# Application of machine learning in jet quenching
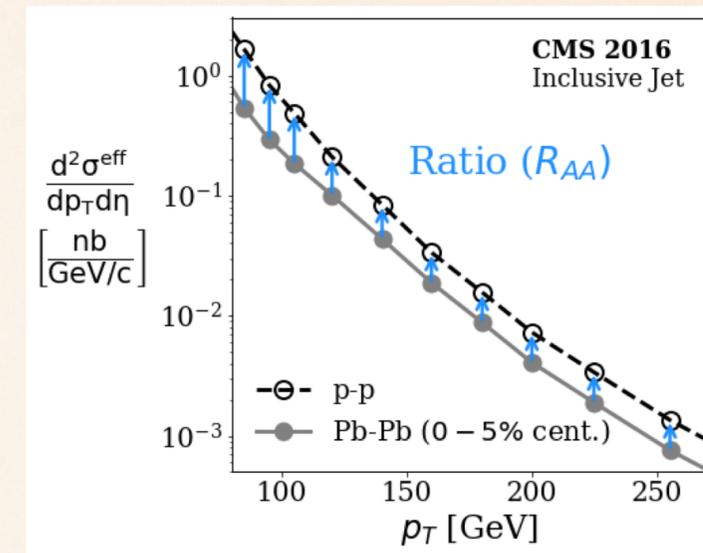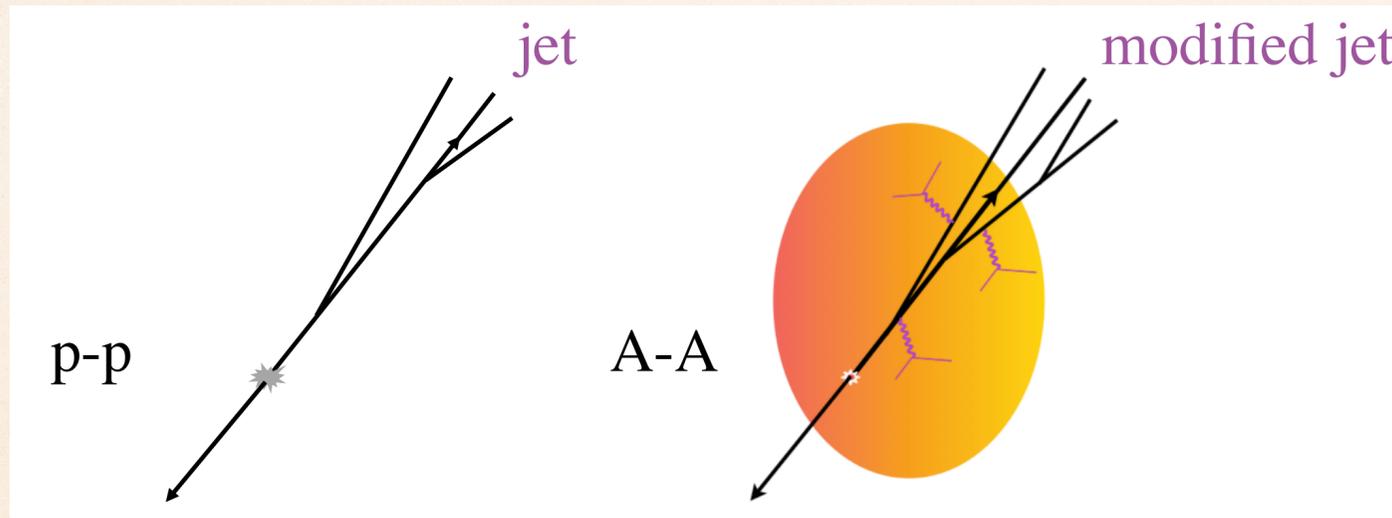
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Jan. 23-26, Wuhan

# Outline

- Prediction of Jet Energy Loss

- Reconstruction of Jet Momentum
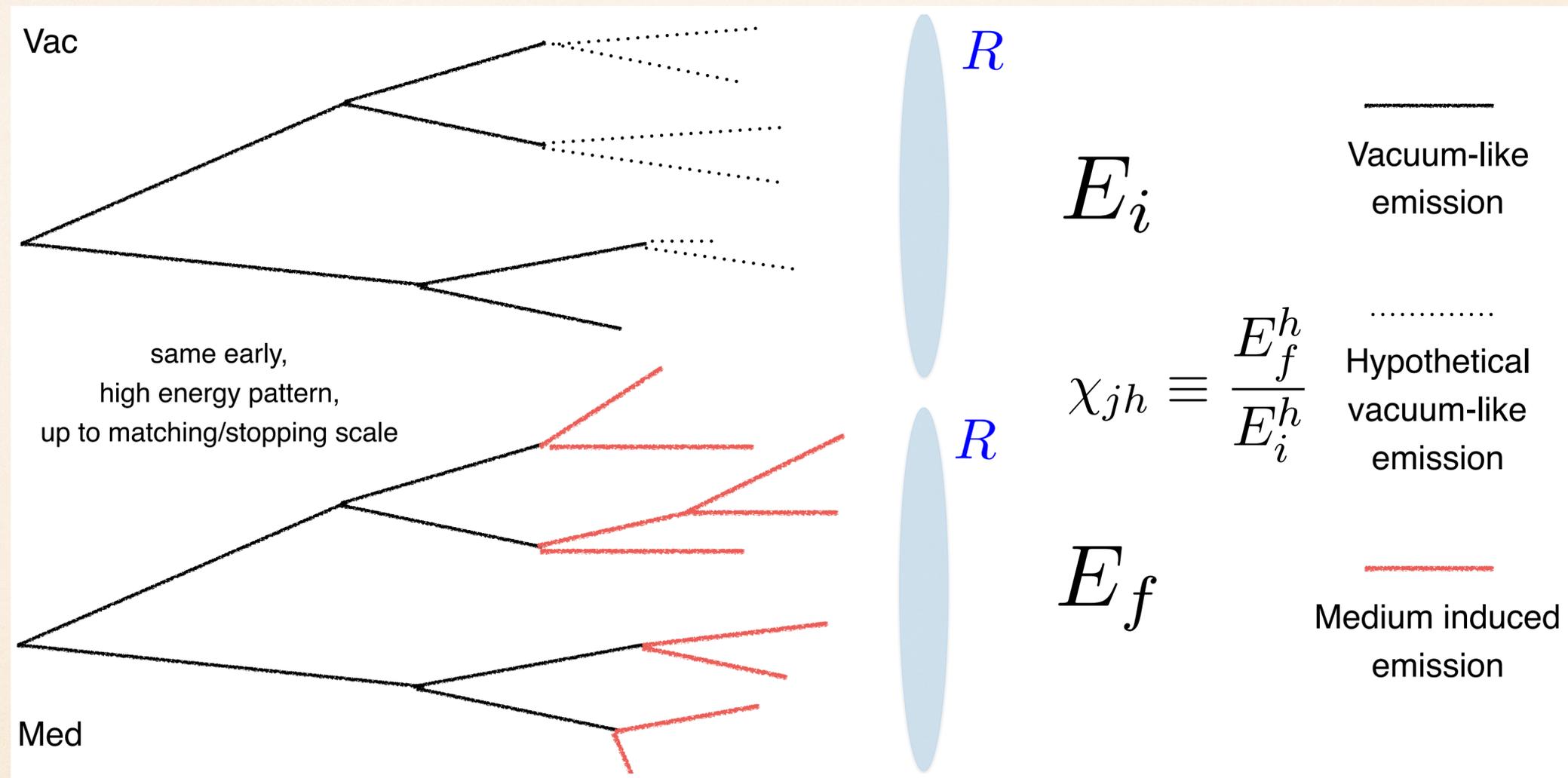
# QGP and Jet Modifications



jet       modified jet

p-p       A-A



- ❖ Quark-gluon plasma (QGP) in heavy-ion collisions: deconfined phase, hot dense medium.

- ❖ Jets, collimated sprays of energetic particles, serving as hard probe to medium properties.

- ❖ Jets are quenched in the medium via parton energy loss.

- ❖ Jet transverse momentum $p_T$ is the key quantity to measure the quenching effects.
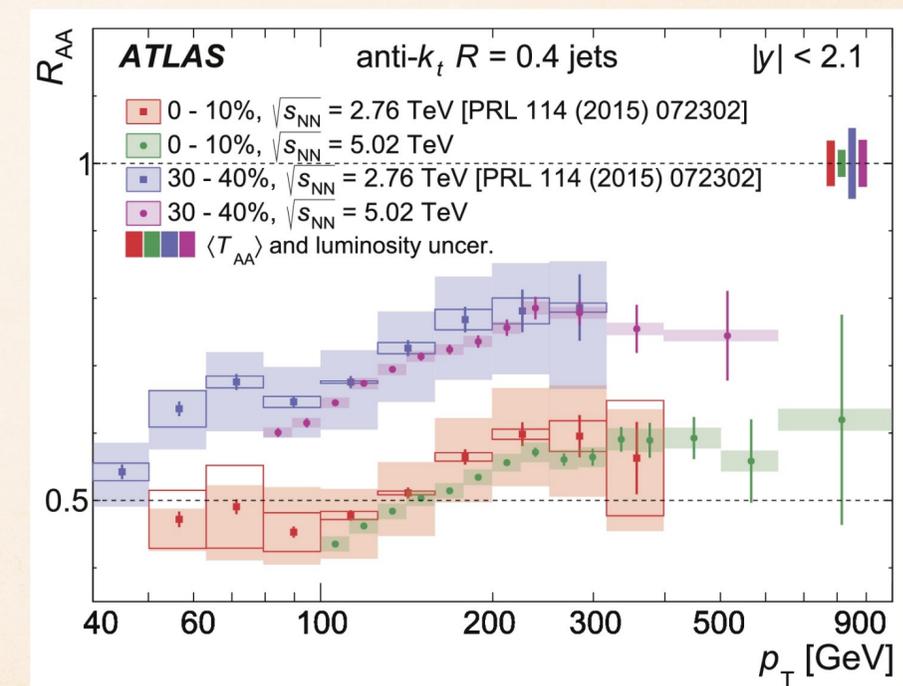
# From event-averaged observables to jet-by-jet energy loss

