Deep Learning on Jet Modification in the Presence of the QGP Background

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ML4Jets2024
Nov 4 – 8, 2024

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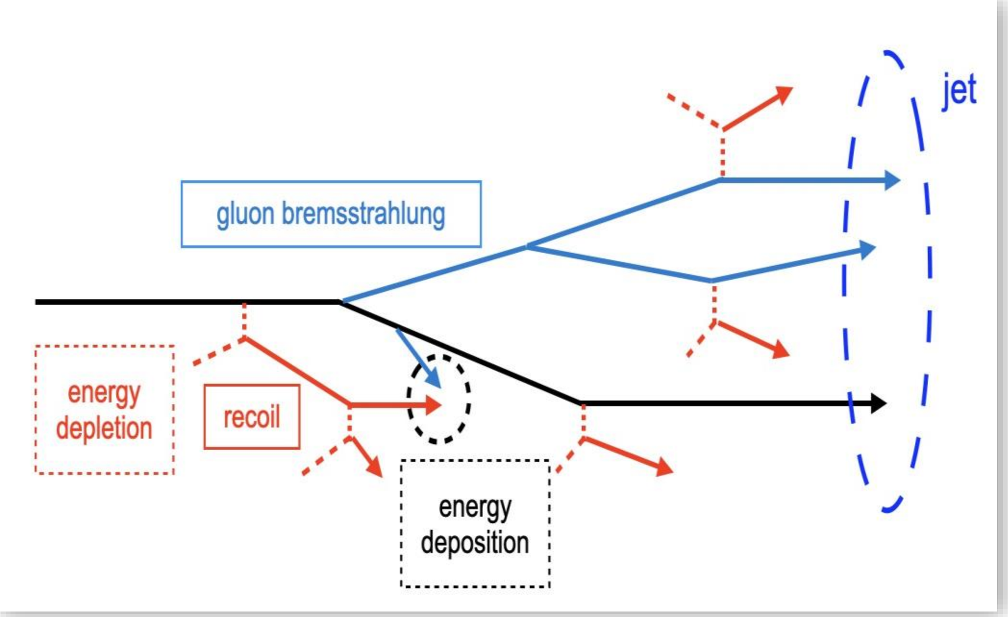
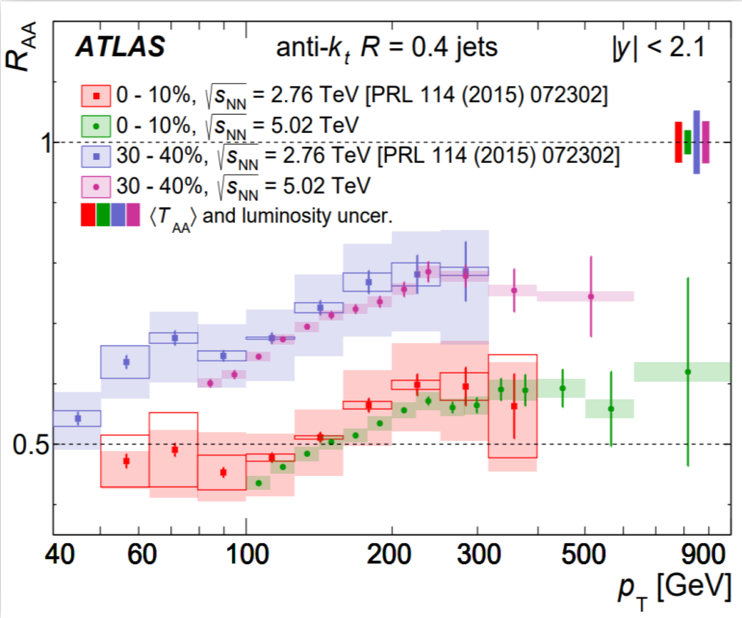
Jets in high-energy nuclear collisions



ATLAS collaboration PLB 790 (2019) 108



- Quark-gluon plasma (QGP) in heavy-ion collisions: deconfined phase, hot dense medium
- Jets are quenched in the medium via parton energy loss, serving as hard probe to medium properties.

$$R_{AA} = \frac{\text{Spectrum in AA}}{\text{Spectrum in pp}}$$

Jet energy loss from a statistical viewpoint

⇩

Energy loss on a jet-by-jet basis

Outline

- Jet Momentum Reconstruction in Heavy-Ion Background
- Extracting Jet Energy Loss on a Jet-by-Jet Basis

Background Subtraction Methods

Conventional method in experiments:

Area-based method

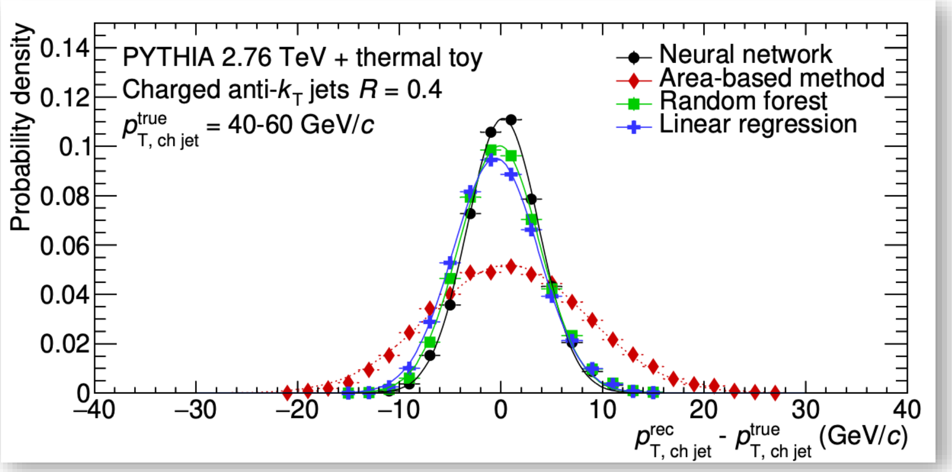
- Event-by-event basis: background momentum density ρ
- For each jet: reconstructed jet momentum $p_T^{rec} = p_T^{raw} - \rho A.$
- Leads to large residual fluctuations

Constituent Subtraction (CS)

- Local subtraction of soft background
- Simultaneously correcting the 4-momentum of the jet and its substructures

ML techniques

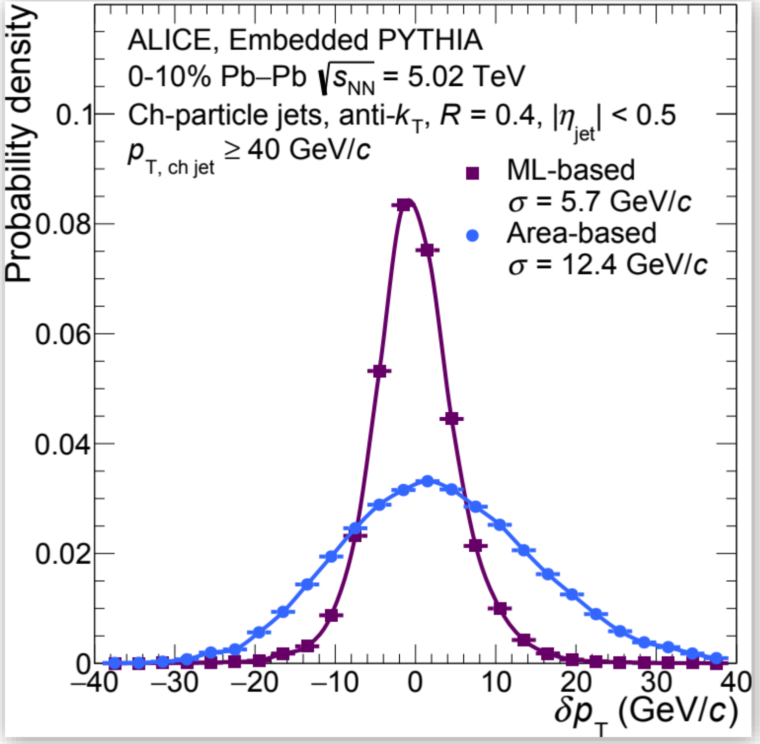
Neural Network, Linear Regression, Random Forest…

