Machine learning based jet p_{T} reconstruction in ALICE

June 16th, Nuclear Physics Seminar at BNL (Remote)

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Wright Laboratory

Yale

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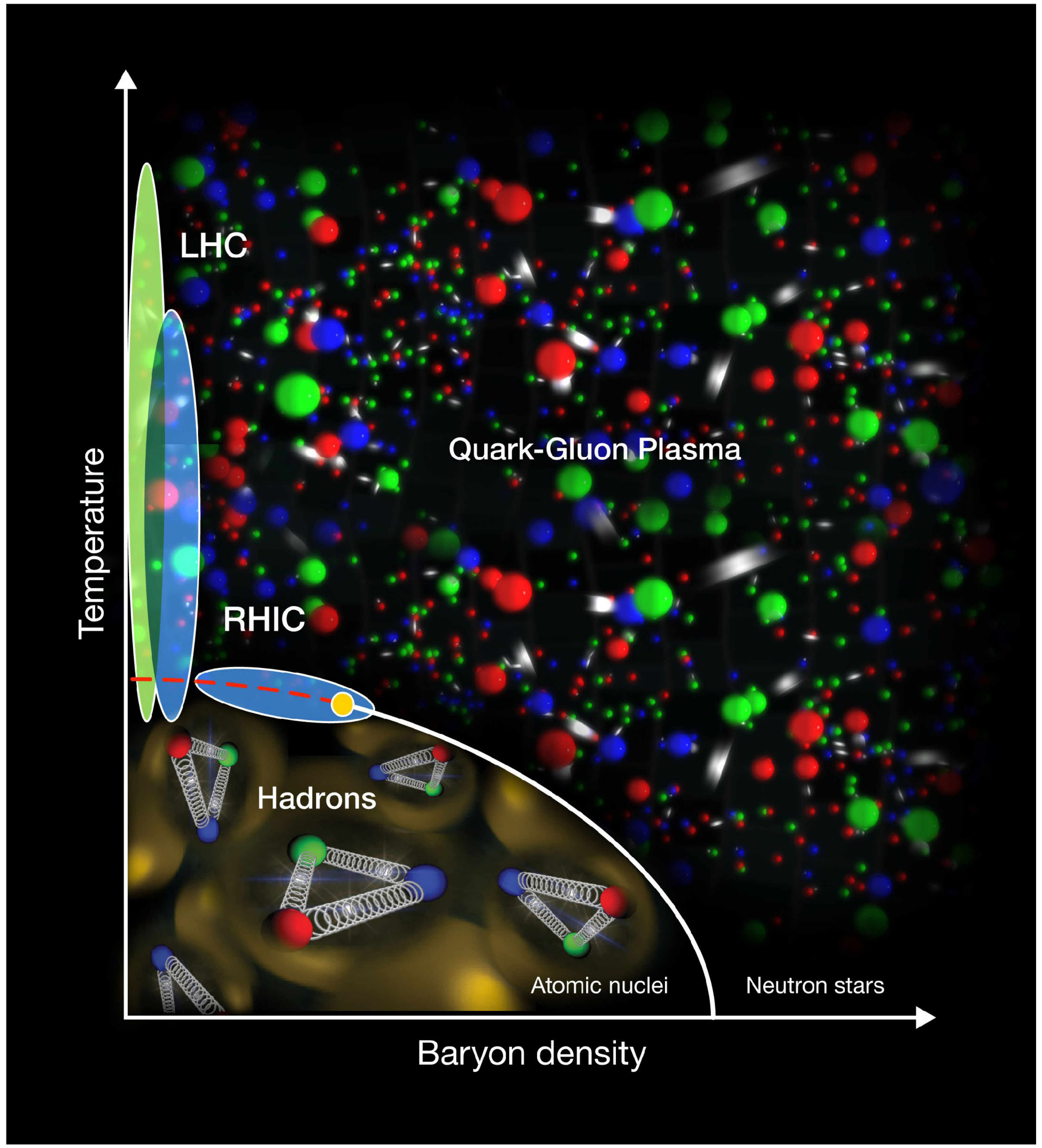
ALICE

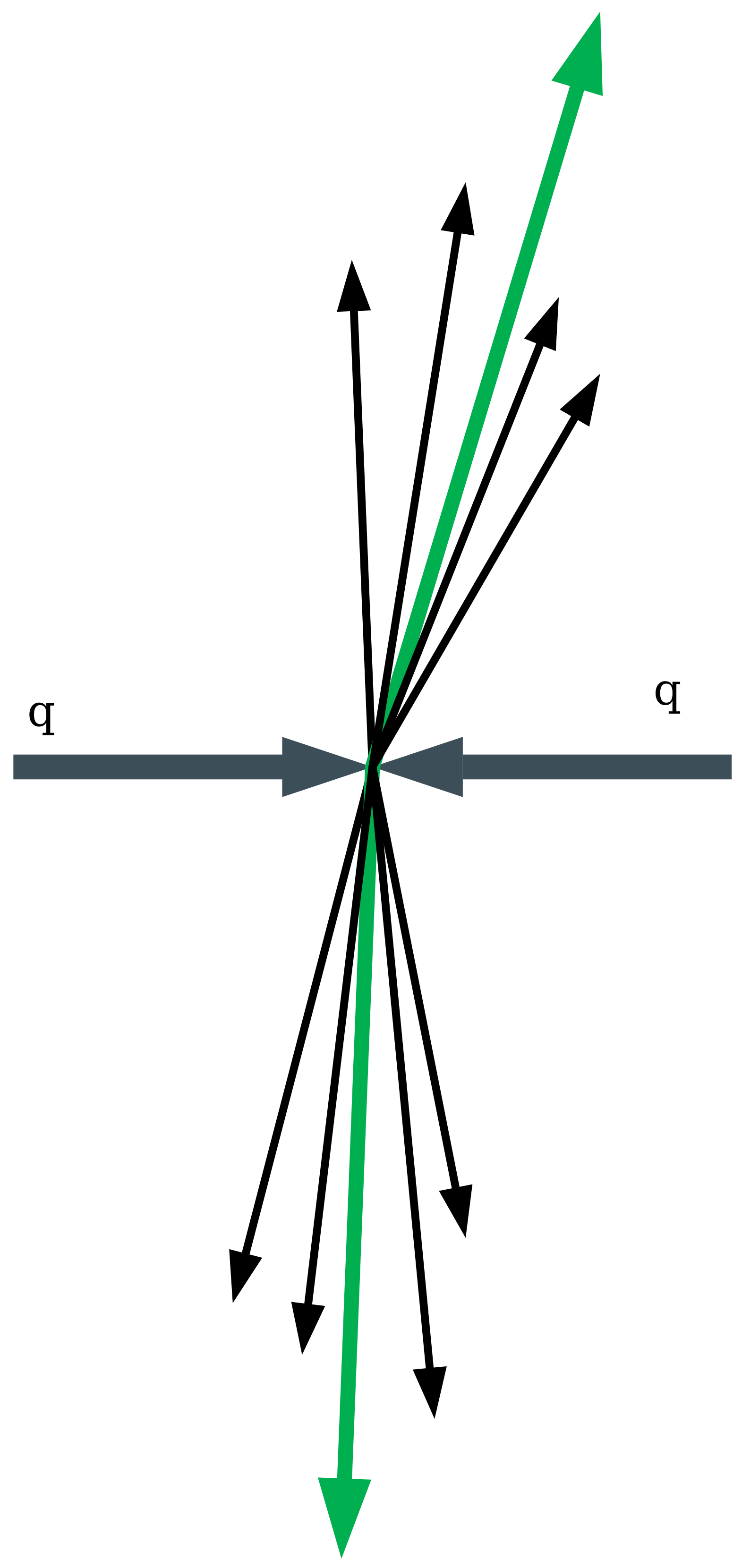
Heavy-ion collisions and the QGP



Phase diagram for strongly interacting matter.

At extremely high temperatures and pressures, QCD matter becomes deconfined in a state referred to as the Quark Gluon Plasma (QGP).

Jets in vacuum

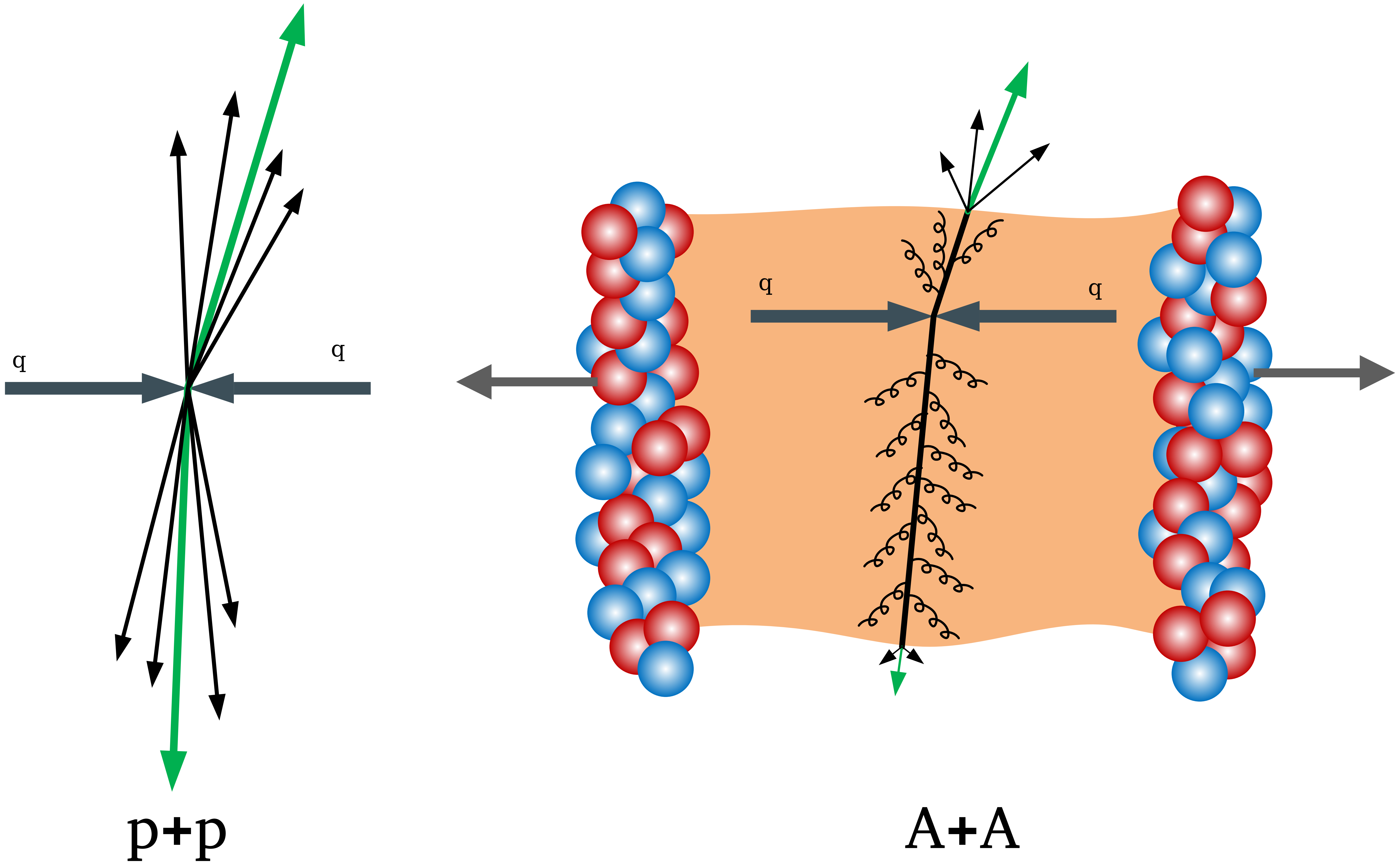


High p_{T} partons produced early in the collision fragment and hadronize into a spray of particles called **jets**.

Jet production calculable in pQCD.

Sensitive to a wide range of physics scales.

Jets as a probe of QGP



High p_{T} parton making up a jet is expected to lose energy through strong interactions with the colored medium.

We call this energy loss **jet quenching**.

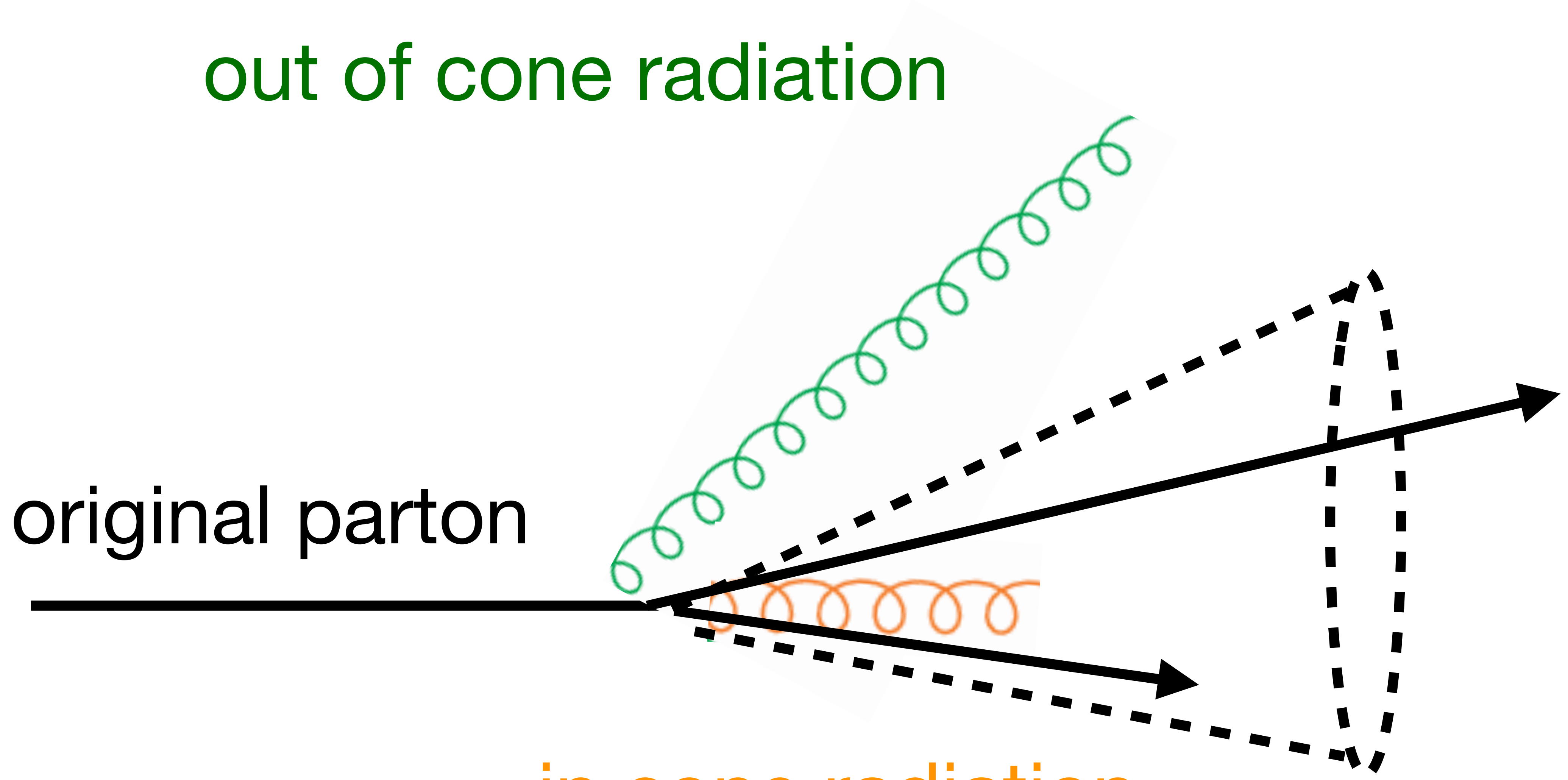
As these partons are produced early in collisions, jets are the ideal probe of QGP evolution!

