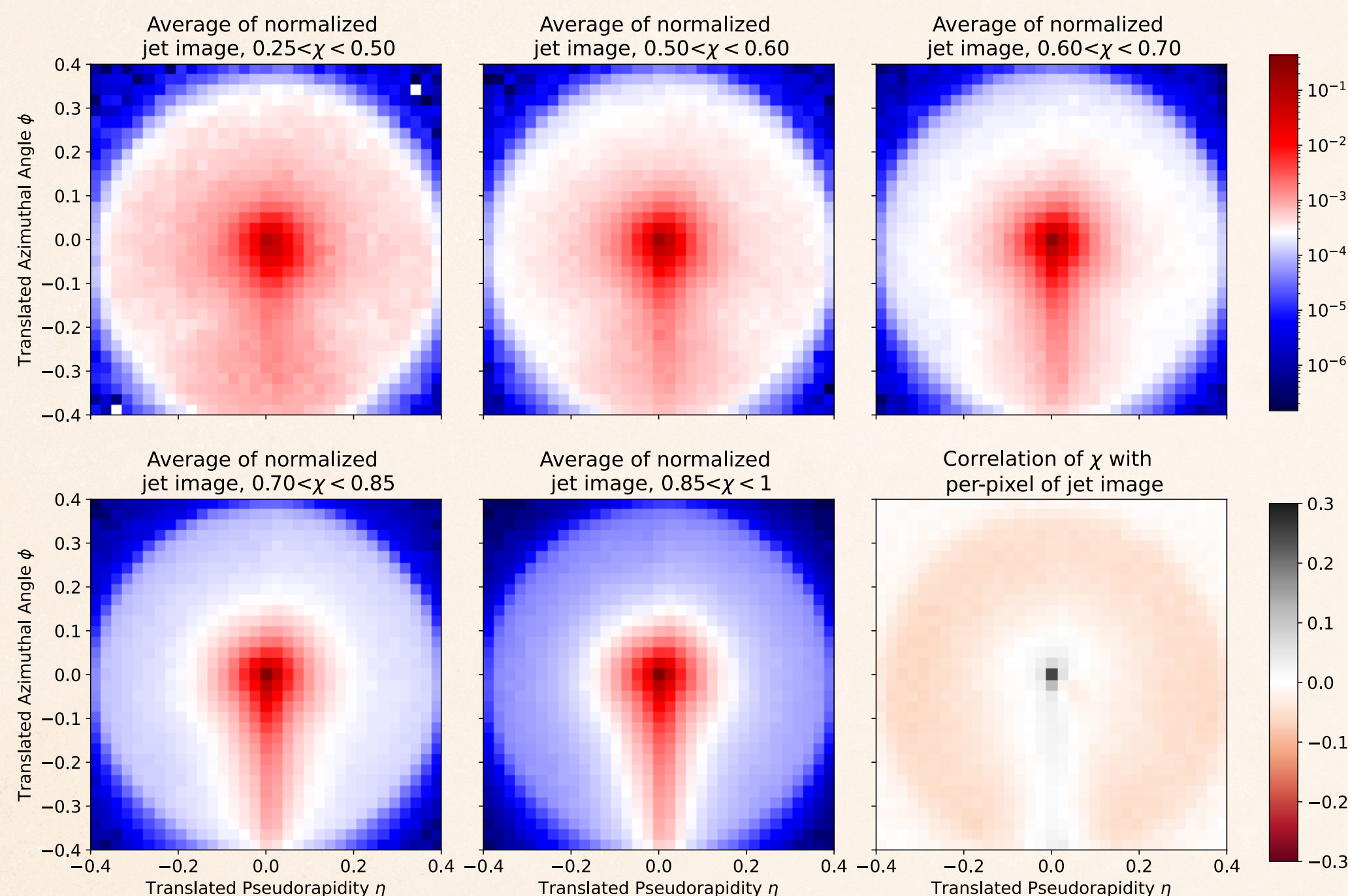


Talk by M. Płoskoń, 28 March, Tuesday, 16:30

Prediction of Jet Energy Loss

YLD, D. Pablos and K. Tywoniuk, JHEP03(2021)206

Hybrid model



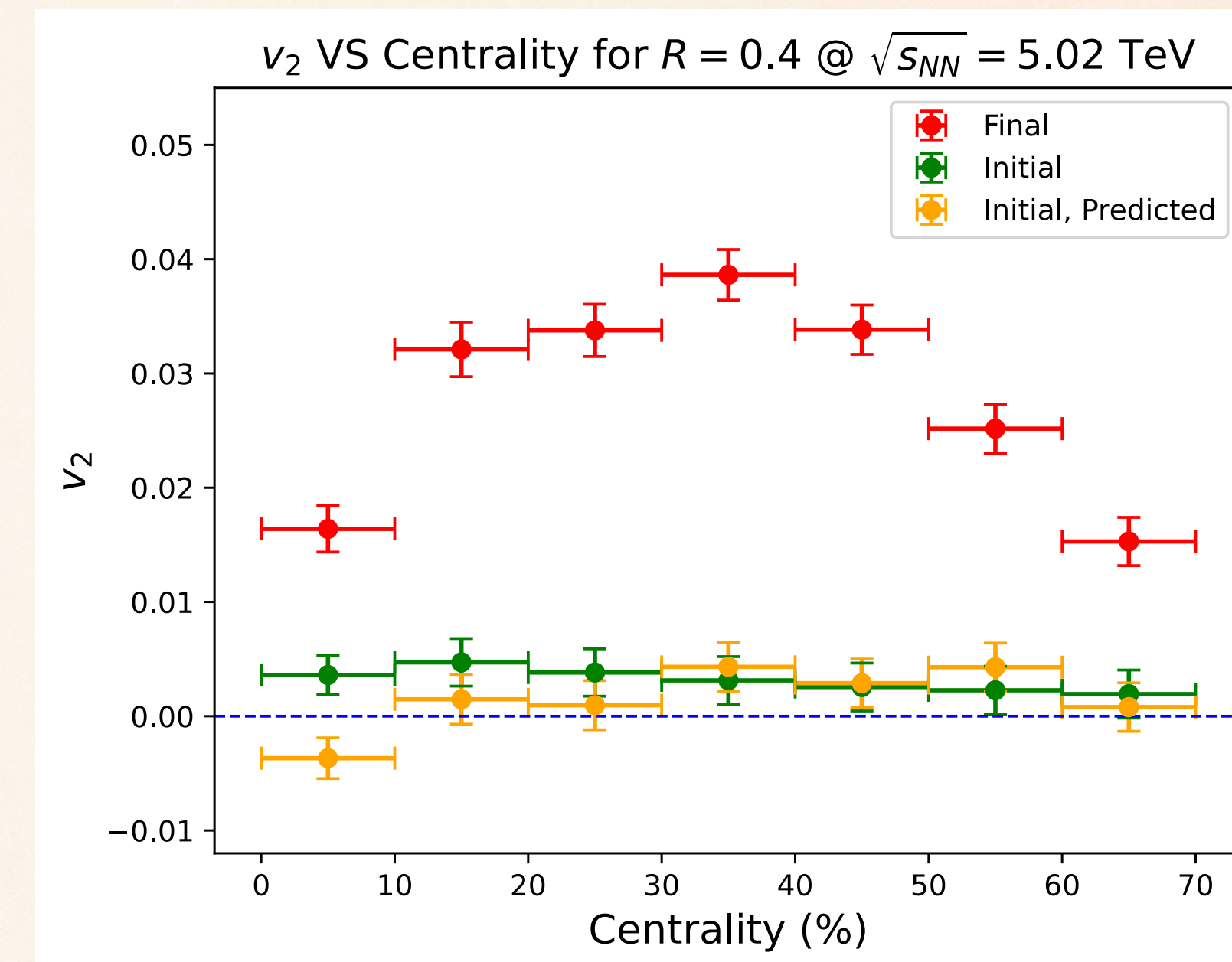