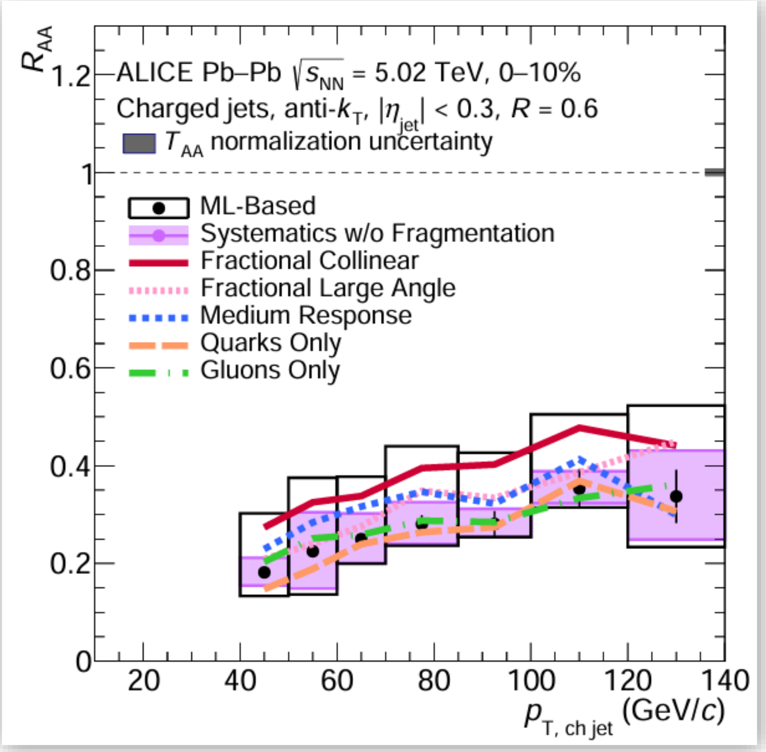


R. Haake and C. Loizides, PHYS. REV. C 99, 064904 (2019)

ML-Based Jet Momentum Reconstruction in ALICE

Acharya S, Adamova D, Adler A, et al.
Phys. Lett. B, 849, 138412(2024).



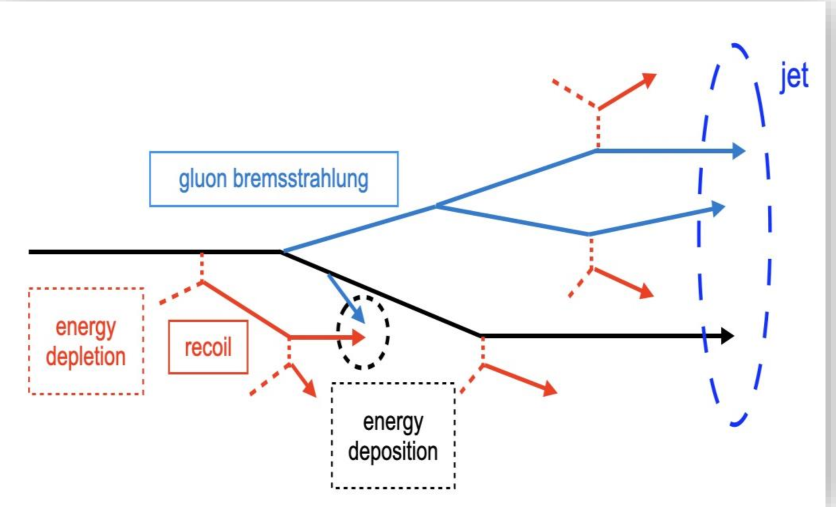


- ML method shows more precise estimate for low p_T jets
- Avoid fragmentation bias in R_{AA} by separate training with Pythia jets and their variants
- How about performance of this pythia-trained model on quenched jets?

Data generation: PYTHIA8 + LBT

- Vacuum jets: PYTHIA8
- Jet interaction with QGP: **L**inear **B**oltzmann **T**ransport model
- PbPb collisions in 0-10% centrality at $\sqrt{S} = 5.02TeV$.
- QGP background: a toy thermal model
- Reconstructed jets with anti-k_T, R=0.4

LBT



Target output: jet true p_T

Sum of the **jet particle p_T in cone**, in the presence of background particles.

Jet observables Input:

- the uncorrected jet momentum,
- the jet transverse momentum, corrected by the area-based method,
- jet mass, radial moment, momentum dispersion, and LeSub,
- the number of constituents within the jet,
- mean and median of all constituent transverse momenta,
- the transverse momenta of the first ten leading.