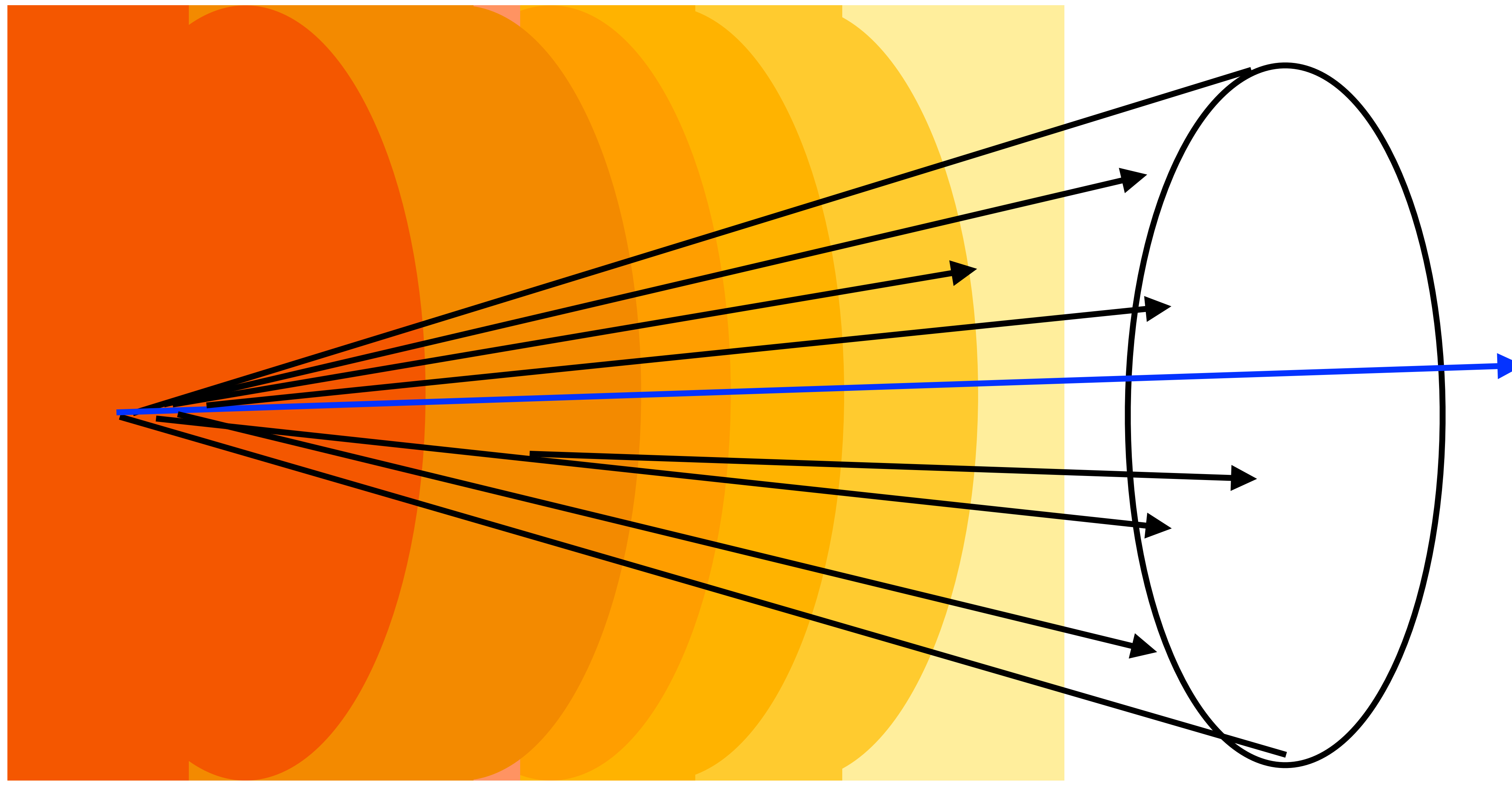
Use pp as reference where any difference is attributed to in-medium effects.

Expected signatures of jet quenching

Parton energy loss leads to a suppression of jet yields.

Modification of the internal structure of the jet.





Jet widens due to momentum broadening.

Medium response adds wake of soft particles to the jet.

Modification might differ depending on path through the medium.

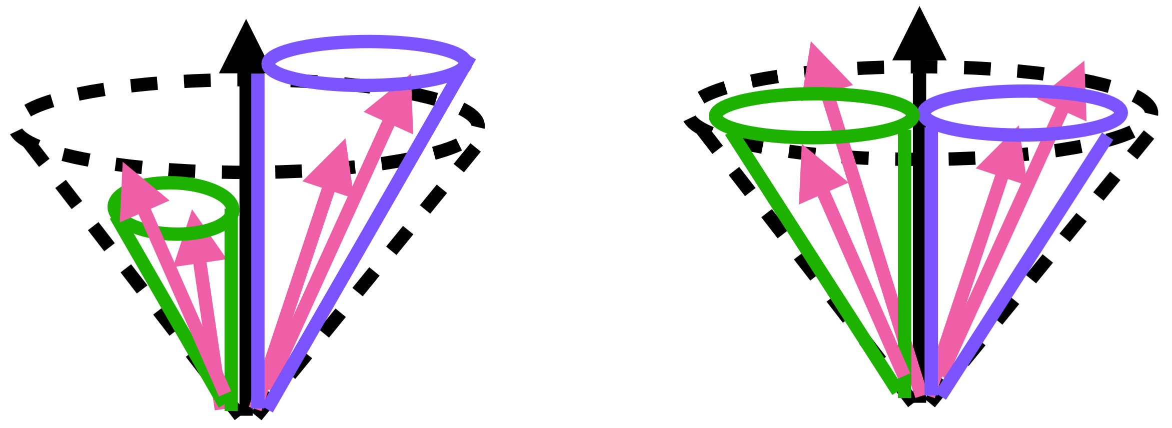
Observables of jet quenching

Experimental observables of jet quenching fall into 3 main categories, each probing a different expected jet quenching effect.

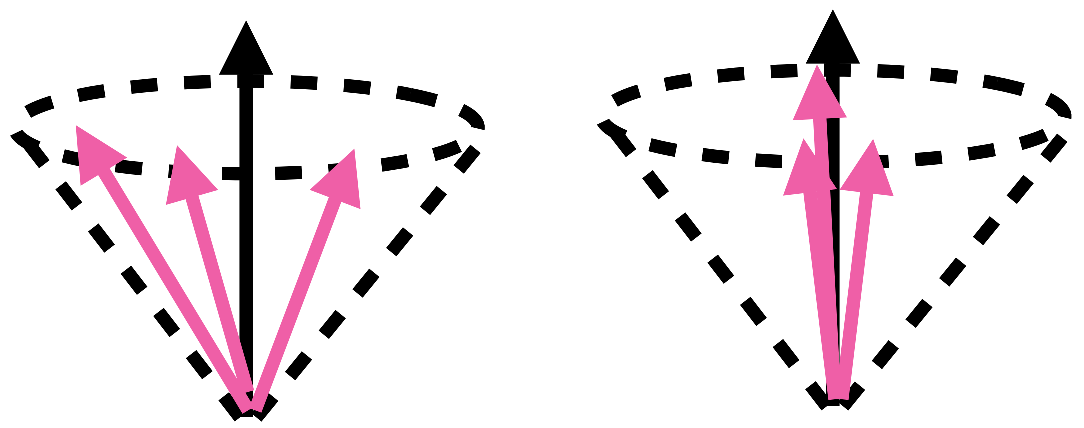
1. Overall Energy Loss: Suppression of inclusive jet yields (more on this later)

