Machine Learning on Jet Quenching inside a Quark-Gluon Plasma

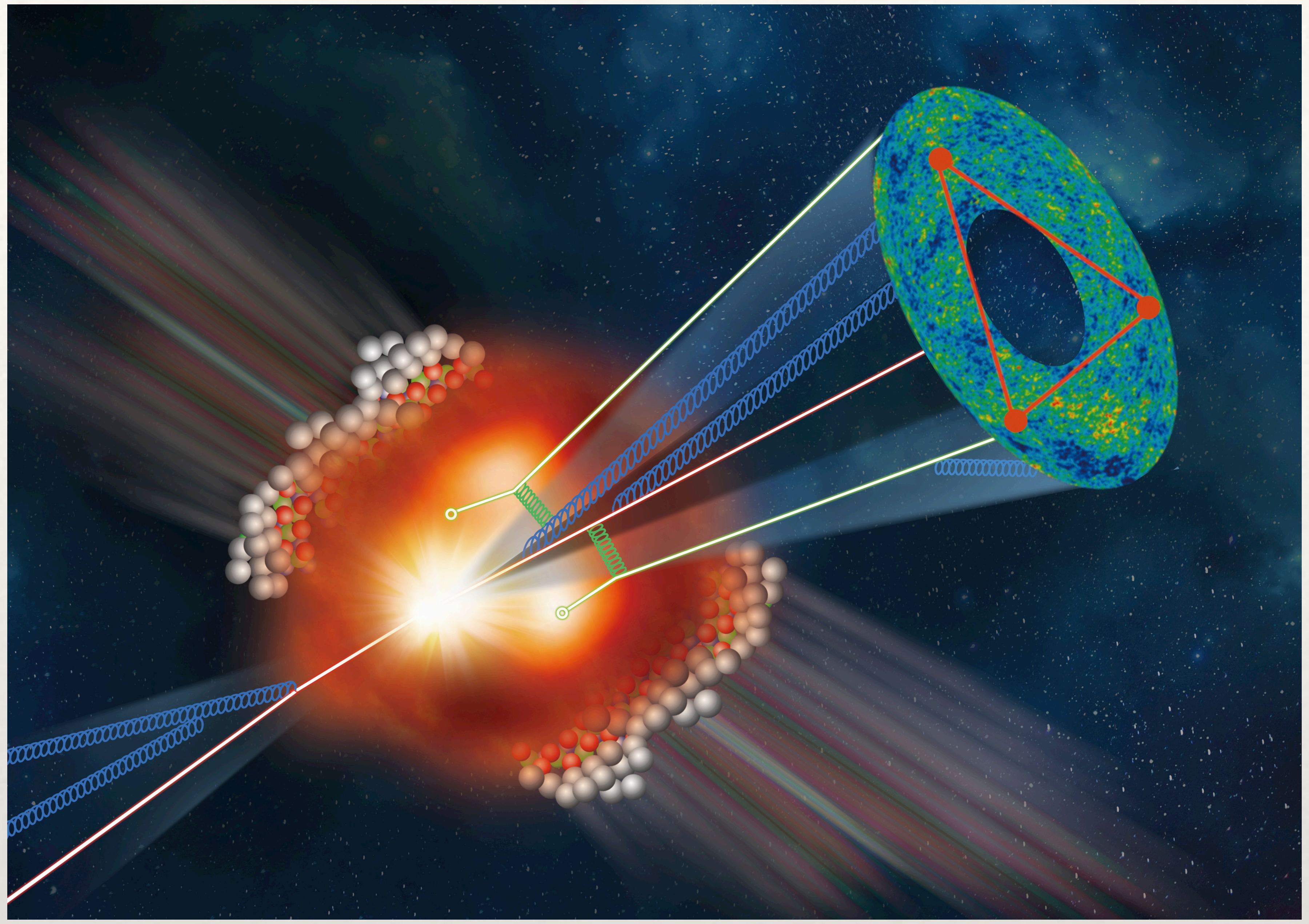
曹杉杉 (山东大学)

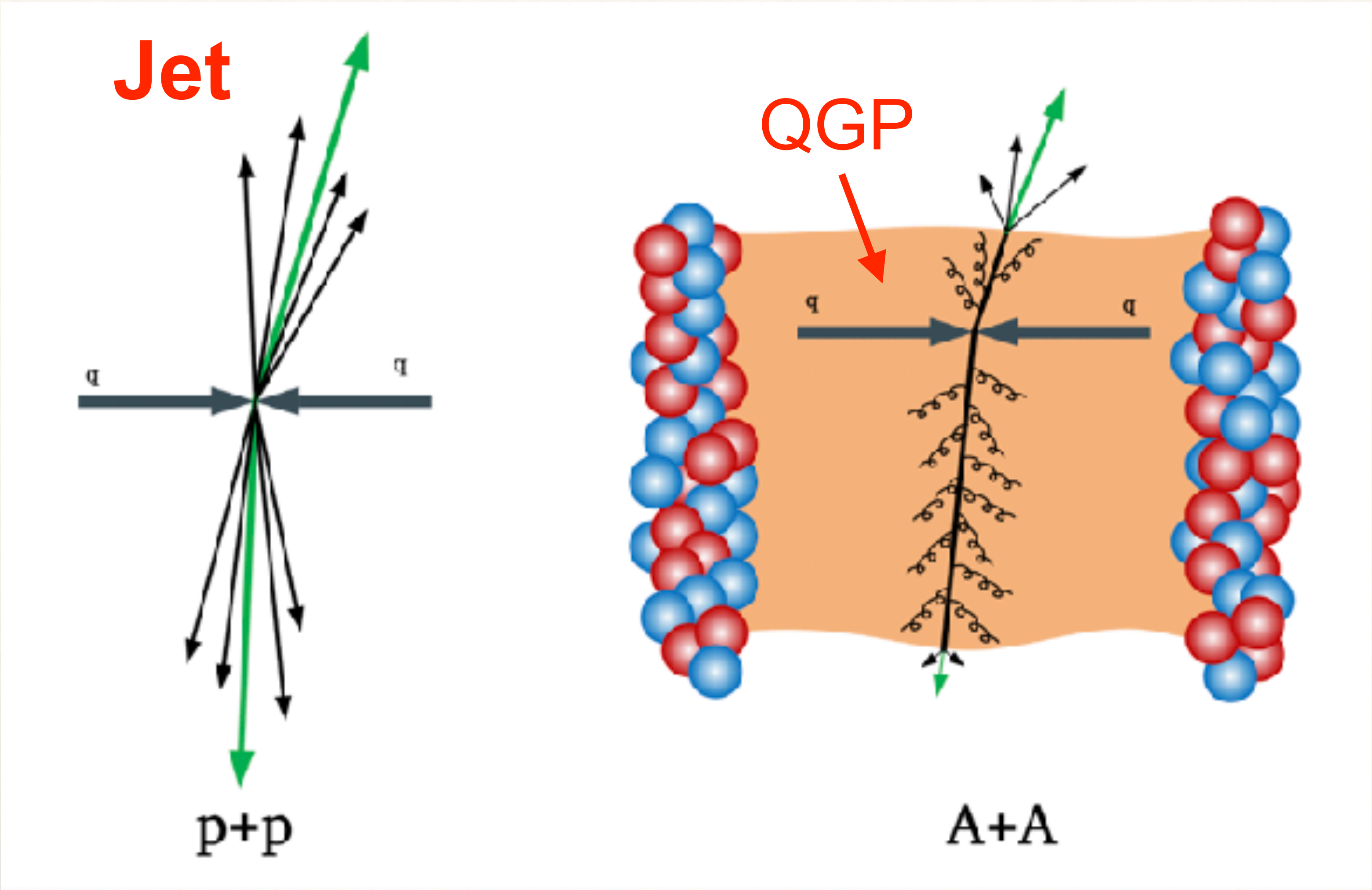
合作者：李然, 杜轶伦

第四届全国核物理及核数据中的机器学习应用研讨会，衡阳

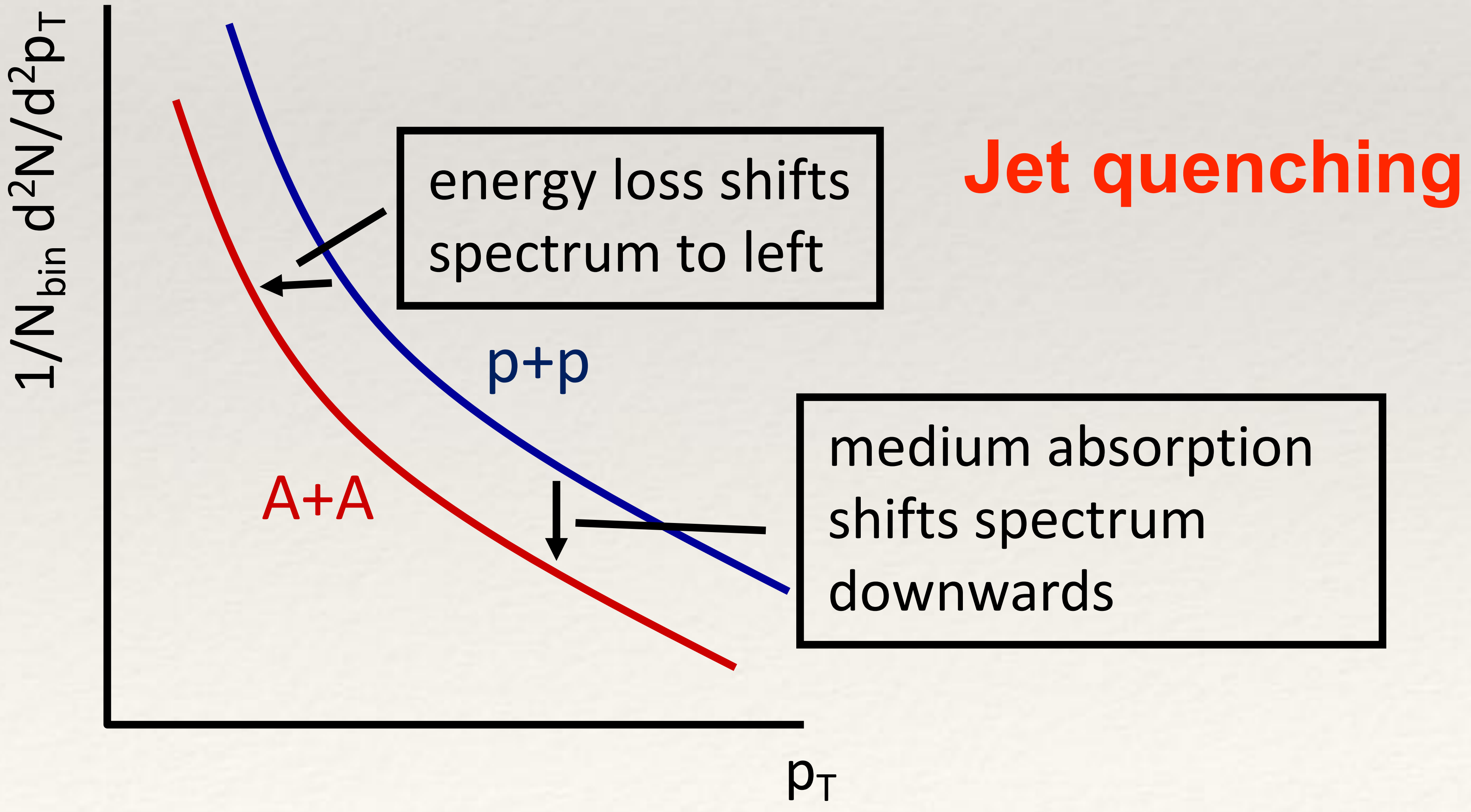
2025年11月1日

Probing quark-gluon plasma (QGP) using jets





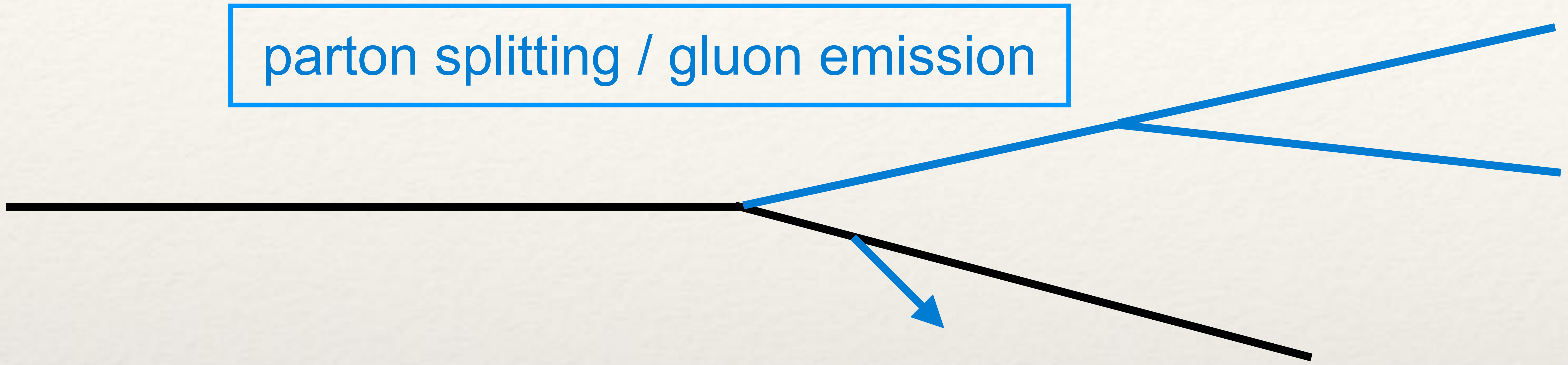
[by M. Rybar / ATLAS]