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

Background

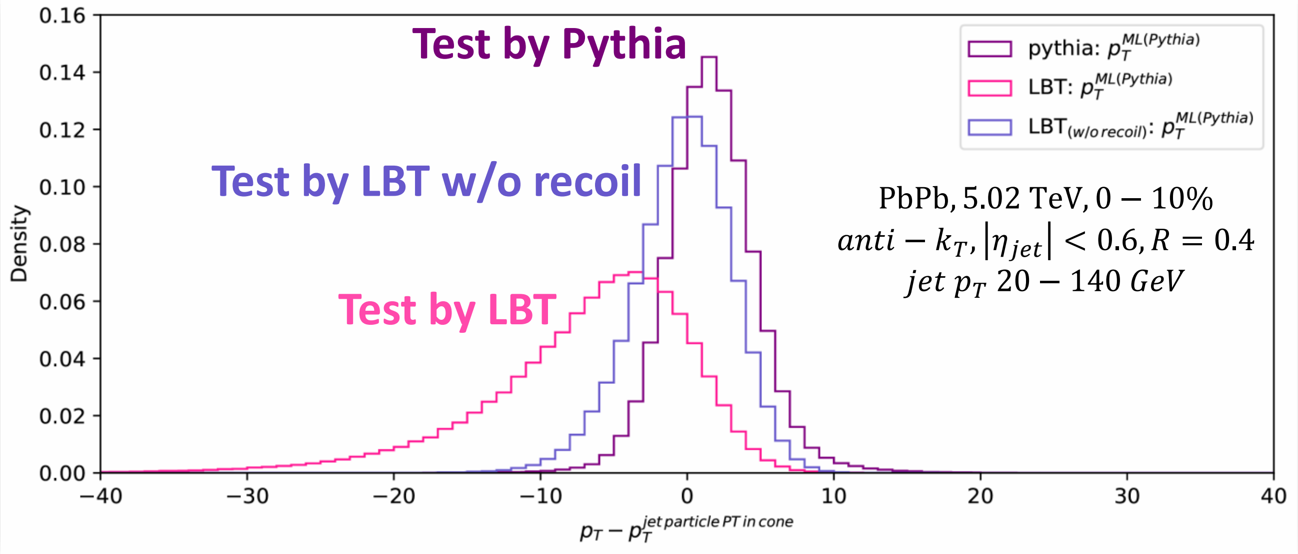
- Following Boltzmann distribution

	$\pi^+ + \pi^-$	
Centrality	dN/dy	$\langle p_T \rangle$
0-5%	1699.80	0.5682 GeV

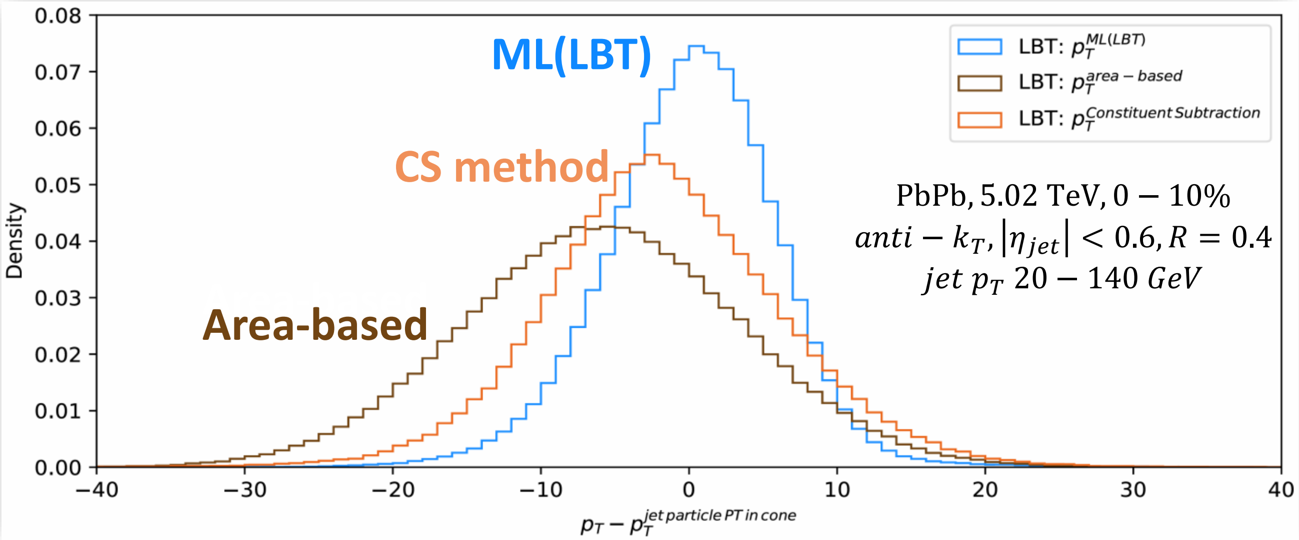
Acharya S, Adamová D, Adhya S P, et al. PHYS. REV. C 101, 044907(2020)

Performance

Training data: Pythia   Output: Jet Particle p_T in cone

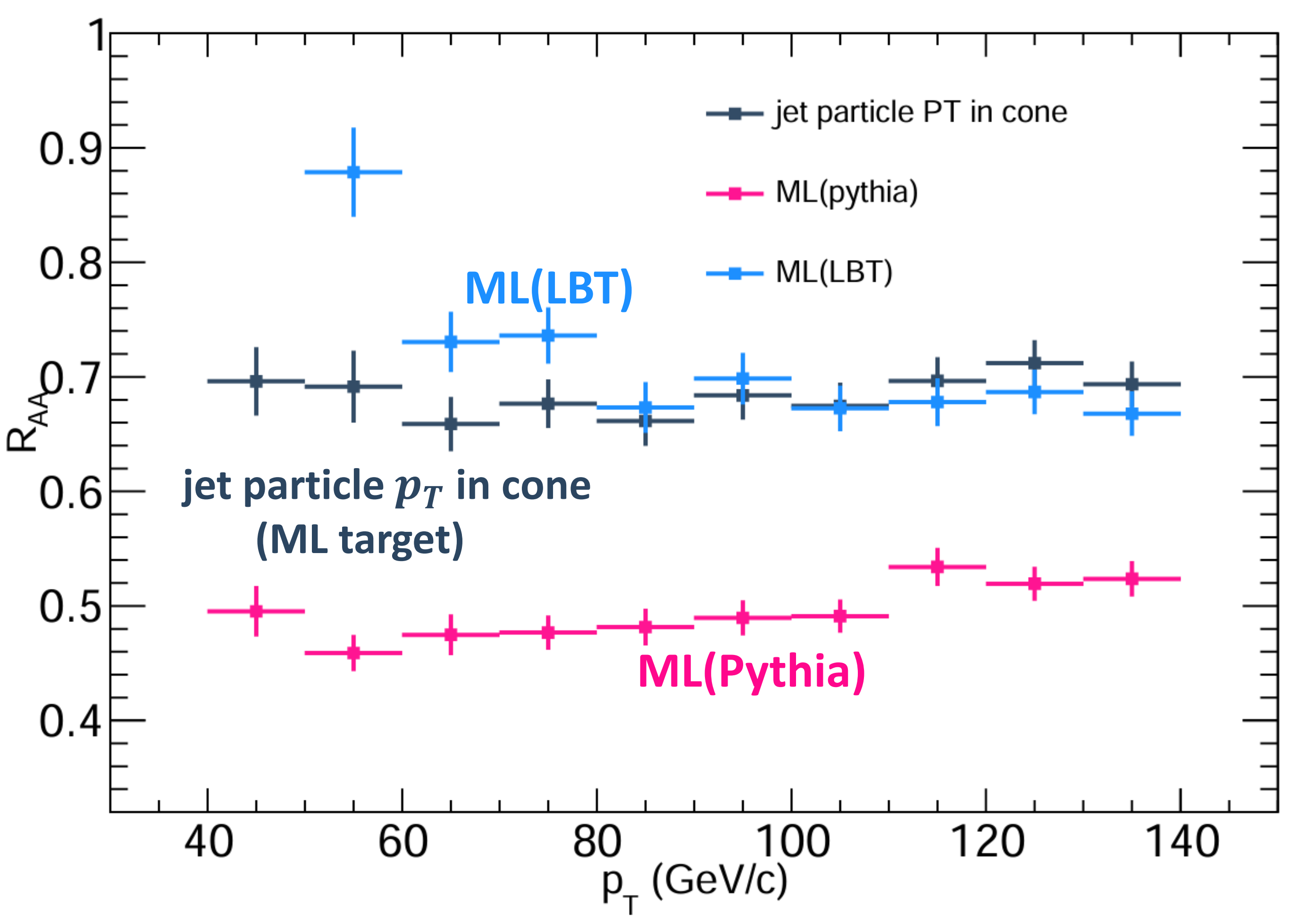


Training data: LBT   Output: Jet Particle p_T in cone



- When trained on PYTHIA jets, the ML model shows a prediction bias when applied to LBT jets.
- ML may consider the recoil particles as background.
  -recoil particle: a particle excited from the medium after colliding with a jet particle
- Prediction bias is significantly reduced when the ML model is trained on LBT jets
- Better than conventional methods