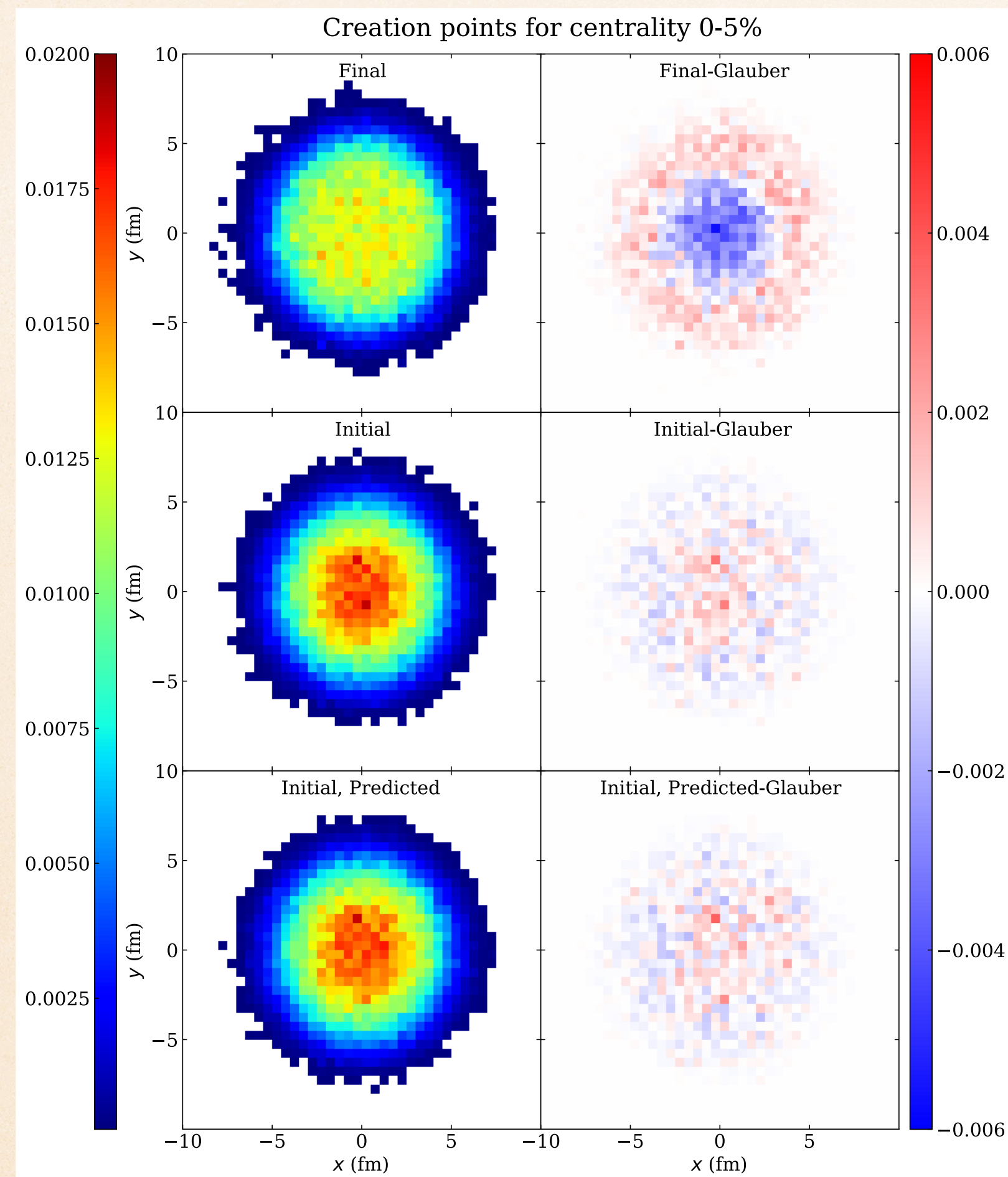
- ❖ Regression analysis of jet energy loss between the **twin jets**
- ❖ Jet quenching increases the **number of soft particles at large angles**
- ❖ Well predicted for a wide range of χ