- Quantify QGP effects on jets by comparing jet spectra between *pp* and AA collisions
- Nuclear modification factor:

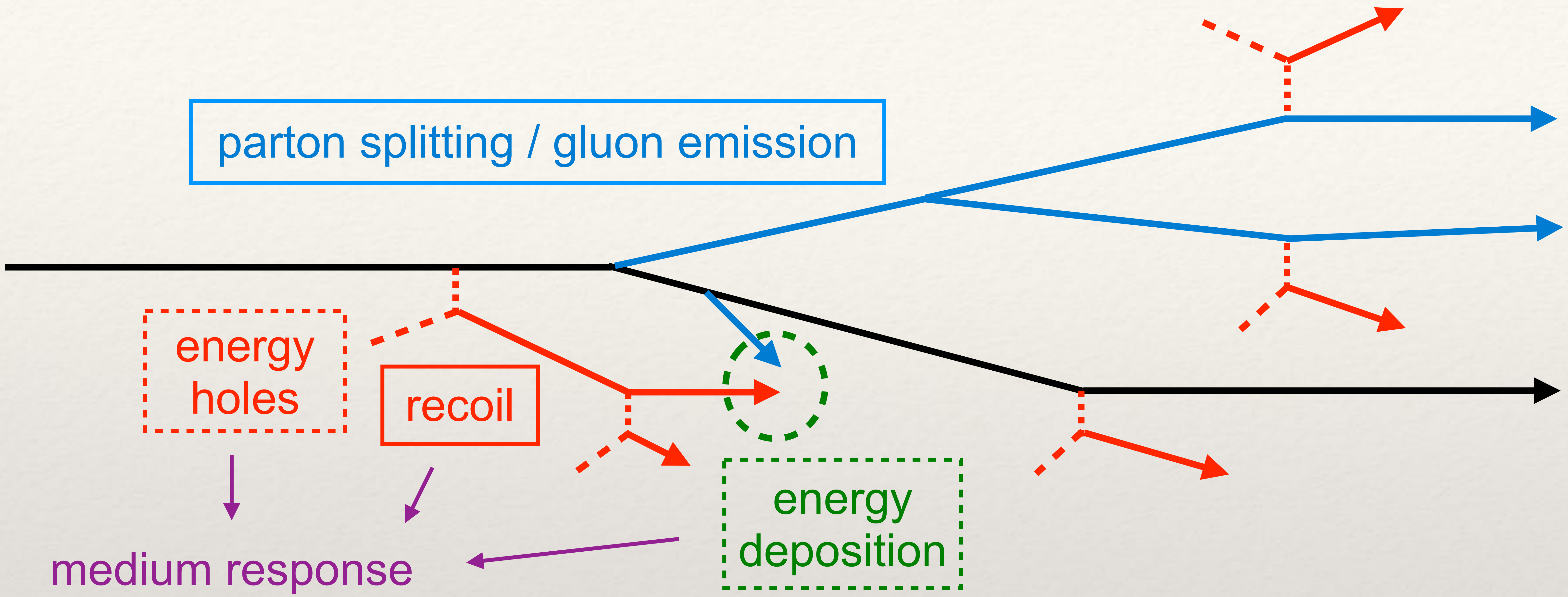
$$R_{AA}(p_T) = \frac{dN^{AA}/dp_T}{\langle N_{coll}^{AA} \rangle \times dN^{pp}/dp_T}$$

Theoretical tools for jets in p+p and A+A collisions



- p+p: parton splittings in vacuum — **Pythia**

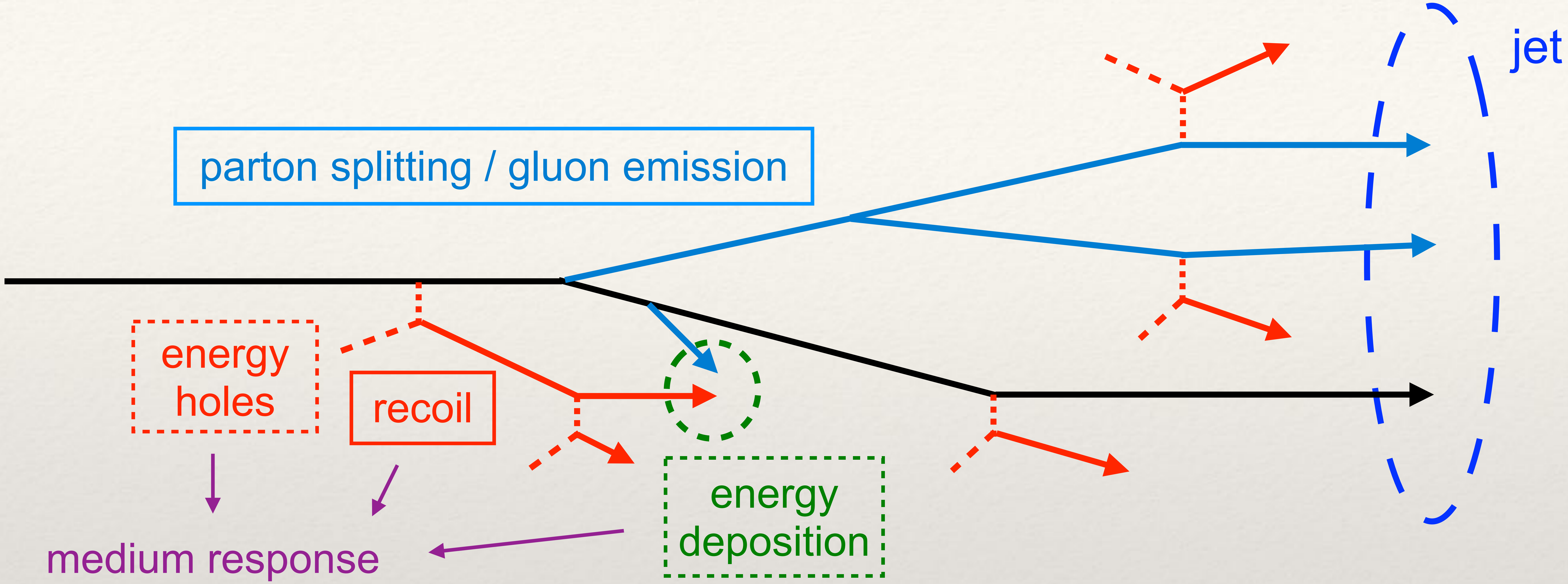
Theoretical tools for jets in p+p and A+A collisions



- p+p: parton splittings in vacuum — **Pythia**
- A+A: parton splittings inside QGP — Linear Boltzmann Transport (**LBT**) model

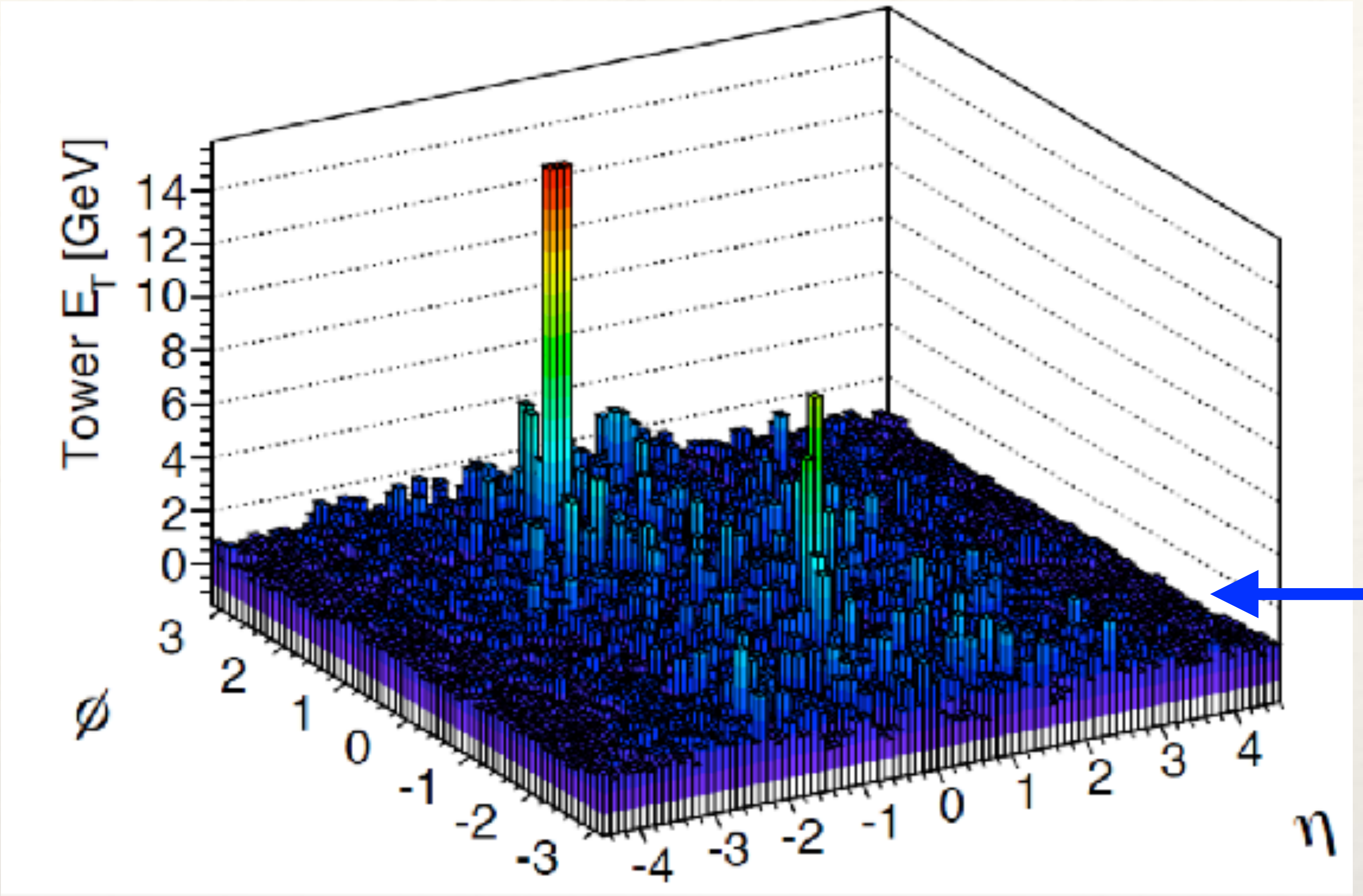
  Medium modified parton splittings + jet-induced medium response

Theoretical tools for jets in p+p and A+A collisions



- p+p: parton splittings in vacuum — **Pythia**
- A+A: parton splittings inside QGP — Linear Boltzmann Transport (**LBT**) model
  Medium modified parton splittings + jet-induced medium response
- Jet reconstruction — **Fastjet** with certain jet finding algorithms

Challenge in bridging theory and experiment



How to remove the QGP background in jet reconstruction?

Area-based method:

- Evaluate $\rho = \text{median}\,(p^{\text{raw}}_{\text{T,jet},i}/A_i)$, $i \in$ (raw) jets reconstructed using all particles, with two hardest ones excluded
- $p_{\text{T,jet}} = p^{\text{raw}}_{\text{T,jet}} - \rho A$.