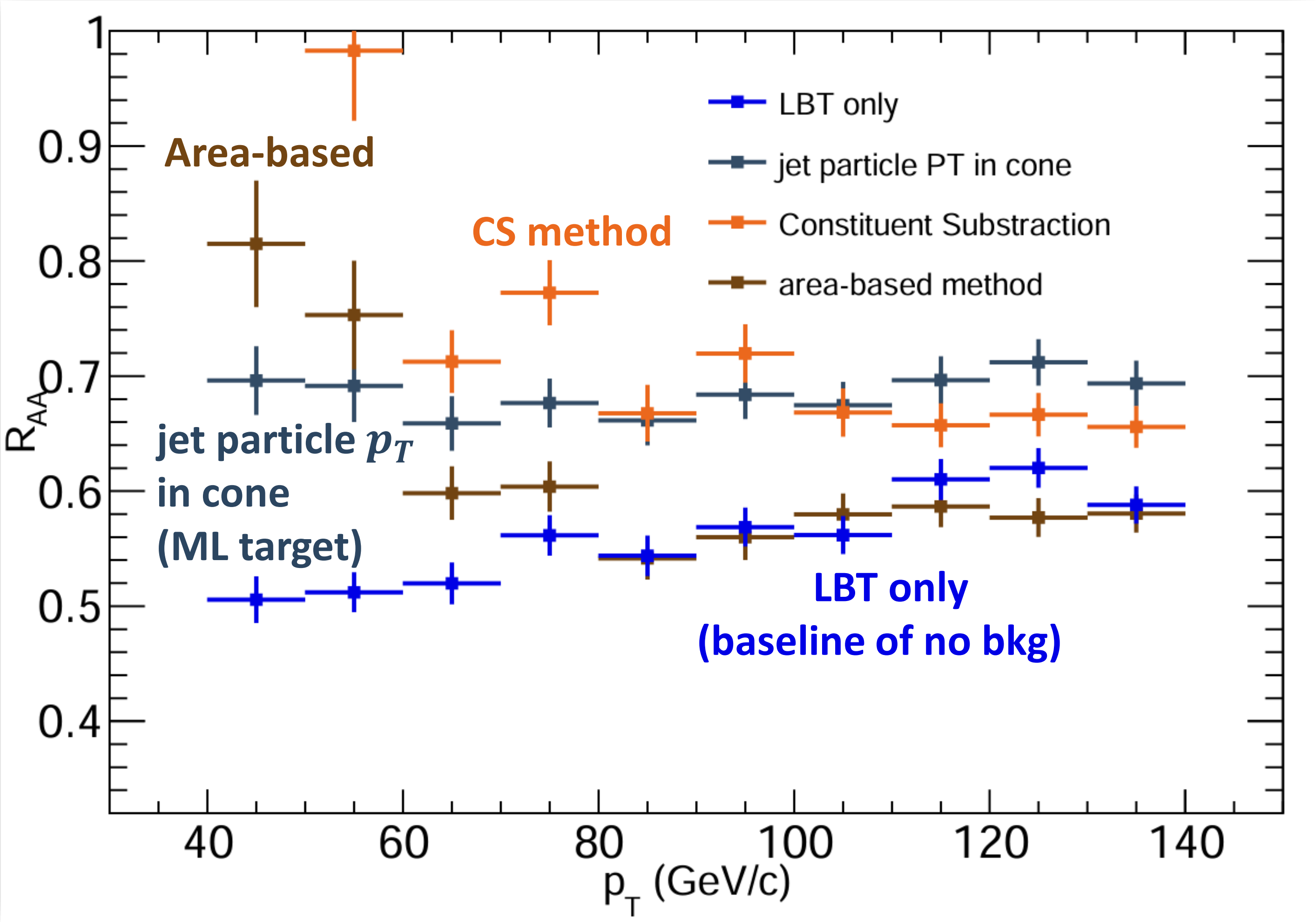
Nuclear Modification Factor R_{AA}



$$R_{AA} = \frac{\text{Spectrum in AA}}{\text{Spectrum in pp}}$$

- R_{AA} with ML(LBT) is much closer to that of "jet particle p_T in cone" than ML(Pythia).

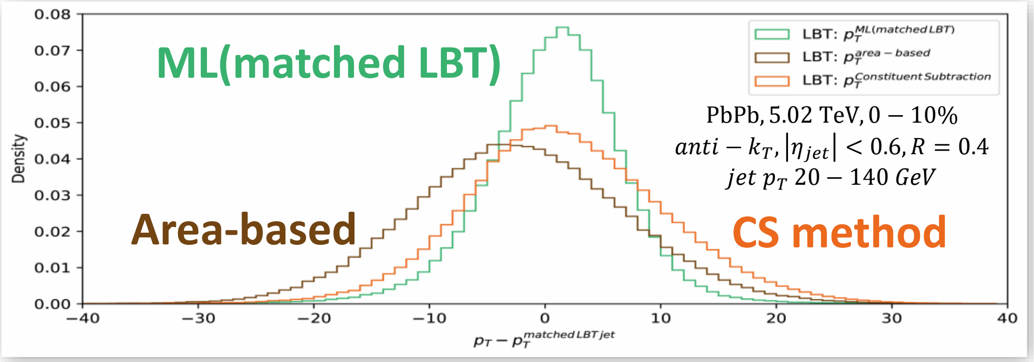
Nuclear Modification Factor R_{AA}



- Area-based: underestimates the R_{AA} in comparison with that of "jet particle p_T in cone"
- CS method: agrees with R_{AA} of "jet particle p_T in cone" down to 70 GeV
- Discrepancy between the ML target output and baseline of LBT-generated jets without background particles (LBT only)