2. Modification of the internal structure of the jet.

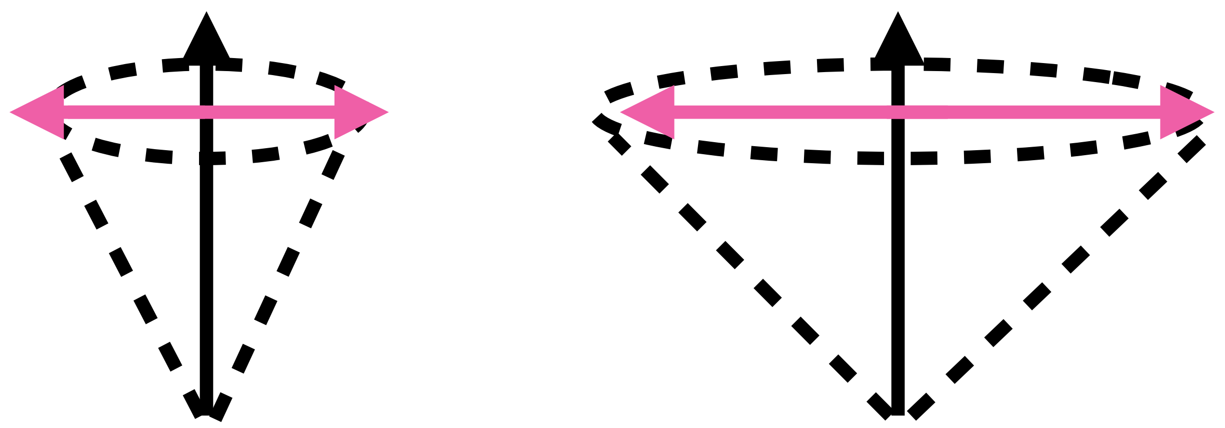
Jet Splittings



Fragmentation Function

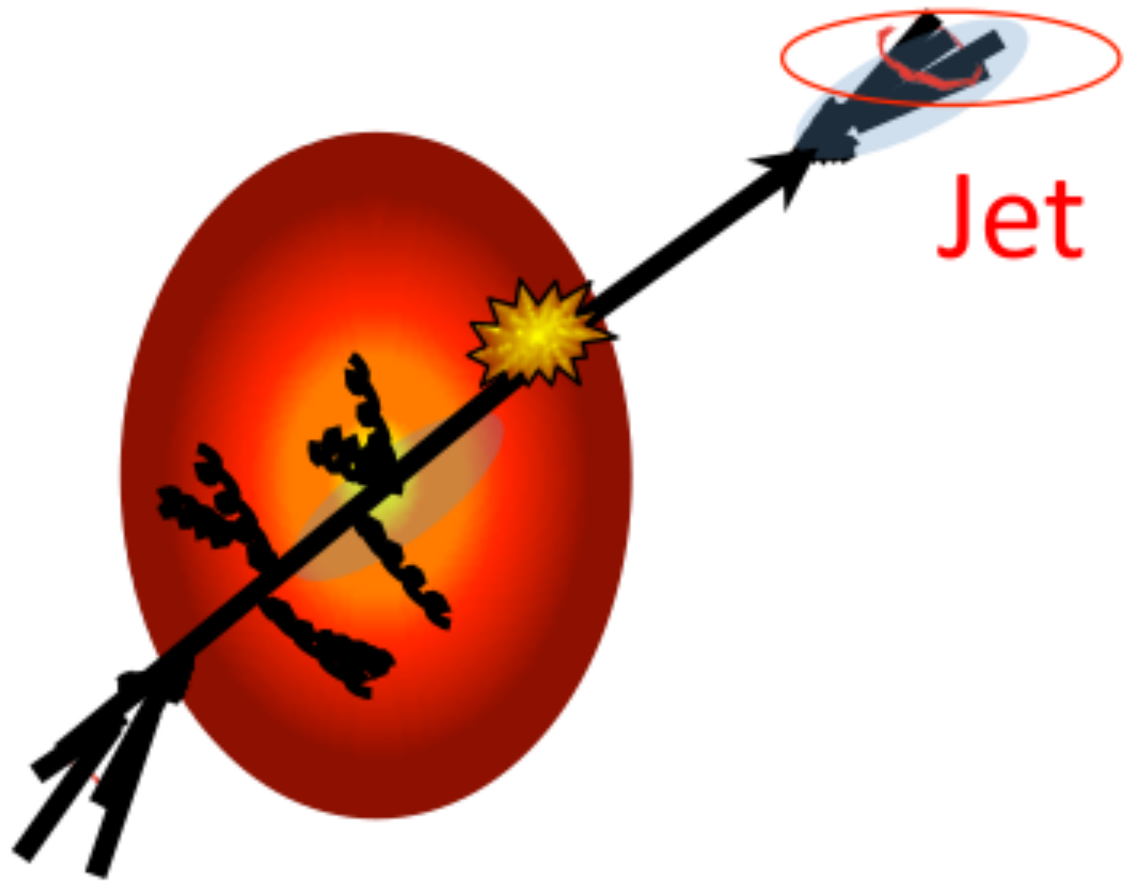


Jet Mass



3. Differential energy loss

Correlations of jets with other objects



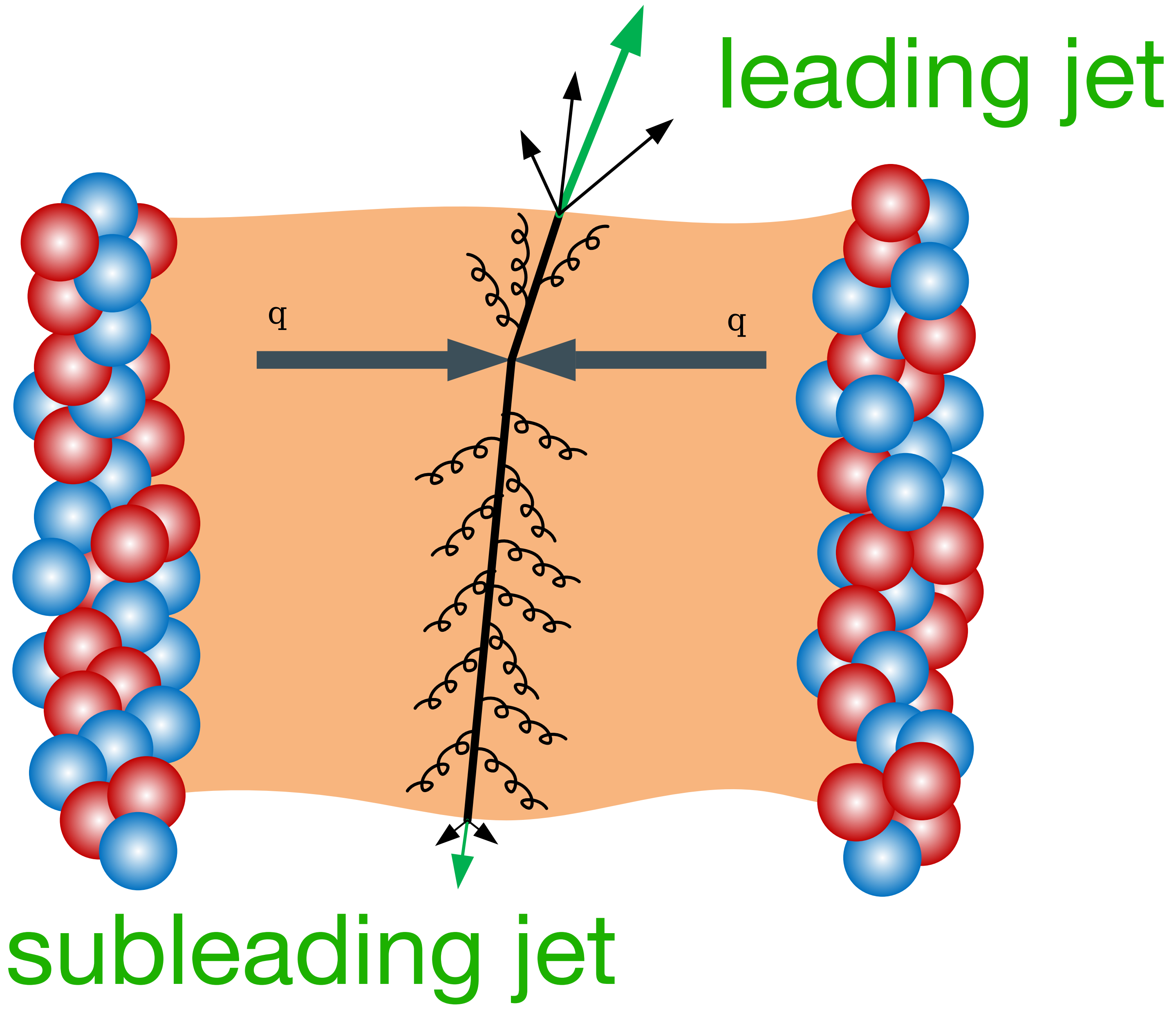
Jet-hadron

Reconstructing jet p_T

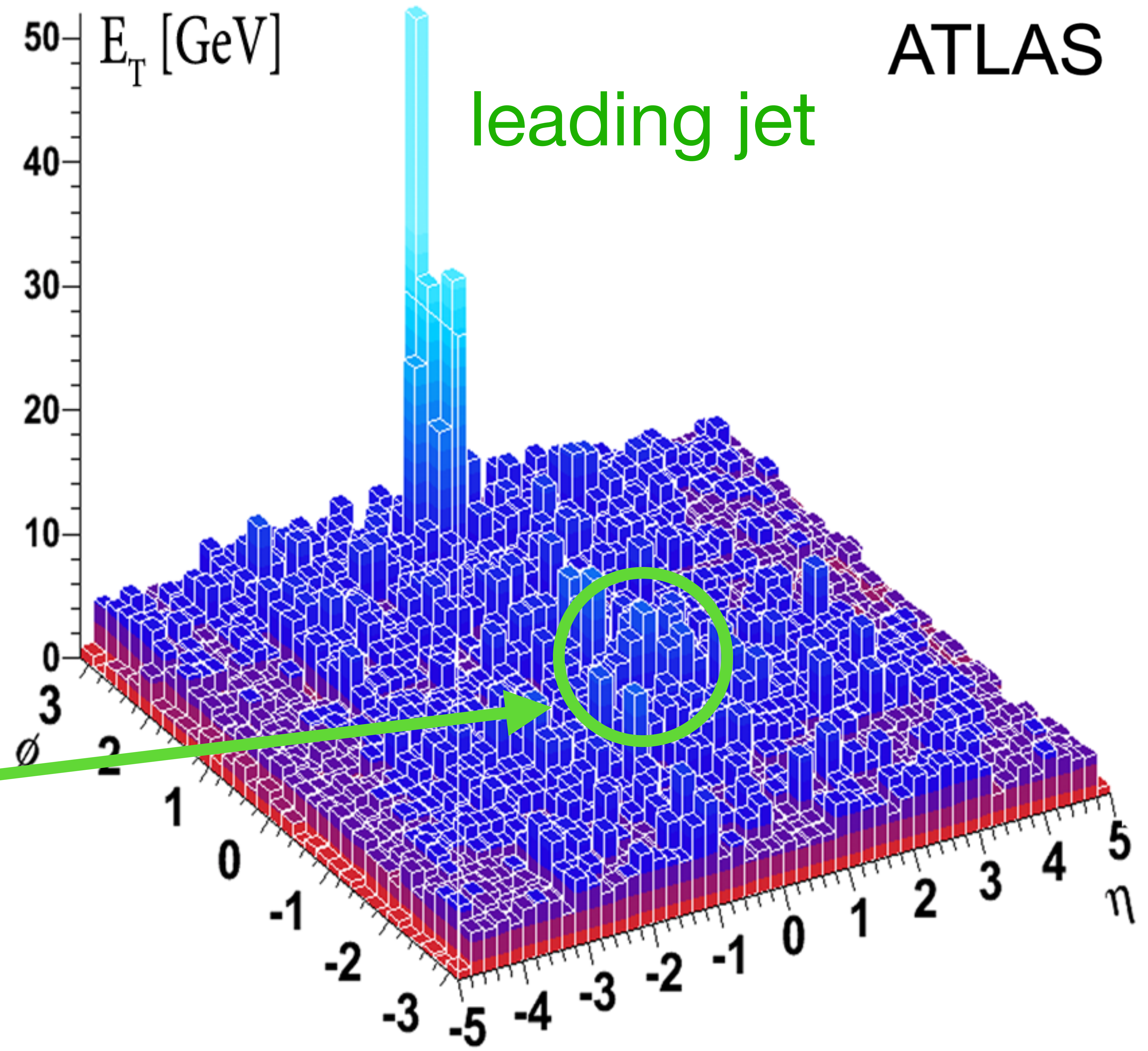
Reconstruction of inclusive jet p_T in heavy-ion collisions is made difficult by the large fluctuating background from the underlying event.

Fluctuations can be on the order of jet itself → hard to distinguish energy from the jet.

Sometimes, upward fluctuations are reconstructed as jets creating “fake jets”.

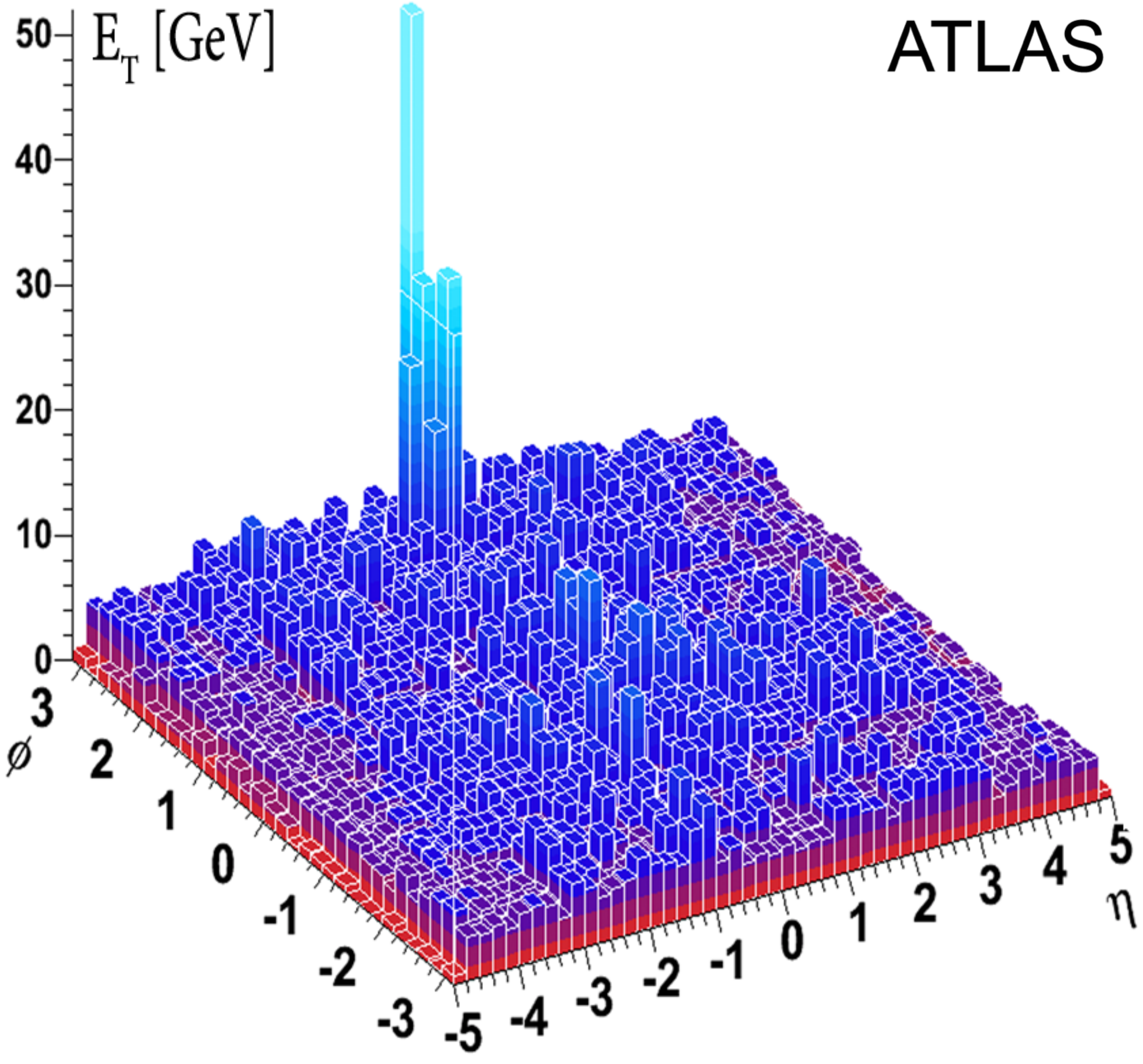


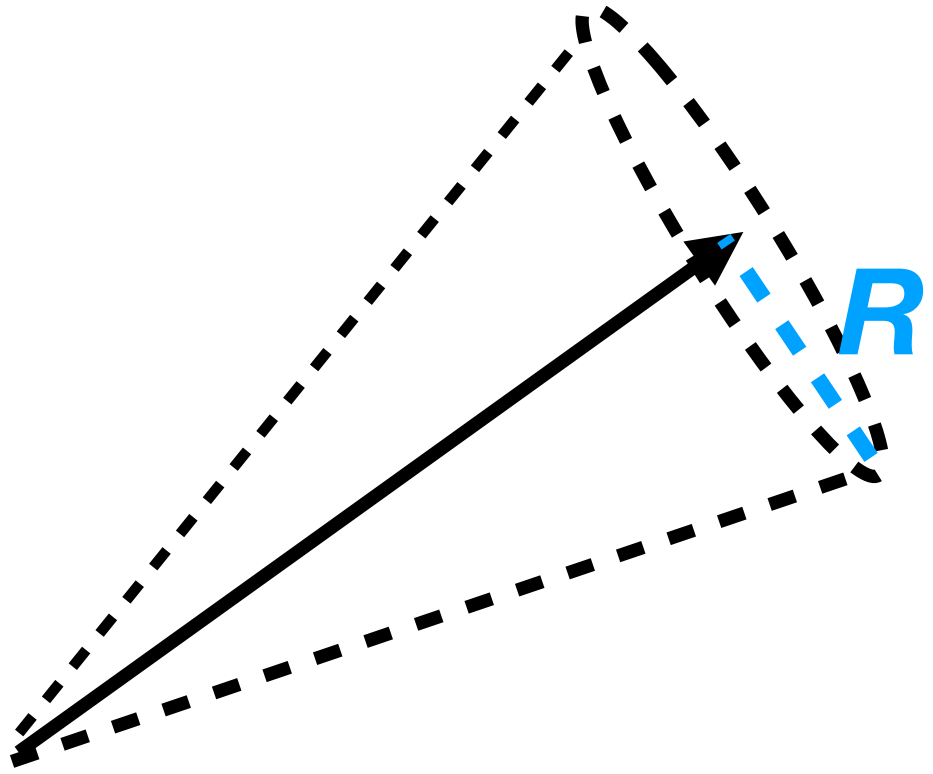
Even by eye, subleading jet hard to find!!