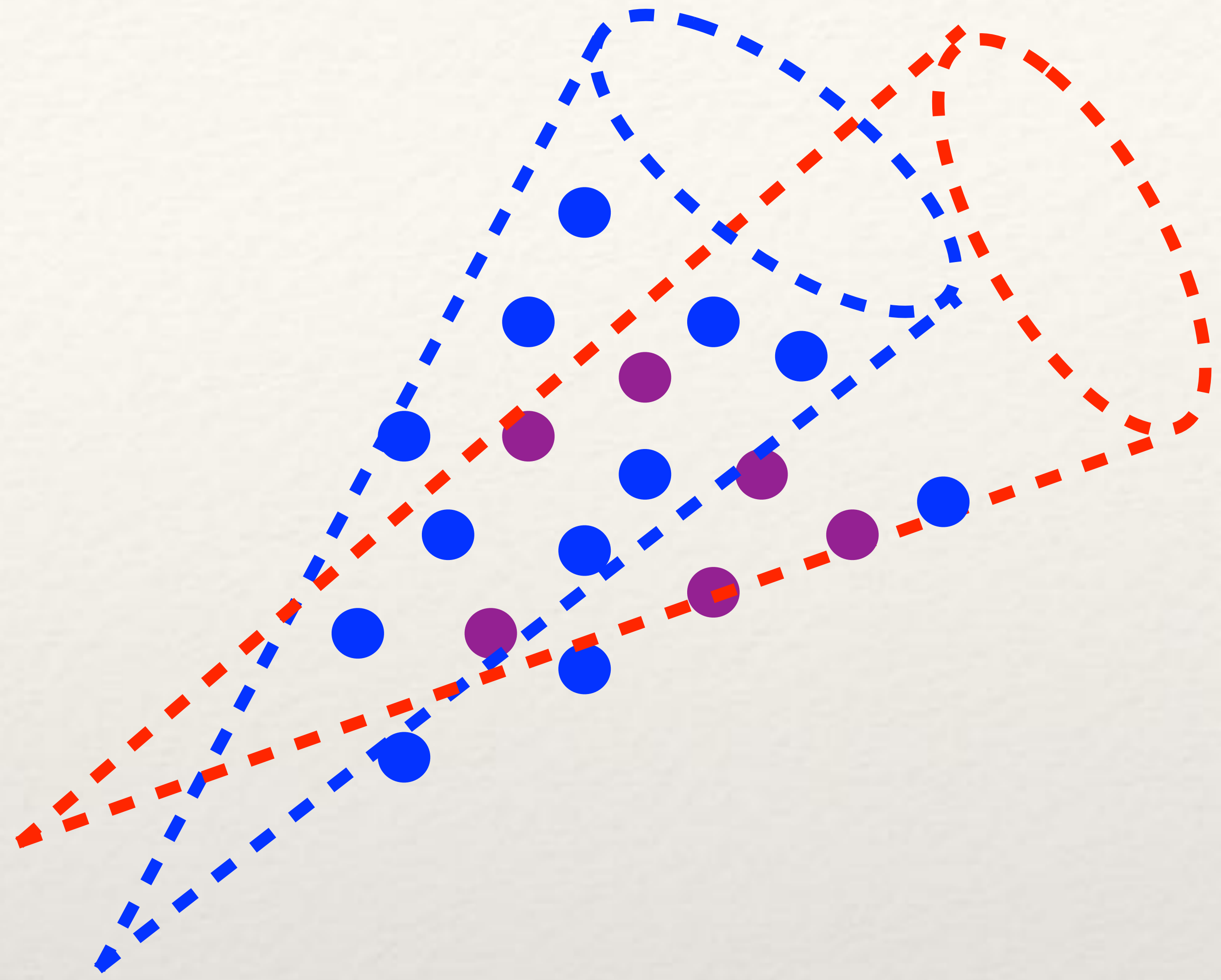
Constituent subtraction (CS) method:

- Sample ghost particles with $p^{\text{g}}_{\text{T}} = \rho A^{\text{g}}$
- Correct p_{T} on particle level: $p_{\text{T},j} \to p_{\text{T},j} - p^{\text{g}}_{\text{T},k}$, $i \in$ all real particles, $k \in$ ghosts near i
- Reconstruct jets using p_{T} - corrected particles

Machine learning method for background subtraction

Model setups:

- Vacuum jets: Pythia
- Medium modification: LBT
- QGP background: thermal statistical model



Target values of jet p_T for :

- Method 1: $p_\mathrm{T}^\mathrm{target} = \sum_{i \in \mathrm{Pythia/LBT}} p_{\mathrm{T},i}$

  p_T of ● in .

- Method 2: match to within

  $\Delta R < 0.4$ and use the p_T of as $p_\mathrm{T}^\mathrm{target}$

● Jet particle from Pythia or LBT

● Background particle from thermal model

Jet constructed using ●

Jet constructed using ● + ●

Machine learning method for background subtraction

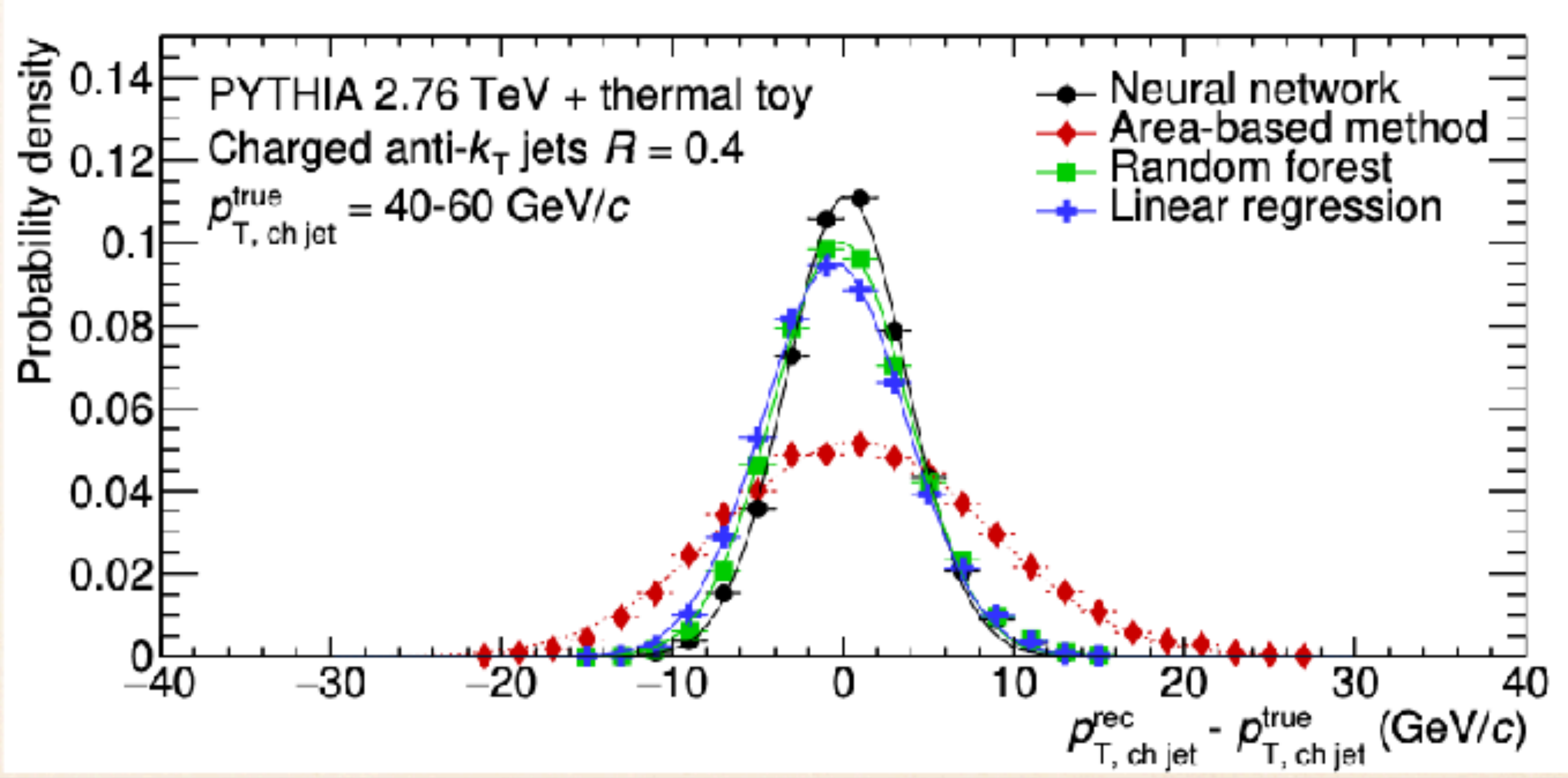
Dense Neural Network (DNN)

Inputs for training

- Uncorrected jet p_T
- Jet p_T corrected by Area-based method
- Jet substructure observables: mass, angularity, momentum dispersion, momentum difference between leading and sub-leading constituents
- Number of constituents
- Mean and medium p_T of jet constituents
- p_T of the first ten hardest particles within the jet

Target: jet p_T

Prior studies

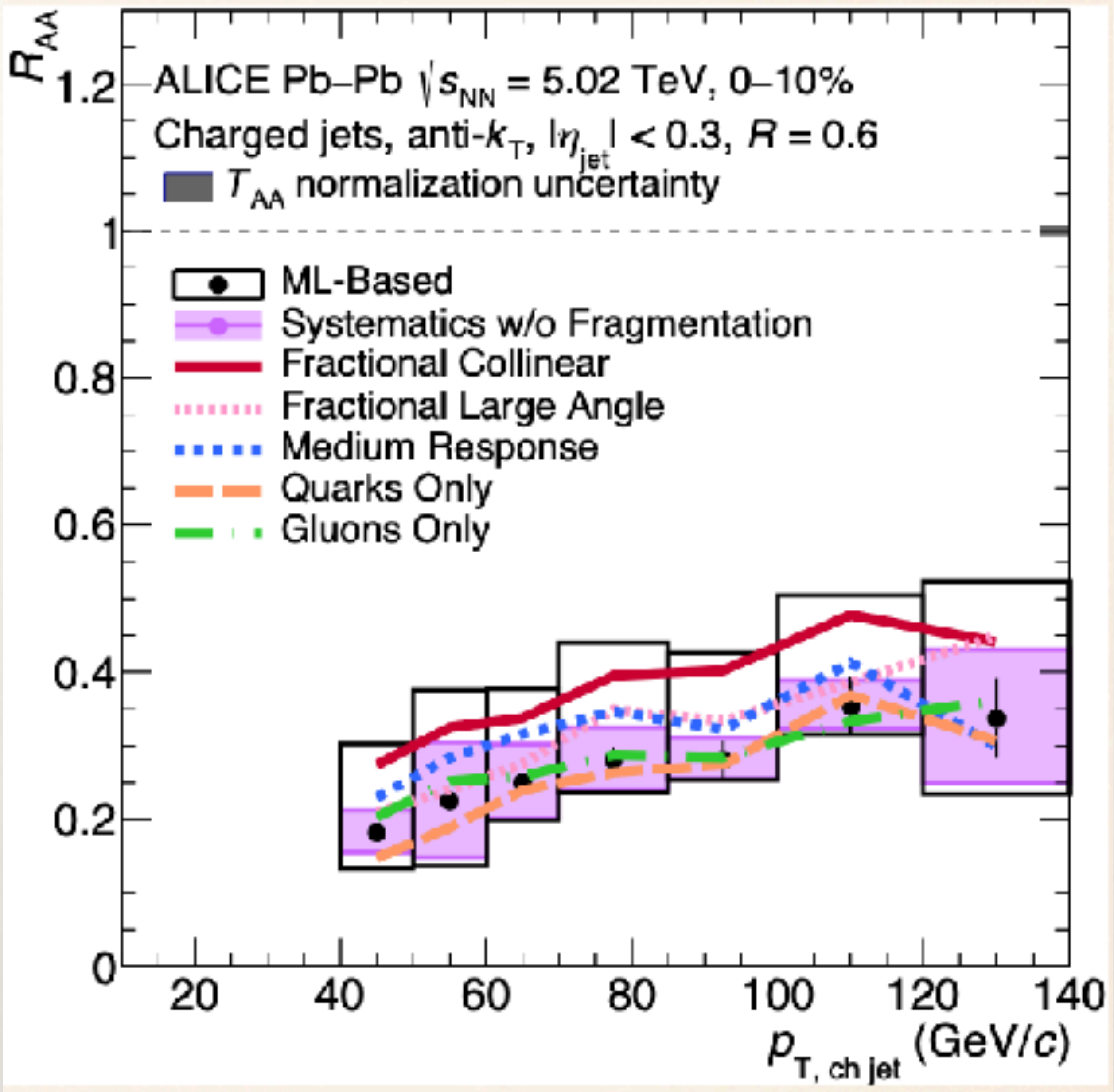


[Haake and Loizides, Phys. Rev. C 99 (2019) 064904]