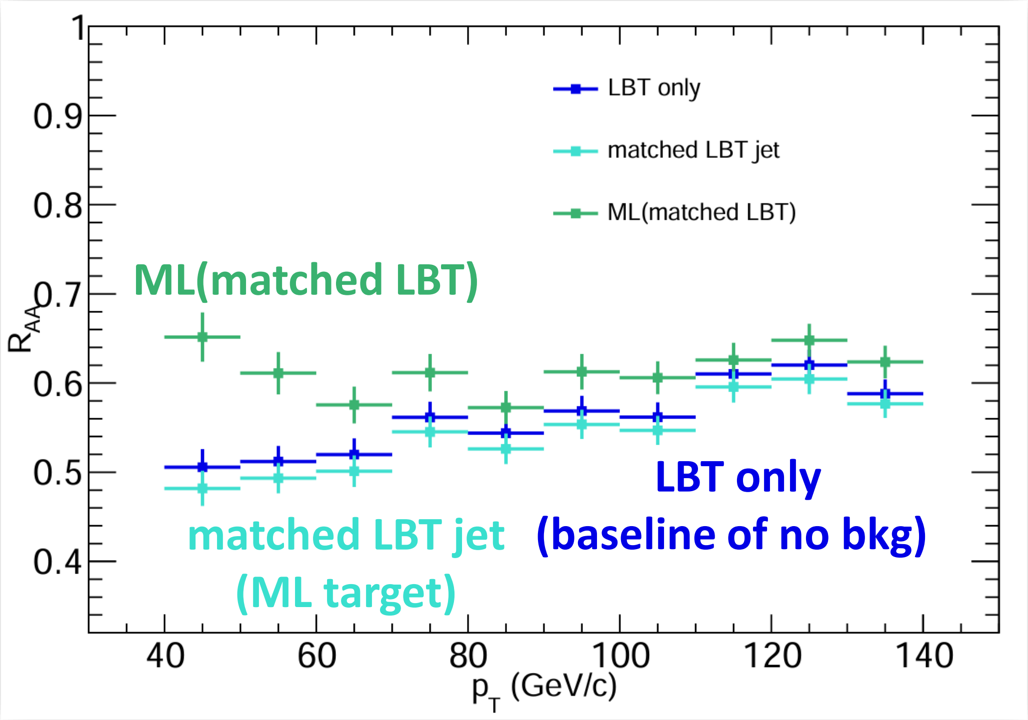
Matching with LBT-only jets

Training data : LBT   Output: Matched p_T

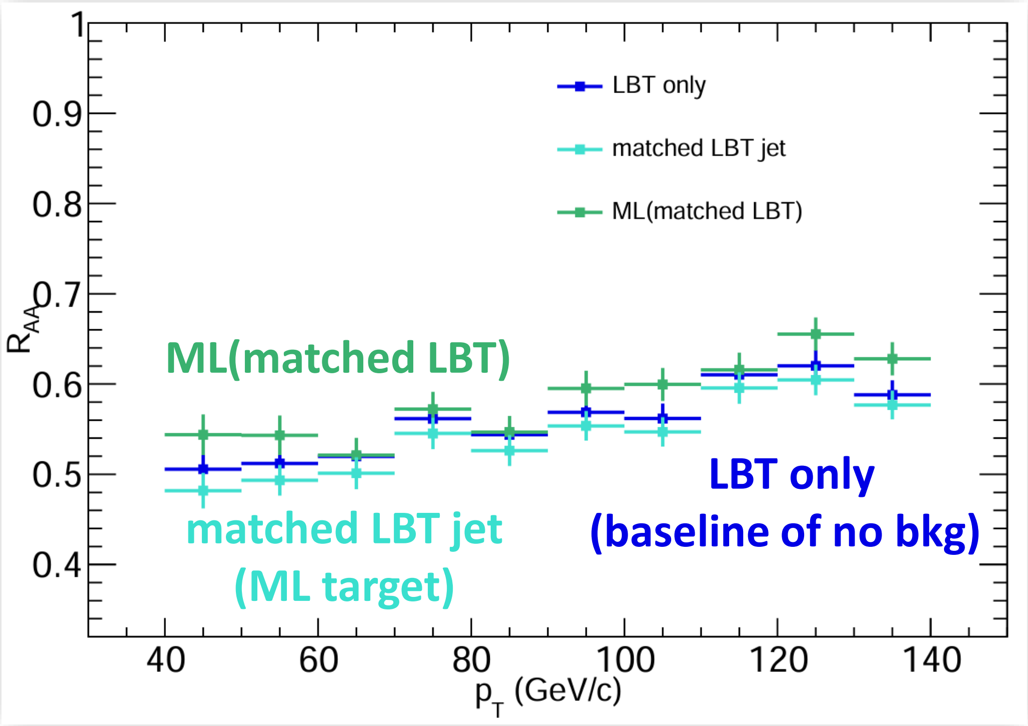


- Matching the jets clustered from LBT particles w/ and w/o background particles.
- Matching criteria: $\Delta\theta<0.4$
- Target output (Matched p_T): the p_T of matched LBT-only jet

Drop fake jets in training



Set fake jets p_T as 0 in training



Outline

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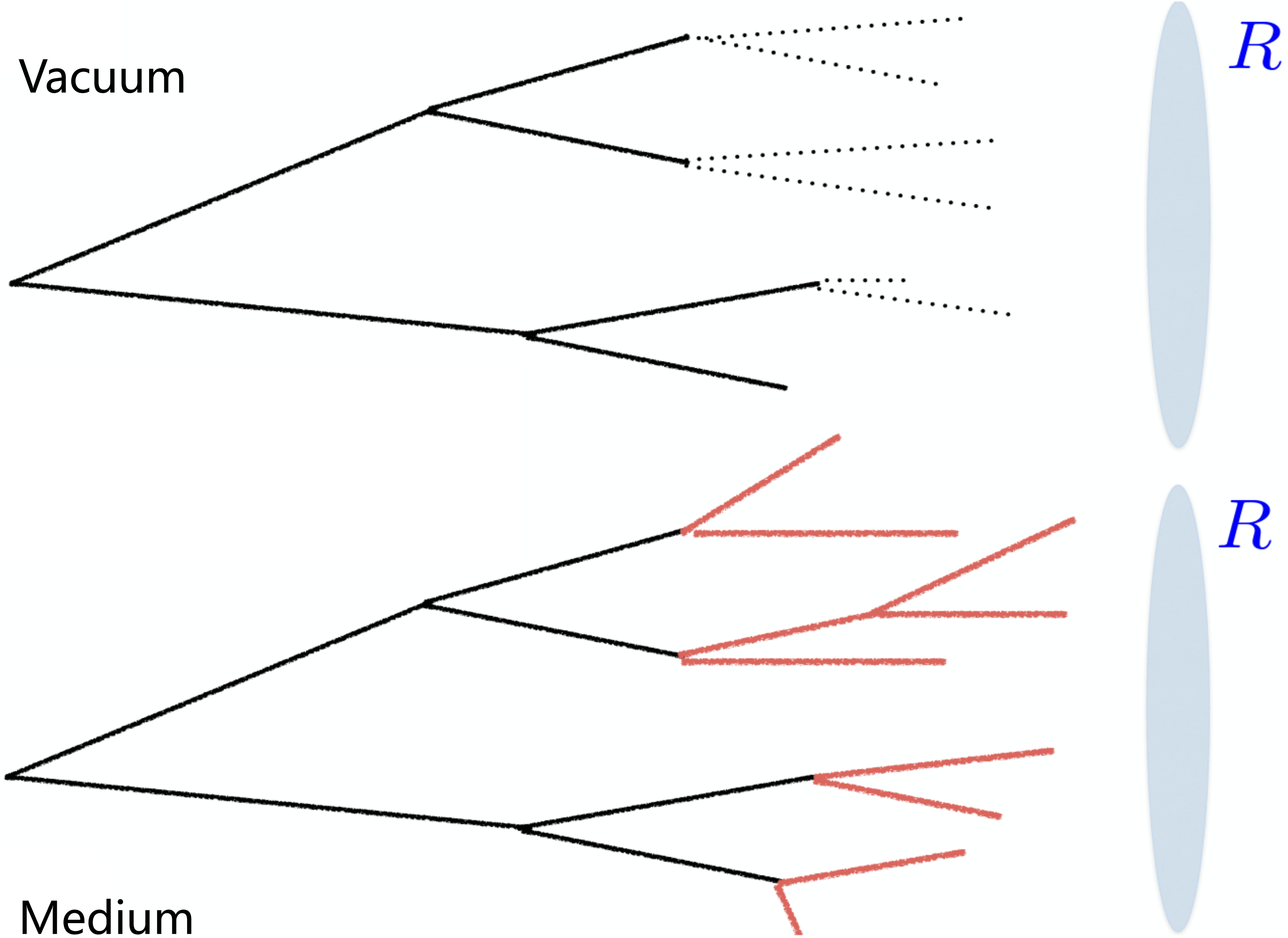
- Extracting Jet Energy Loss on a Jet-by-Jet Basis