## Defining the energy loss ratio

Vac

$R$

$E_i$

——
Vacuum-like emission

same early,
high energy pattern,
up to matching/stopping scale

$R$

$$\chi_{jh} \equiv \frac{E_f^h}{E_i^h}$$

··········
Hypothetical vacuum-like emission

$E_f$

——
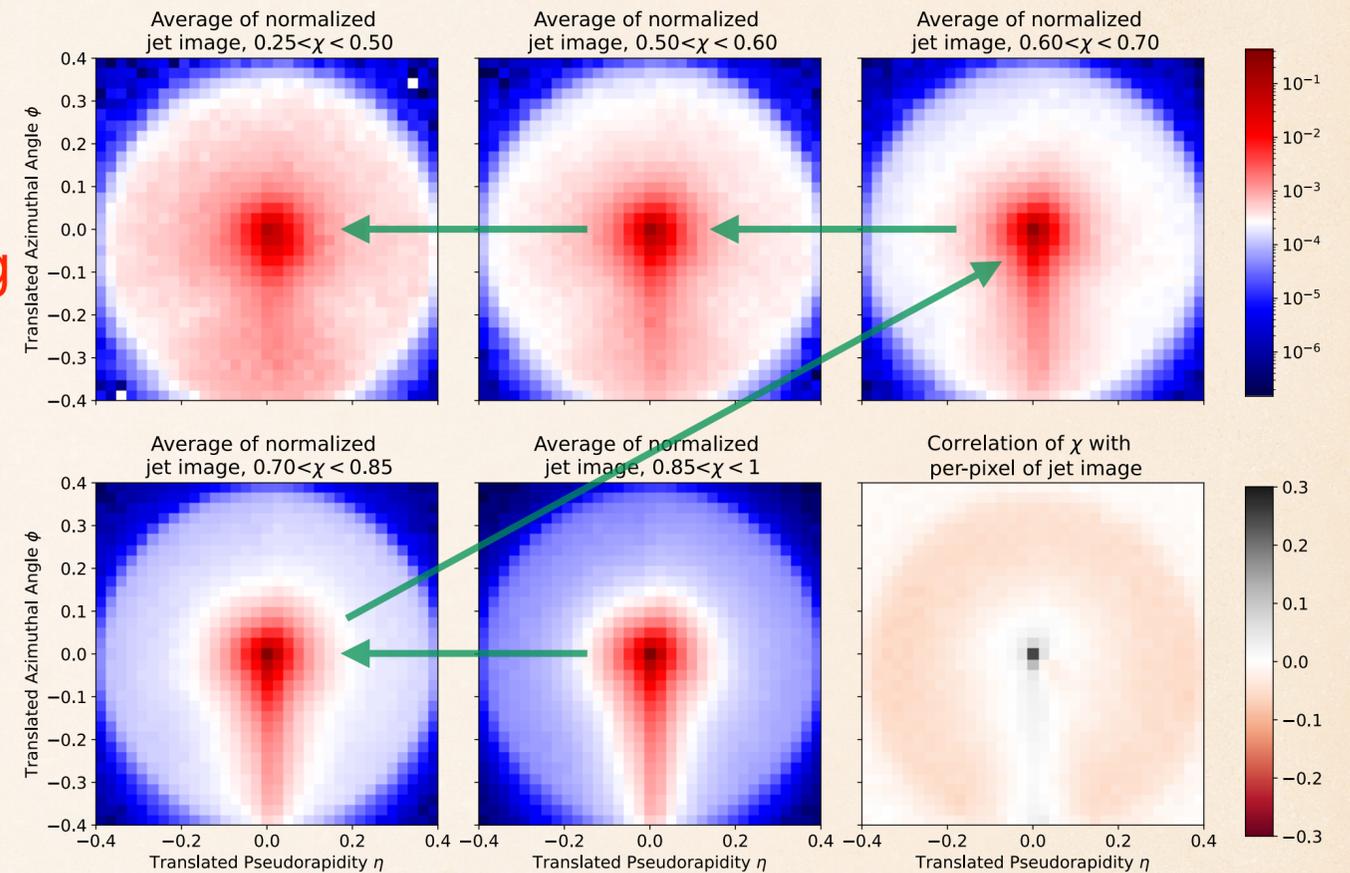Medium induced emission

Med

## Generalizable jet energy loss ratio

# Prior efforts: Strong/weak hybrid model

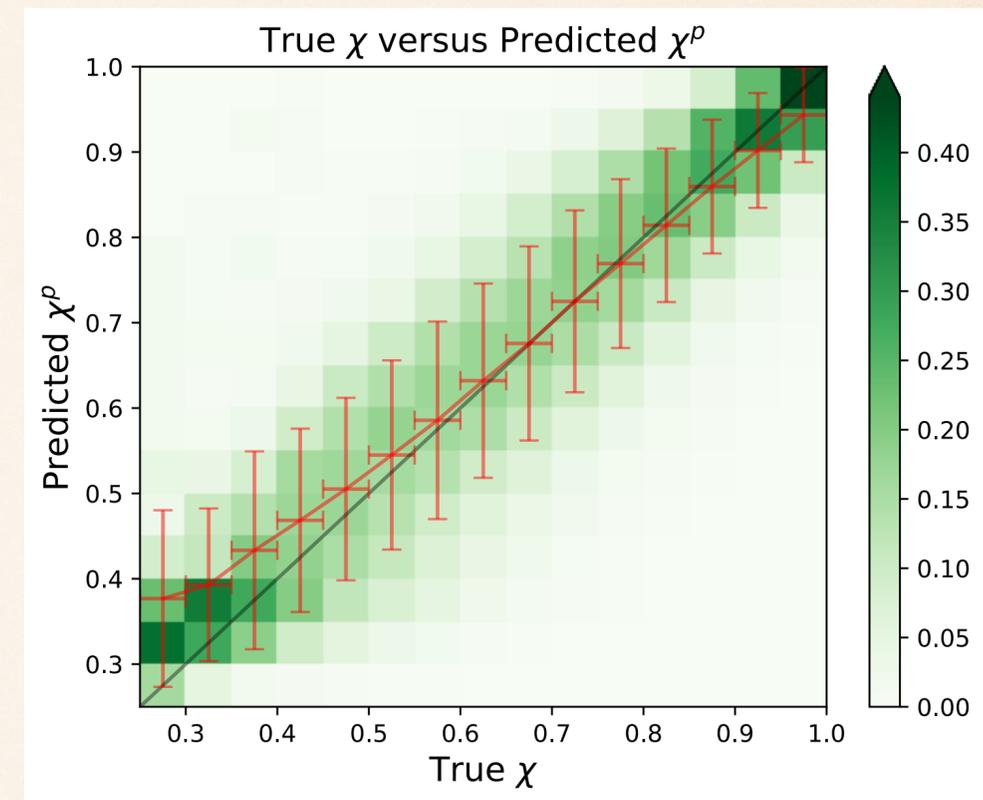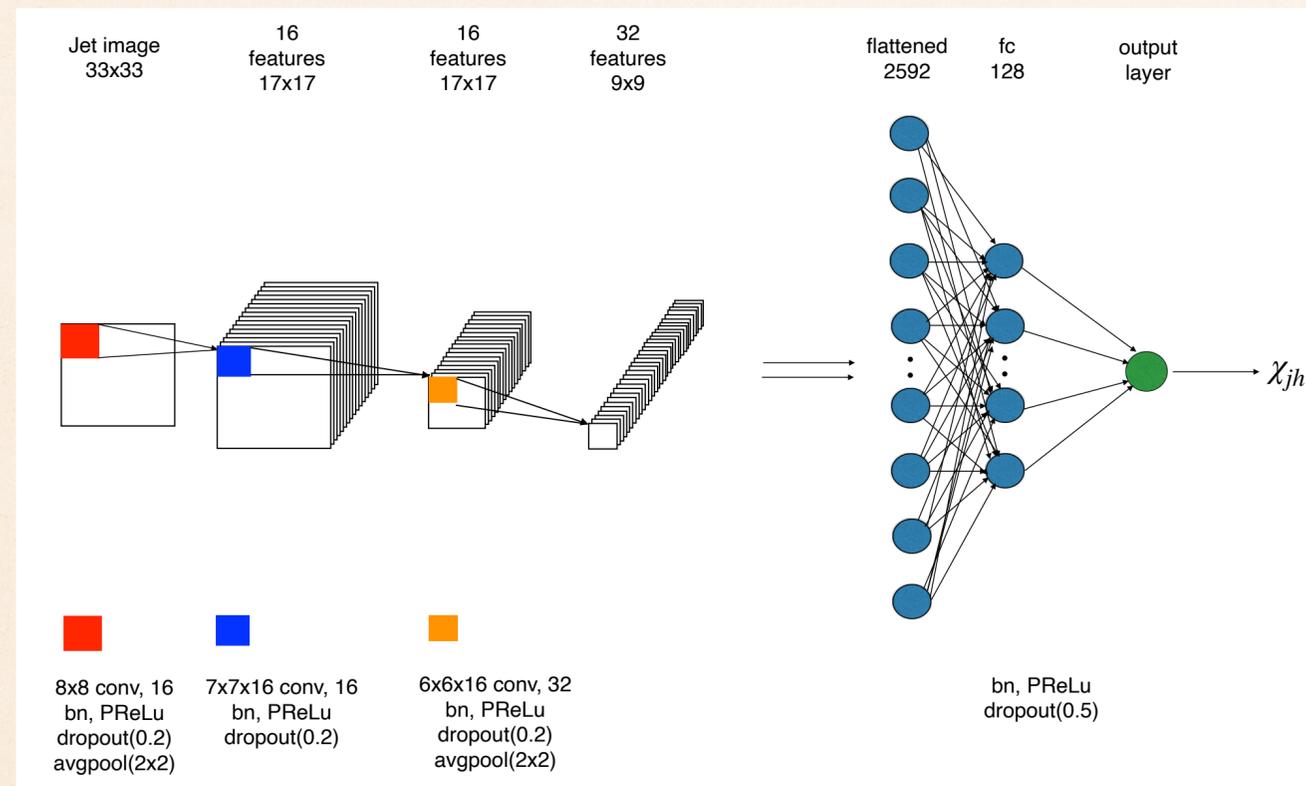YLD, D. Pablos and K. Tywoniuk, JHEP03(2021)206
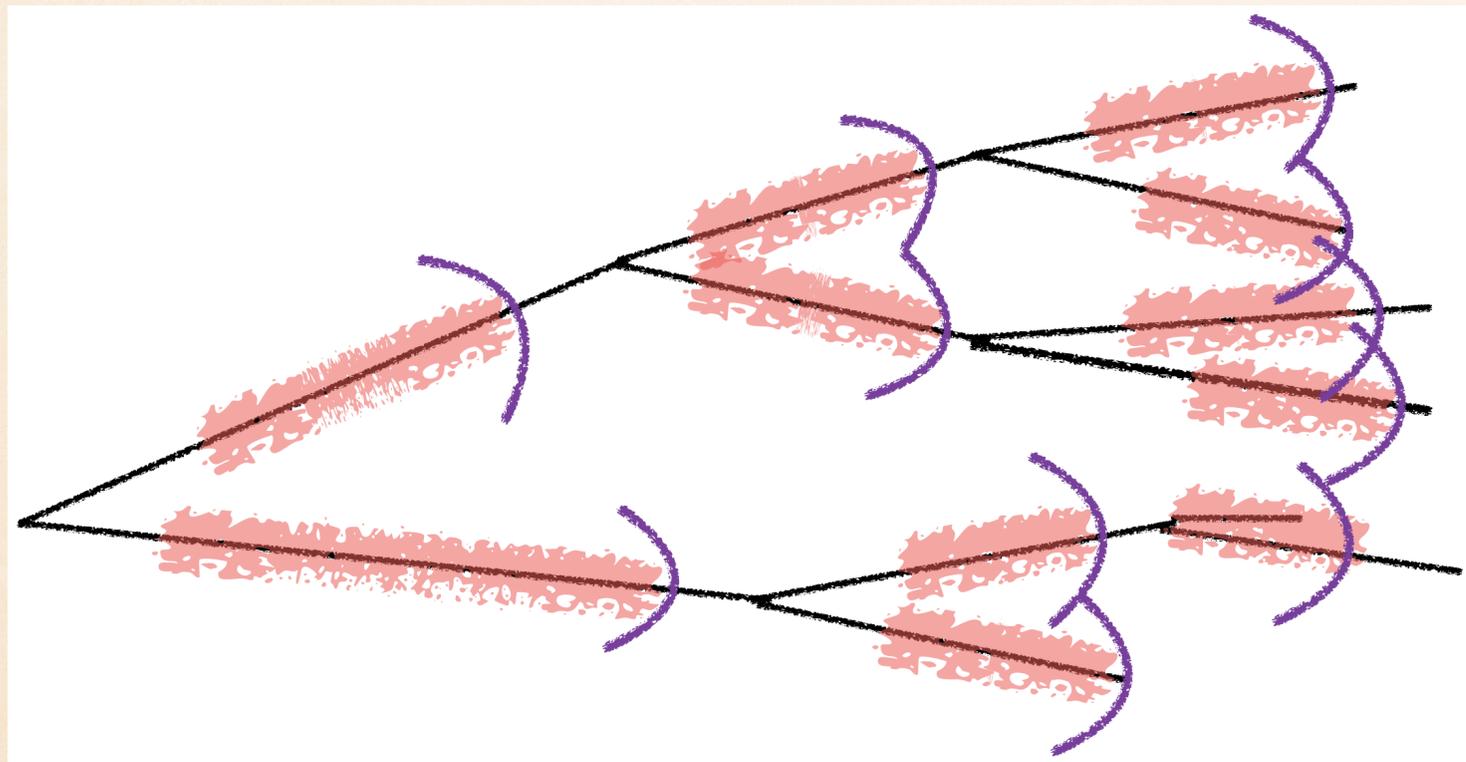


Strongest quenching

Weakest quenching

Pearson Coefficients

- PYTHIA8 down to hadronization scale
- Strongly coupled energy loss at every stage
- Hadrons from the hydro. wake (medium response)

Jet quenching increases the number of soft particles at large angles
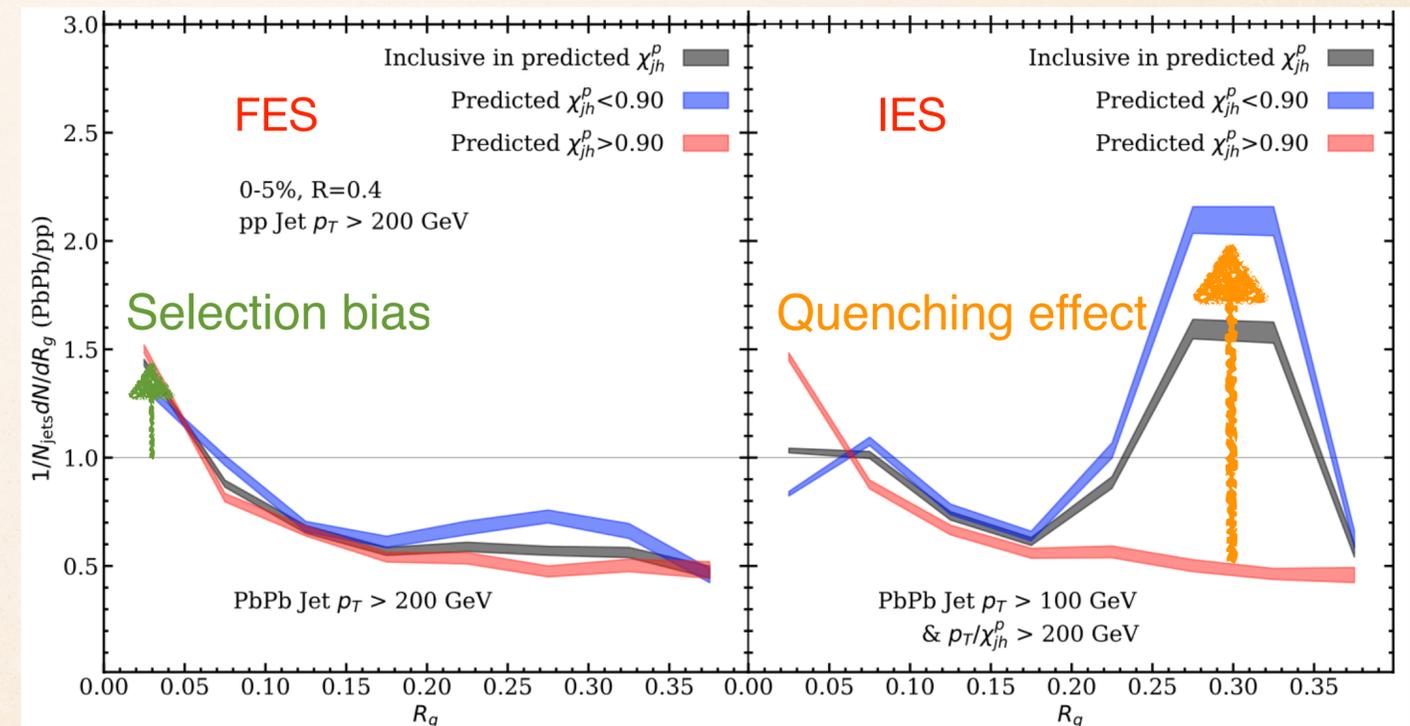
# CNN Prediction of Jet Energy Loss

- ❖ Regression analysis of jet energy loss between the twin jets with CNN

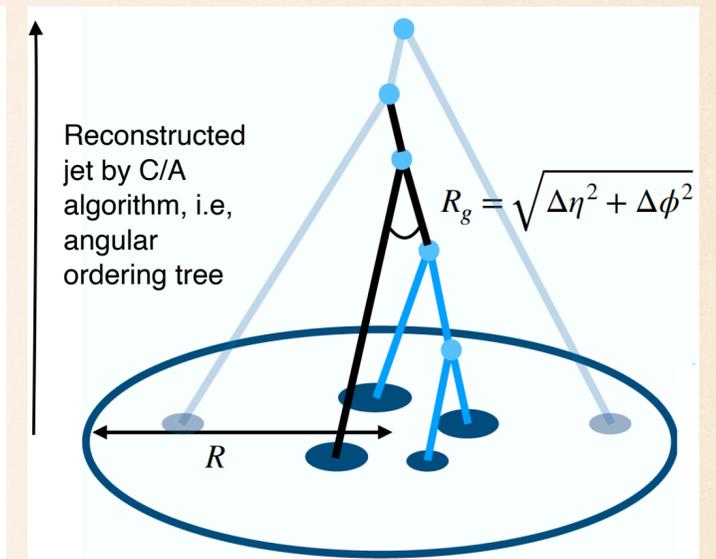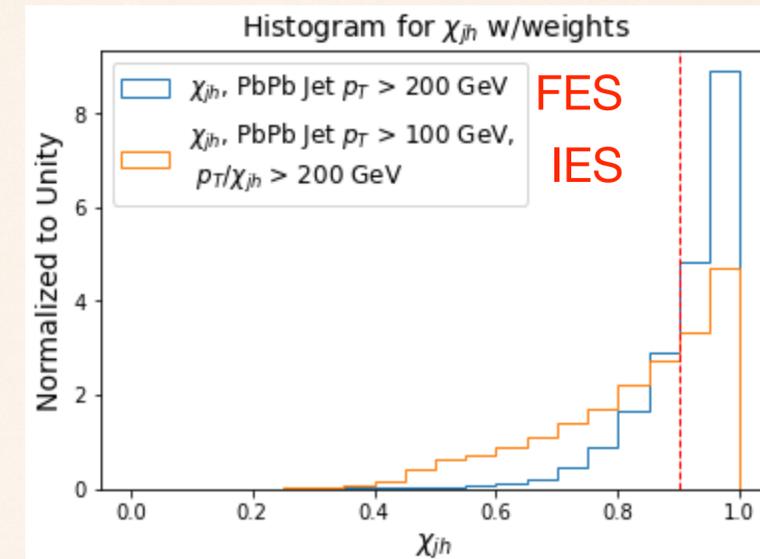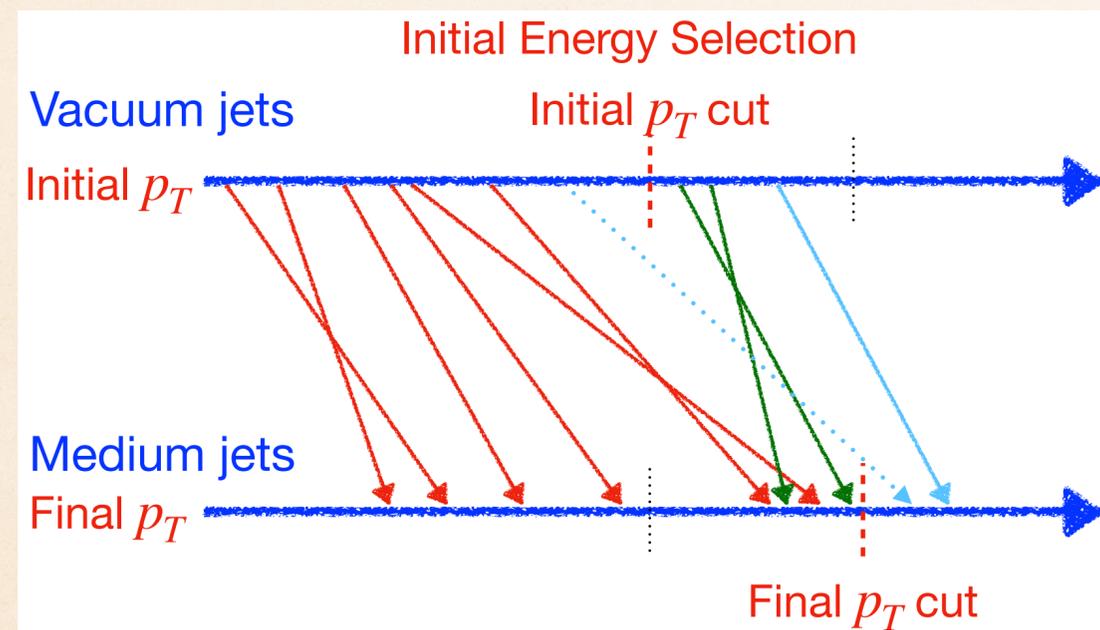- ❖ Well predicted for a wide range of $\chi$