- ML-based methods outperform the Area-based method in predicting jet p_T
- ML models are trained using vacuum (**Pythia**) jets without the QGP effects

Machine learning method for background subtraction

Prior studies



[ALICE, Phys. Lett. B 849 (2024) 138412]

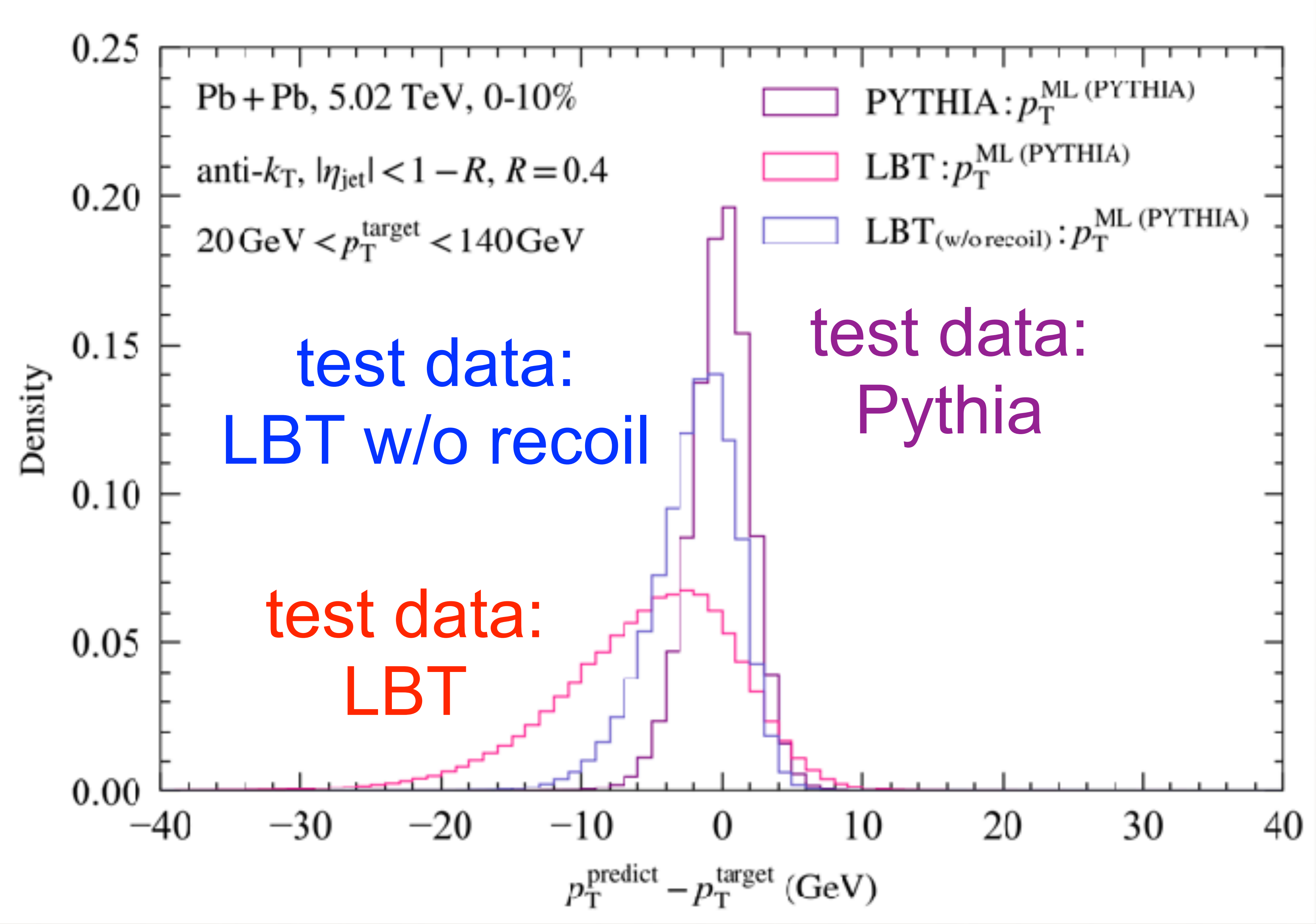
- Successful application in ALICE measurement
- ML models are trained using **Pythia** jets + **toy models** of different medium effects separately

This work

- ML models trained using realistic medium-modified jets (**LBT jets**)
- Explore the physical interpretation behind the superior performance of the improved ML models

Effects of realistic medium modification on ML performance

Pythia-trained ML model (DNN)

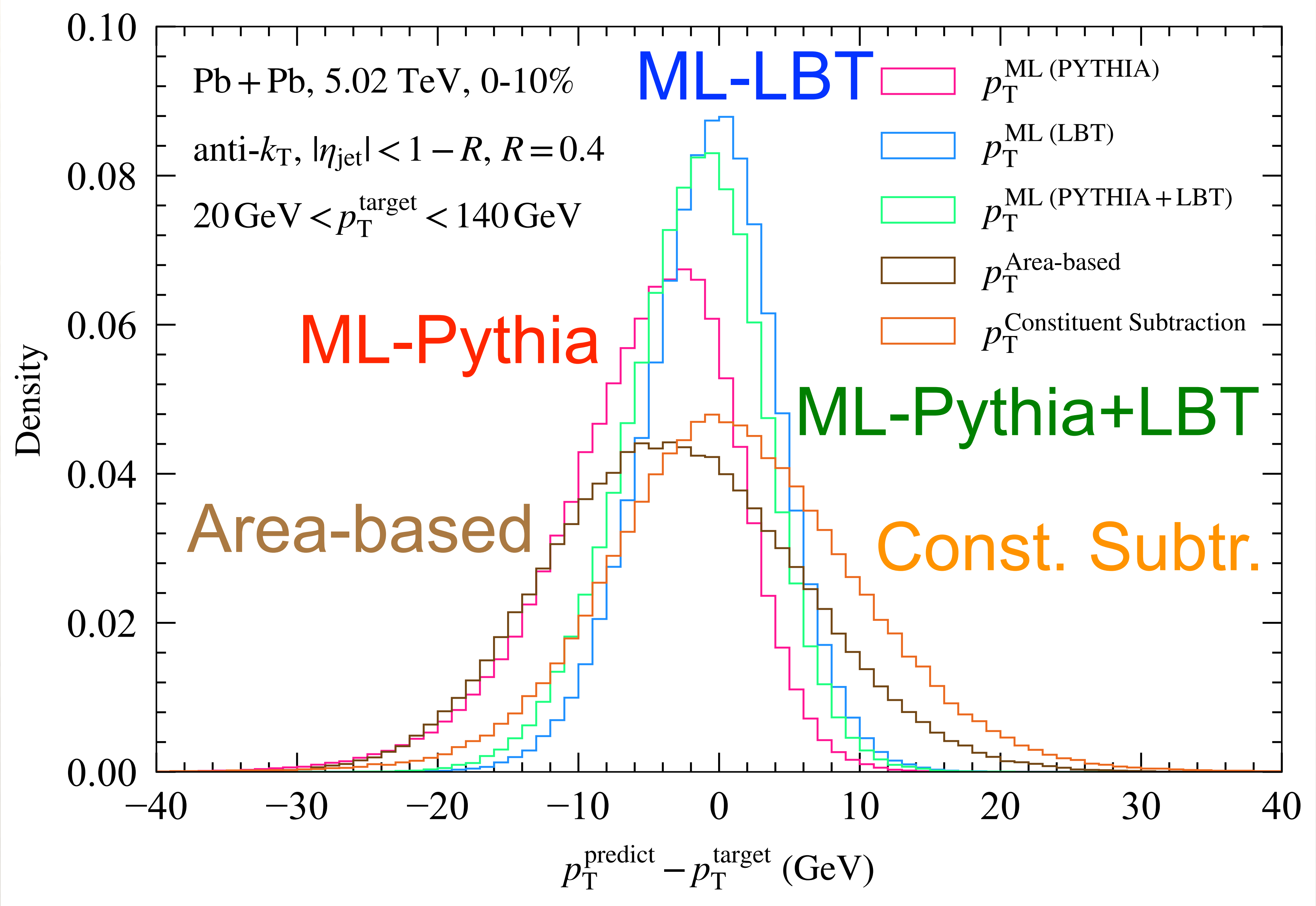


Li, Du, SC, Phys. Lett. B 870 (2025) 139940

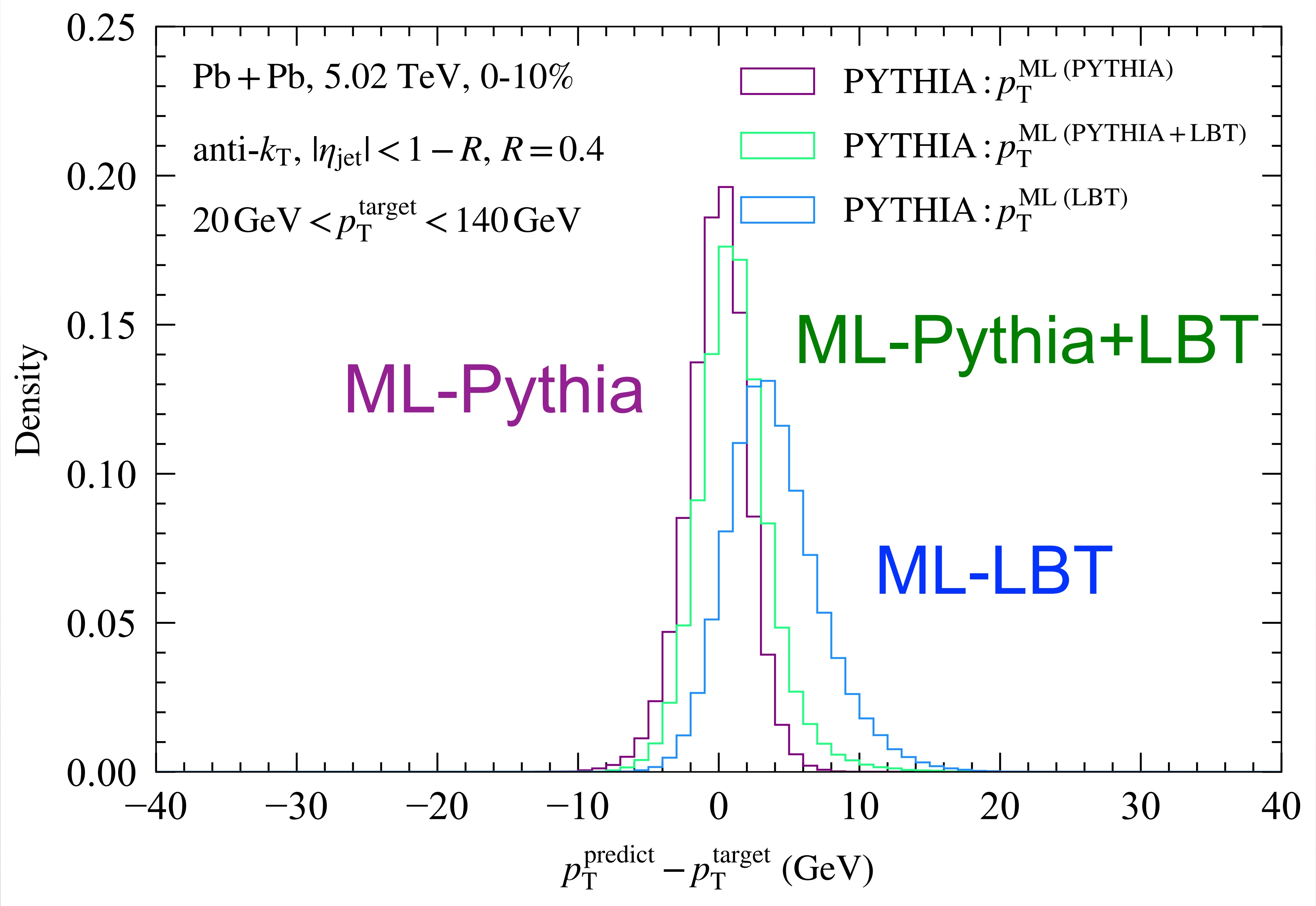
- Performs well on test data generated by Pythia
- Under-predicts the p_T^{target} of medium modified (LBT) jets, over-subtracts background
- Restores reasonable performance if medium response (recoil) are excluded from LBT
- Conclusion: ML model trained using vacuum jets is incapable of recognizing medium response particles in quenched jets