Define the Energy Loss Ratio



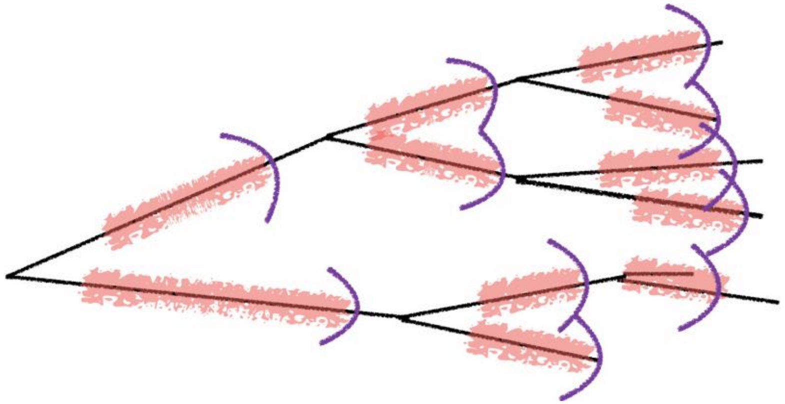
E_i

E_f

$$\chi \equiv \frac{E_f}{E_i}$$

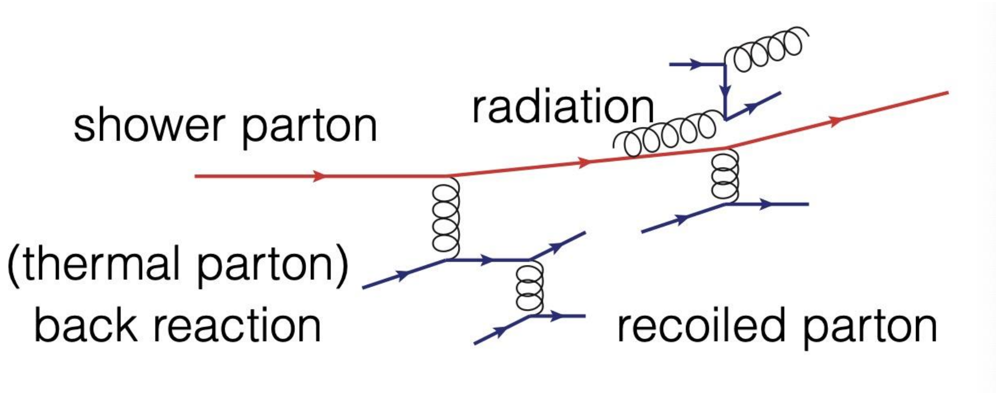
Previous work

hybrid strong/weak coupling model



Testing on a different quenching model

Linear Boltzmann Transport model



Only jet particles

More applicable in experiments

Introduce & Subtract background

- Following Boltzmann distribution

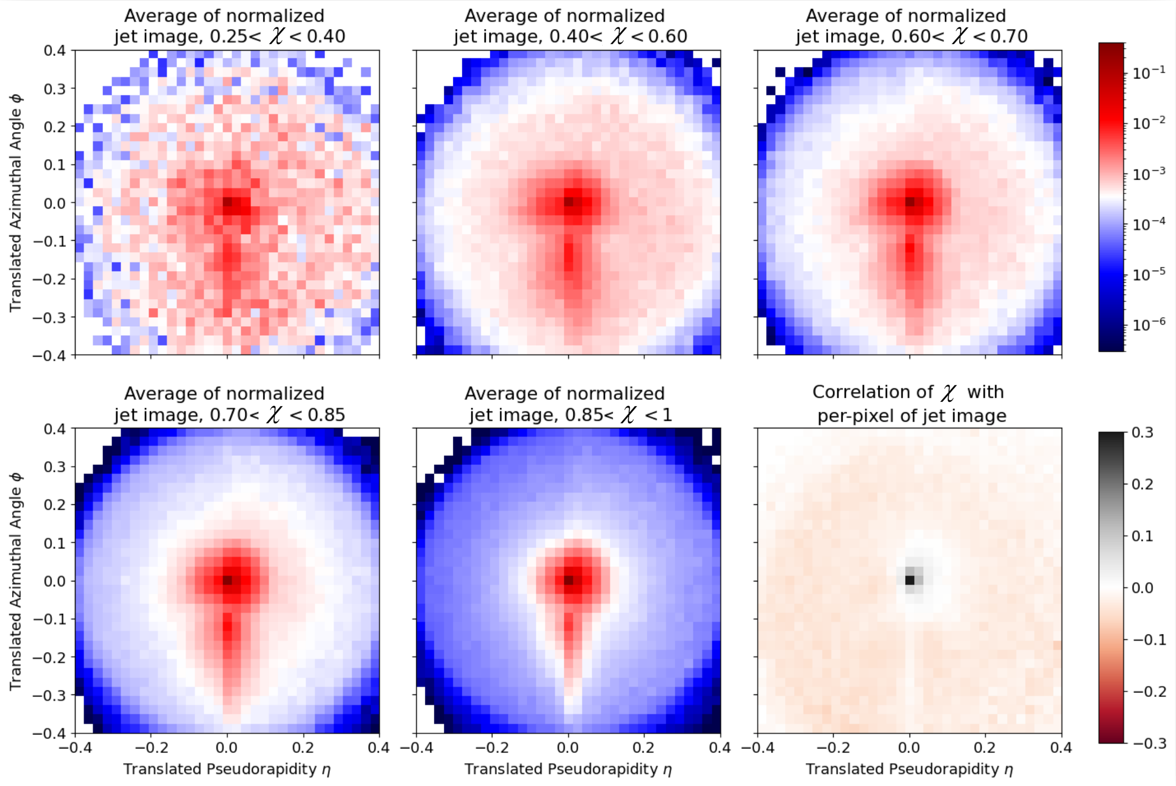
$\pi^+ + \pi^-$		
Centrality	dN/dy	$\langle p_T \rangle$
0-5%	1699.80	0.5682

- Constituent Subtraction

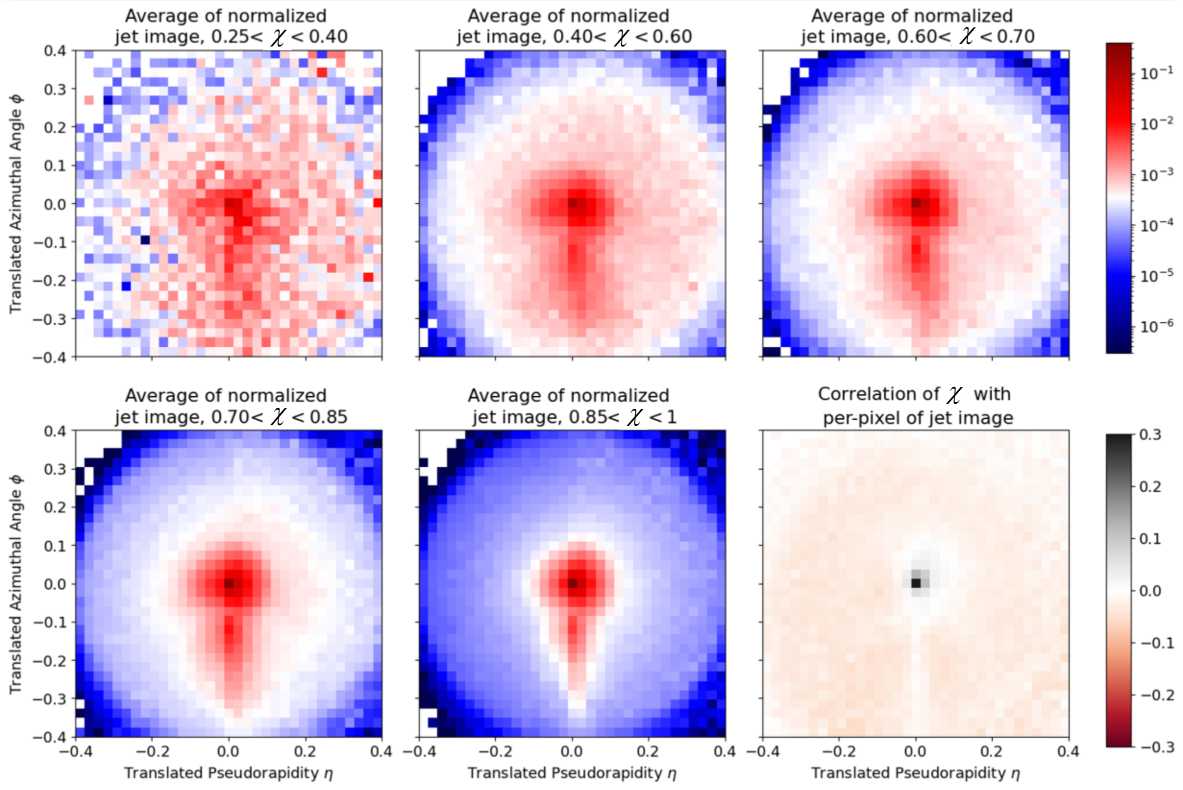
Y.-L. Du, D. Pablos and K. Tywoniuk, JHEP03 (2021) 206