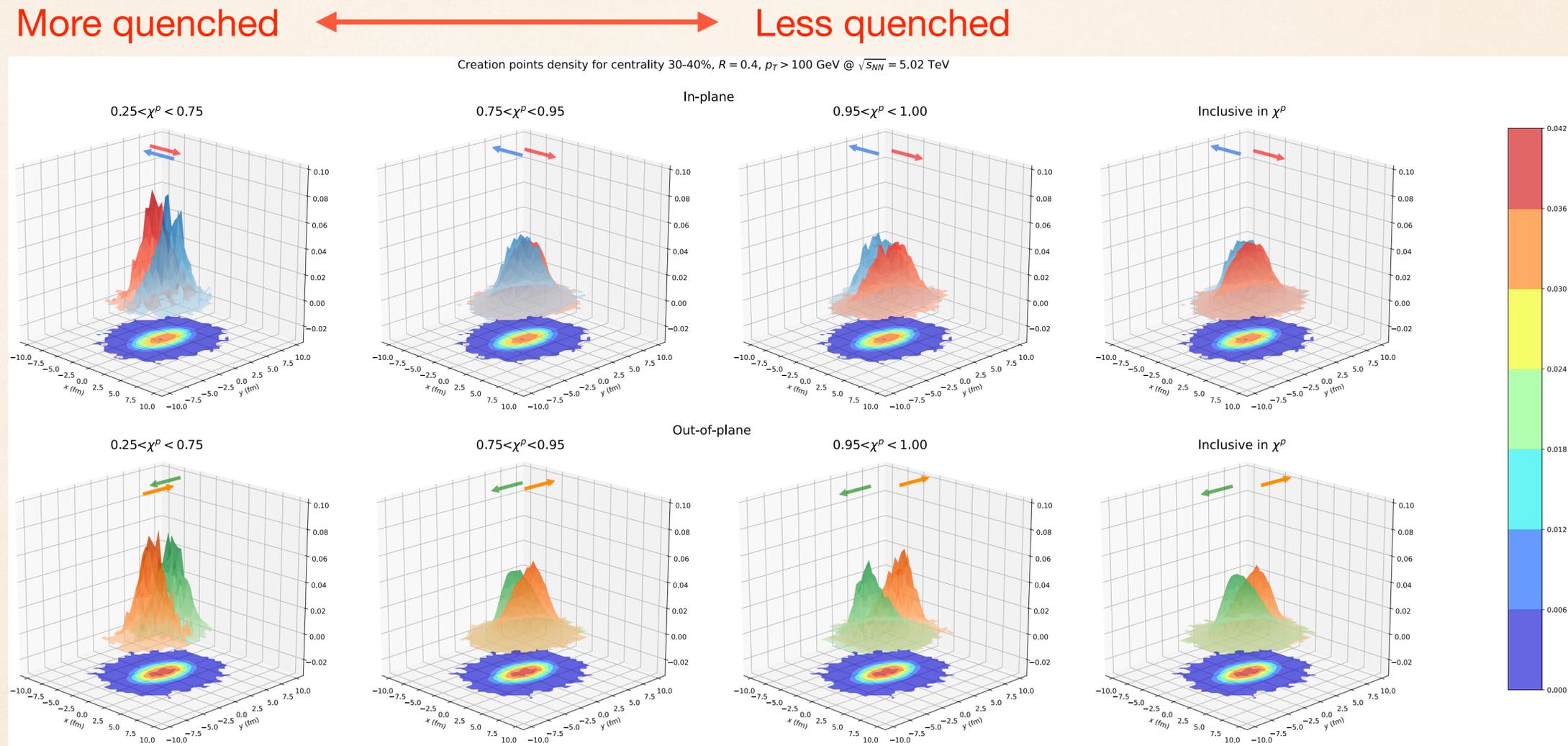# Initial VS Final Energy Selection: Apple-to-apple comparison

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

$$z_g = \frac{p_{\mathrm{T,sublead}}}{p_{\mathrm{T,lead}} + p_{\mathrm{T,sublead}}}$$



Final Energy Selection

Vacuum jets

Initial $p_T$ cut

Initial $p_T$

Medium jets

Final $p_T$

Final $p_T$ cut

Initial Energy Selection

Vacuum jets

Initial $p_T$ cut

Initial $p_T$

Medium jets

Final $p_T$

Final $p_T$ cut

Histogram for $\chi_{jh}$ w/weights

$\chi_{jh}$, PbPb Jet $p_T > 200$ GeV — FES

$\chi_{jh}$, PbPb Jet $p_T > 100$ GeV, $p_T/\chi_{jh} > 200$ GeV — IES

Normalized to Unity

$\chi_{jh}$

Reconstructed jet by C/A algorithm, i.e, angular ordering tree

$R_g = \sqrt{\Delta\eta^2 + \Delta\phi^2}$

$R$

FES

IES

Inclusive in predicted $\chi_{jh}^p$

Predicted $\chi_{jh}^p < 0.90$

Predicted $\chi_{jh}^p > 0.90$

Inclusive in predicted $\chi_{jh}^p$

Predicted $\chi_{jh}^p < 0.90$

Predicted $\chi_{jh}^p > 0.90$

0-5%, R=0.4
pp Jet $p_T > 200$ GeV

Selection bias

Quenching effect

$1/N_{jets}dN/dR_g$ (PbPb/pp)

PbPb Jet $p_T > 200$ GeV

PbPb Jet $p_T > 100$ GeV & $p_T/\chi_{jh}^p > 200$ GeV

$R_g$

$R_g$

$\frac{d\sigma}{d}$

Pb–Pb

ALI

# Towards jet tomography

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

More quenched ⟷ Less quenched



Creation points density for centrality 30-40%, $R = 0.4$, $p_T > 100$ GeV @ $\sqrt{s_{NN}} = 5.02$ TeV

◈ Strong correlation between jet traversed length $L$ and energy loss $\chi$

◈ Selecting jets with different $\chi$ will naturally select jets that traversed different $L$: Great potential to make tomographic application!
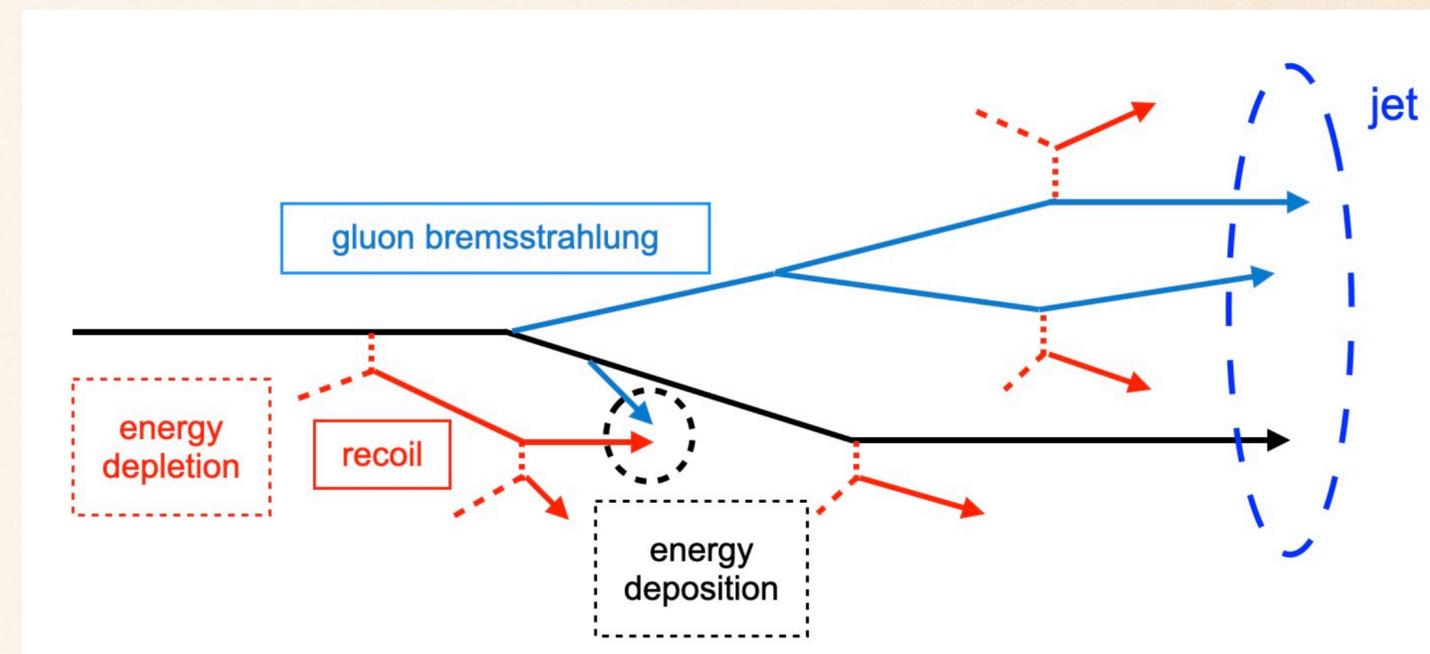
# Challenges from the QGP background

◈ Vacuum jets: PYTHIA8 model

◈ Jet interaction with QGP: Linear Boltzmann Transport (LBT) model

◈ Pb-Pb collisions in 0-10% centrality at $\sqrt{S}$=5.02TeV

◈ QGP background: a toy thermal model

## Background

| $\pi^+ + \pi^-$ | |
|---|---|
| $\mathrm{d}N/\mathrm{d}y$ | $< p_T >$ |
| 1699.80 | 0.5682 GeV |

$p_T$ follows a Boltzmann distribution



gluon bremsstrahlung

energy depletion    recoil

energy deposition

jet

## LBT model

• Jet $p_T$ — sum of the LBT jet particle $p_T$ within jet cone, in the presence of background particles