Performance of different ML models

Test on quenched jet data



Test on vacuum jet data

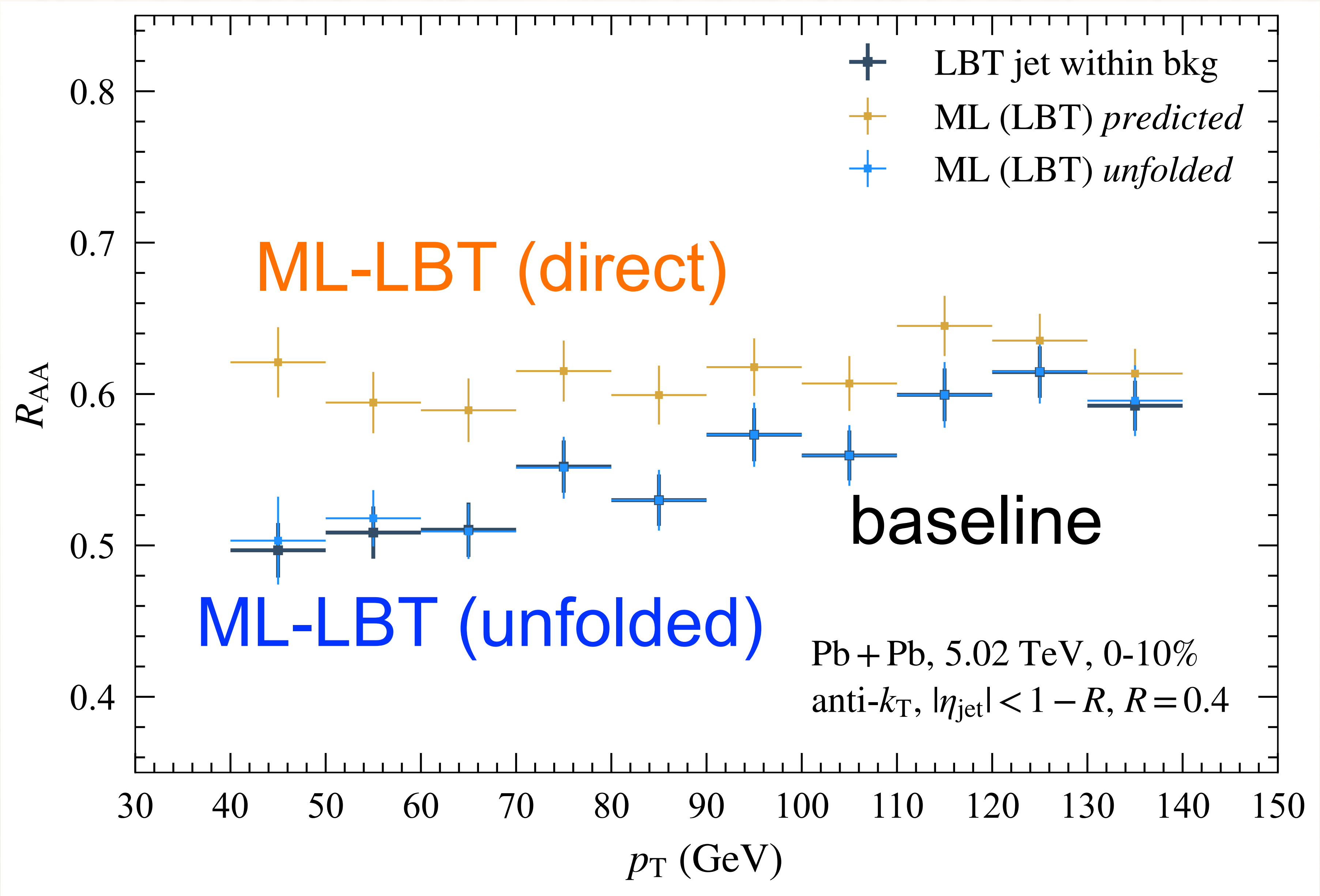


Li, Du, SC, Phys. Lett. B 870 (2025) 139940

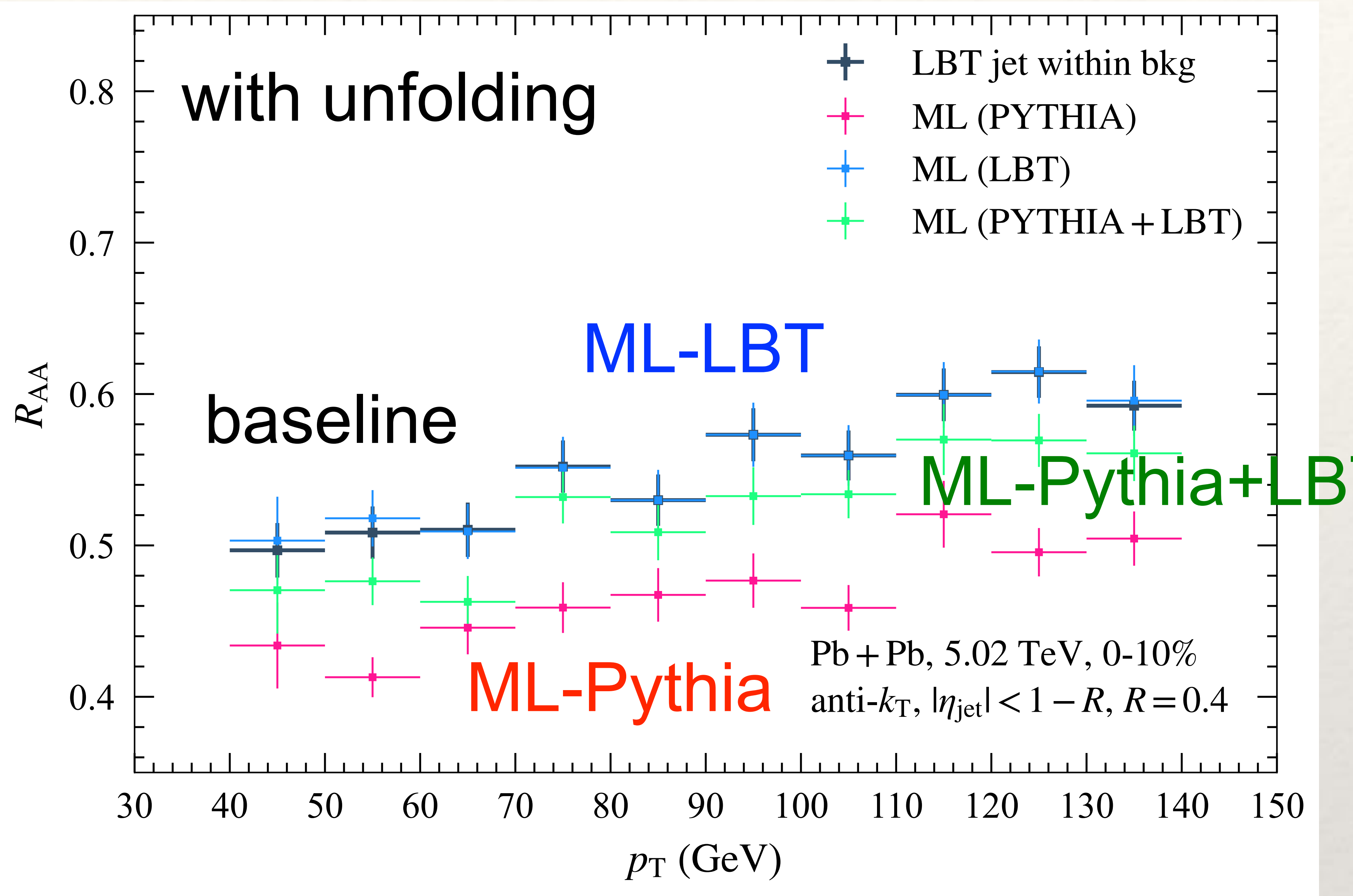
- ML-LBT provides an accurate prediction on p_T^{target} of quenched jets
- Combining Pythia and LBT dataset for training can predict p_T^{target} of quenched and vacuum jets simultaneously, demonstrating its robustness in diverse environments
- ML models outperform traditional methods in removing the QGP background

Performance on predicting the jet R_{AA}

Effect of unfolding



Different ML models



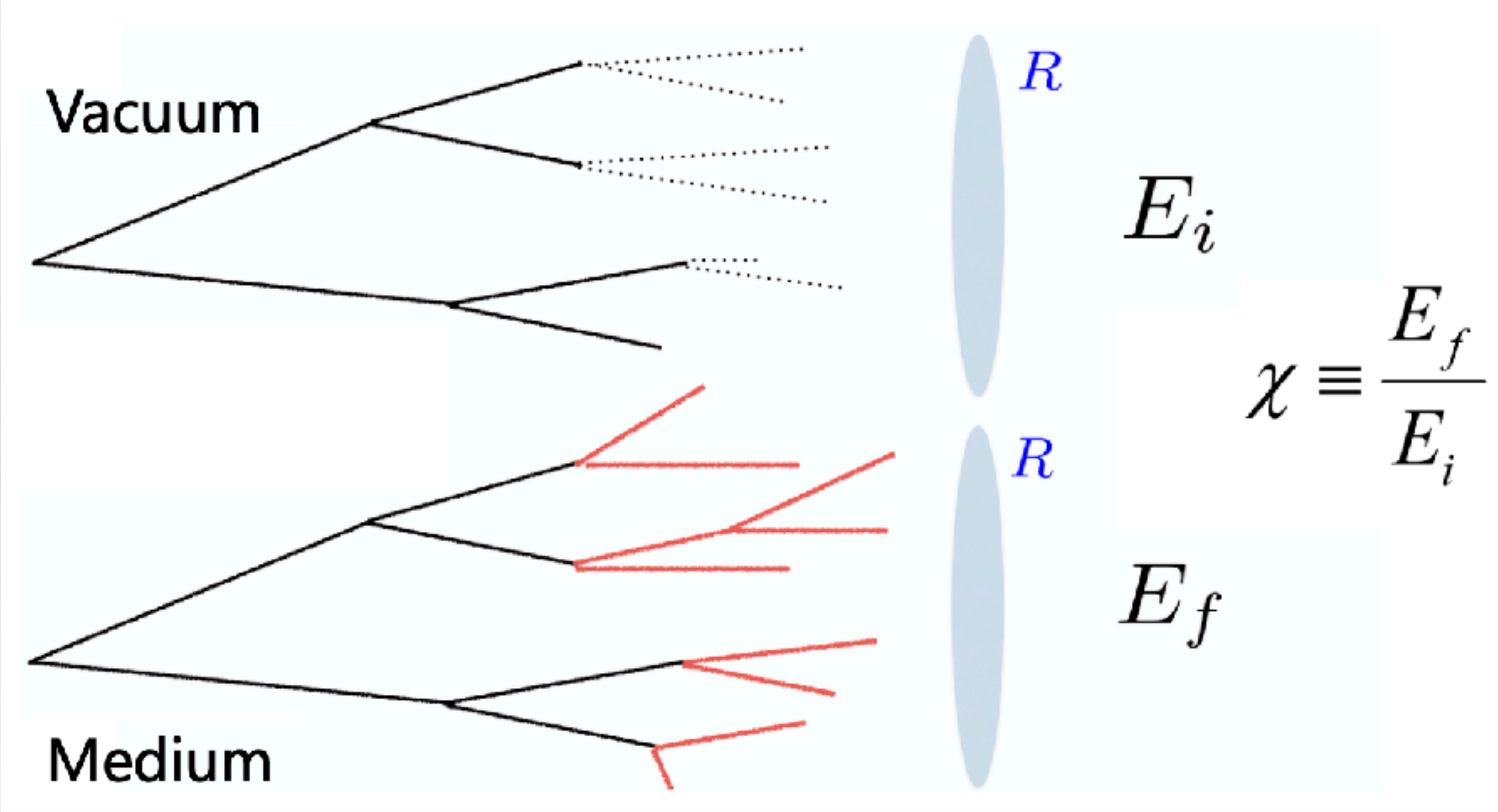
Li, Du, SC, Phys. Lett. B 870 (2025) 139940

- Direct application of ML-LBT over-predicts the jet R_{AA}: residual distribution of p_T^{target} + steeply falling p_T spectra of jets, can be effectively corrected by unfolding
- ML-Pythia under-predicts the jet R_{AA} even with unfolding: over-subtraction of background
- Conclusion: it is necessary to include realistic quenching effects in training ML models

From event-averaged observables to jet-by-jet energy loss

Event-averaged jet observables depends on jet spectra

- Slight inaccuracy in jet energy loss theory may result in large uncertainties in observables
- Selection bias exists in many observables



Can we infer jet-by-jet energy loss from the structure of each quenched jet?