Input (size)	Output	Network	Loss
FF (10)	χ_{jh}	FCNN	0.0058
Jet shape (8)	χ_{jh}	FCNN	0.0033
FF, jet shape (18)	χ_{jh}	FCNN	0.0032
FF, jet shape, features (25)	χ_{jh}	FCNN	0.0028
Jet image & FF, jet shape, features (25)	χ_{jh}	API: CNN&FCNN	0.0028

Interpretability!

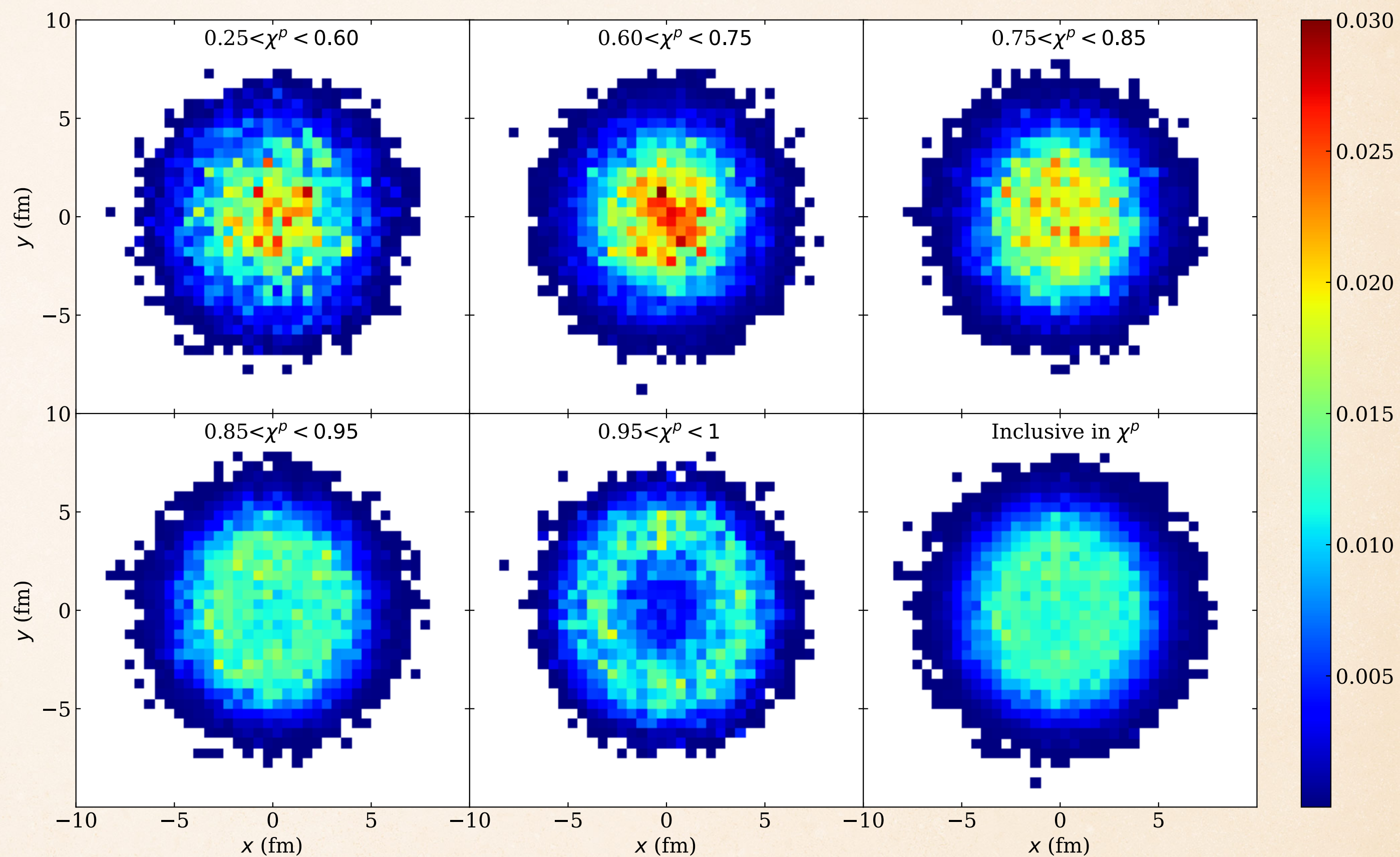
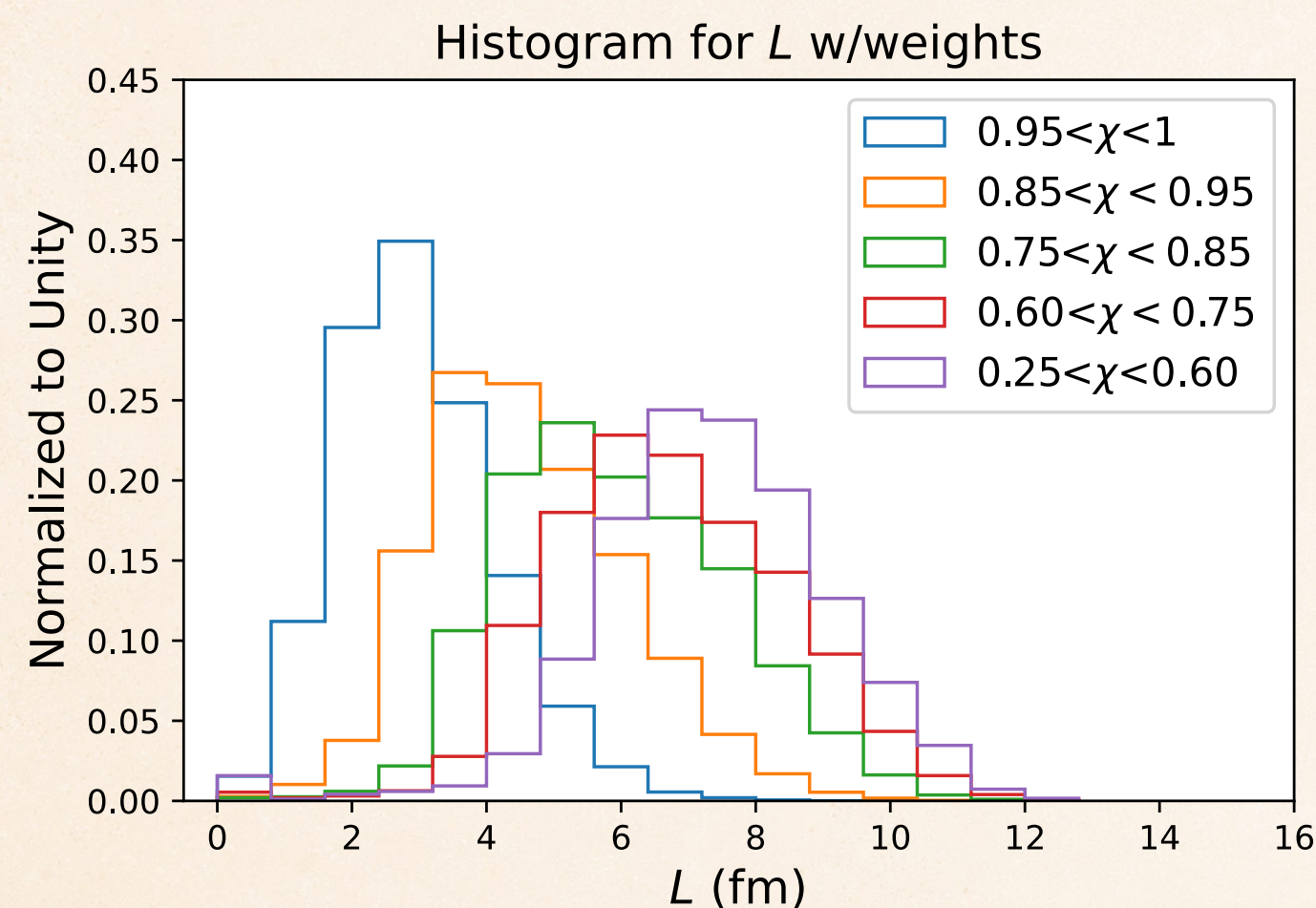
Genuine Configuration Profile