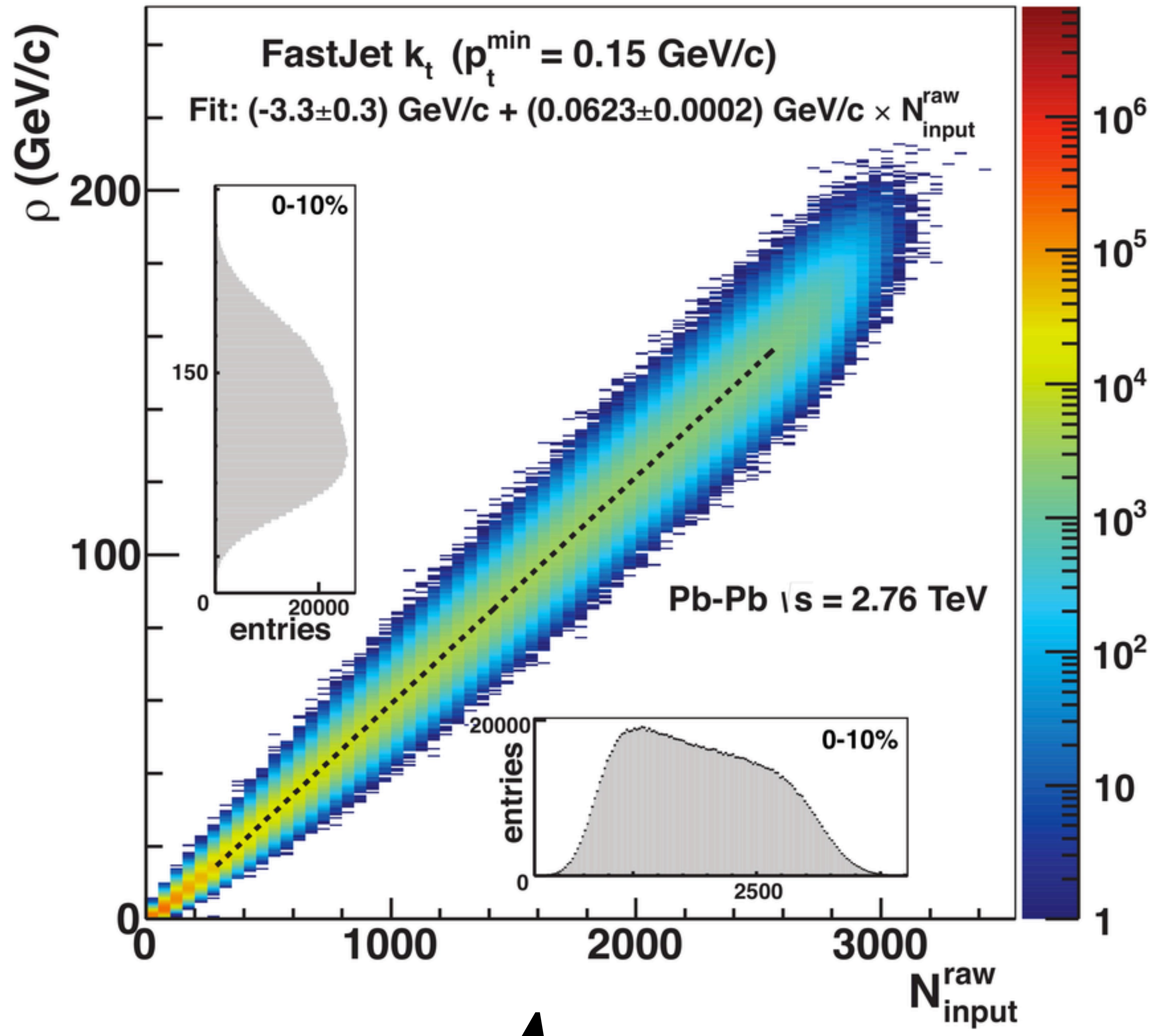
Area-Based Method

Area based method: Pedestal subtraction of event-averaged momentum density.





JHEP 1203 (2012) 053



$$p_{\mathrm{T,rec}} = p_{\mathrm{T,raw}} - \rho A$$

1. Estimate and subtract the pedestal

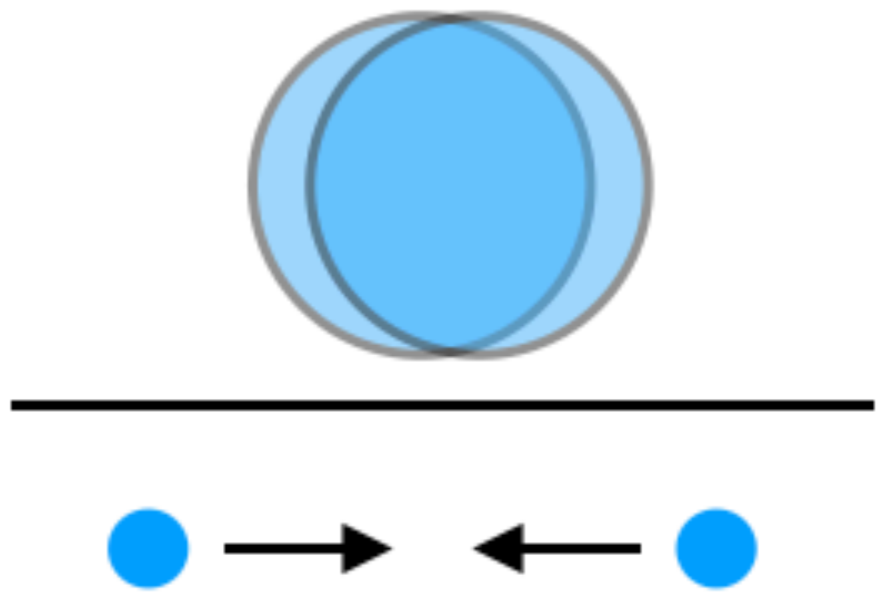
2. Leading track bias to remove fake contributions

3. Correct for residual fluctuations via unfolding

Nuclear Modification Factor: R_{AA}

We measure the suppression of jet yields by the nuclear modification factor (R_{AA}).

$R_{\mathrm{AA}} =$



$$= \frac{\frac{1}{N_{\mathrm{event}}} \frac{d^2 N_{\mathrm{jet}}^{\mathrm{PbPb}}}{dp_{\mathrm{T}} dy}\Big|_{\mathrm{cent}}}{\langle T_{\mathrm{AA}} \rangle \frac{d^2 \sigma_{\mathrm{jet}}^{\mathrm{pp}}}{dp_T dy}}$$

Ratio of yield in Pb—Pb to the expected yield if no hot or dense medium was present.

$R_{\mathrm{AA}} < 1$ → Suppression

$R_{\mathrm{AA}} = 1$ → No Modification

$R_{\mathrm{AA}} > 1$ → Enhancement

Old: Suppression is a signature of QGP formation.

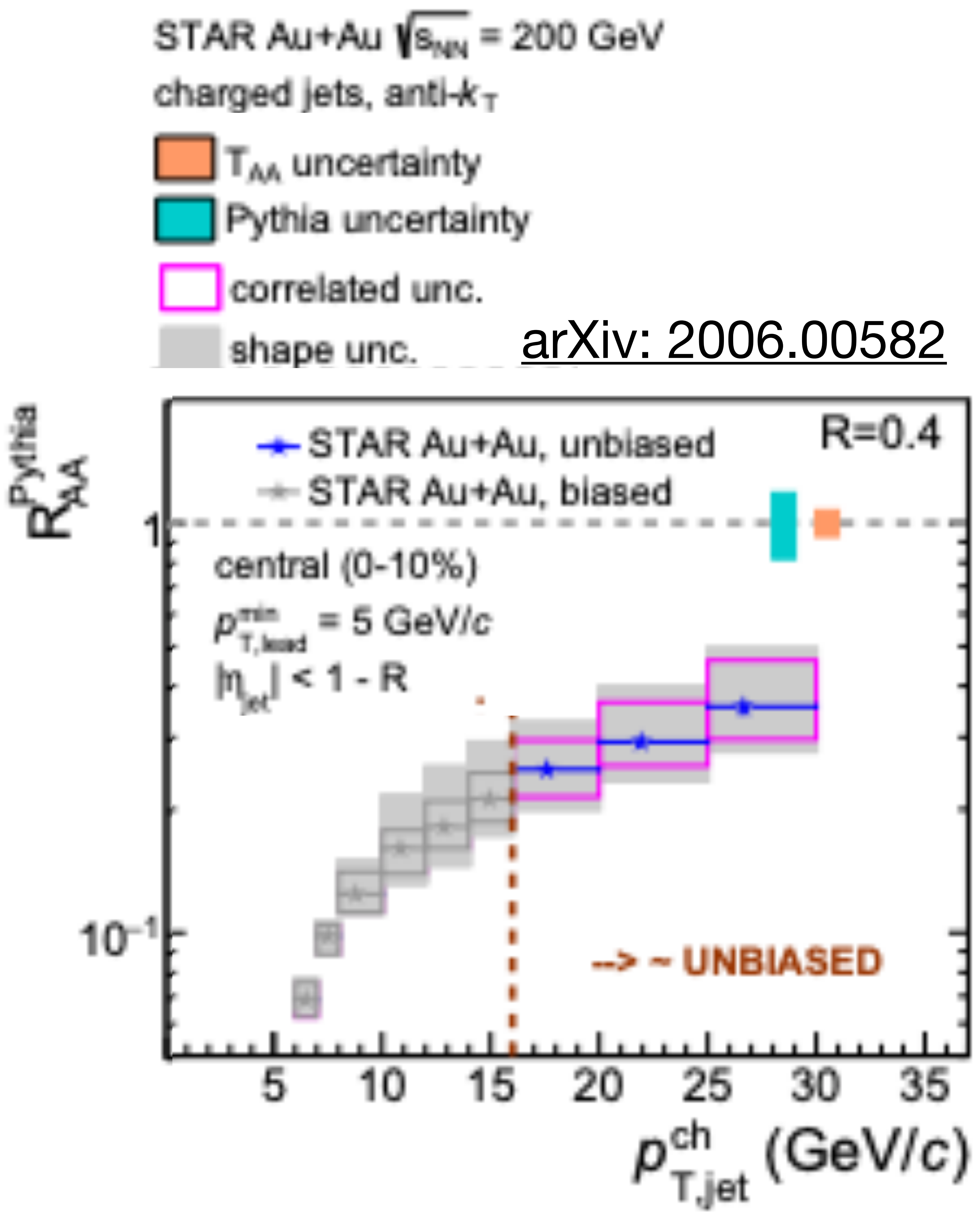
New: Use measurements of suppression to further understand QGP medium.

Measurements of inclusive jet R_{AA}

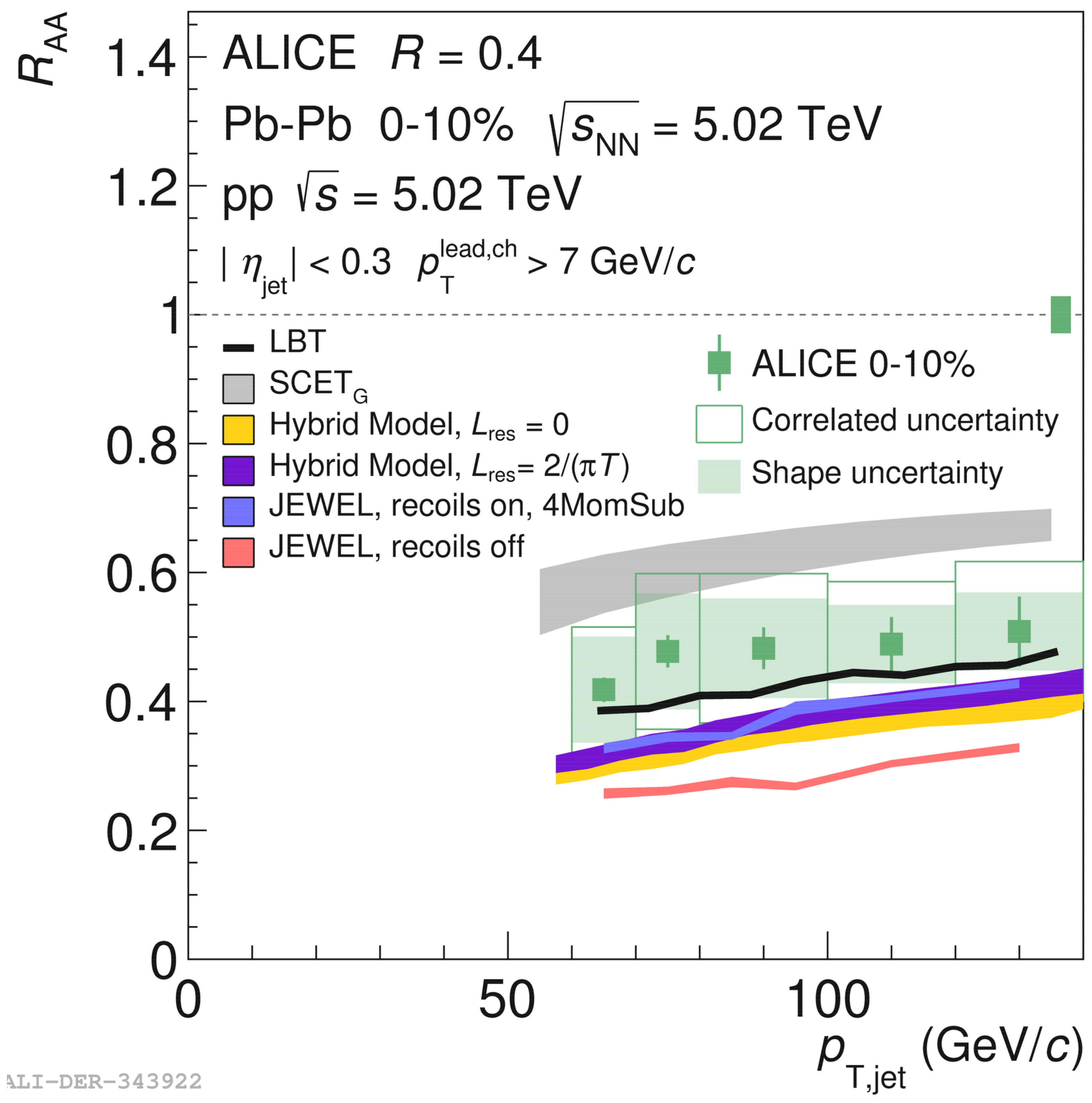
Many measurements of the inclusive jet R_{AA} for R = 0.4 jets in central 0-10% collisions.