- Prior efforts:

  Du, Pablos, Tywoniuk, JHEP 03 (2021) 206; Phys. Rev. Lett. 128 (2022) 012301.

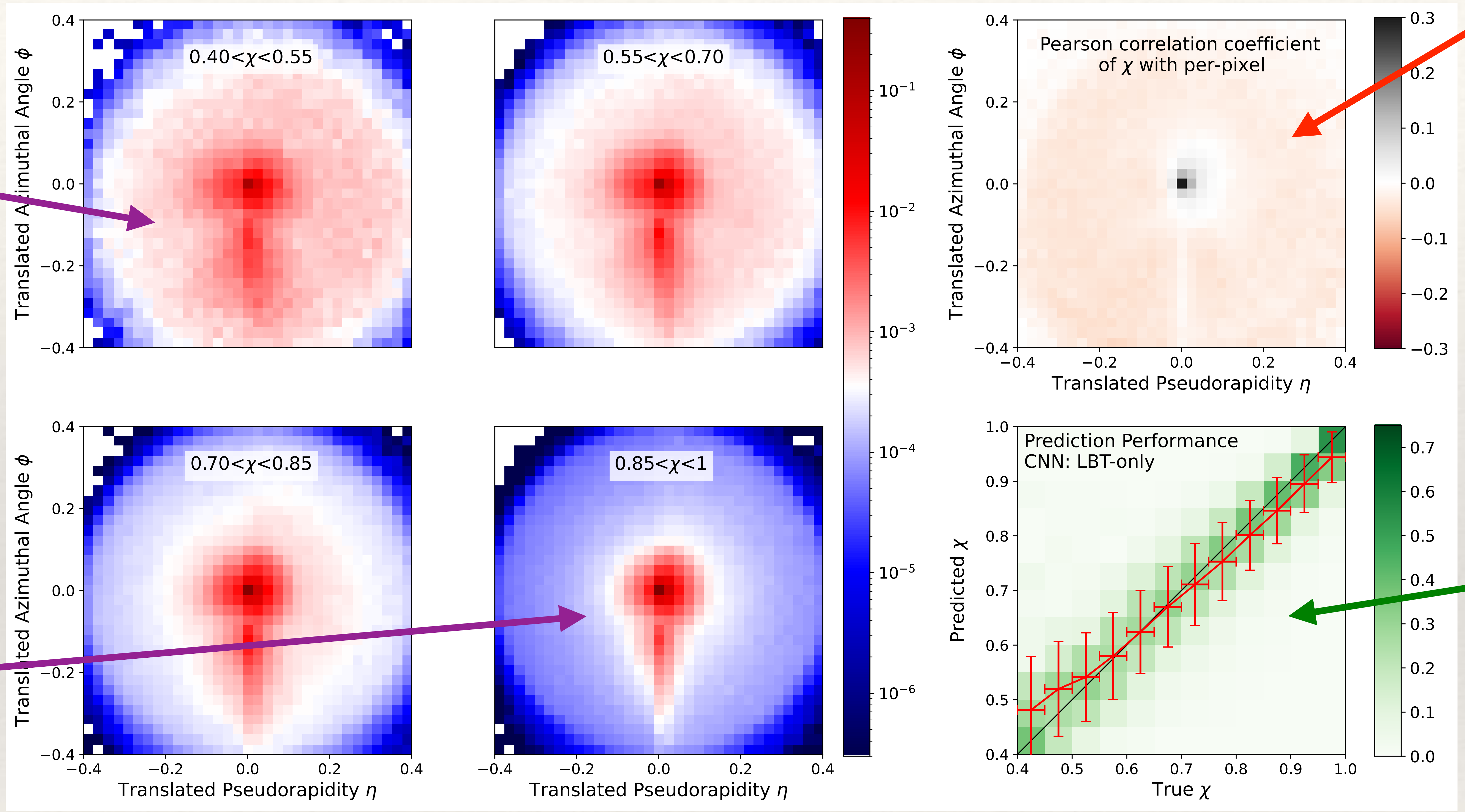
- This work:
  - Model dependence
  - Effects of the QGP background
  - Accuracy improvement

Convolutional neural network for predicting jet energy loss

Image of LBT jets, no QGP background

strongest energy loss

weakest energy loss



Pearson coeff.

Less quenching → more energy in the center, but less energy appears at large radius (medium response)

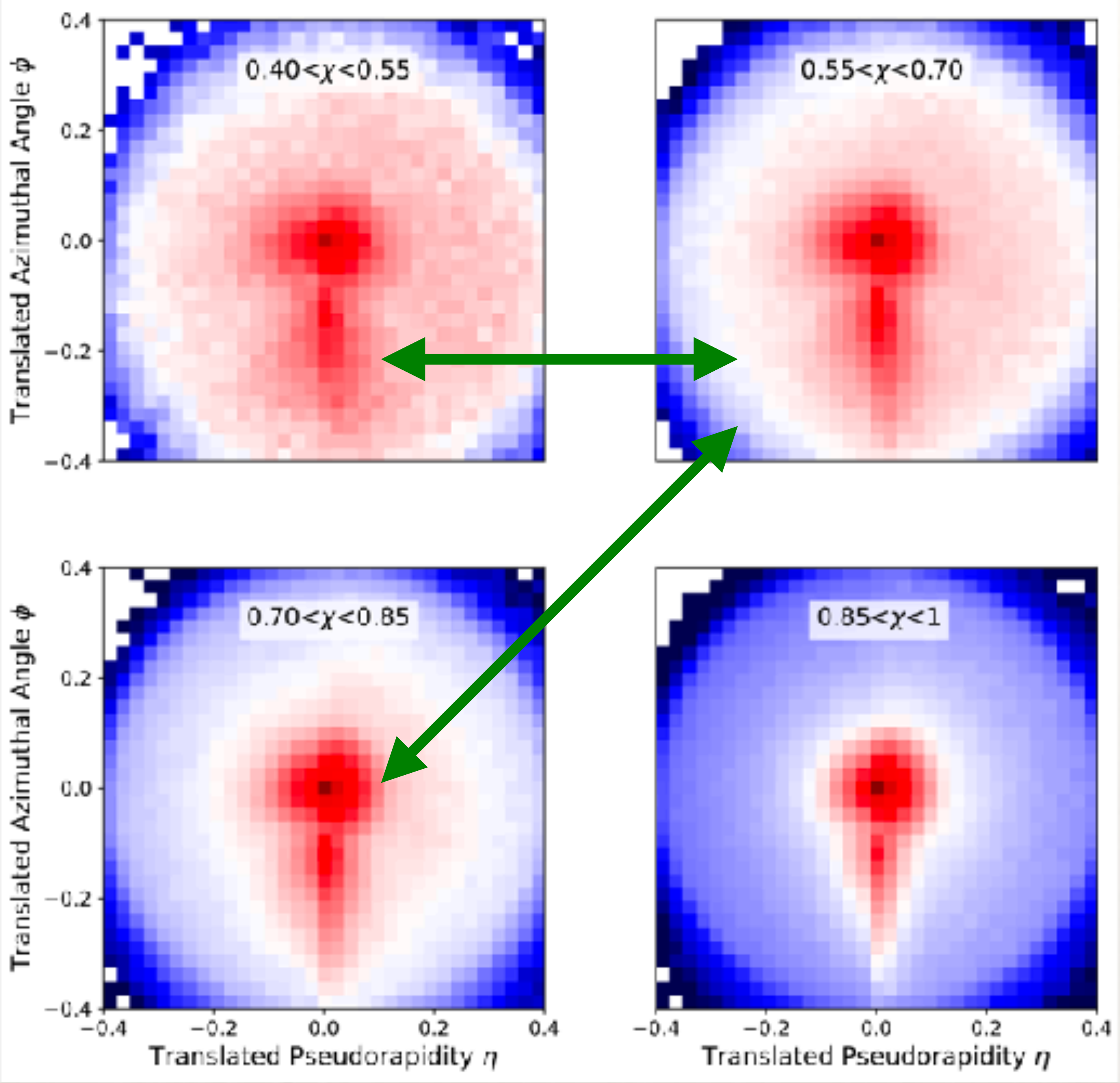
prediction performance

Li, Du, SC, arXiv:2508.20856

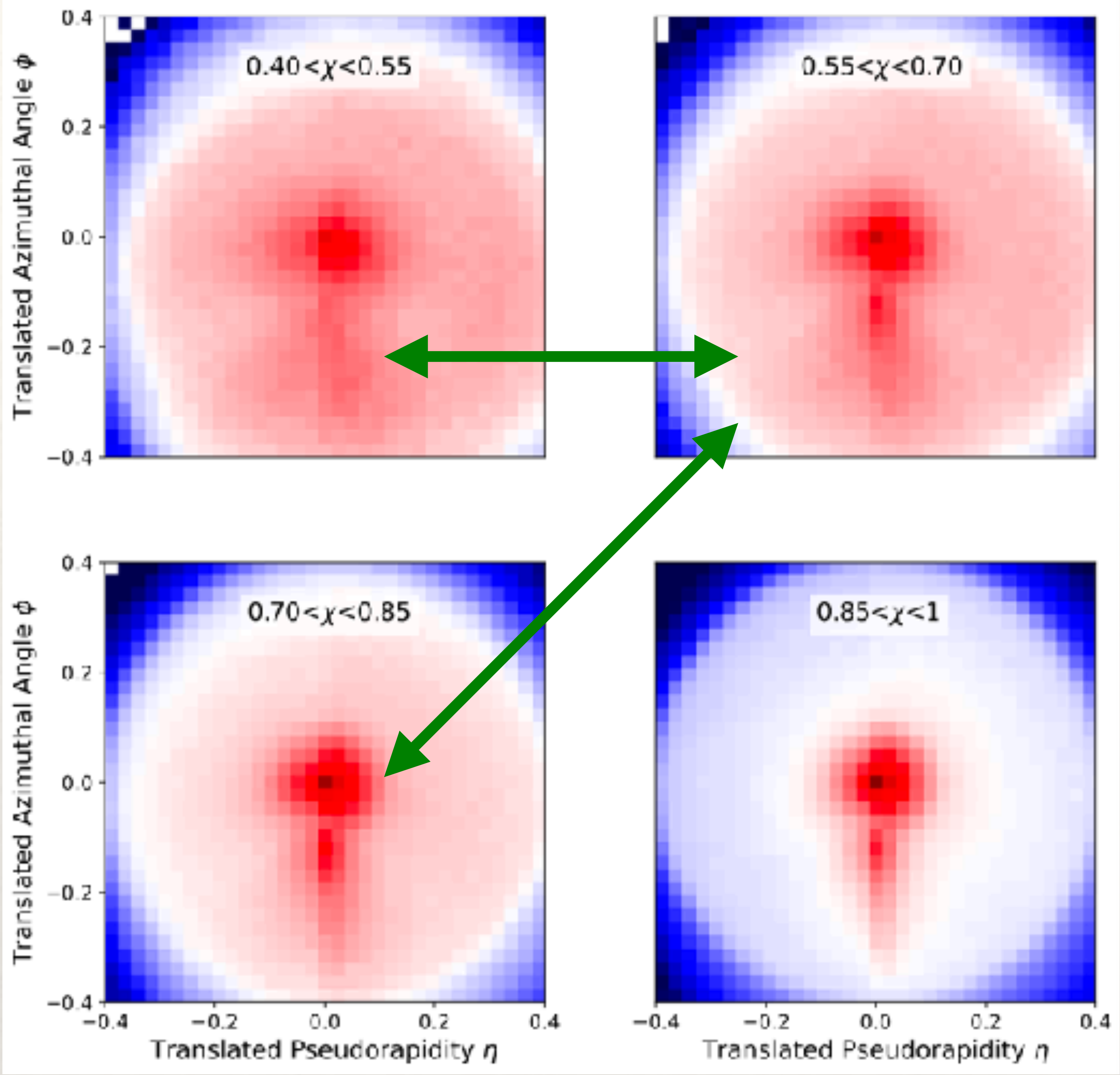
- More quenched jets: more jet energy transported from small to large radius
- CNN can grasp features of jet images and accurately predicts jet-by-jet energy loss