# CNN prediction performance on LBT jets

Ran Li, YLD, Shanshan Cao, *arXiv:2508.20856*

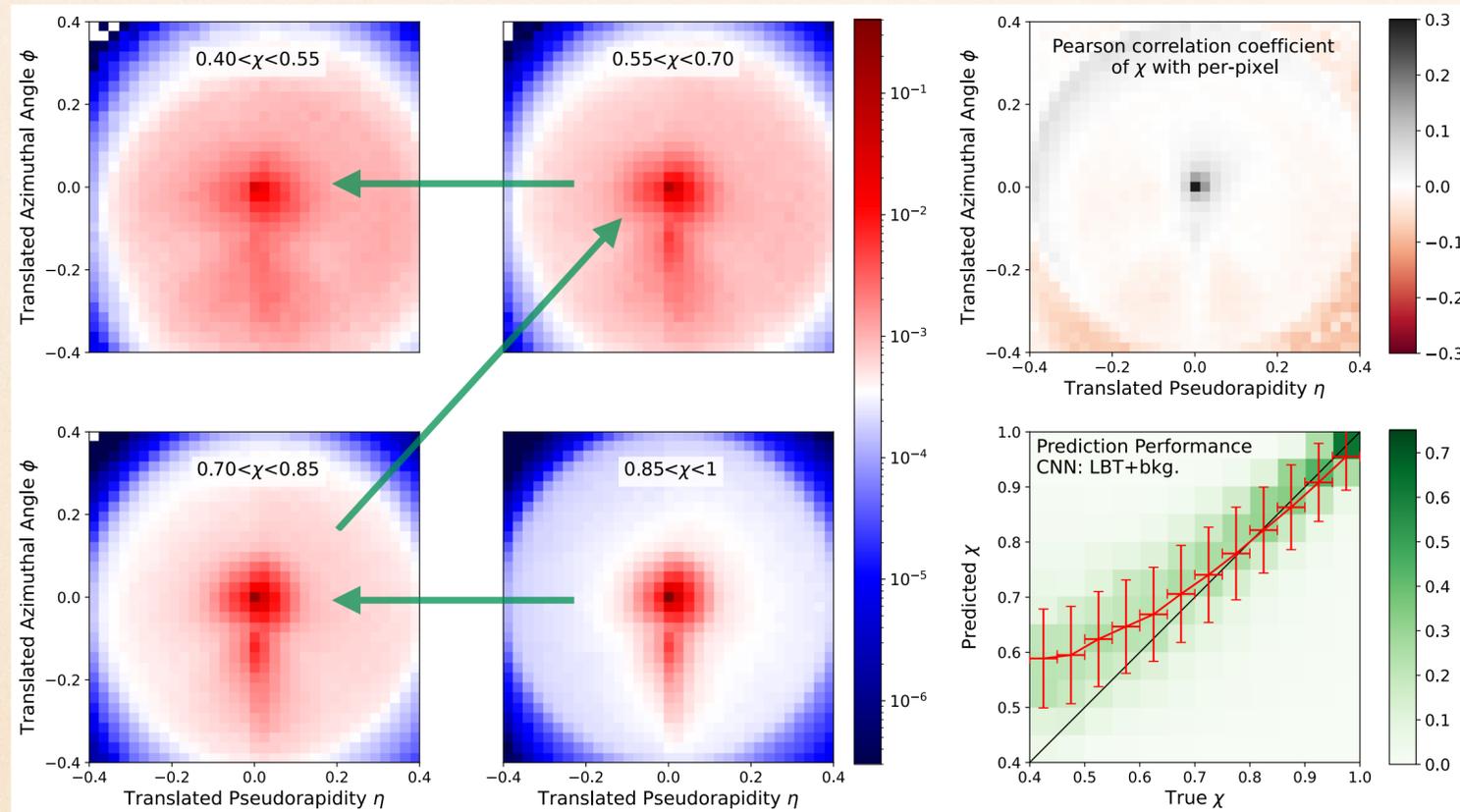LBT jets without QGP background

LBT jets within QGP background
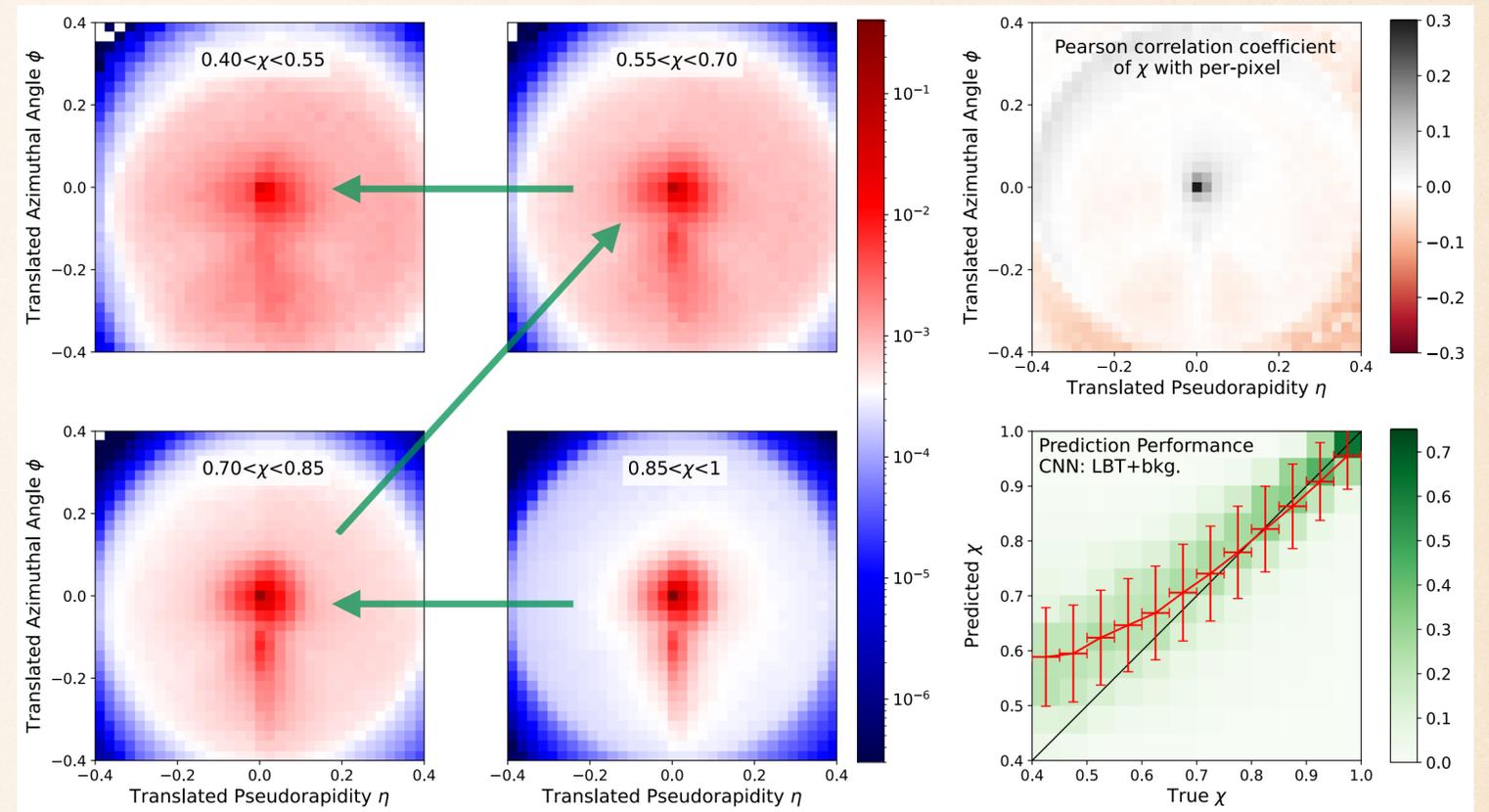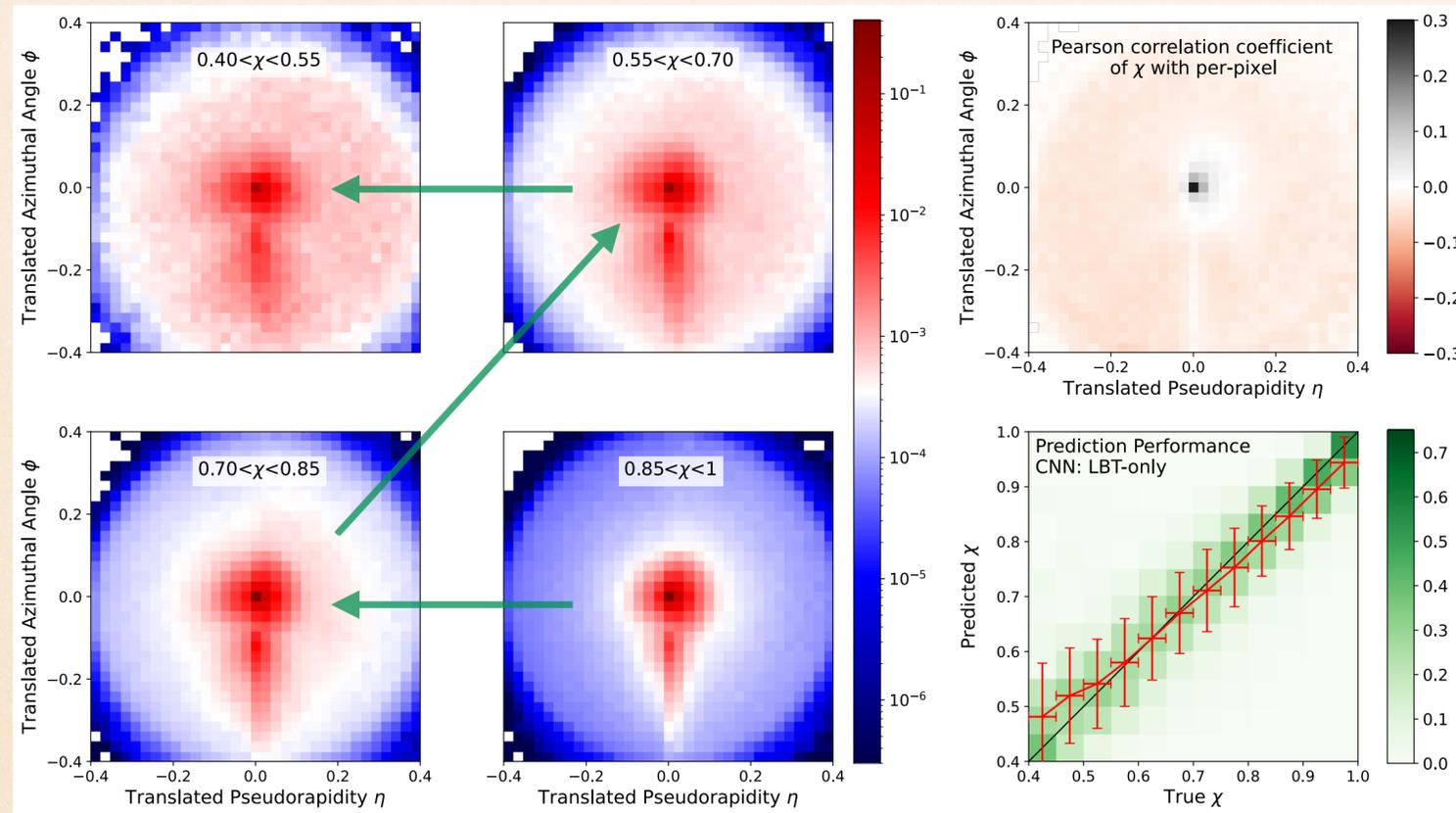


◈ CNN prediction performance on LBT jets is comparable with that on jets from Hybrid model

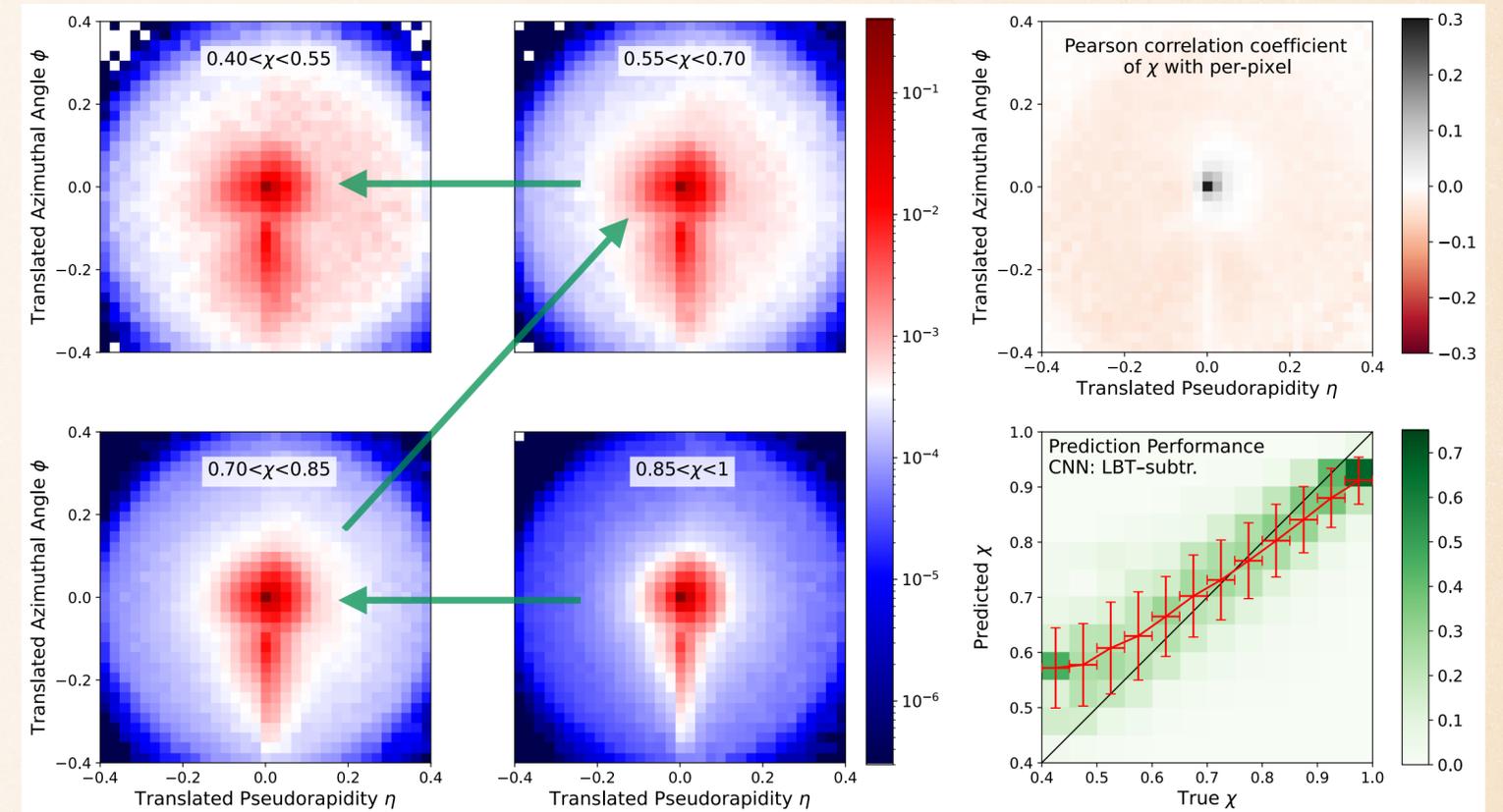◈ QGP background weakens the correlations between jet images and energy loss ratio, leading to degraded performance

# CNN prediction performance on LBT jets

Ran Li, YLD, Shanshan Cao, *arXiv:2508.20856*

LBT jets within QGP background

LBT jets with QGP bkg. subtracted



❖ The correlations between jet images and energy loss ratio is largely recovered via subtraction of background particles (Constituent Subtraction method), as well as the CNN prediction performance
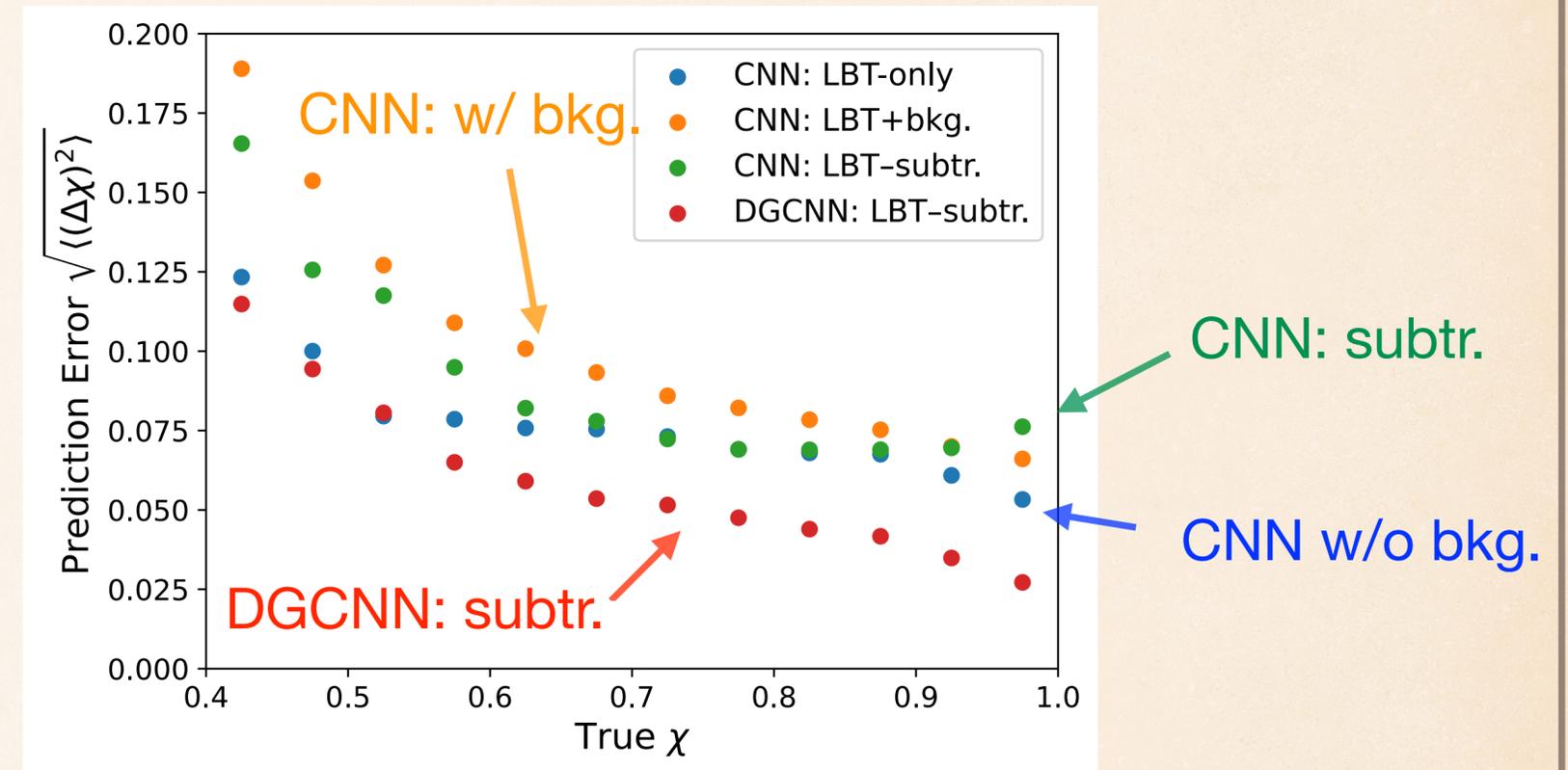
❖ How to further improve?

# DGCNN on point cloud of LBT jets after bkg. subtr.

Ran Li, YLD, Shanshan Cao, *arXiv:2508.20856*
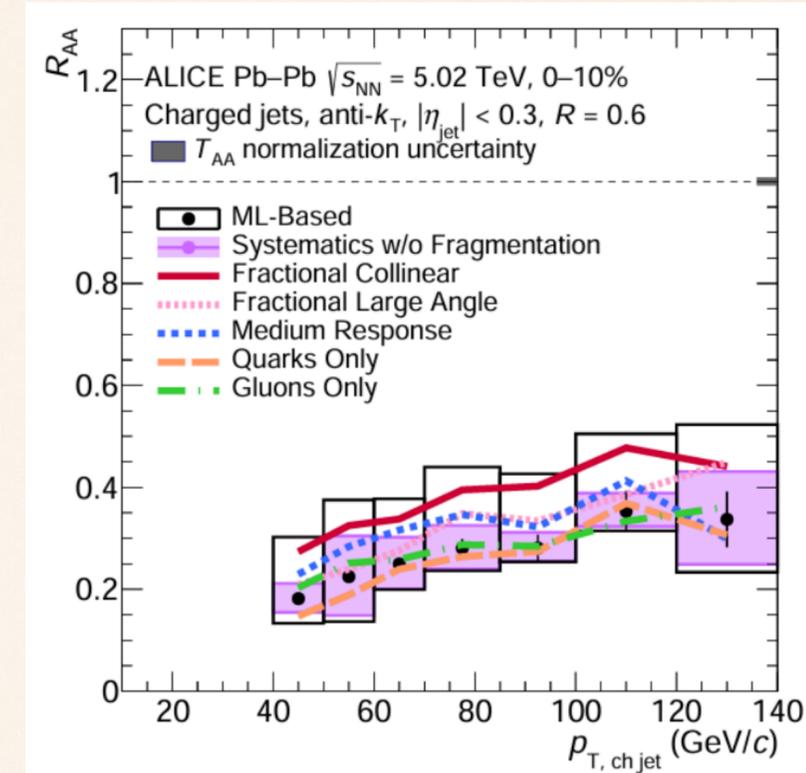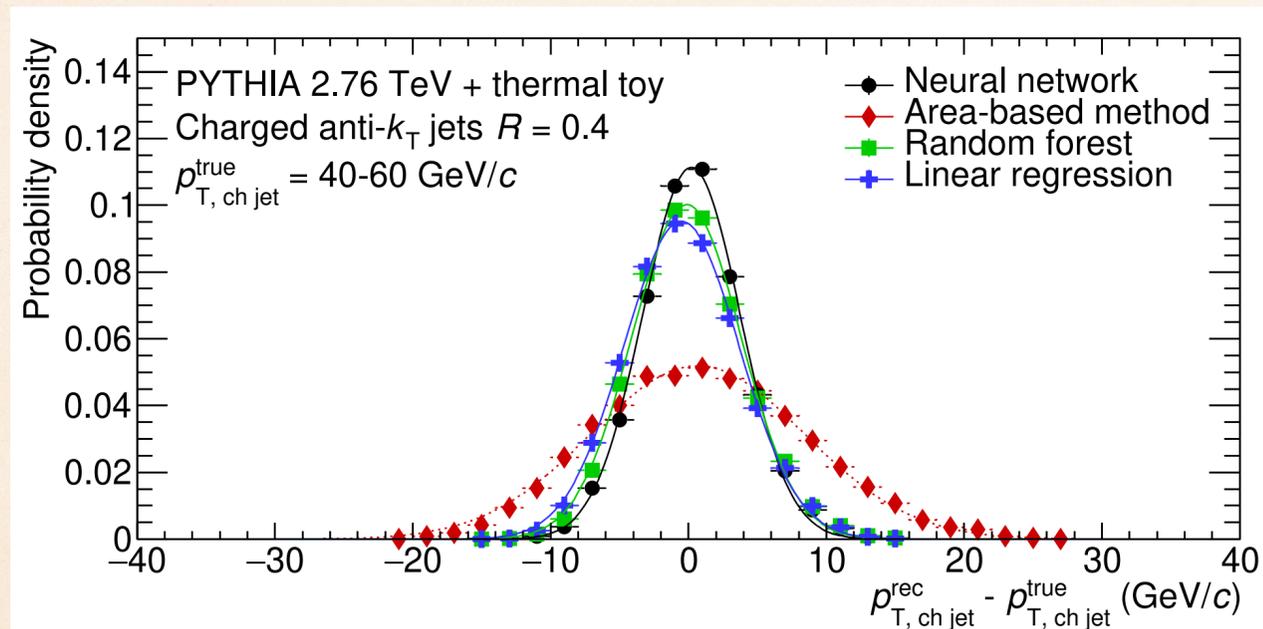
DGCNN Performance