See suppression across many different scales!

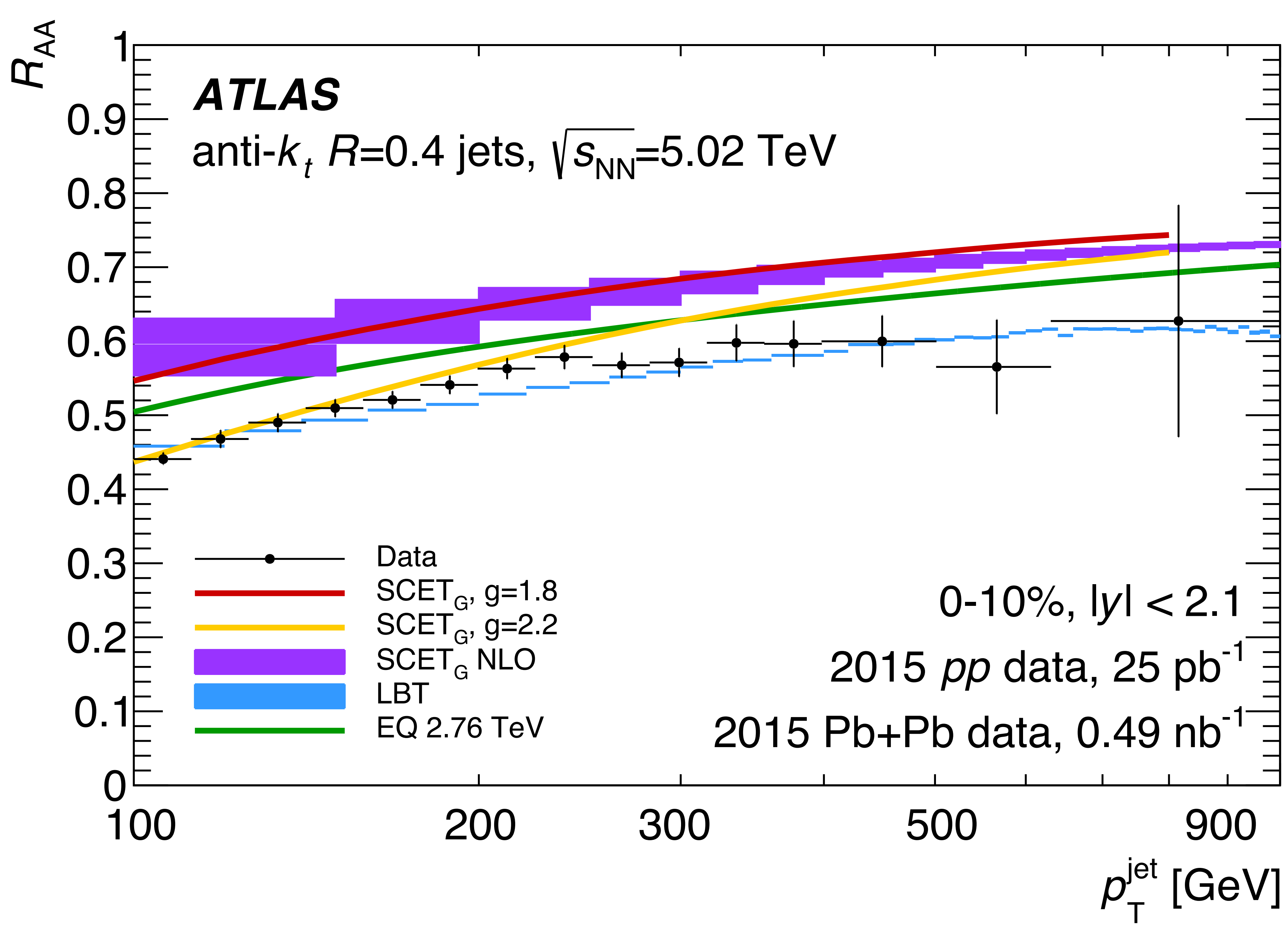
arXiv: 2006.00582



Phys. Rev. C 101 034911 (2020)



Phys. Lett. B 790 (2019) 108



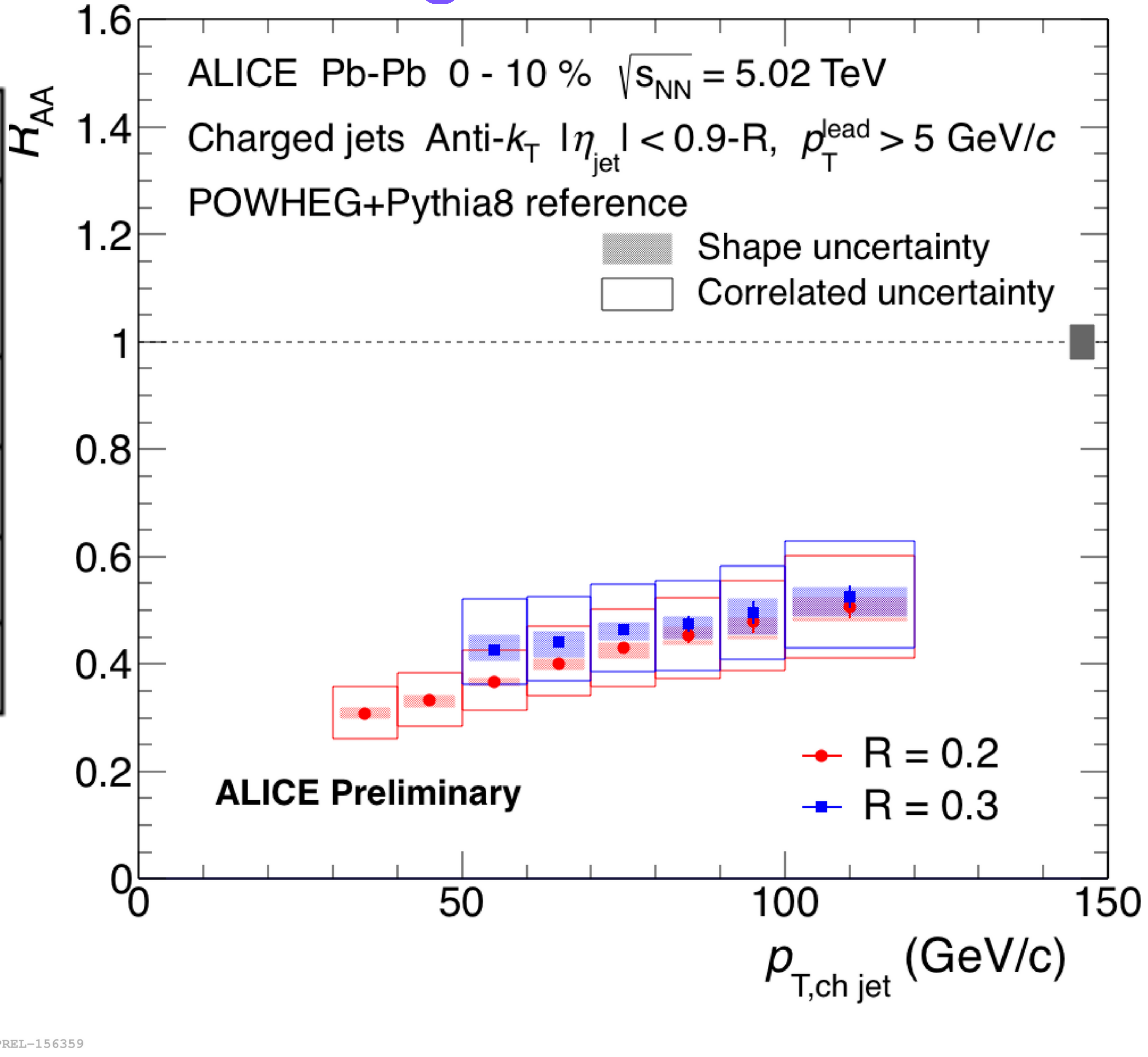
Where are we now in ALICE? *(area based method)*

Inclusive Jet Measurement Summary

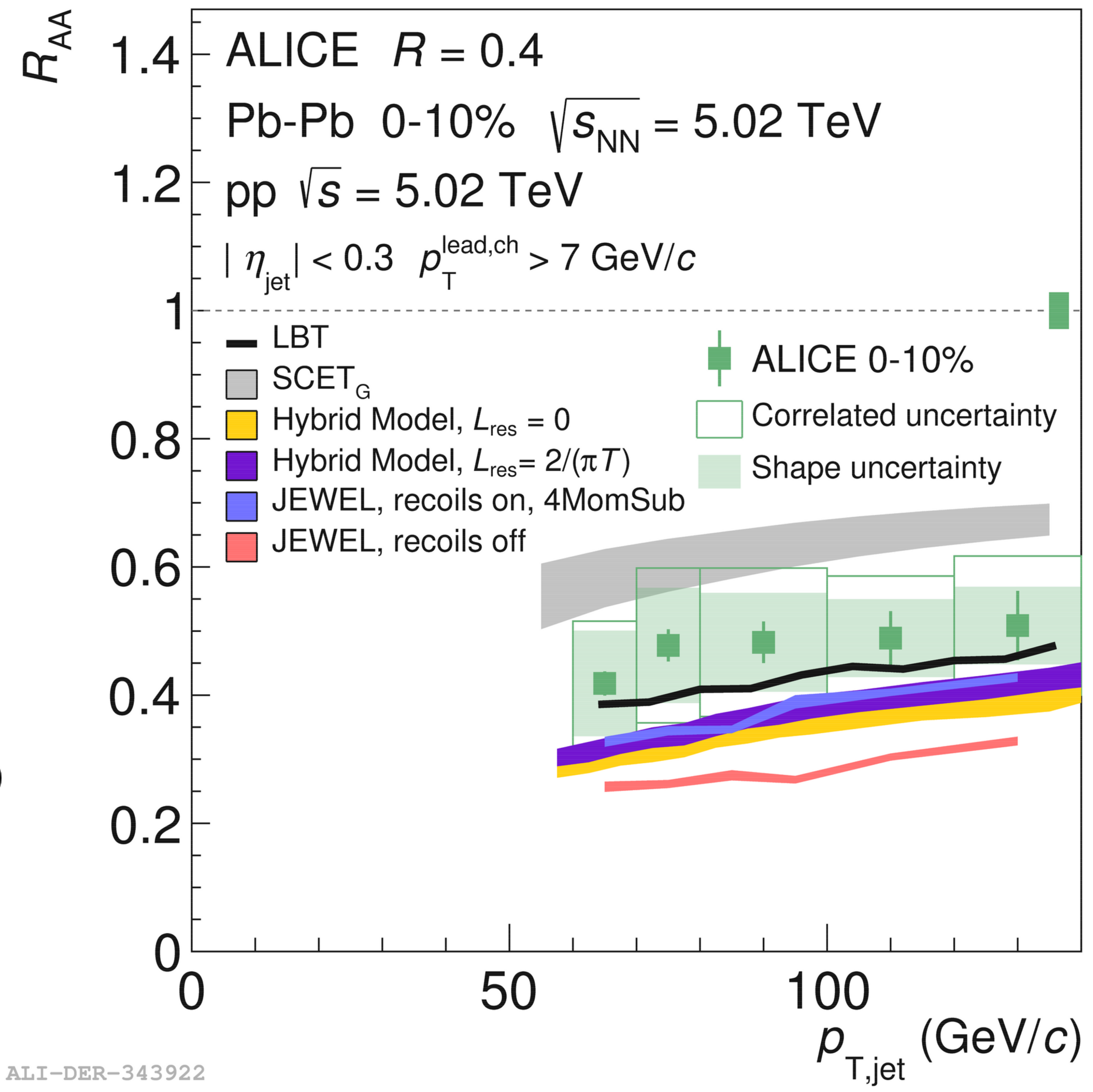
	Lower p_T Cutoff (GeV/c)	
R	Charged Particle Jets	Full Jets
0.2	30	40
0.3	50	60
0.4	N/A	60
0.6	N/A	N/A

We see a suppression!