Effects of the QGP background

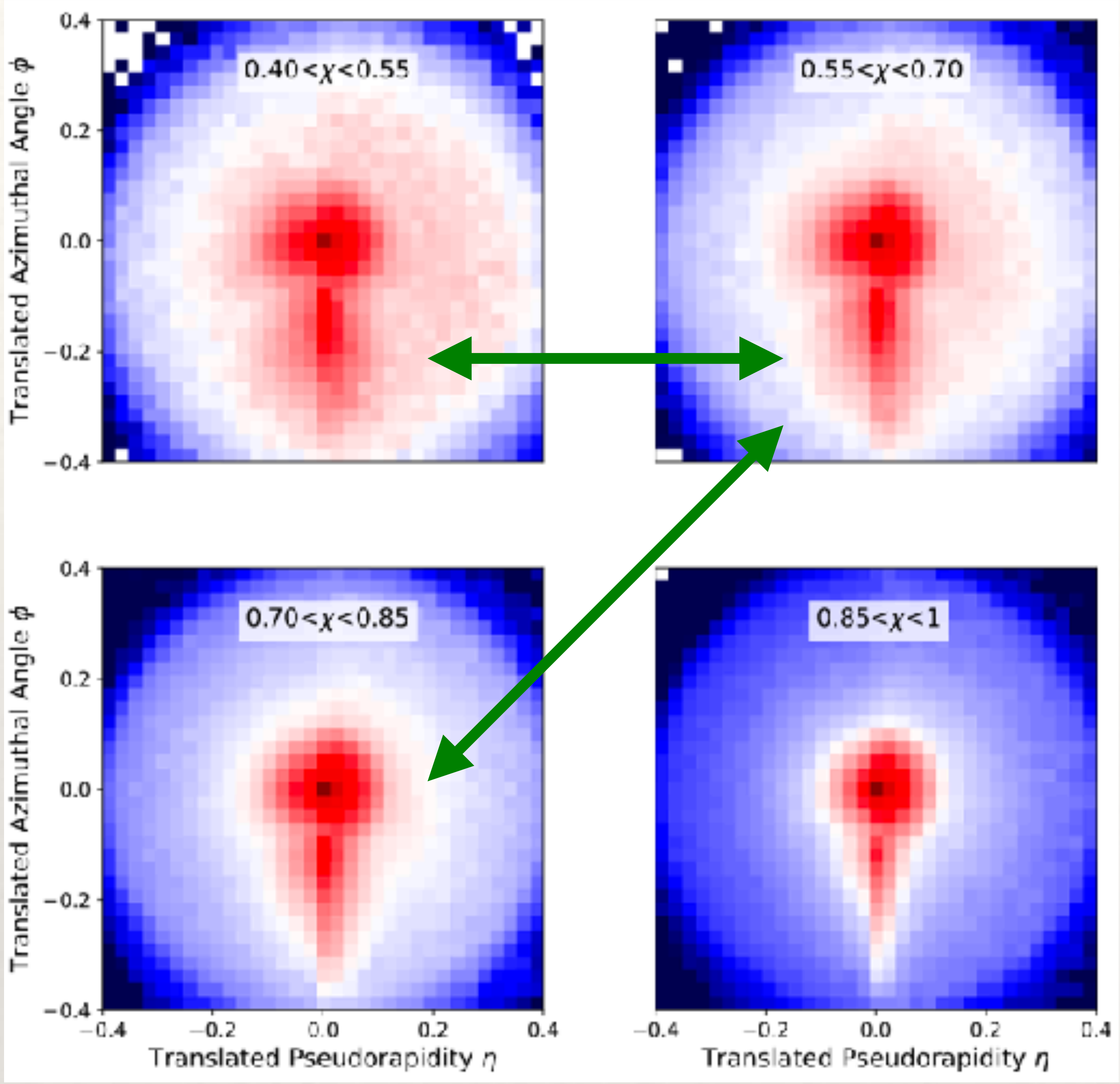
no bckg.



bckg. added



bckg. added and subtracted

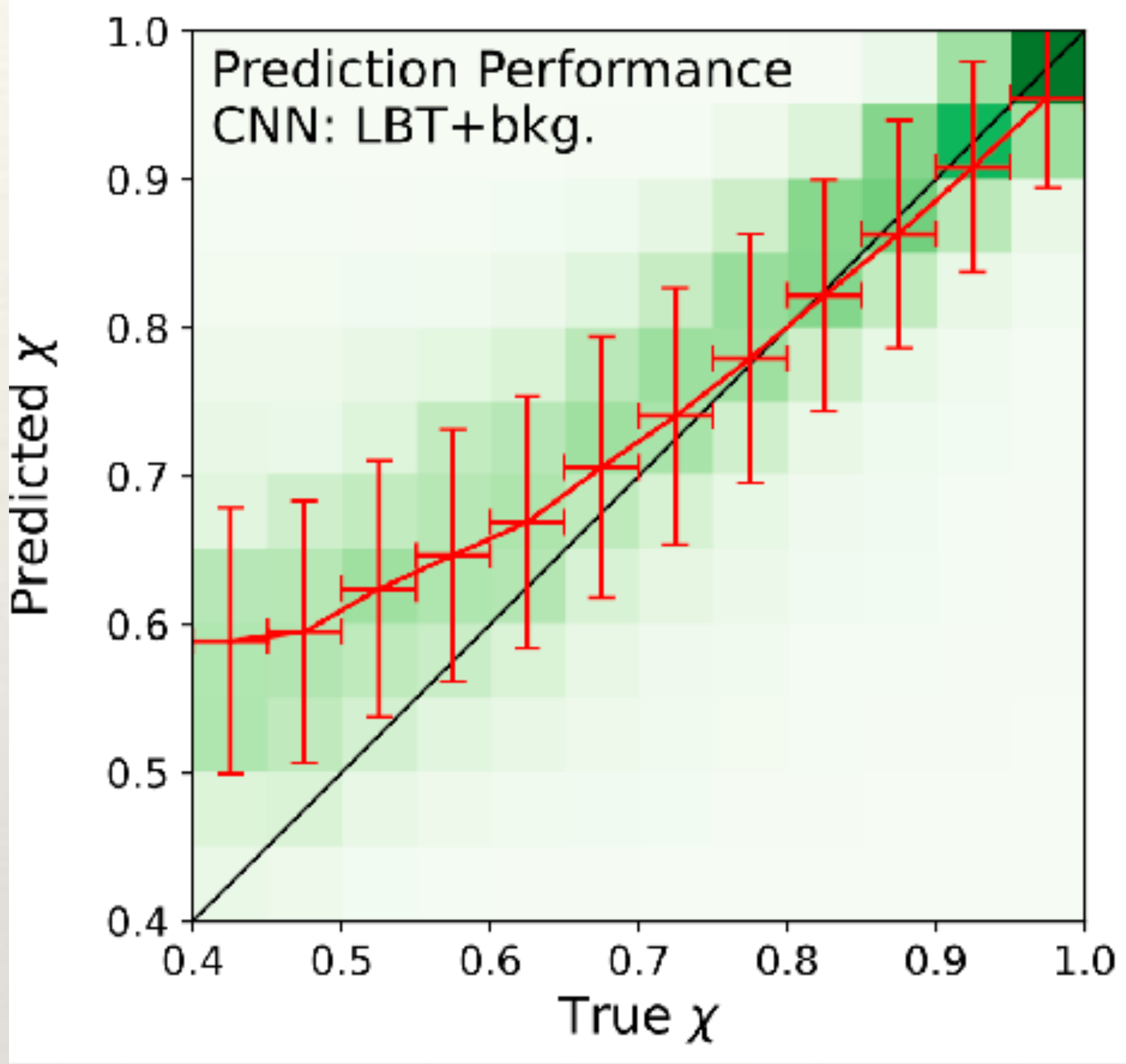


[Li, Du, SC, arXiv:2508.20856]

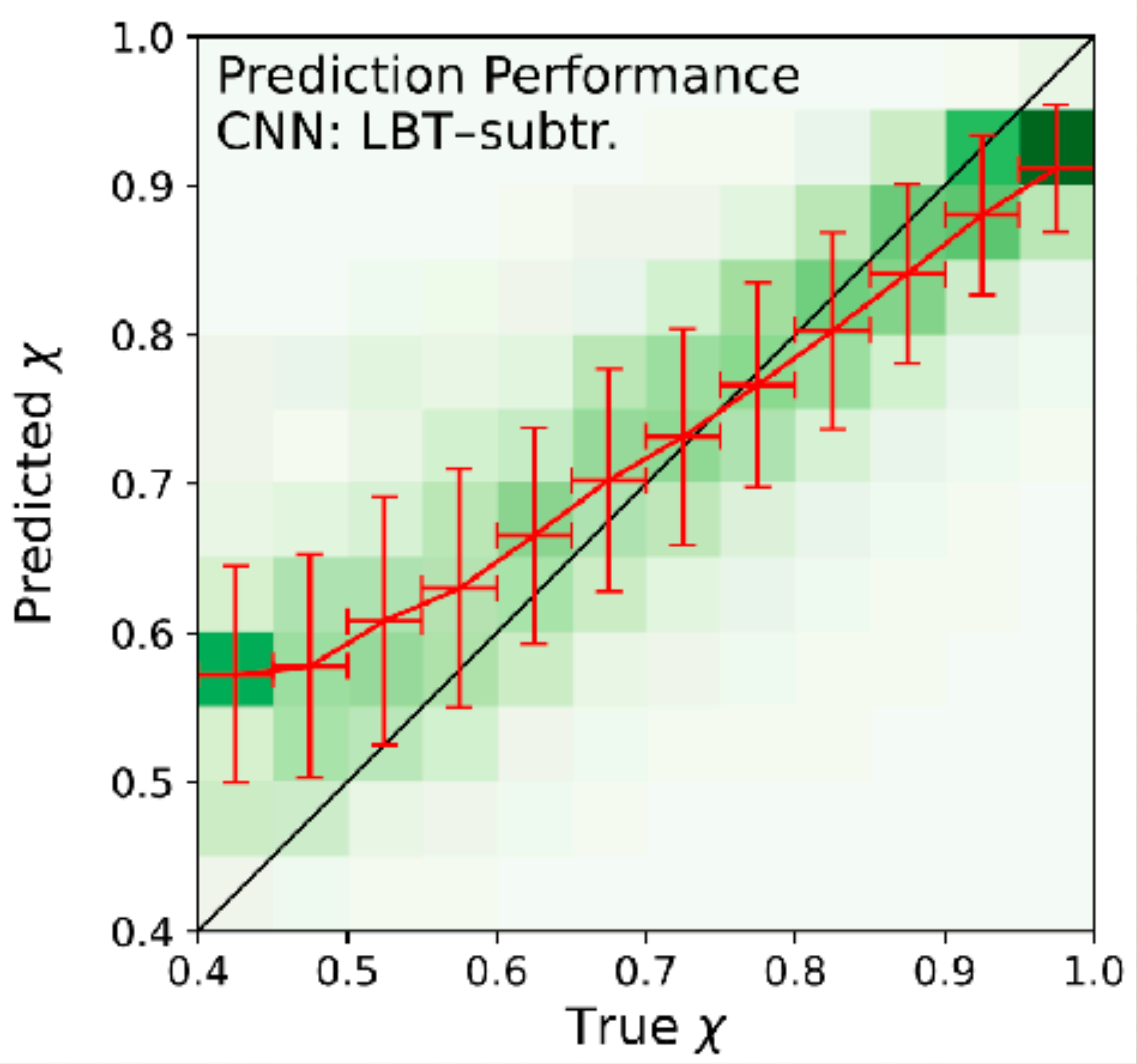
- Background reduces distinction between jet images when quenching is strong — similar features between medium response particles and background particles
- Removing background using the Constituent Subtraction can partially restore the features of quenched jet images