Jet image and pre-processing

Without Background



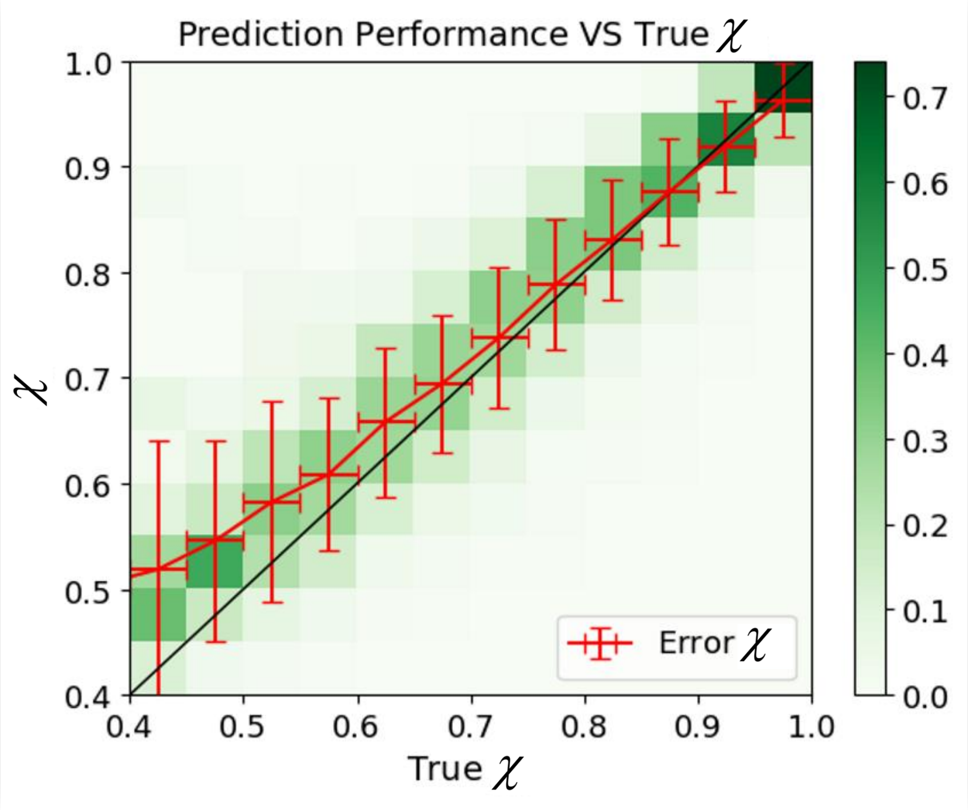
Introduce & Subtract Background



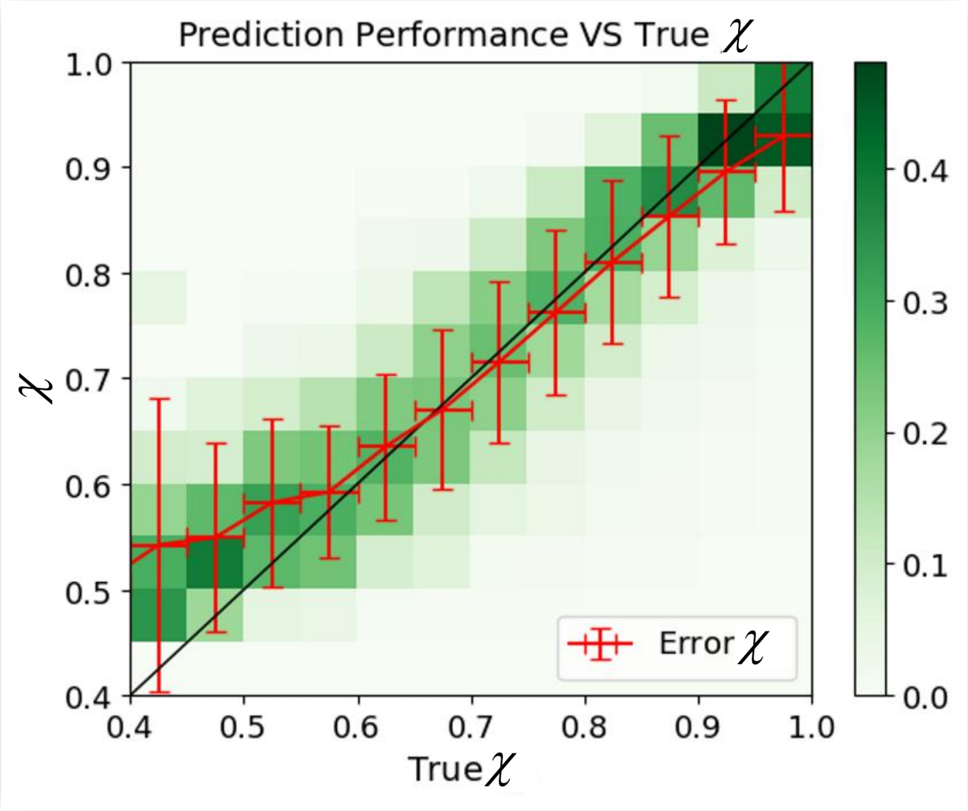
- With constituent subtraction, jet images largely revert to their original patterns, free from background interference.
- Jet quenching increases the number of soft particles at large angles.

Prediction performance

Without Background



Introduce & Subtract Background



- Well predicted for a wide range of χ
- Slightly decreases when introducing background

Summary

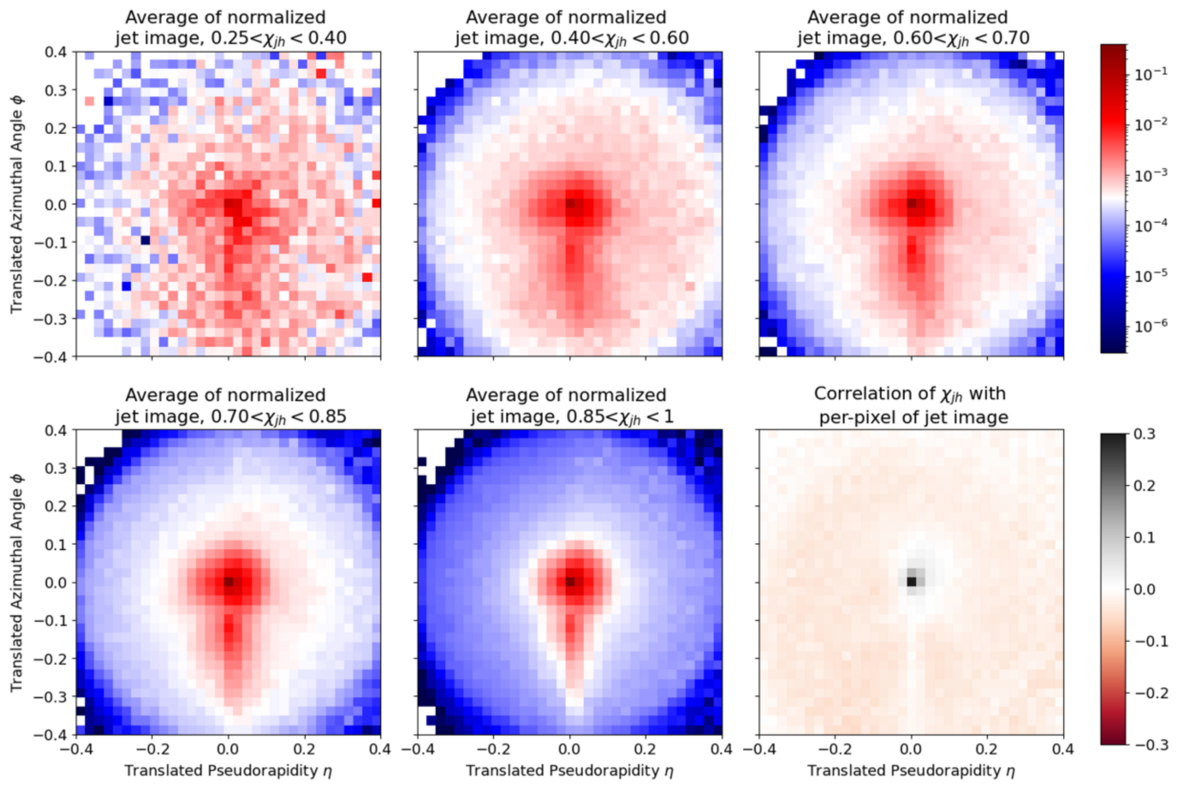
- Machine learning method provides a more precise estimate for the jet momentum by training with the quenched jets.
- By training with matched jets, we can obtain R_{AA} more accurately.
- CNN can effectively extract energy loss ratio jet-by-jet from jet image in the presence of QGP background.
- Machine learning is applicable to more realistic environment.