Charged Particle Jets



Full Jets

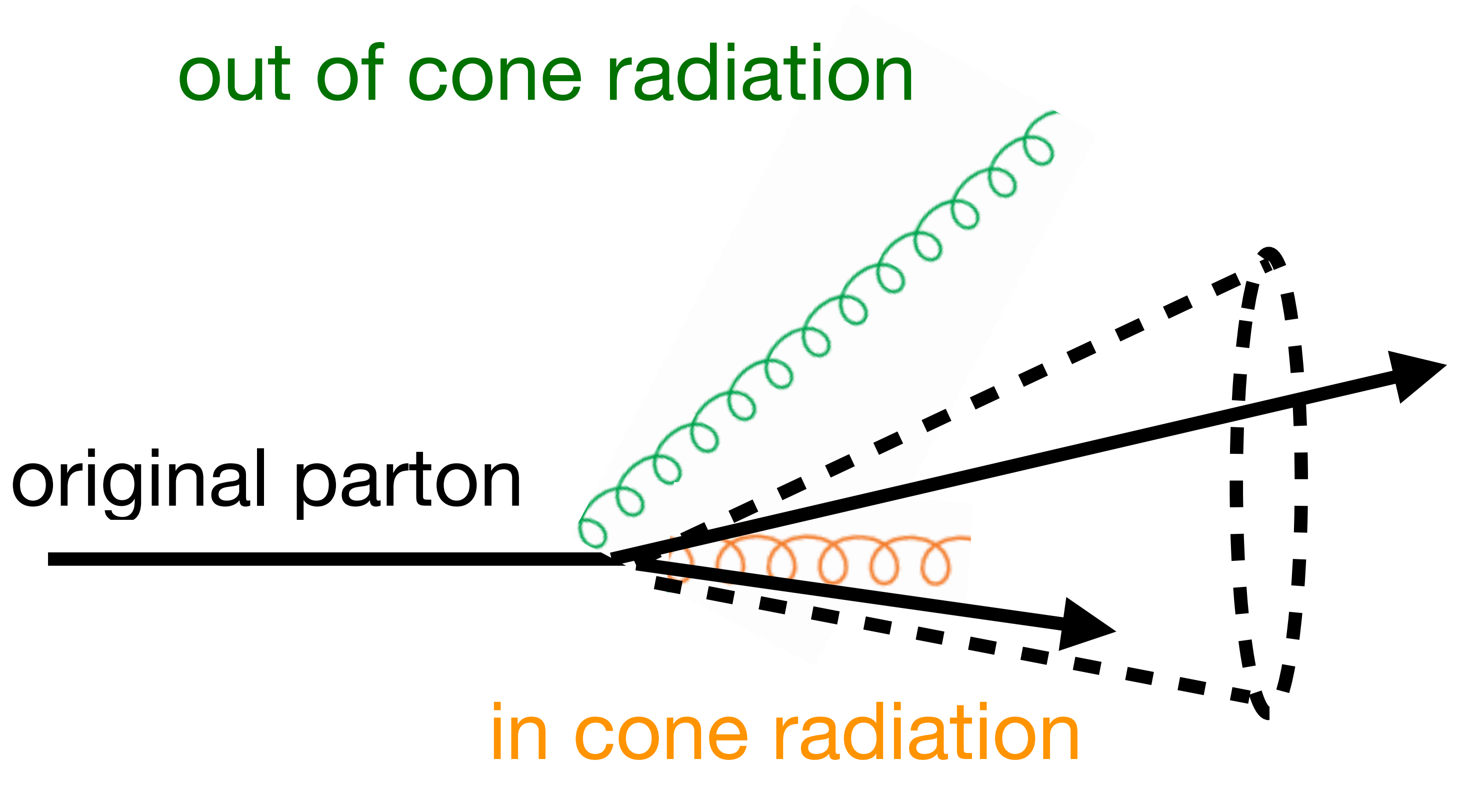


ALICE benefits from precise tracking at low p_T.

Prevented from going lower by large fake jet contribution at these low jet p_Ts!

Pushing to low p_T and large R

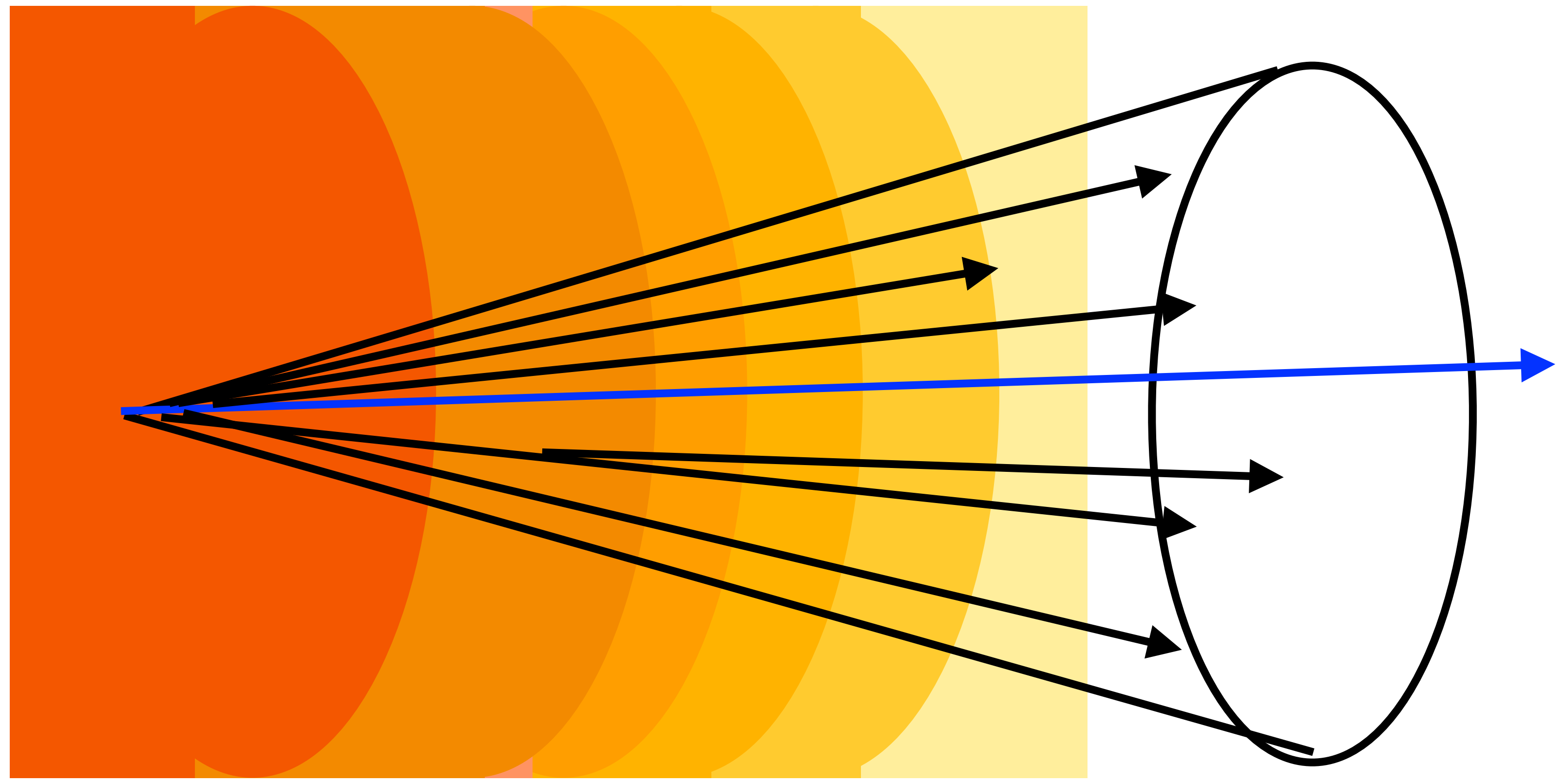
Many differential measurements of nuclear modification separate out energy loss effects.



Momentum broadening causes energy to be lost outside of the jet cone → R_{AA} ↘

Recover energy deposited in the medium → R_{AA} ↗

Recoiling medium adds energy to jet cone →R_{AA} ↗



Wider jets have more complex structure, which could experience more quenching → R_{AA} ↘

Different jets with different structure experience these effects differently

→*measure dependence of* R_{AA} *on* p_T ***and*** *R!*

Remember: Low p_T and large *R* are difficult regions to study with inclusive jet probes.

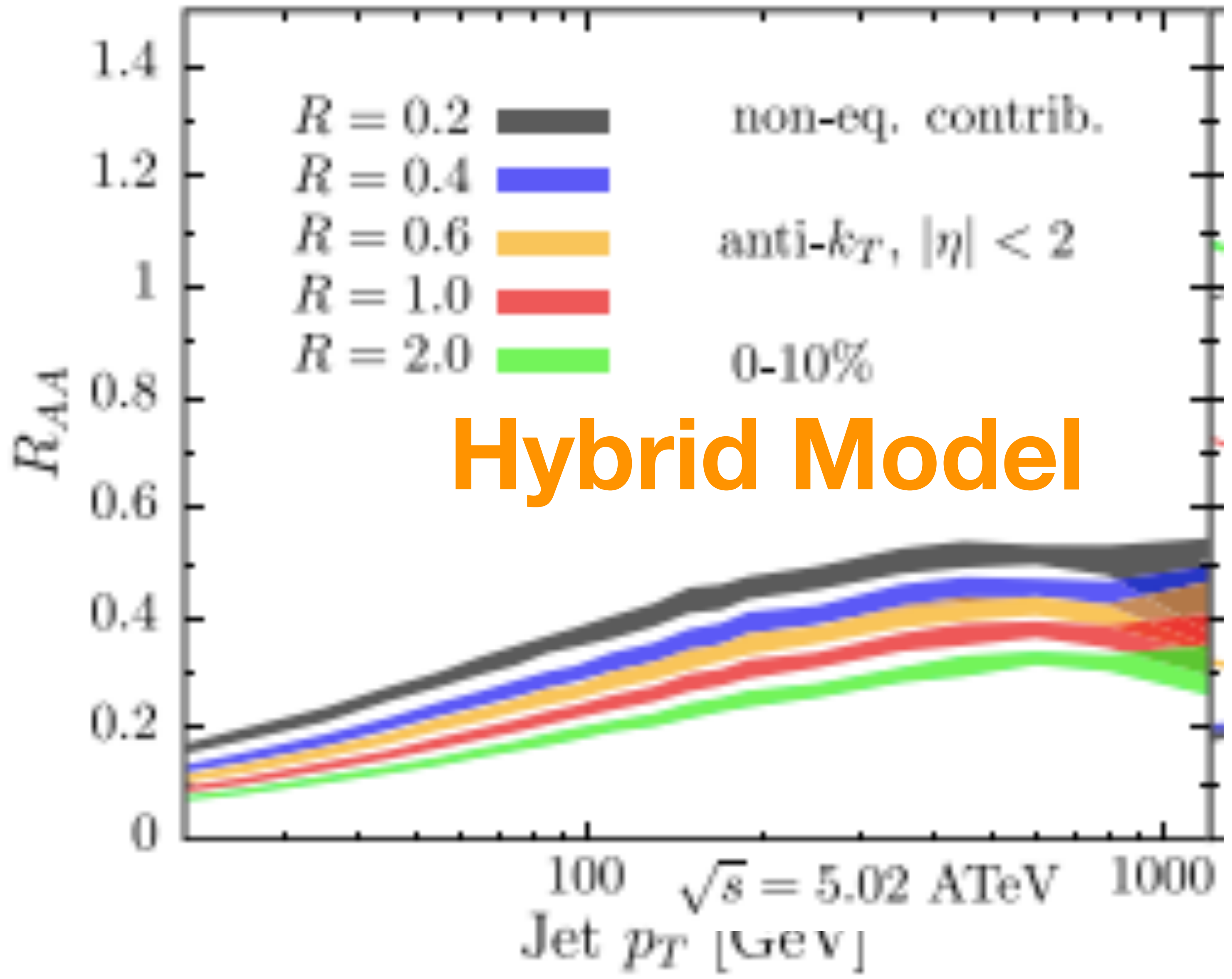
What does theory say?

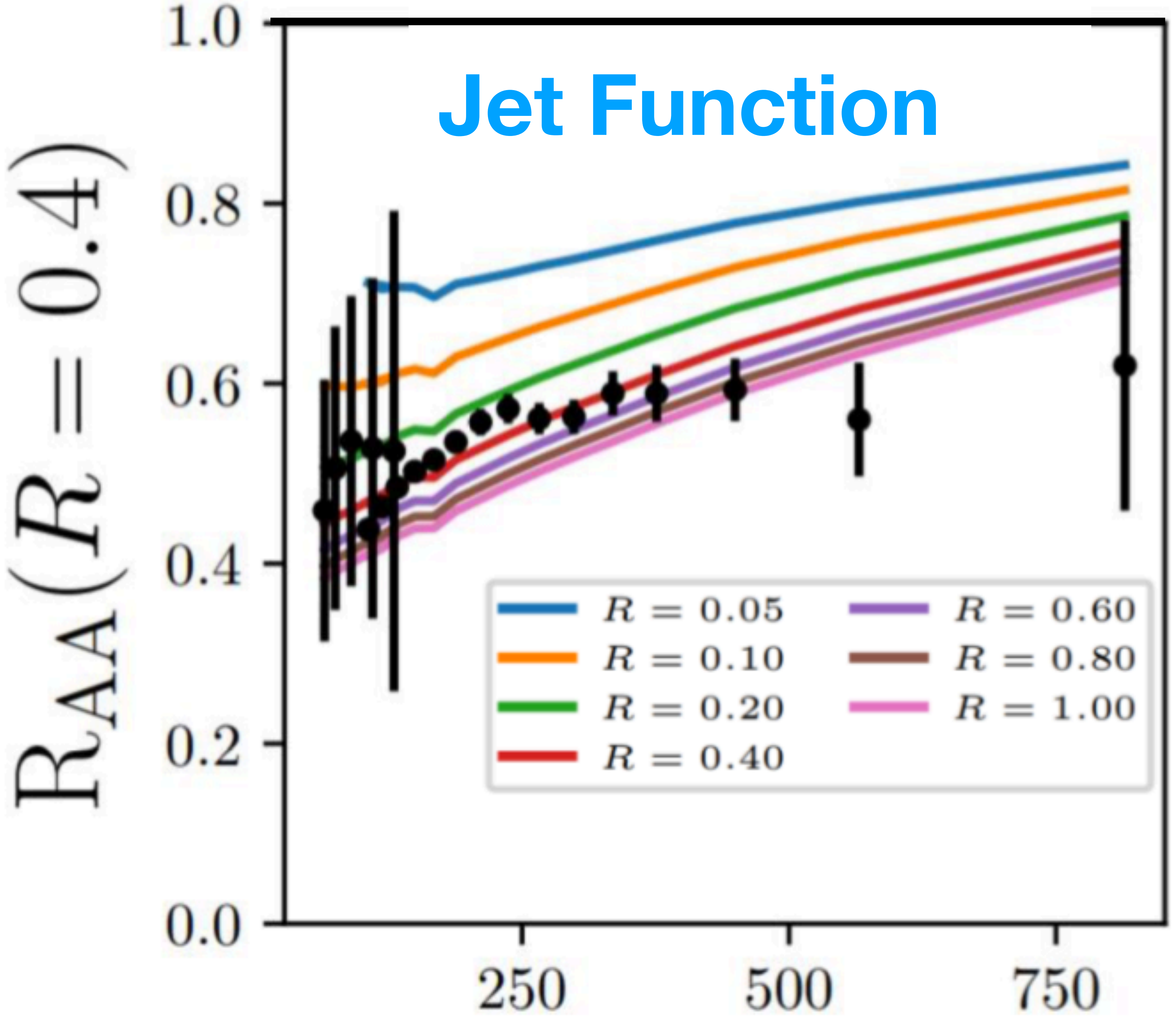
R_{AA} decreases with R → as R increases, effect of out-of-cone energy loss and quenching of complex internal structure increases!