Prediction Errors



More quenched ⟷ Less quenched
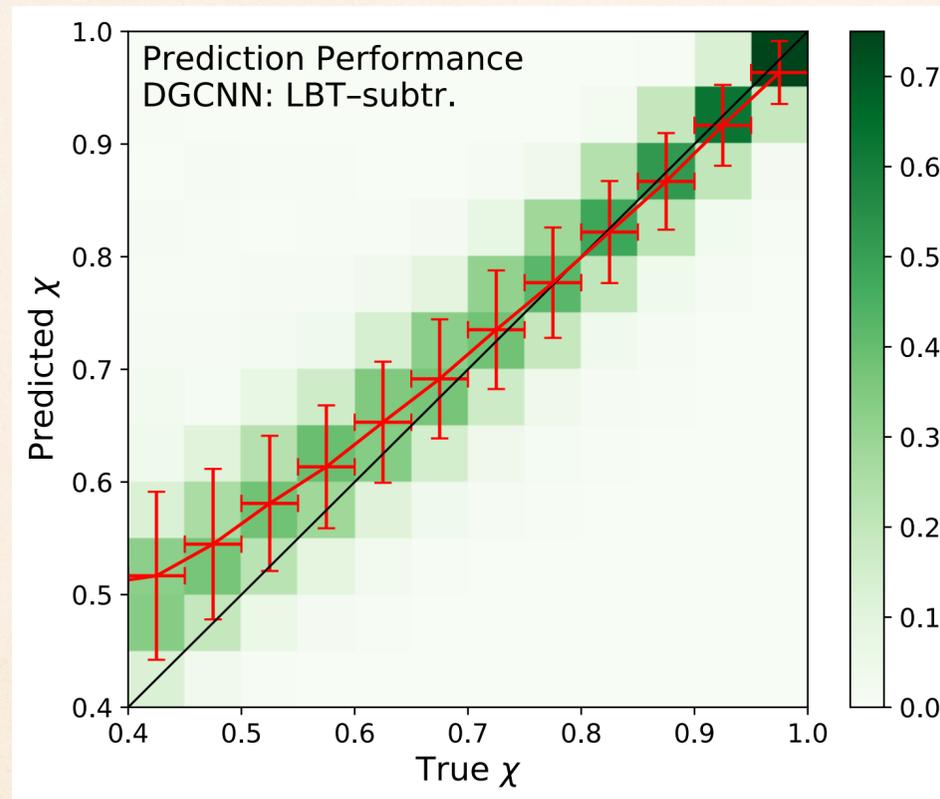
❖ DGCNN takes point cloud representation of jets as input, keeping the full jet information

❖ DGCNN achieves the best performance in all scenarios

# Jet Momentum Reconstruction in ALICE

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

ALICE: *PLB* 849 (2024): 138412



- ML-based methods outperform the traditional Area-based method in predicting jet momentum in the presence of the QGP background

- ML models are trained using PYTHIA jets without quenching effects

- Successful application in ALICE measurement

- ML models are trained using PYTHIA jets + toy models of different quenching effects separately to avoid the training bias and quantify the systematics errors

- Why not train different jet fragmentation patterns simultaneously?

# Effects of realistic medium modification on ML performance
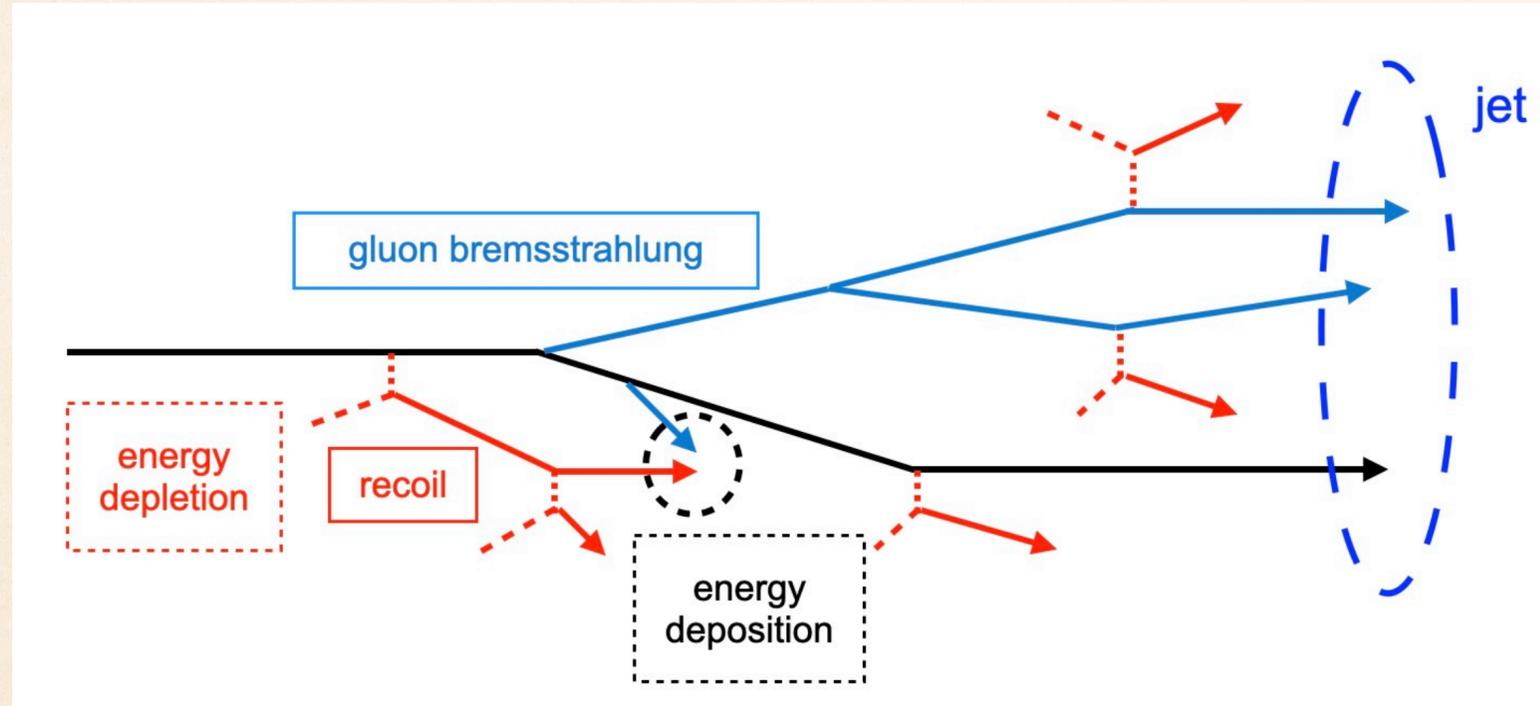
LBT model
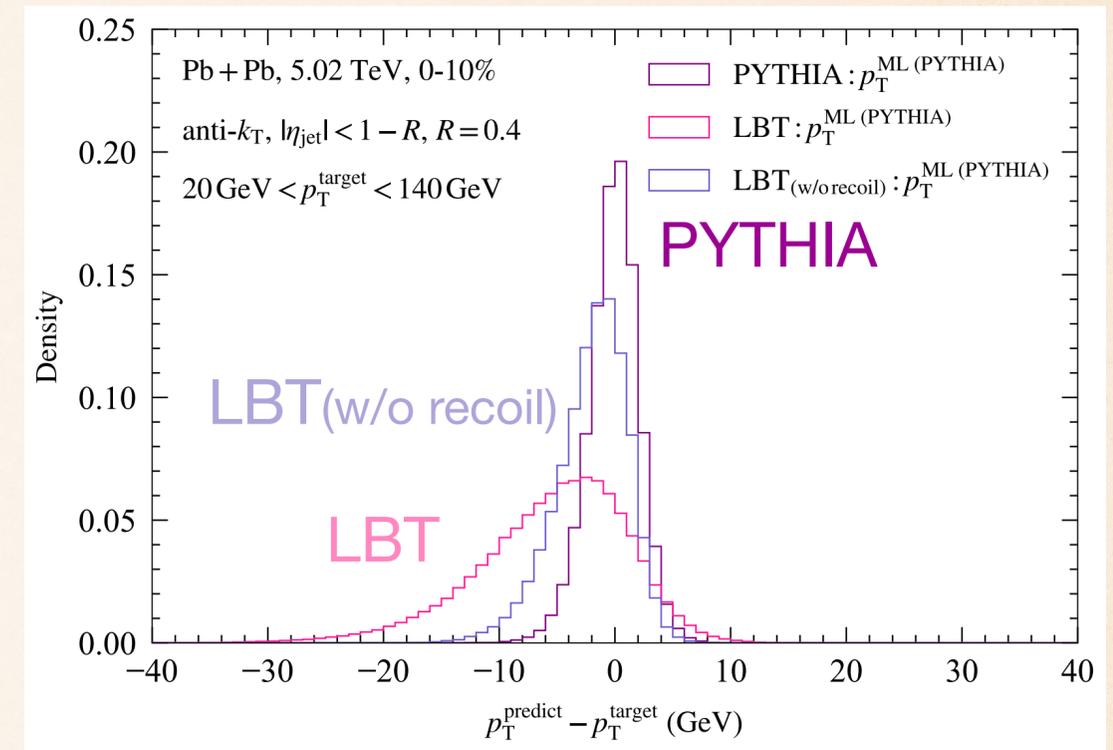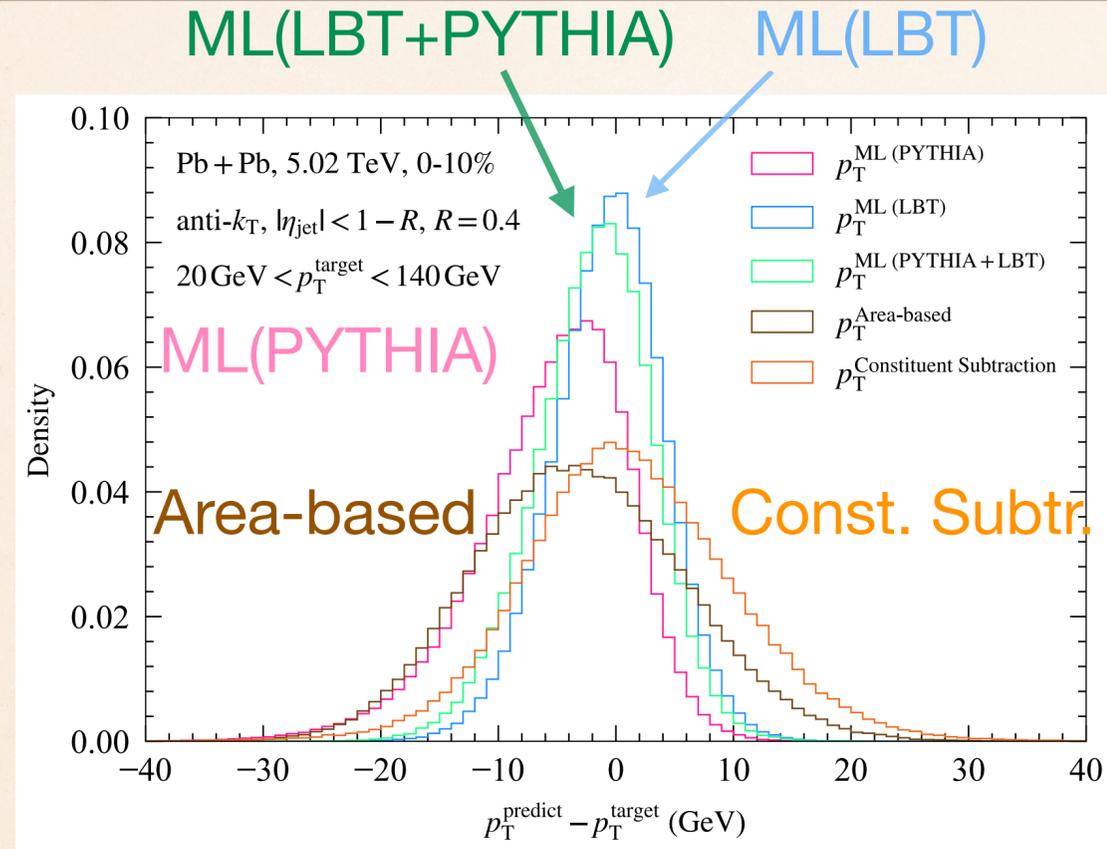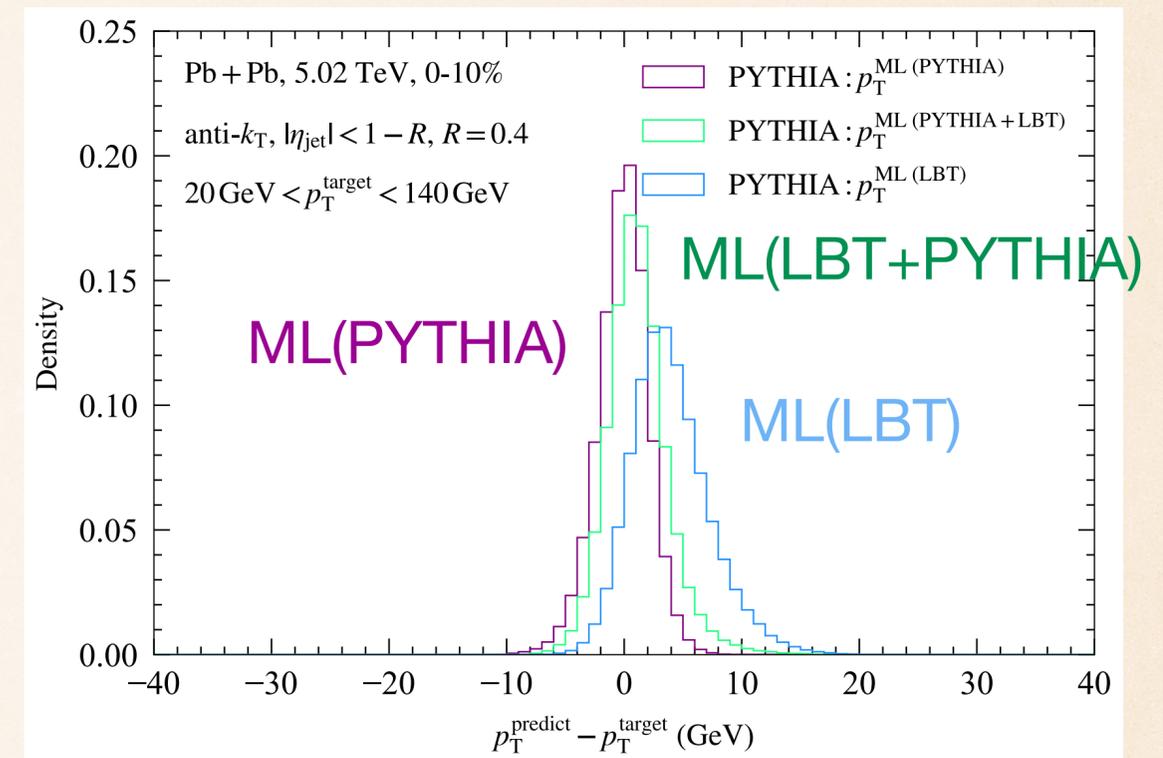


Test PYTHIA-trained ML on different datasets

- PYTHIA-trained ML has a prediction bias when applied on LBT jets.

- The bias is reduced when the ML model is applied on LBT jets without recoil particles: Recoil particles may be considered as the background.

- Conclusion: ML model trained using vacuum jets is incapable of recognizing medium response particles in quenched jets

# Performance of different ML models

ML(LBT+PYTHIA)  ML(LBT)

ML(PYTHIA)

Area-based  Const. Subtr.