YLD, D. Pablos and K. Tywoniuk, PHYS. REV. LETT. 128, 012301 (2022)



- ❖ Initial Energy Selection (IES) “removes” final state interactions (selection bias), since we record “all” jets
- ❖ IES provides access to the genuine jet creation point (path length) distribution and possible initial-state jet anisotropy

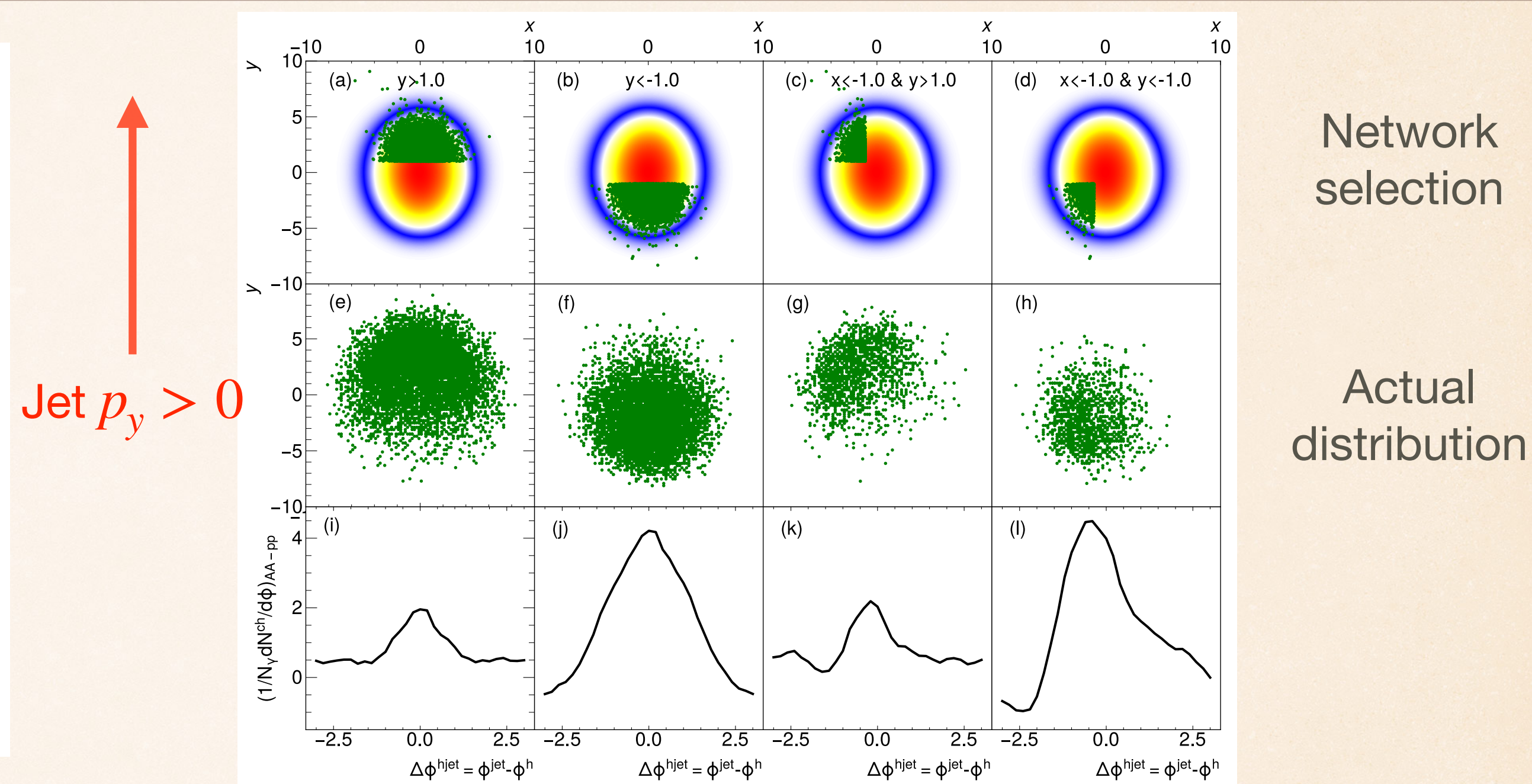
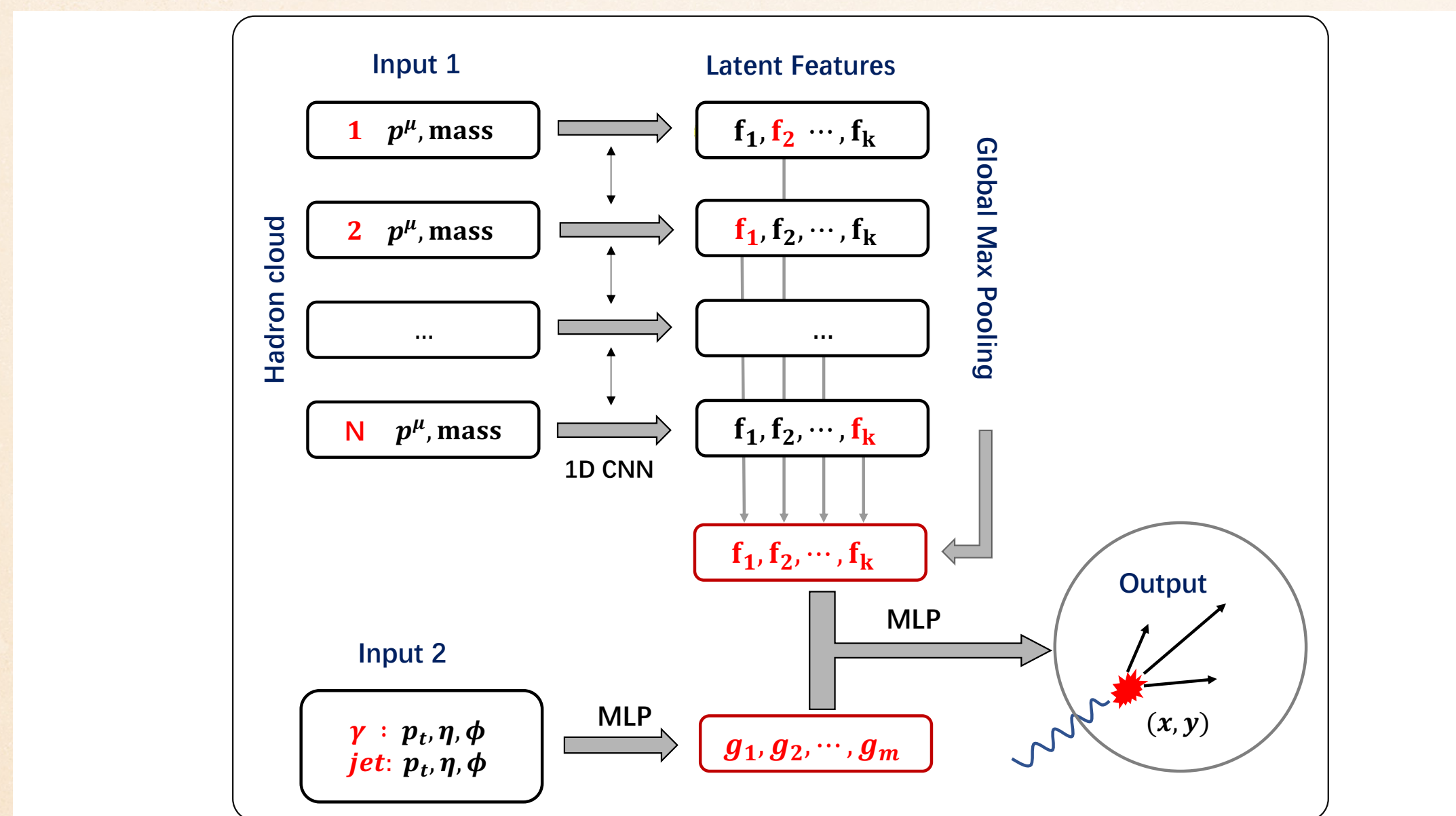
Towards jet tomography



- ❖ Strong correlation between L and χ
- ❖ Selecting jets with different χ will naturally select jets that traversed different L
- ❖ Great potential to make tomographic application!