Phys. Rev. Lett. 124, 052301

Hybrid model with no medium contributions →

What happens if we add in medium effects?

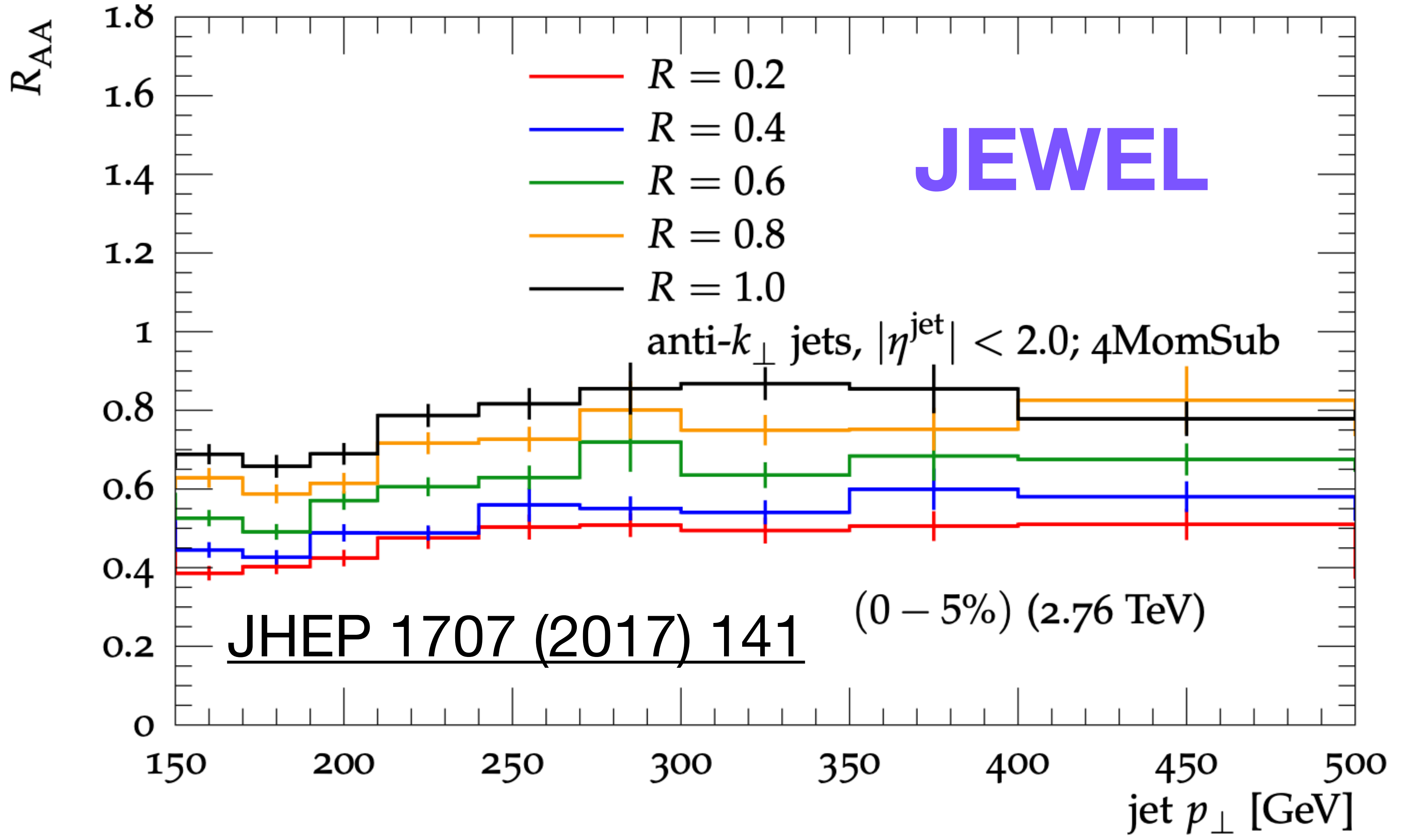


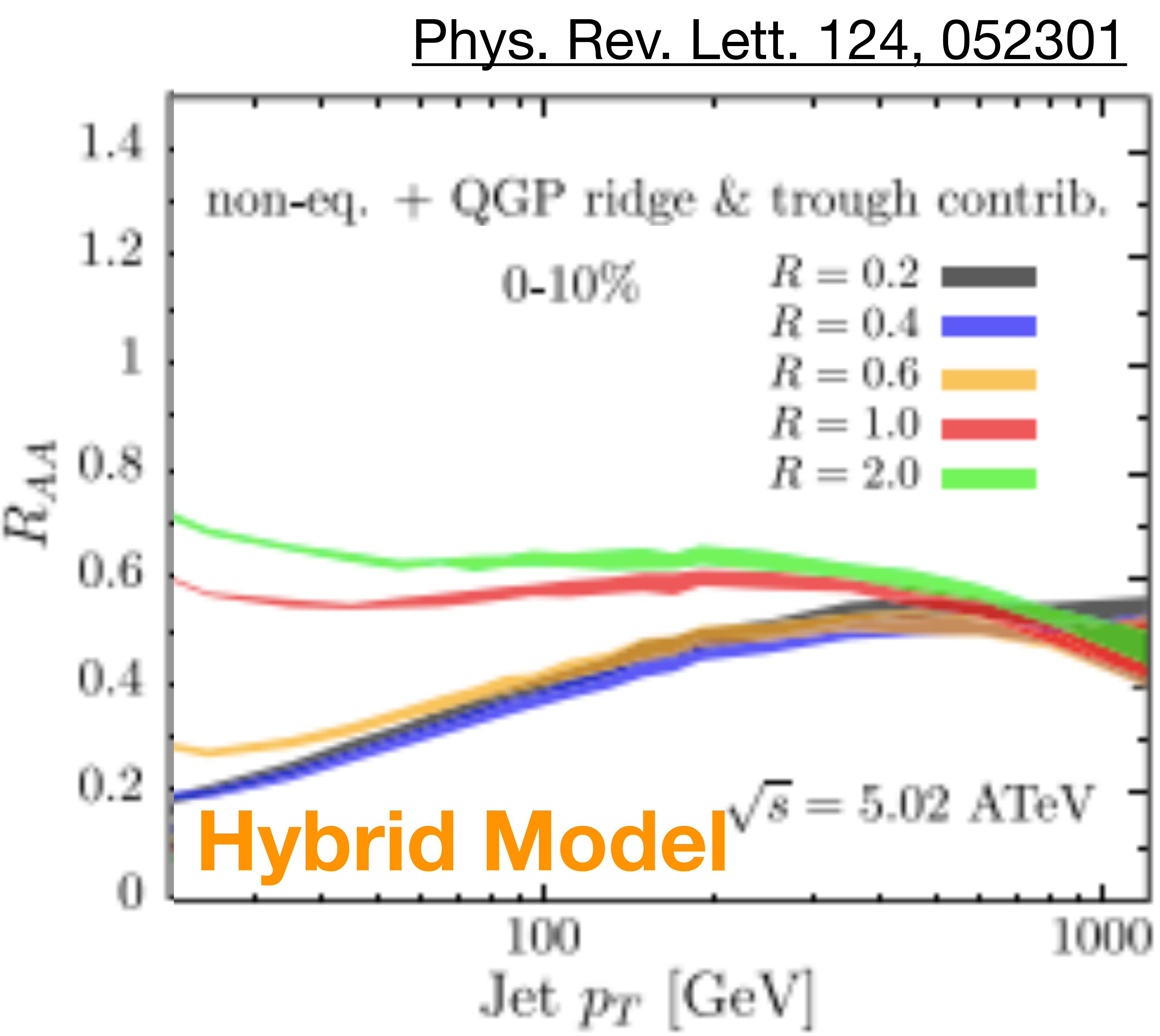


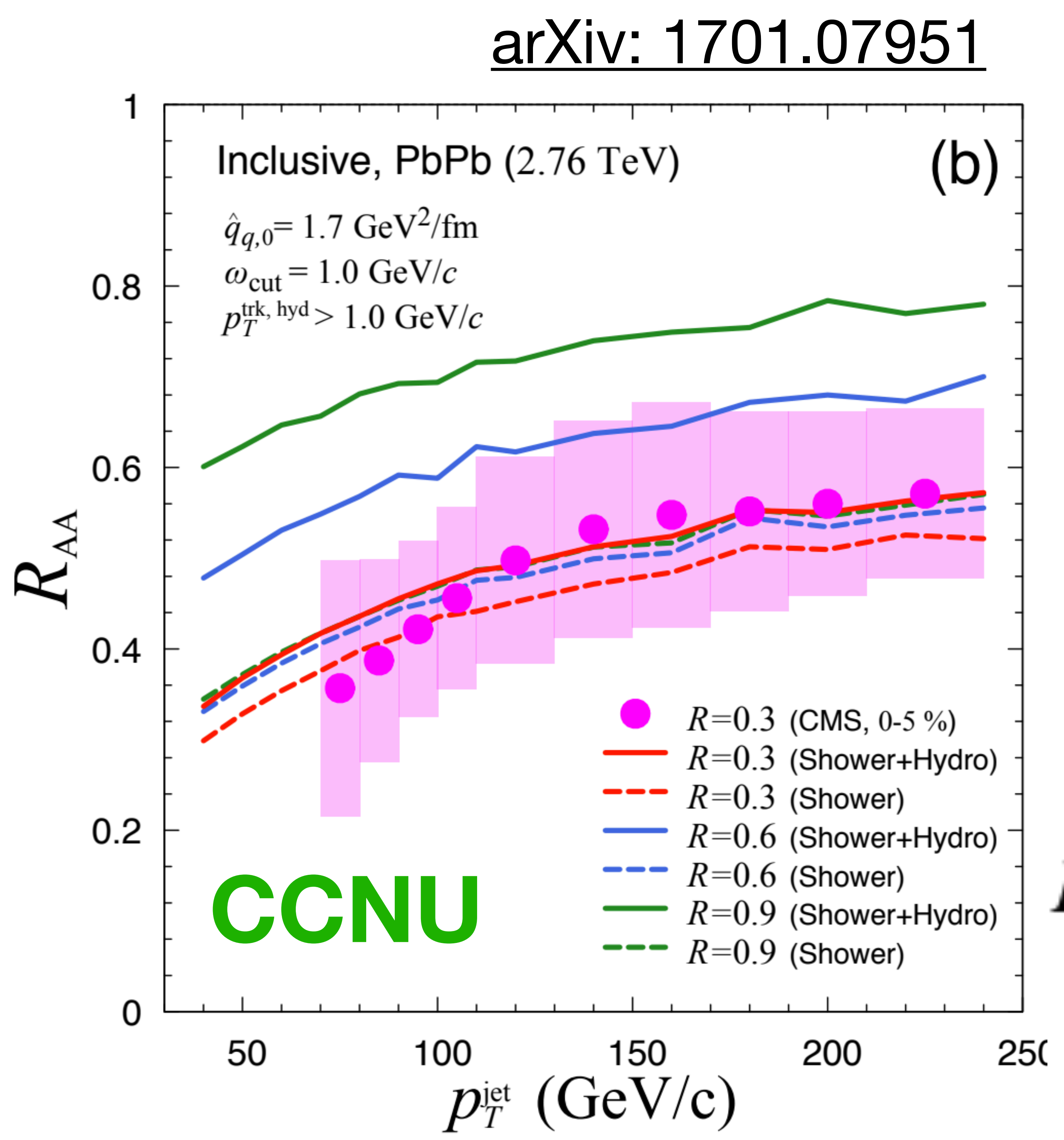
What do other models say?

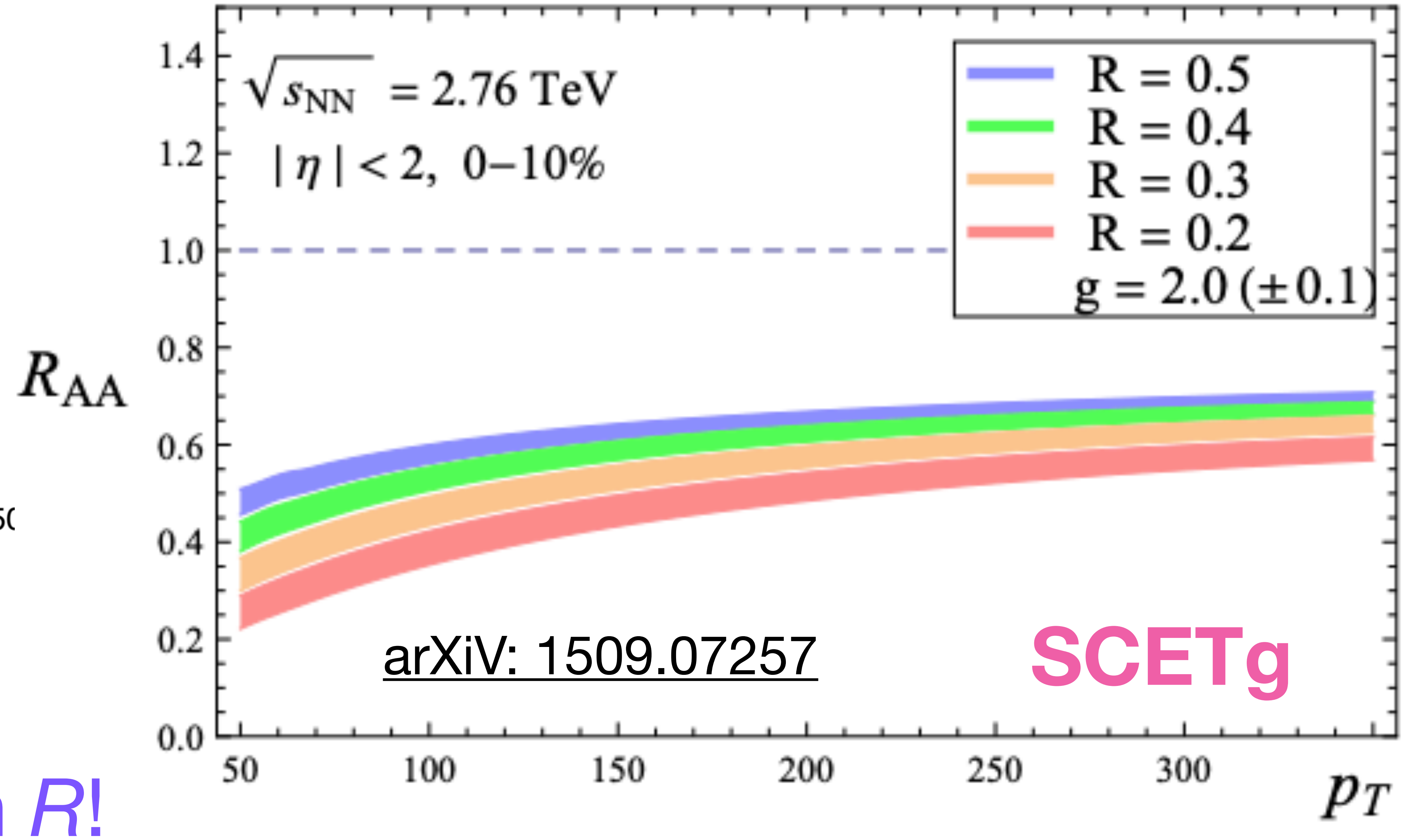
What does theory say?