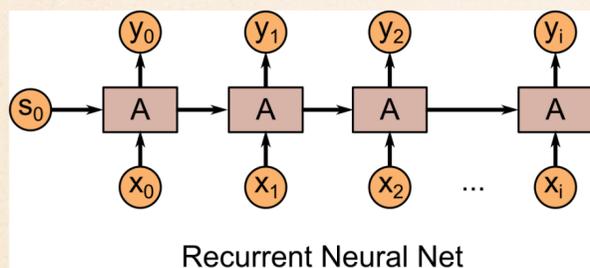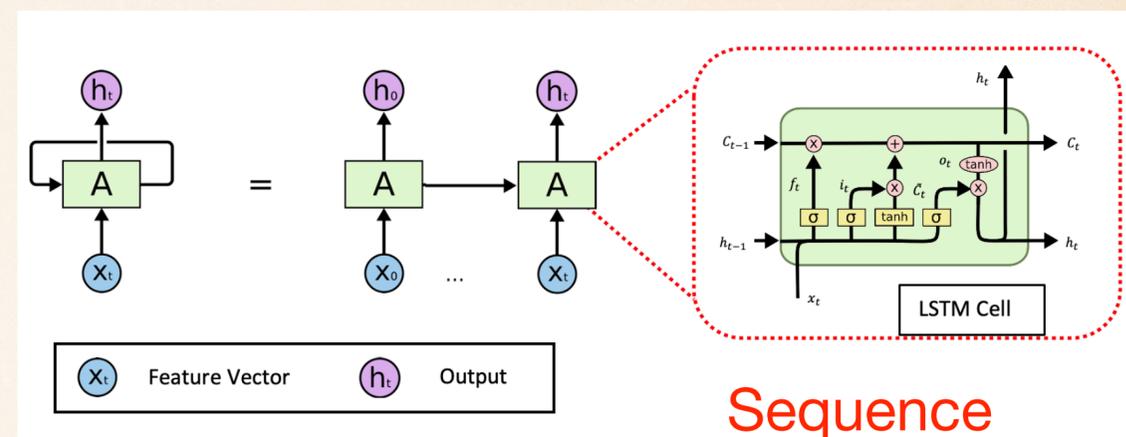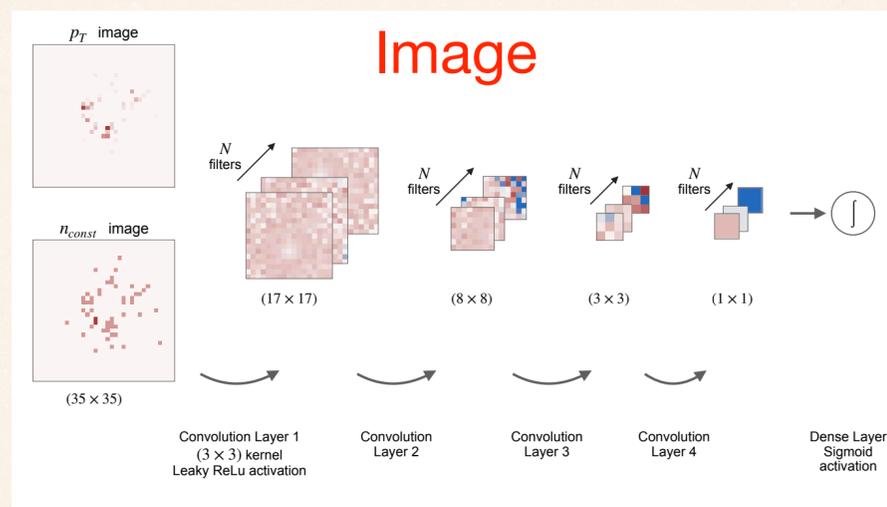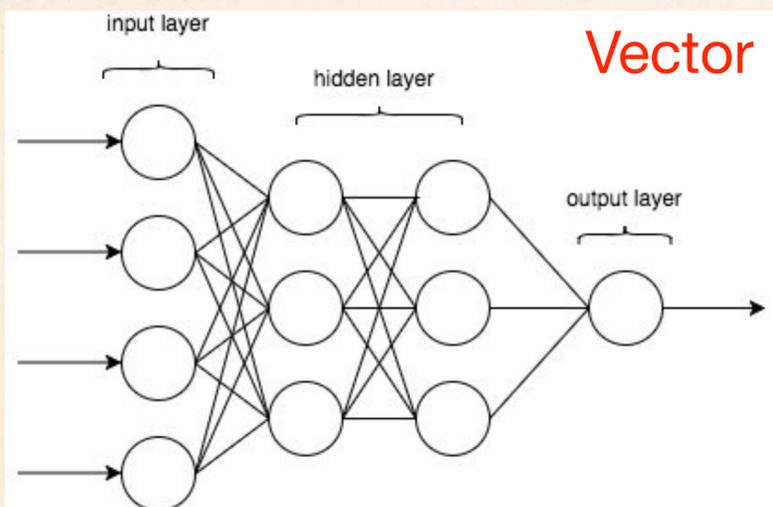Testing on LBT data



ML(LBT+PYTHIA)

ML(PYTHIA)

ML(LBT)

Testing on PYTHIA data

❖ The bias is reduced when the ML model is trained by LBT jets directly or by LBT+PYTHIA jets.

❖ LBT+PYTHIA-trained ML can make accurate predictions on PYTHIA and LBT data simultaneously, demonstrating strong robustness.

❖ ML methods are more accurate than conventional methods (Area-based & Constituent Subtraction ).

# Summary & Outlook

◈ DGCNN, *taking full jet information*, can obtain good prediction performance on jet energy loss in the presence of QGP background.

◈ To better reconstruct jet momentum with machine leaning, training the ML models with various realistic quenched jets simultaneously are recommended to obtain strong robustness and generalizability.

• Develop novel ML models, e.g., transformer, to deal with jet & background particles directly to improve the prediction accuracy and avoid the procedure of background removal.

• Reduce model dependence: Incorporate quenched jets from various MC models.

• Include the realistic anisotropic QGP background for better generalizability in experiments.

# Machine Learning Tools for Jets

Vector

Image

$p_T$ image

$n_{const}$ image

$(35 \times 35)$

$(17 \times 17)$  $(8 \times 8)$  $(3 \times 3)$  $(1 \times 1)$

Convolution Layer 1
$(3 \times 3)$ kernel
Leaky ReLu activation

Convolution Layer 2

Convolution Layer 3

Convolution Layer 4

Dense Layer
Sigmoid
activation

input layer

hidden layer

output layer

$h_t$   $h_0$   $h_t$

$A$   =   $A$   $A$

$x_t$   $x_0$   ...   $x_t$

LSTM Cell

$x_t$ Feature Vector   $h_t$ Output

Sequence

Graph

$y_0$   $y_1$   $y_2$   $y_i$

$s_0$   $A$   $A$   $A$   ...   $A$

$x_0$   $x_1$   $x_2$   $x_i$

Recurrent Neural Net

PointNet → Bed

Point cloud

Tree

$A_{Branch}$

$A_{Branch}$

$A_{Leaf}$ $A_{Leaf}$ $A_{Leaf}$ $A_{Leaf}$

that  movie  was  cool

Recursive Neural Net

❖ Many tools suit a lot for jets

❖ A tremendous amount of applications in HEP arXiv:2102.02770

# Genuine Configuration Profile

Creation points for centrality 0-5%



$v_2$ VS Centrality for $R = 0.4$ @ $\sqrt{s_{NN}} = 5.02$ TeV
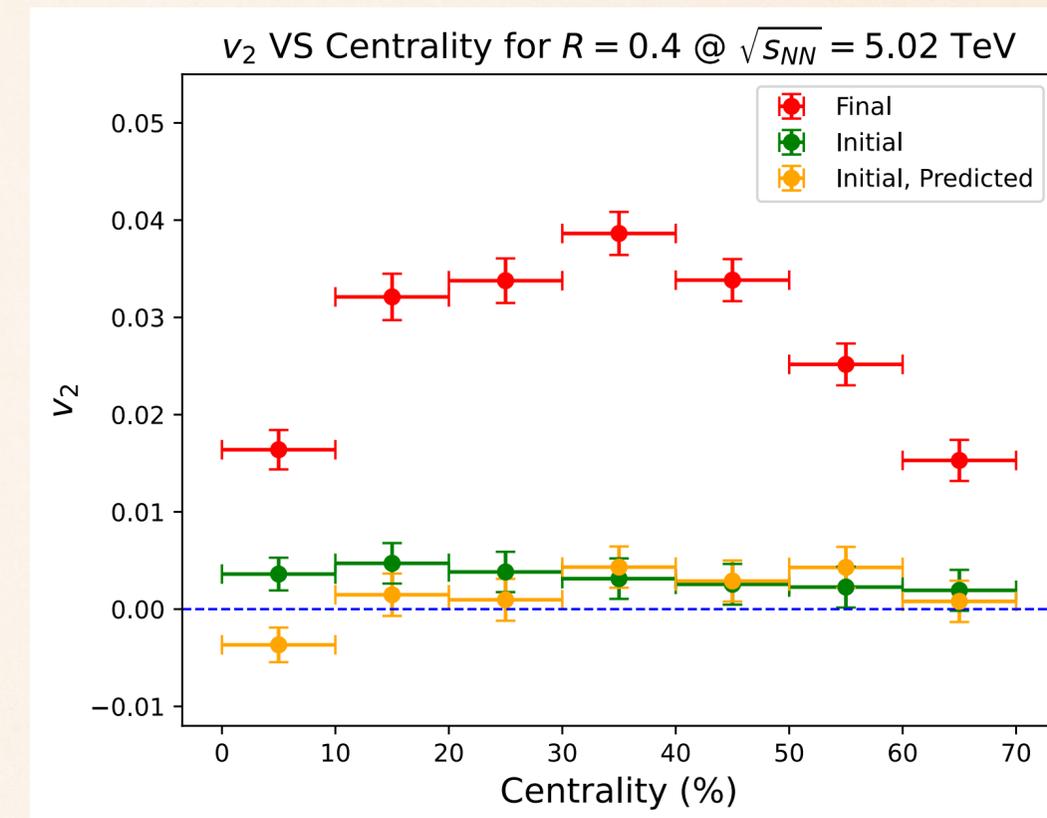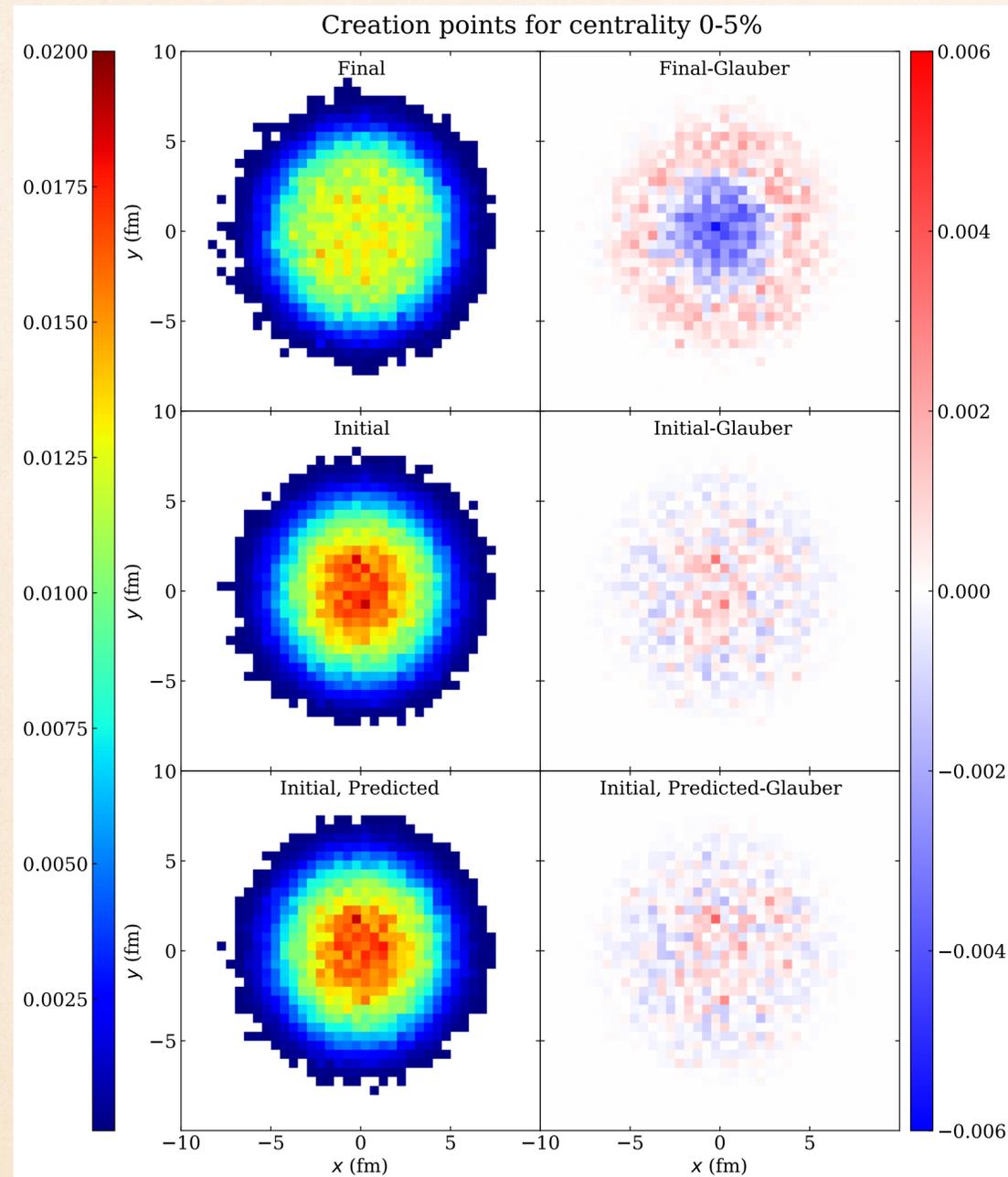
- ❖ Initial Energy Selection (IES) "removes" final state interactions (selection bias), since we record "all" jets