Prediction of Jet Production Positions

Z. Yang, Y. He, W. Chen, *et al.*, arXiv:2206.02393

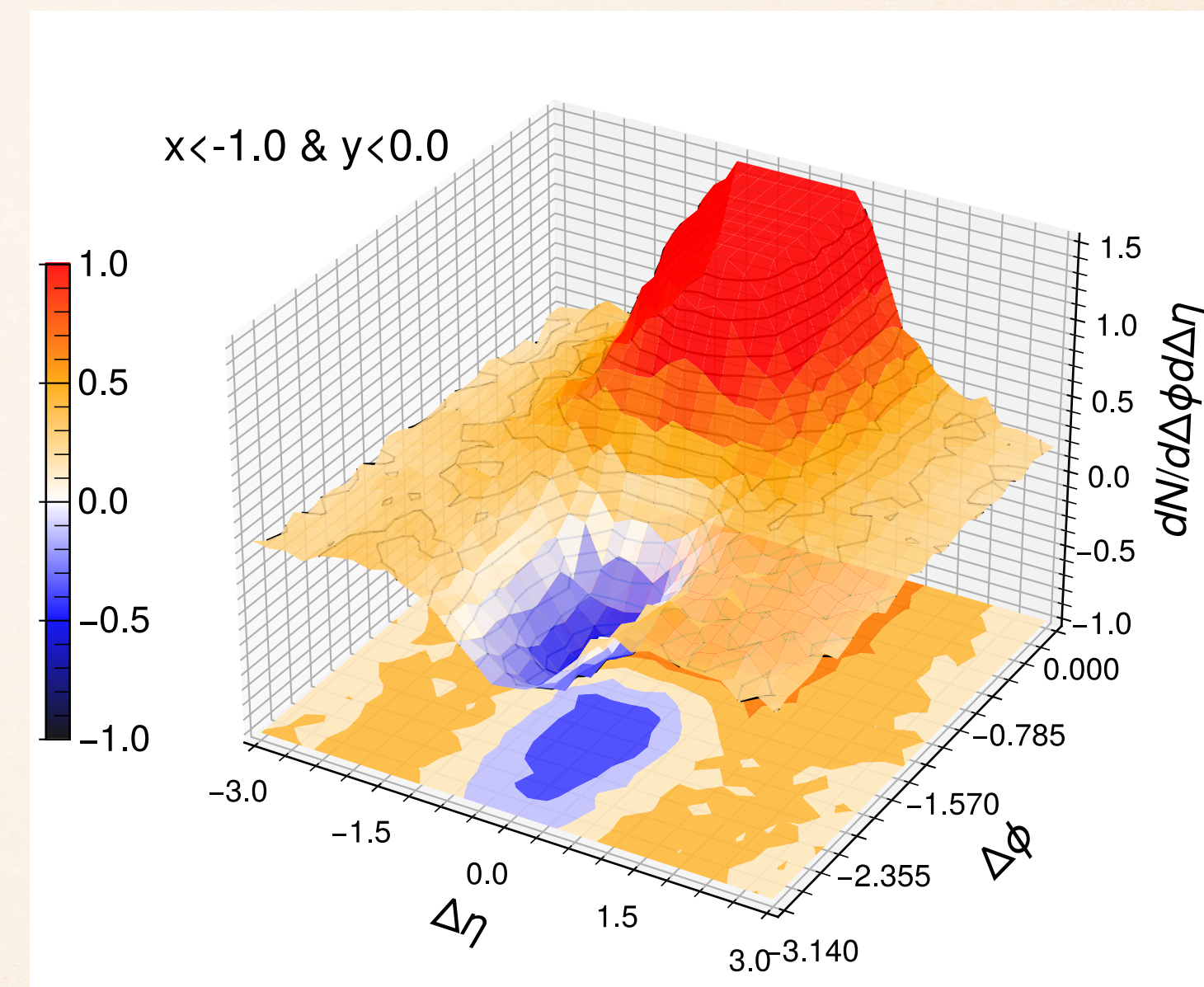
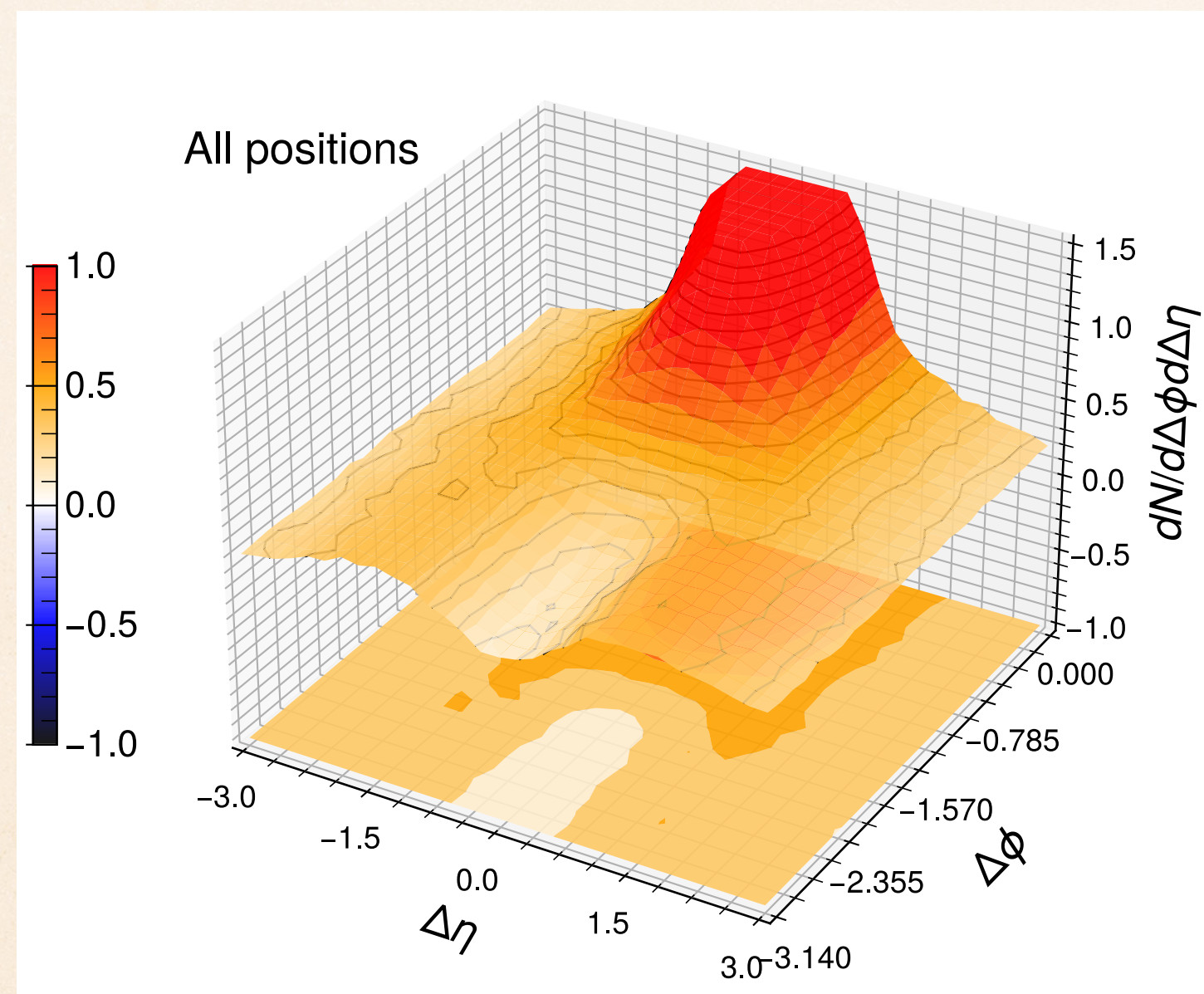