THANK YOU

Back up

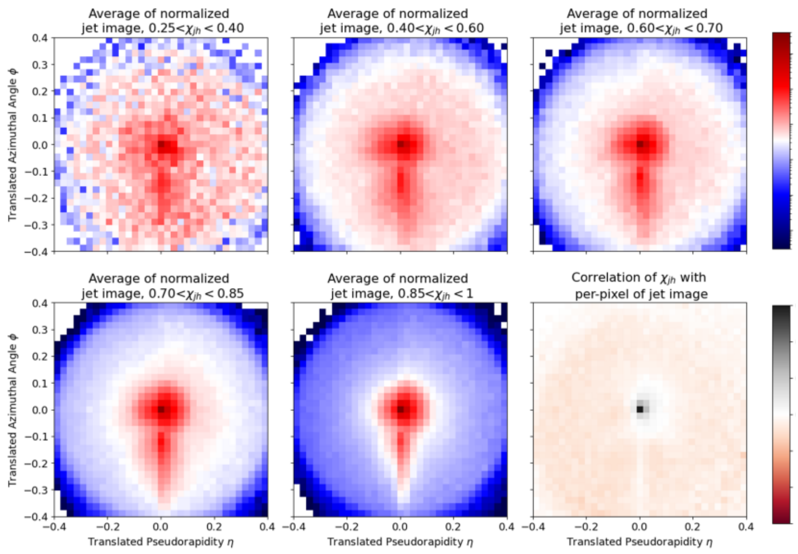
Jet image and pre-processing

- The total p_T of jet constituents deposited in the pixel of (η, φ) space with 33 η-bins and 33 φ-bins.
- Translation: the hardest groomed subjet is at (η, φ) = (0, 0).
- Rotation: the second hardest groomed subjet is at −π/2.
- aligning the first principal component of pixel intensity distribution along the vertical axis.
- Parity flip: right side of jet image has a larger pixel intensity sum

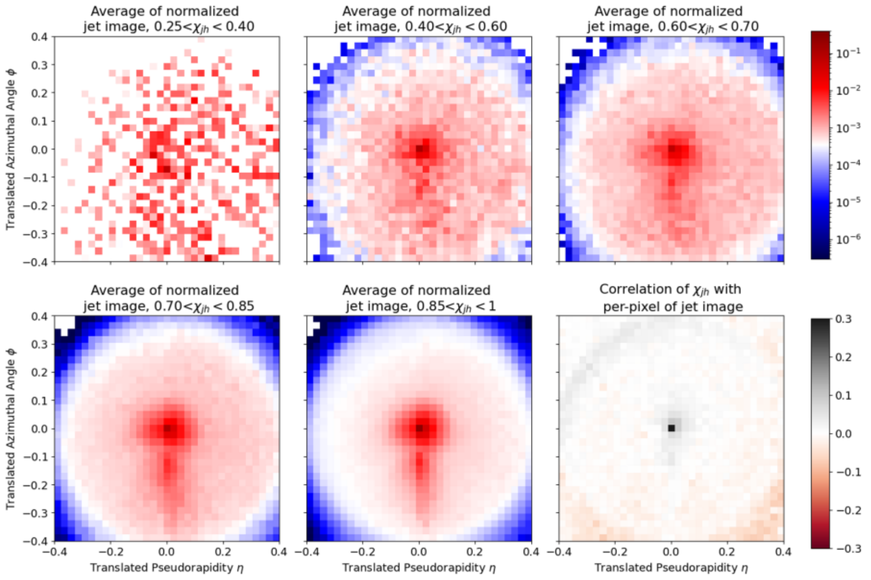


Input

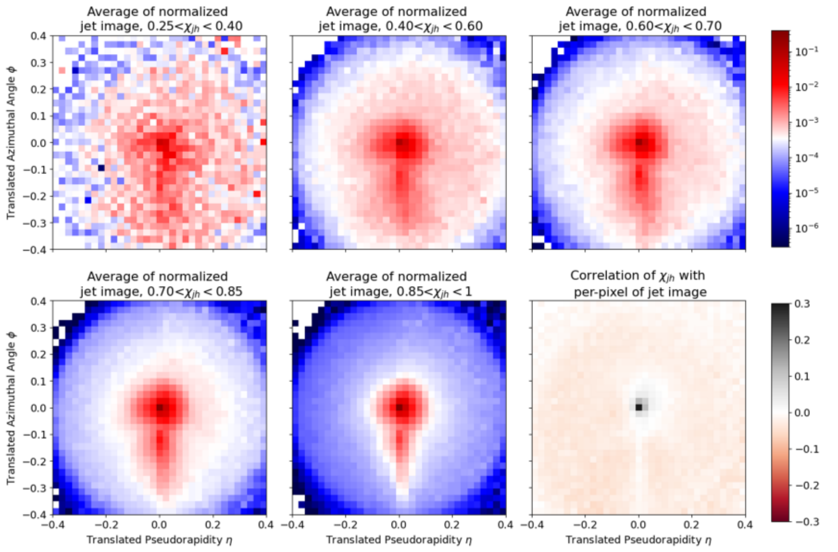
No background



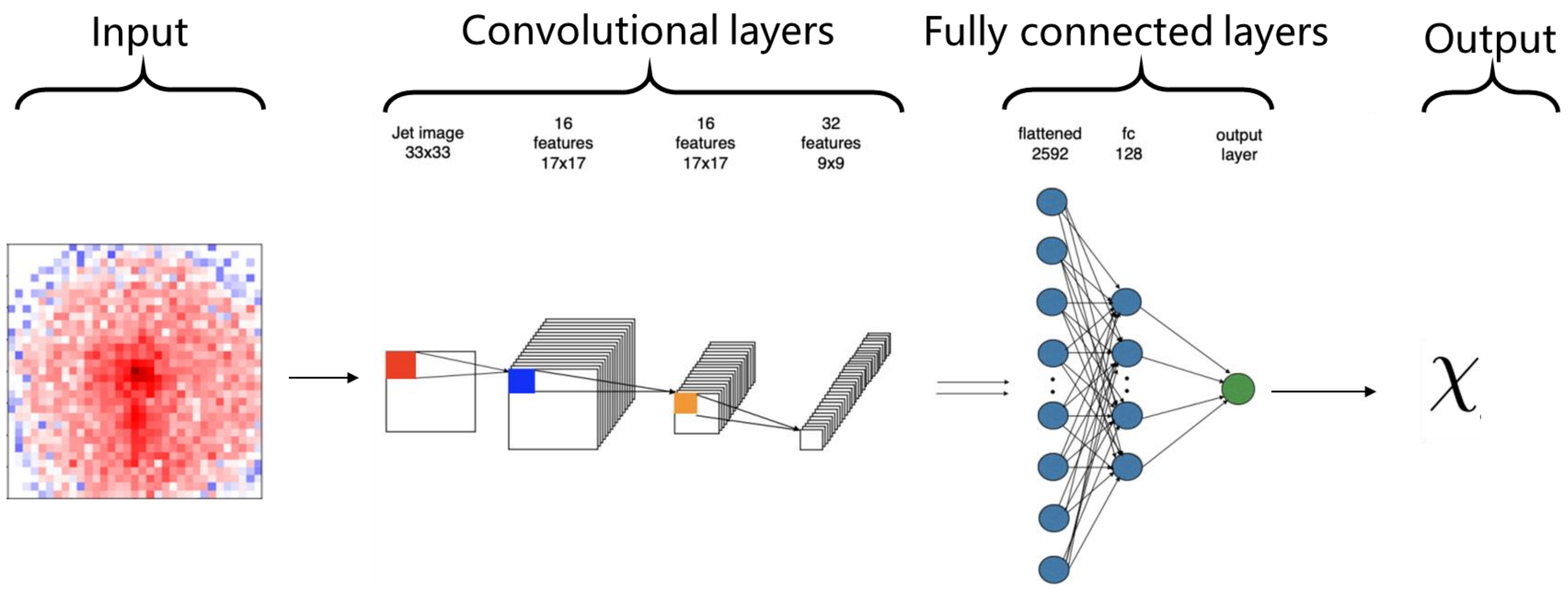
Background w/o subtraction



Introduce Background & subtract



Convolutional Neural Network (CNN)



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