Effects of the QGP background

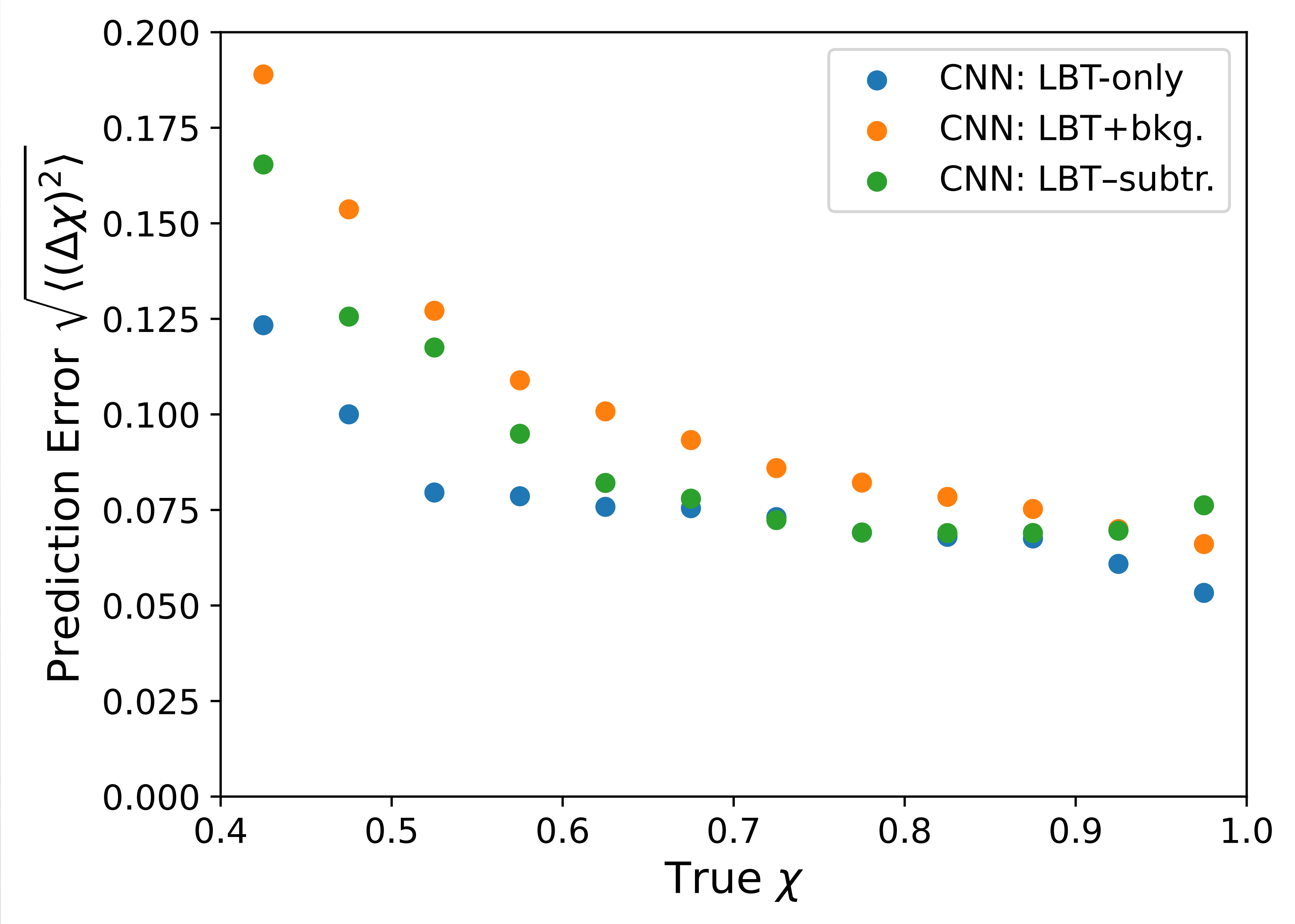
bckg. added



bckg. added and subtracted



prediction errors



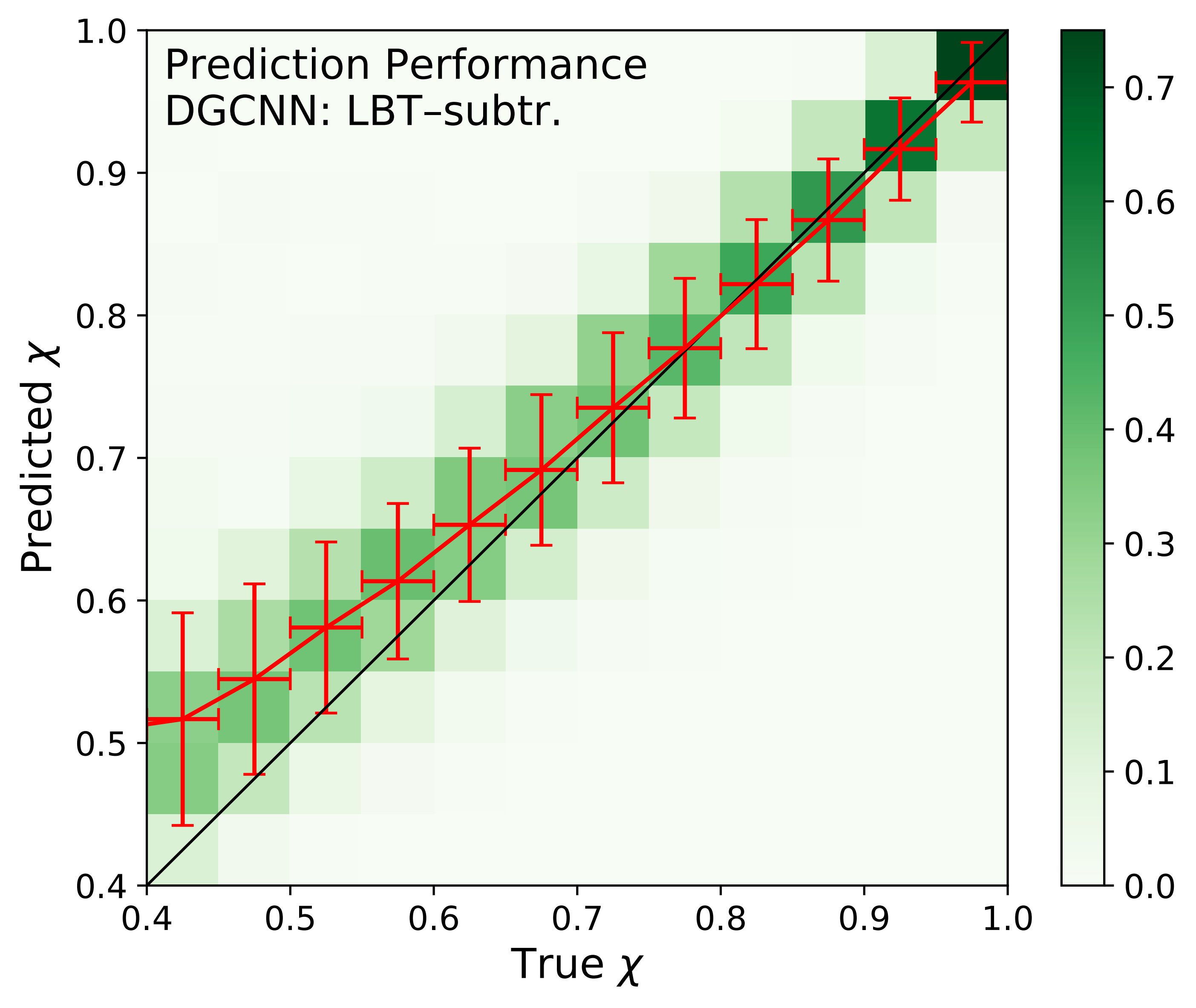
[Li, Du, SC, arXiv:2508.20856]

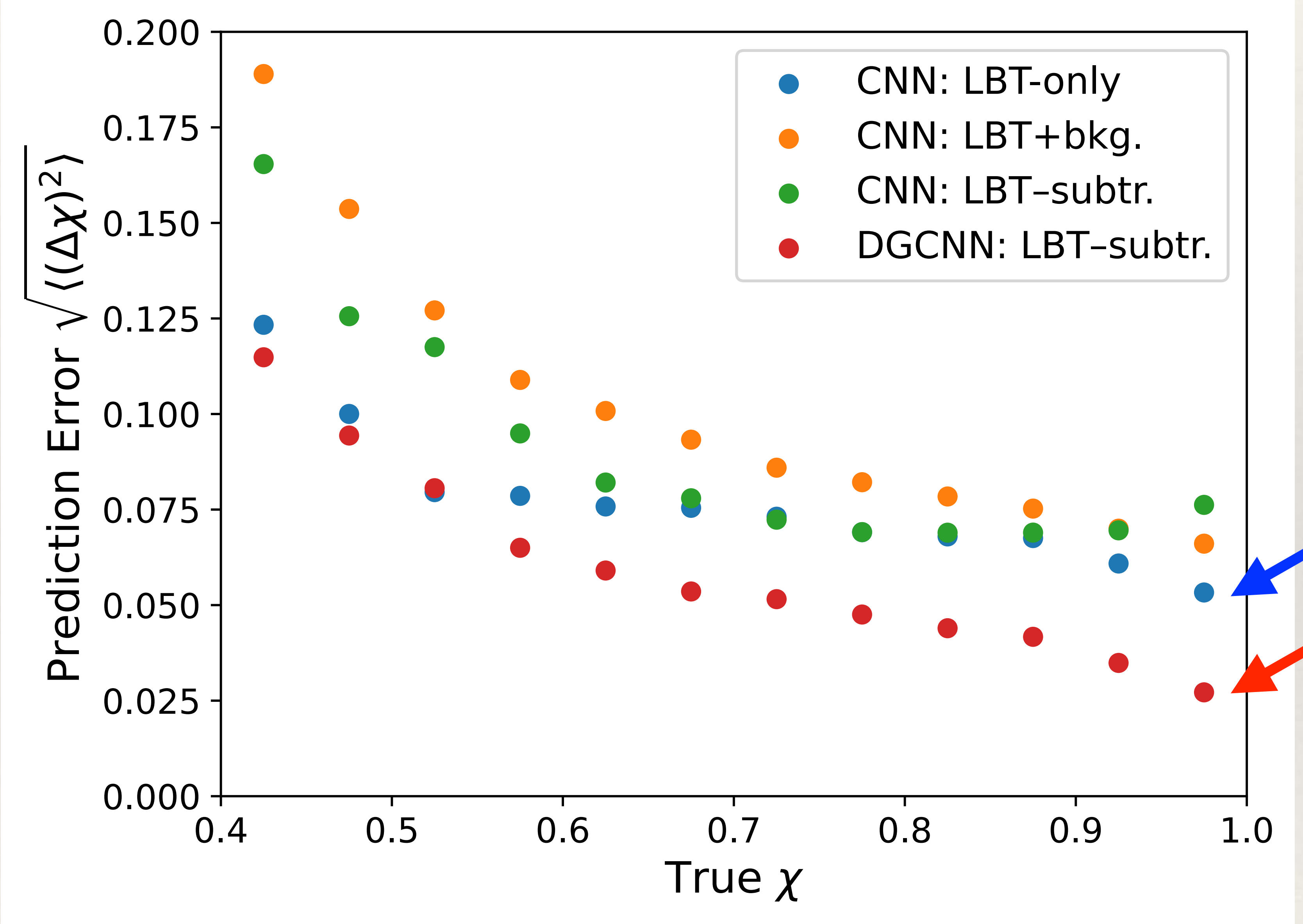
more quenched ⟷ less quenched

- Background reduces the accuracy of CNN when jet energy loss is strong
- Removing background using Constituent Subtraction partially restores the CNN accuracy, but is still less accurate than the scenario without background

From CNN to DGCNN

- Jet image → CNN ➡ point cloud → dynamic graph CNN (DGCNN)
- ParticleNet architecture for DGCNN [Qu, Gouskos, Phys. Rev. D 101 (2020) 056019]
- Inputs to point cloud: distance between points in the $(\Delta\eta, \Delta\phi)$ plane, 16-nearest neighbors are identified to construct edges, particle four momenta as features of edges





CNN w/o bckg

DGCNN

Li, Du, SC, arXiv:2508.20856

- Good performance of DGCNN on predicting jet-by-jet energy loss with background introduced and subtracted, even better than the CNN scenario without introducing background

Summary

Application of ML to jet quenching in high-energy nuclear collisions

- DNN outperforms traditional background subtractions in reconstructing jet p_T
- Using realistic quenched jet data is essential for ML in heavy-ion collisions
- ML models can predict jet-by-jet energy loss based on their inner structures
- DGCNN outperforms CNN amidst QGP background contamination

More technical details: poster by Ran Li

Thank you!