- ❖ IES provides access to the genuine jet creation point (path length) distribution and possible initial-state jet anisotropy
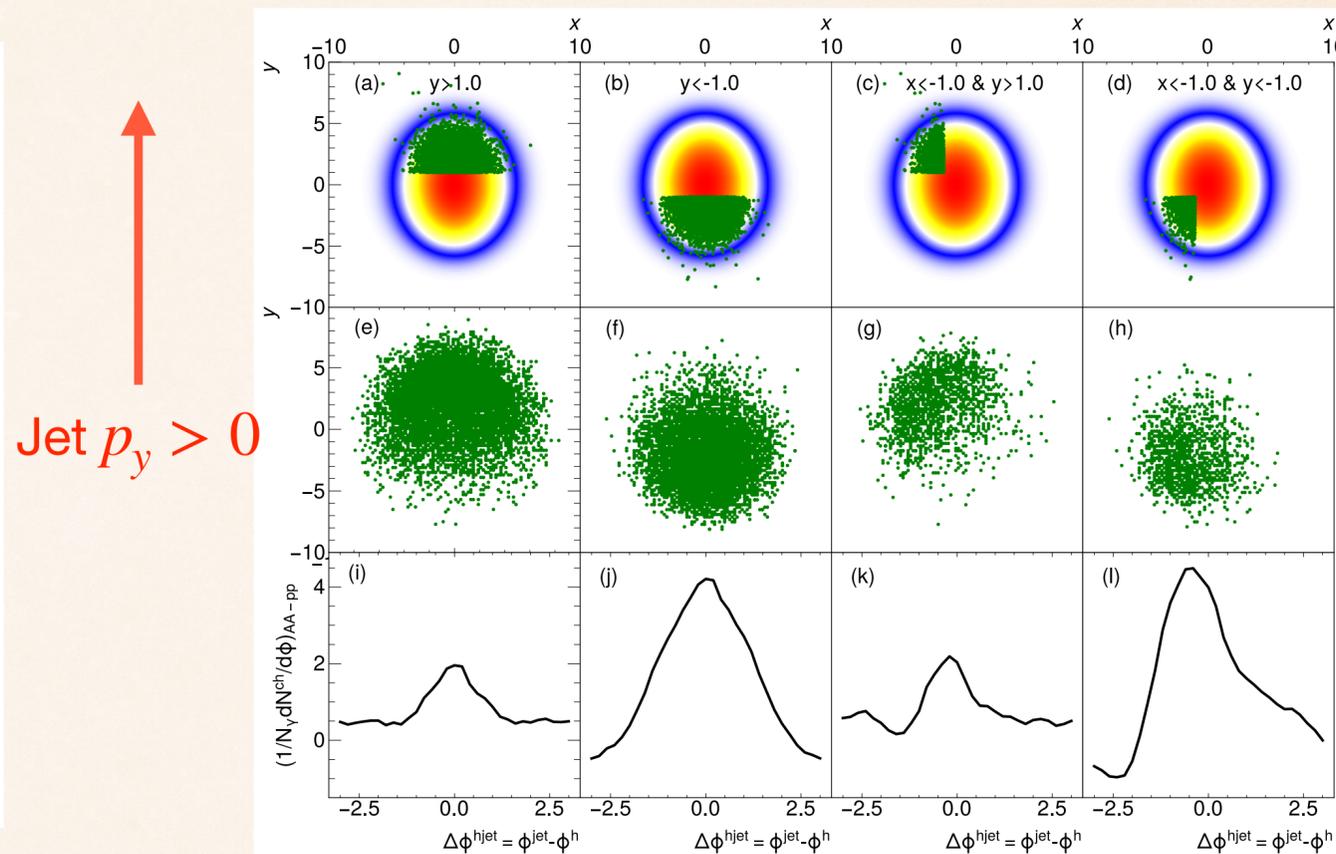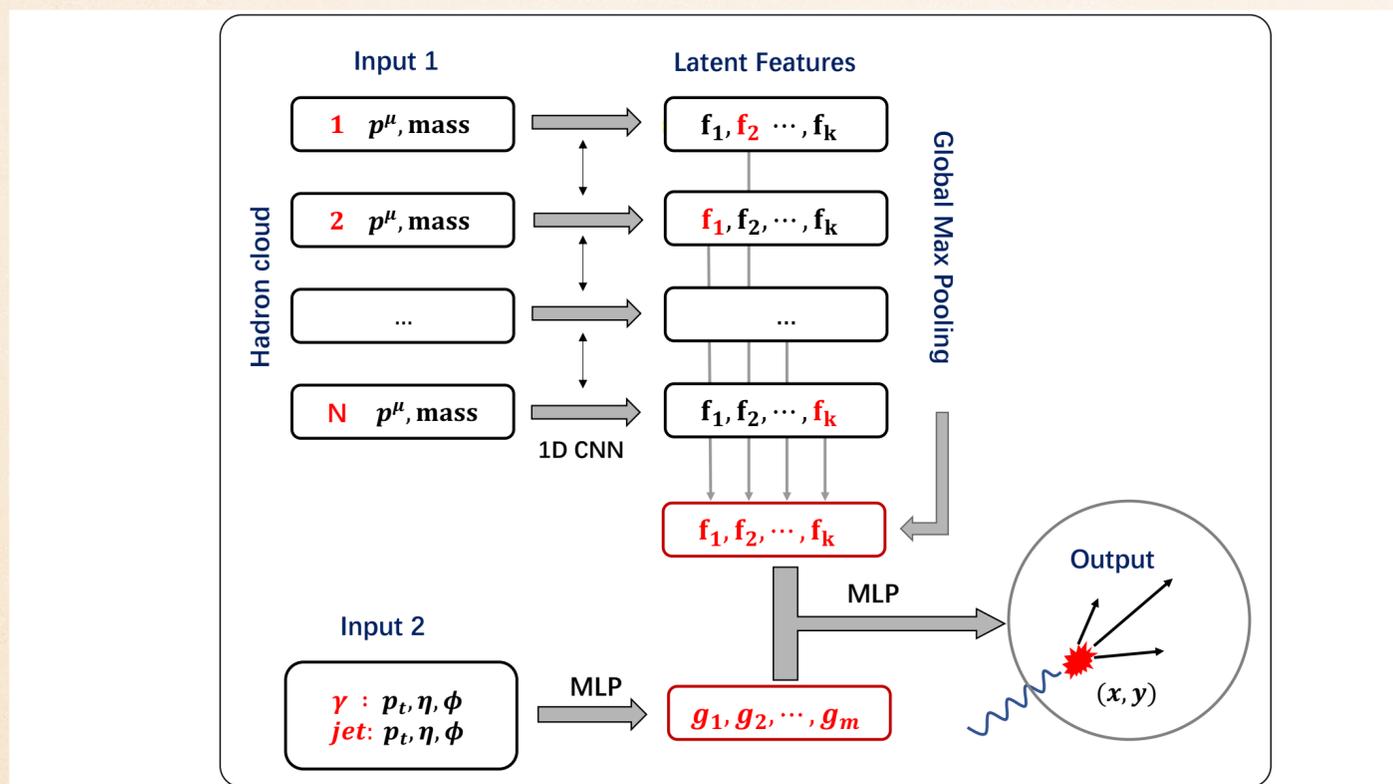
# Towards jet tomography
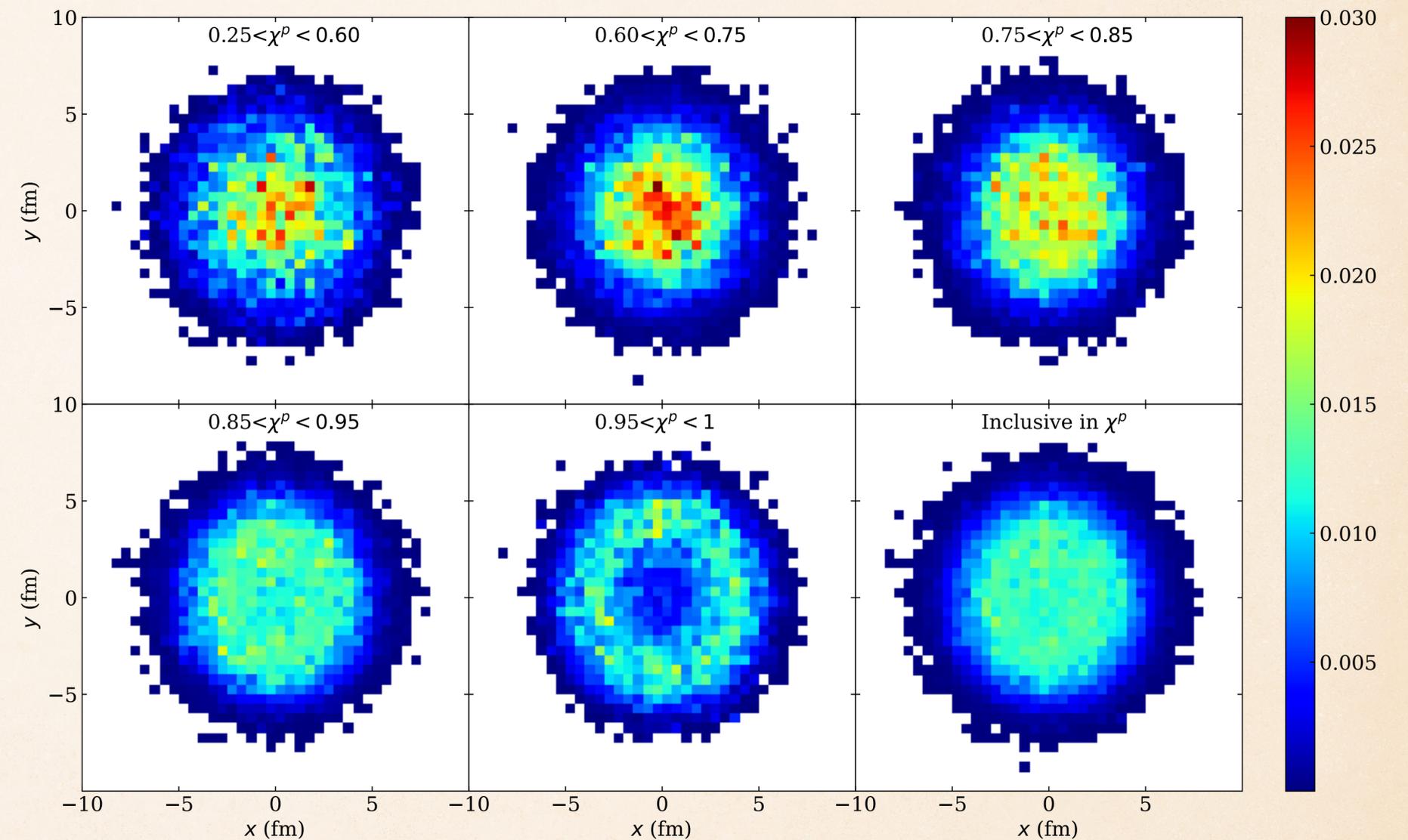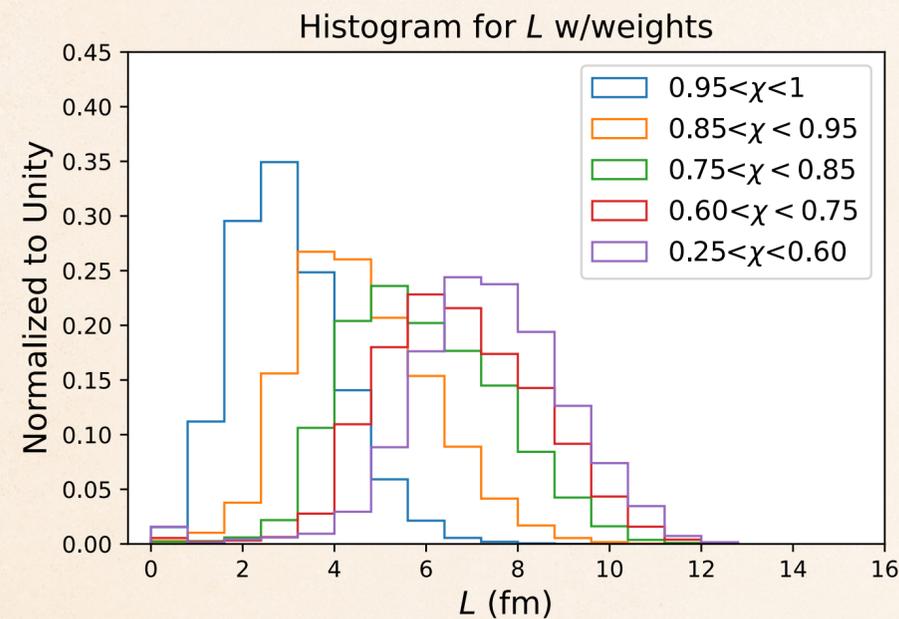
* Strong correlation between jet traversed length $L$ and energy loss $\chi$

* Selecting jets with different $\chi$ will naturally select jets that traversed different $L$

* Great potential to make tomographic application!

# Prediction of Jet Production Positions

Jet $p_y > 0$

Network selection

Actual distribution

- ❖ Point cloud network employs hadrons' momentum, mass and $\gamma$/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
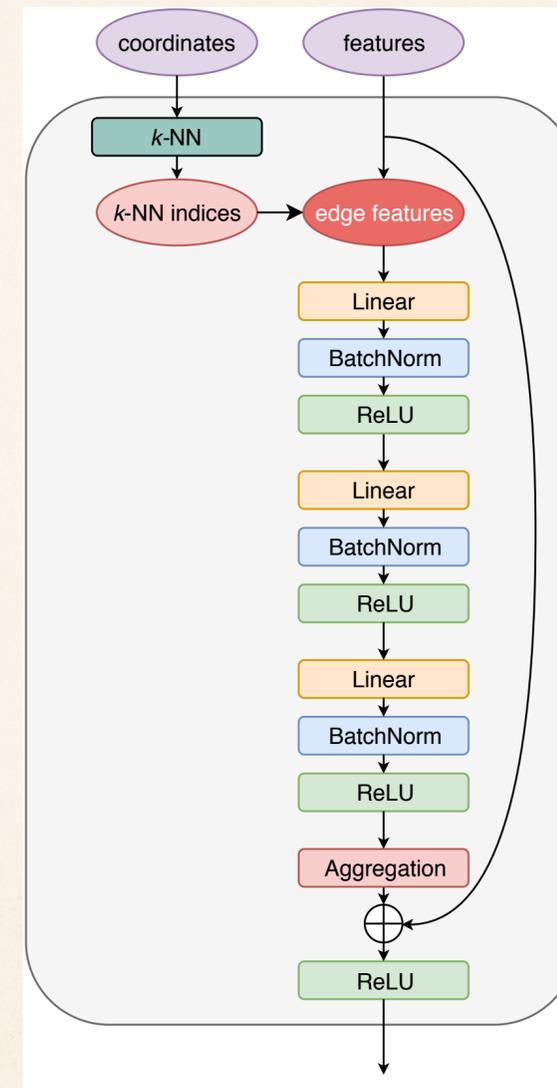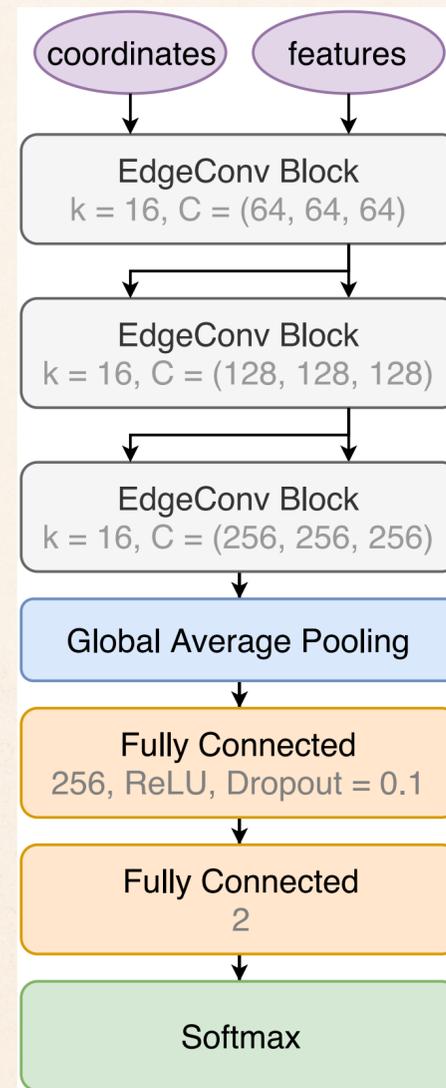
# Diffusion Wake signal amplified by DL jet tomography