- ❖ Point cloud network employs **hadrons' momentum, mass and γ /jet info** to predict jet production position (x,y)
- ❖ Select jets by their positions and directions to have a larger yields of soft hadron from medium response and induced radiation

Talk by X-N WANG, 28 March, Tuesday, 10:00

Diffusion Wake signal amplified by DL jet tomography

$p_T^\gamma = 200-250$ GeV/c, $p_T^{\text{jet}} > 100$ GeV/c,
 $p_T^h = 1-2$ GeV/c in 0-10% Pb+Pb @ 5.02 TeV



Talk by X-N WANG, 28 March, Tuesday, 10:00

Summary

- ❖ **Various neural networks** with different representations of jet data are **applicable** in the study of jet quenching (e.g., DNN, CNN, RNN, RecNN, Point Cloud, Graph NN...)
- ❖ Jet p_T reconstruction in ALICE — **First** application on **exp. data**
- ❖ Classifications (q/g jets, quenched or not)
- ❖ Regressions (energy loss, production points)

Outlook

- ◆ **Generalizability** to other MC quenching models? **Model independence**
- ◆ **Interpretability**? Connection with theory?
- ◆ **Applicability** to more realistic environment: **fluctuating/correlated background**?
- ◆ Better performance from **state-of-the-art** neural networks? **Quantum machine learning**?
- ◆ Novel applications:
 - ◆ Extract **traversed length**?
 - ◆ Unfold **vacuum twin jet properties** apart from jet energy? **Apple to apple comparison**
 - ◆ With unsupervised ways...