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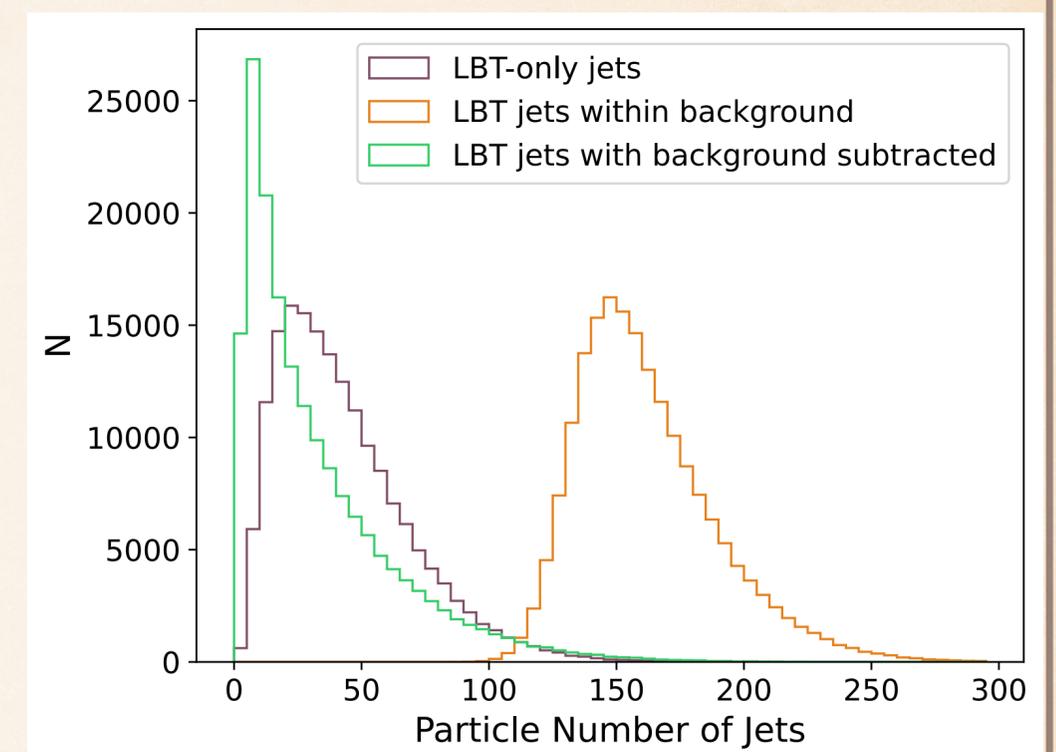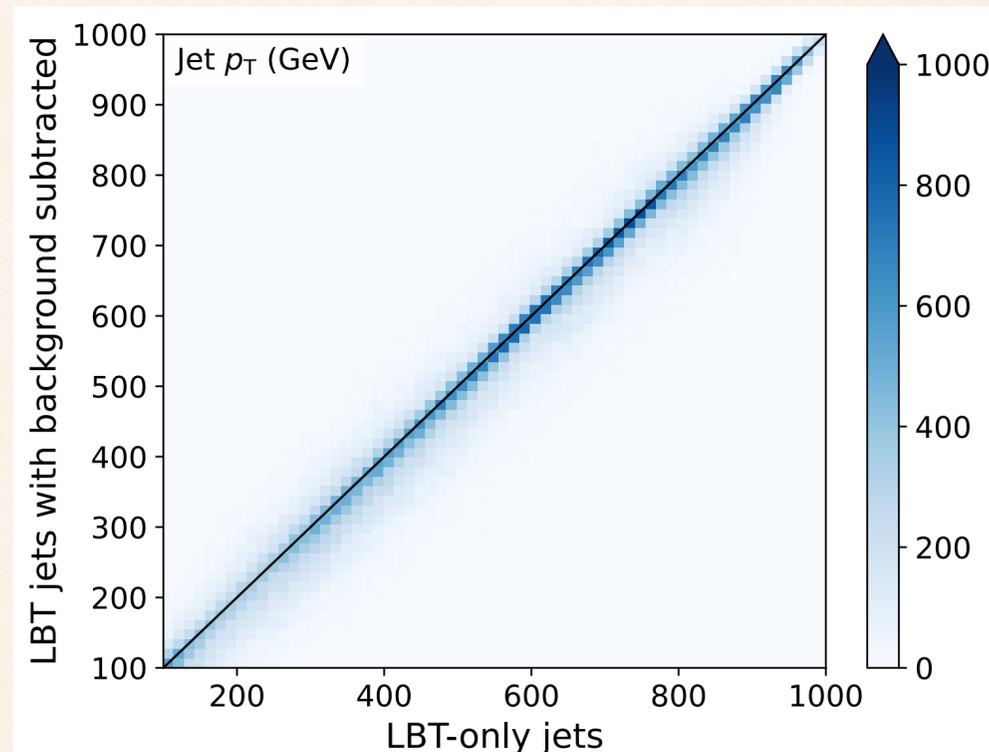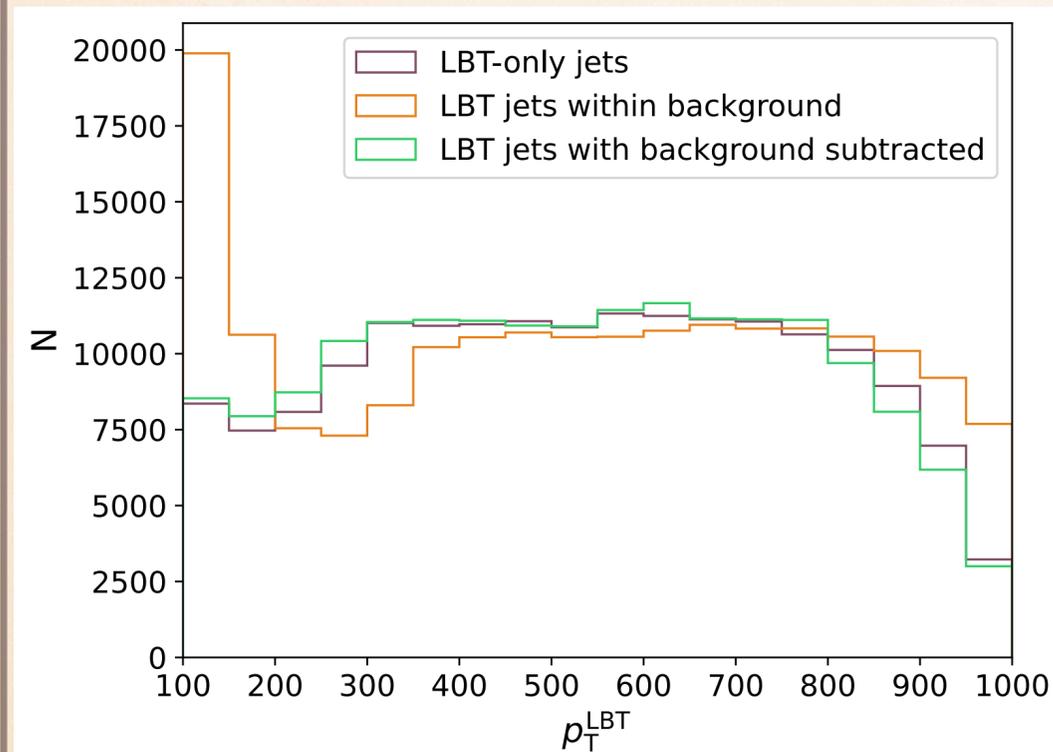
$p_T^h$=1-2 GeV/c in 0-10% Pb+Pb @ 5.02 TeV
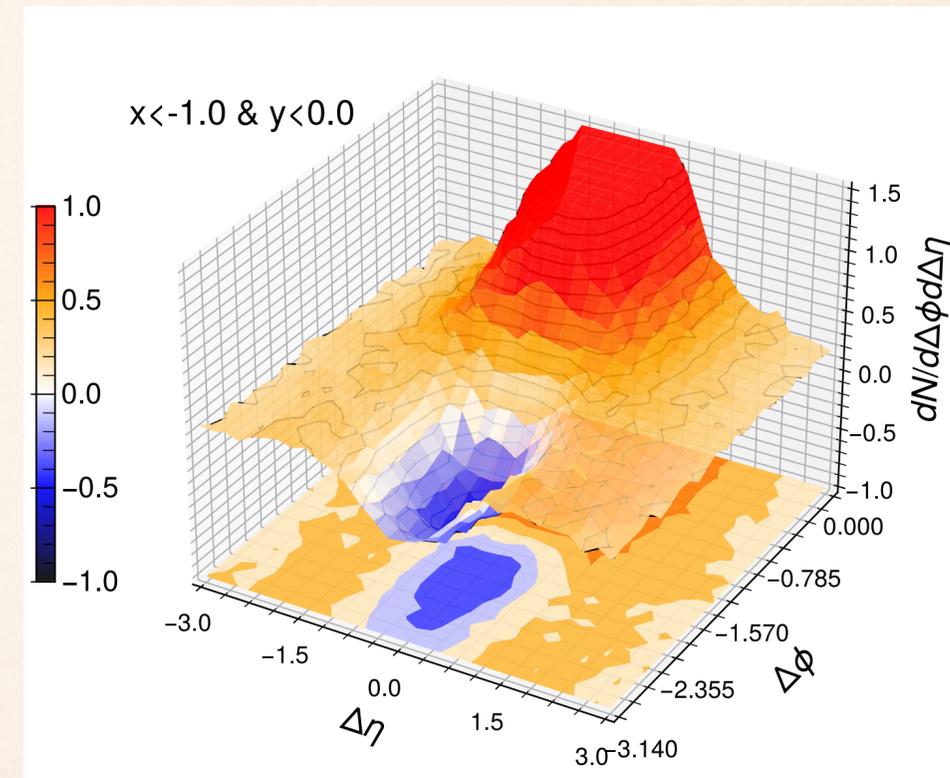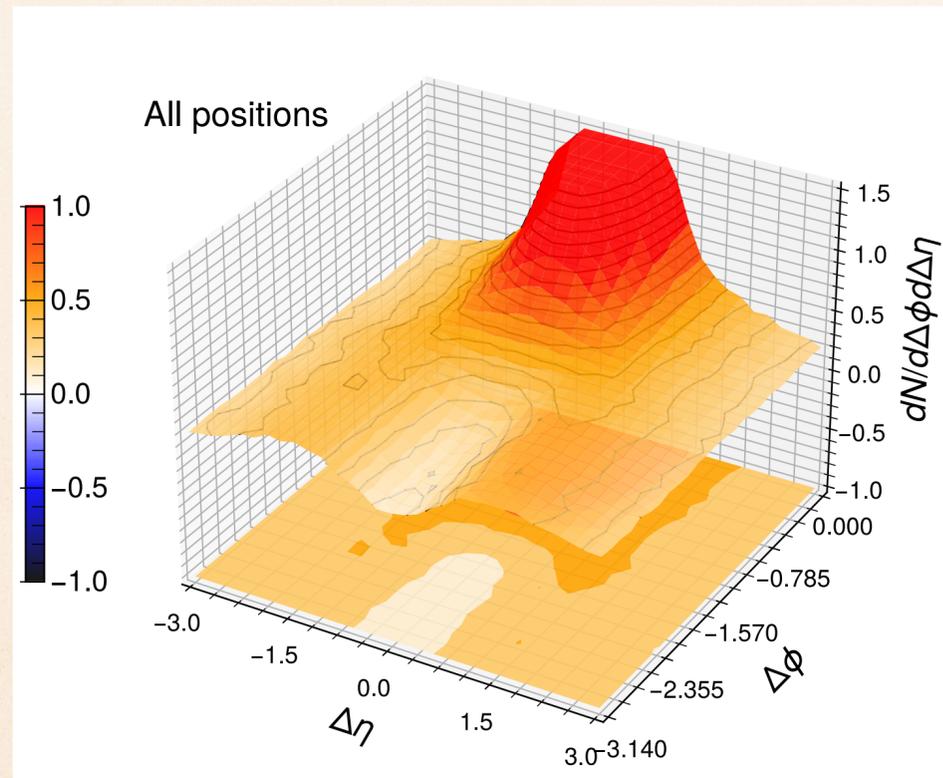
# Dynamical Graph Convolutional Neural Network

# Background Removal of Constituent Subtraction
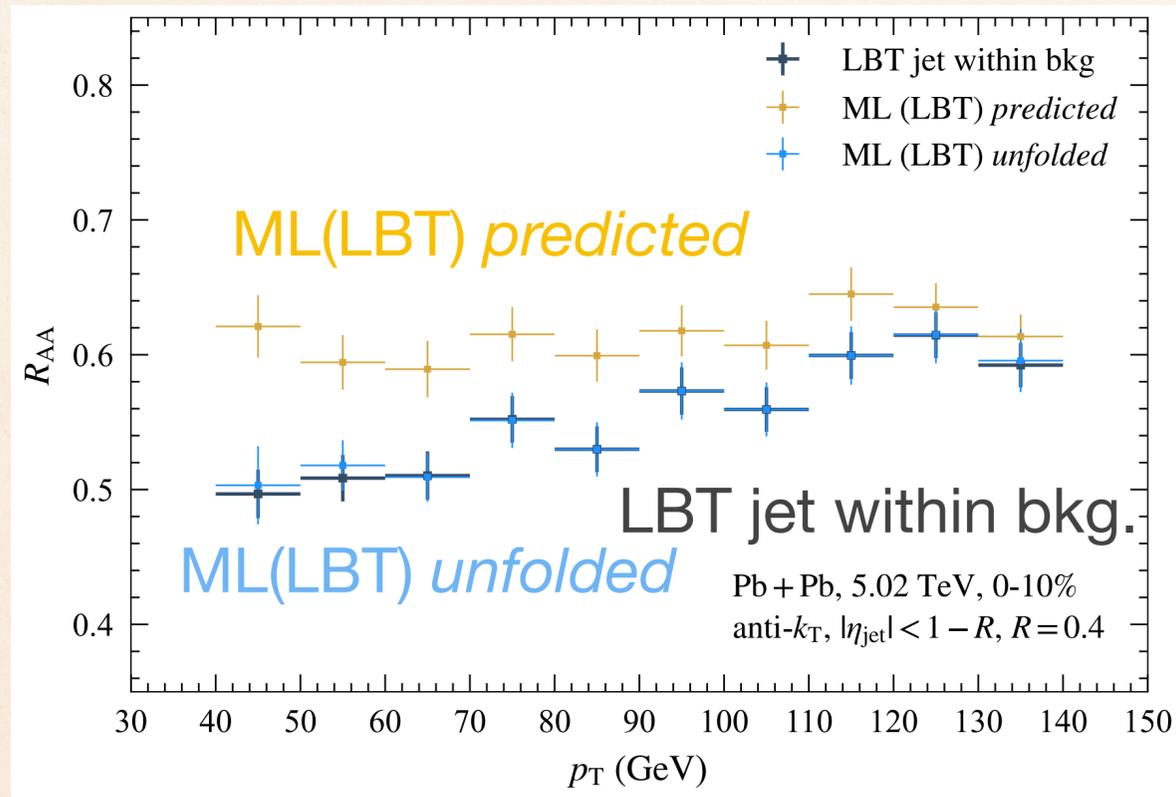
- Jet $p_T$ can be well reproduced

- Particle number of jets is slightly over-subtracted

# Jet Nuclear Modification Factor $R_{AA}$

Effect of unfolding

Different ML models
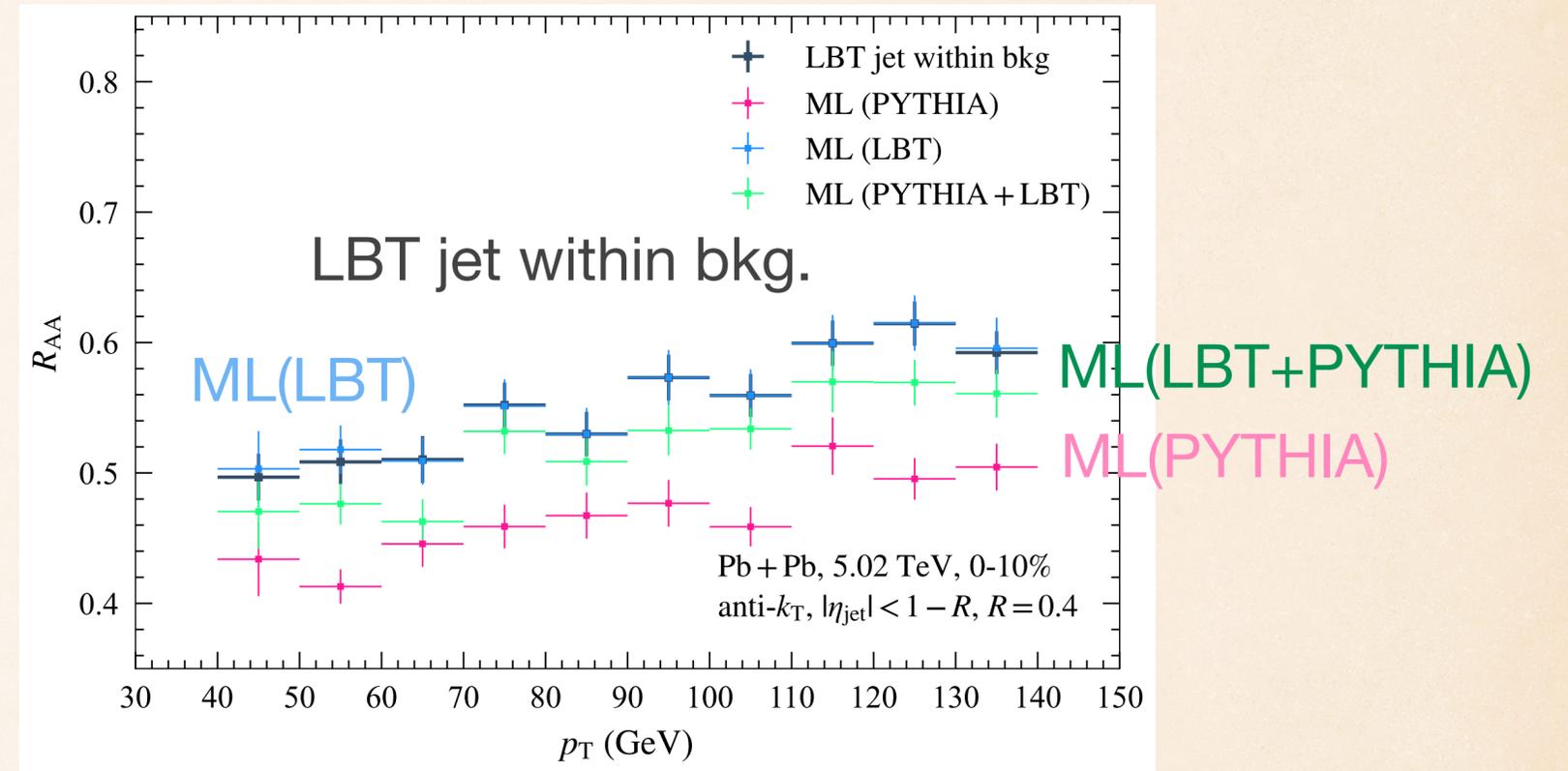


- ❖ Direct application of ML(LBT) over-predicts the jet $R_{AA}$ due to residual distribution of $p_T^{\text{target}}$ +steeply falling $p_T$ spectra of jets, can be effectively corrected by unfolding

- ❖ $R_{AA}$ from ML(LBT) & ML(LBT+PYTHIA) are closer to that of the current target baseline "LBT jet within bkg." than $R_{AA}$ from ML(PYTHIA).

- ❖ Conclusion: it is necessary to include realistic quenching effects in training ML models