R_{AA} increases with *R* → as *R* increases, effect of recoiling medium and recovery of lost energy becomes stronger!



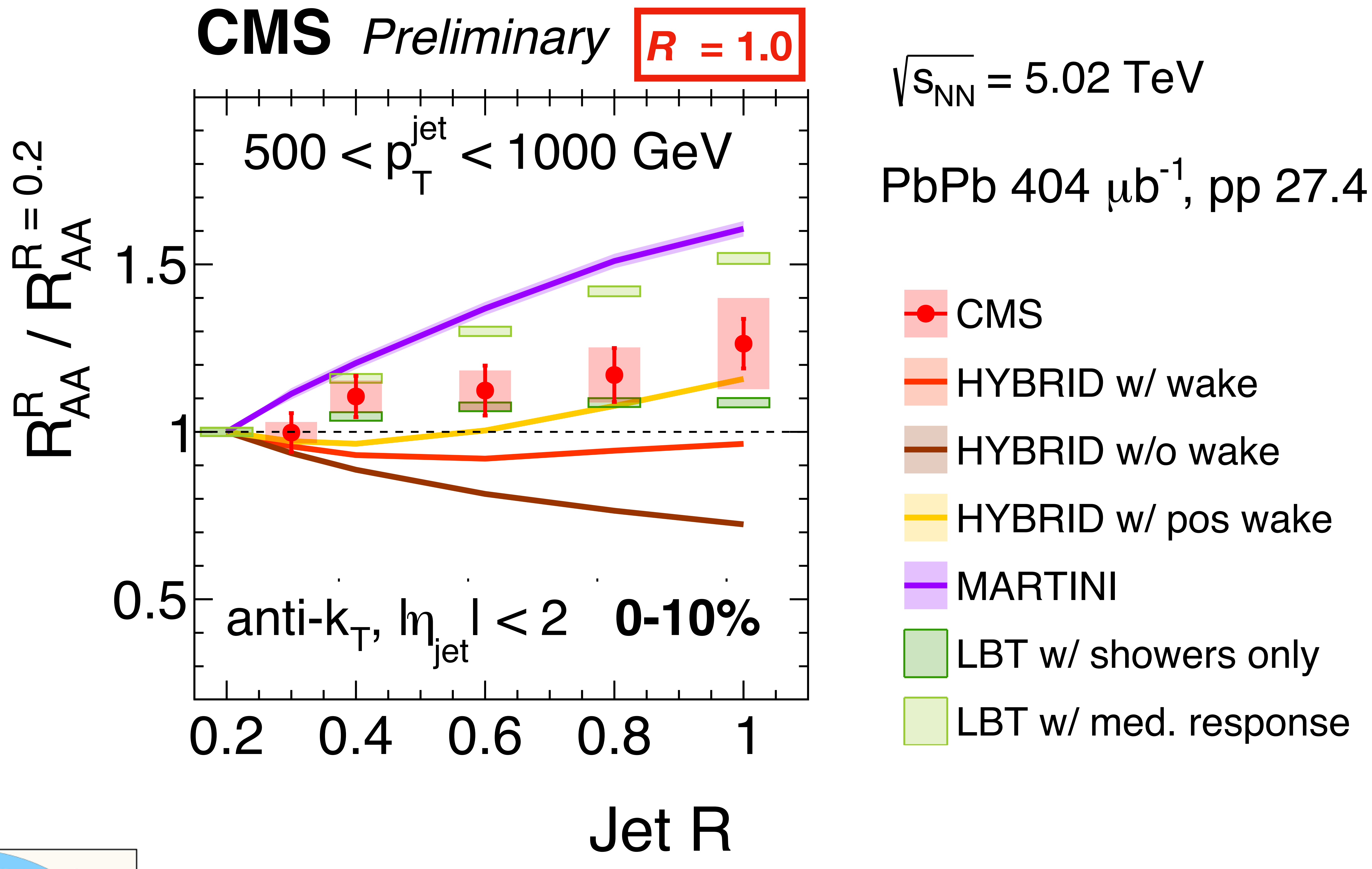






Need to come up with new strategies to extend experimental measurements to lower in p_T and larger in *R*!

What does experiment say?



CMS goes to high p_T

Now measure up to R = 1.0!

Small increase in R_{AA} with increasing R observed.

Looking at R-dependence is a good way to distinguish models!

CMS-PAS-HIN-18-014

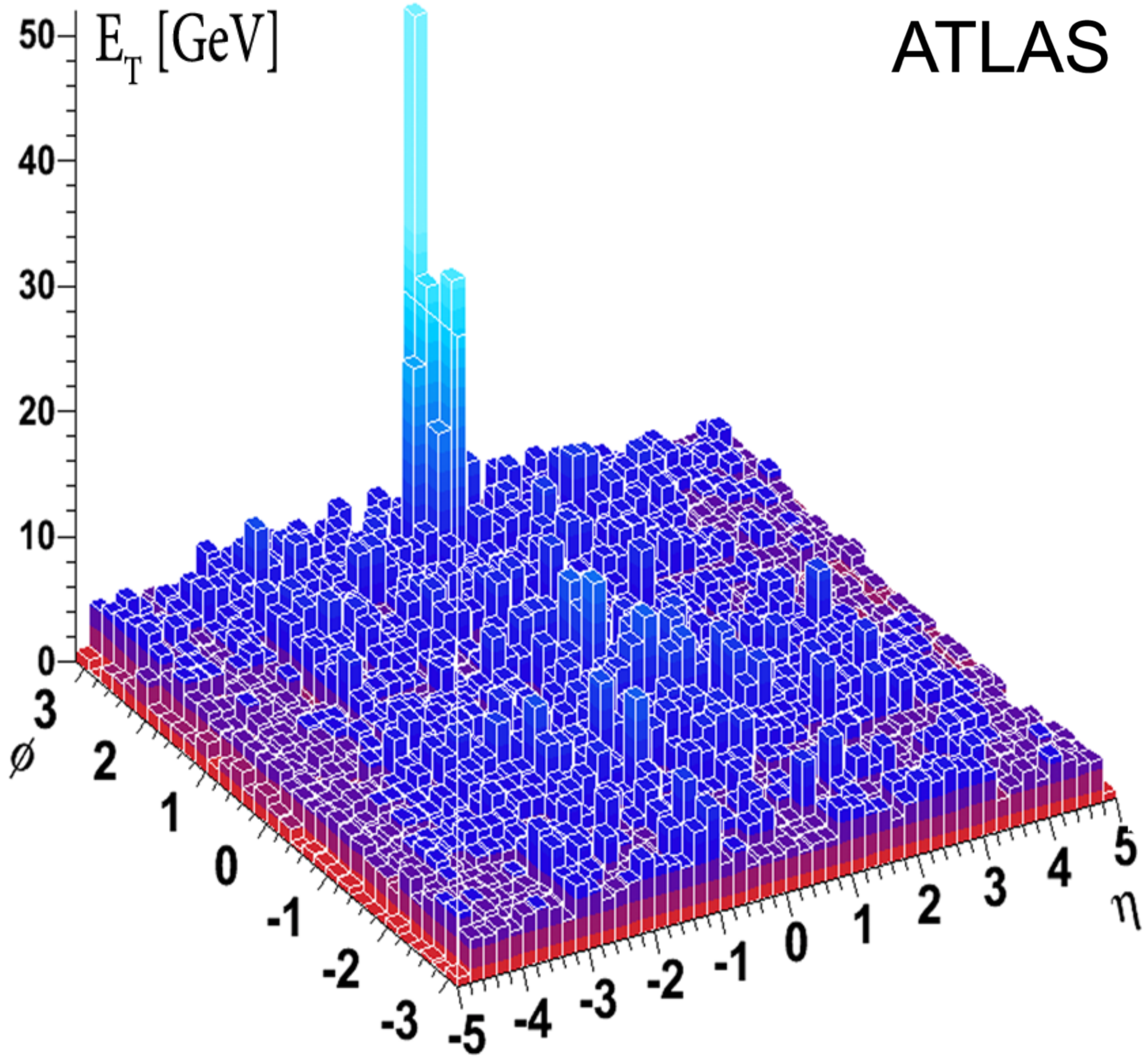
CMS: High p_T, Large R, Full Jets

HP Talk by Christopher McGinn

Want to see low p_T as well, what could ALICE do?

What could ALICE uniquely do?

$$p_{\mathrm{T,rec}} = p_{\mathrm{T,raw}} - \rho A$$



ALICE has the ability to measure at low p_{T}, limited by background subtraction.

Current mapping from $p_{\mathrm{T,raw}} \rightarrow p_{\mathrm{T,rec}}$ ignores

→ any fluctuations in the background

→ neutral part could fluctuate differently

→ background is uncorrelated with jet signal

Ideal mapping from $p_{\mathrm{T,raw}} \rightarrow p_{\mathrm{T,rec}}$ would be complex and would differ for each jet

→ difficult to derive from expert knowledge

Could machine learning help?

(Brief) intro to machine learning

Machine improves performance by learning from experience, while being robust to obstacles.

Two different types of tasks

1. **Classification:** group objects in predefined classes.

Ex: Classifying dogs vs. bagels

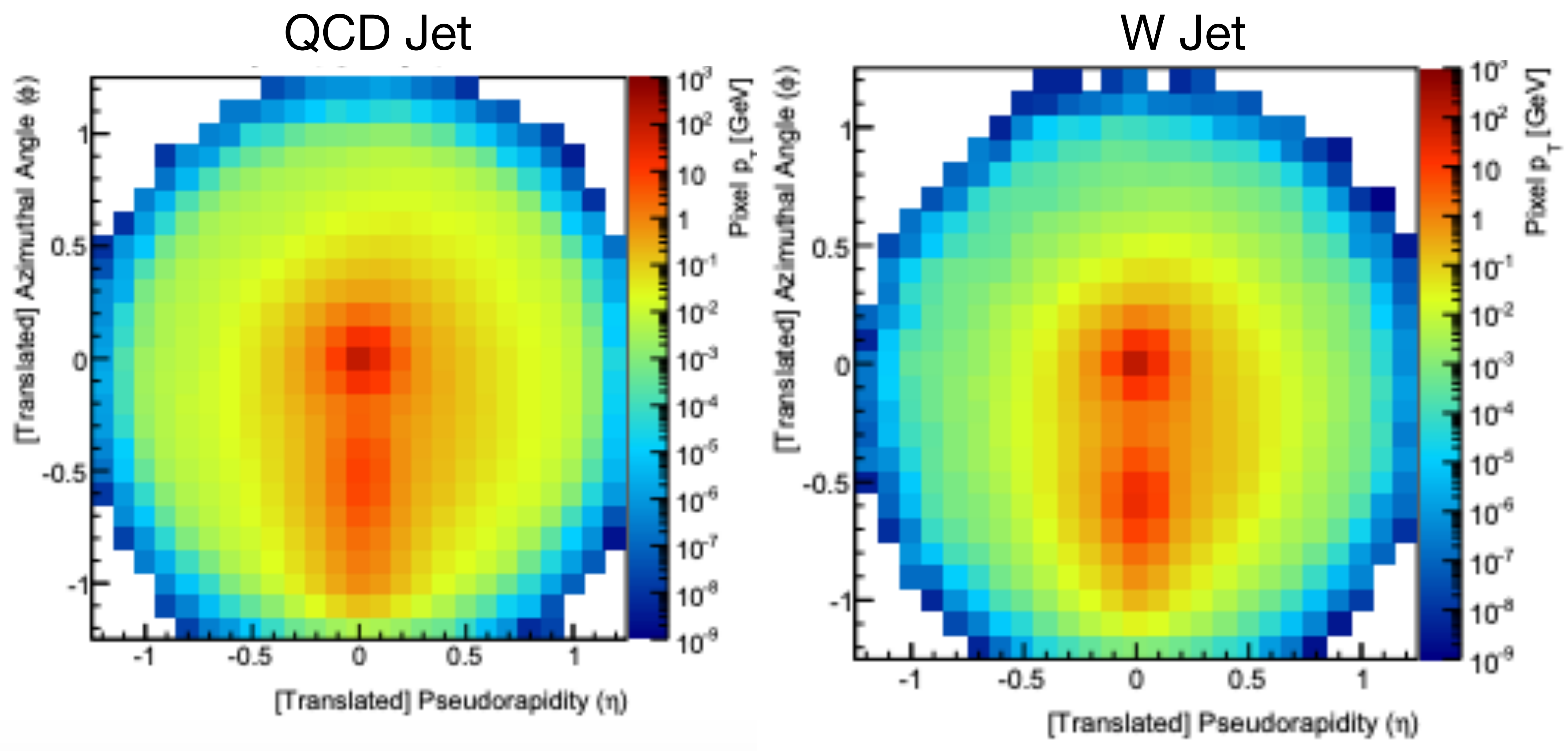
2. **Regression:** Assign a predicted value to each sample.

Ex: Predicting stock market prices

(Brief) intro to machine learning

Two different types of learning

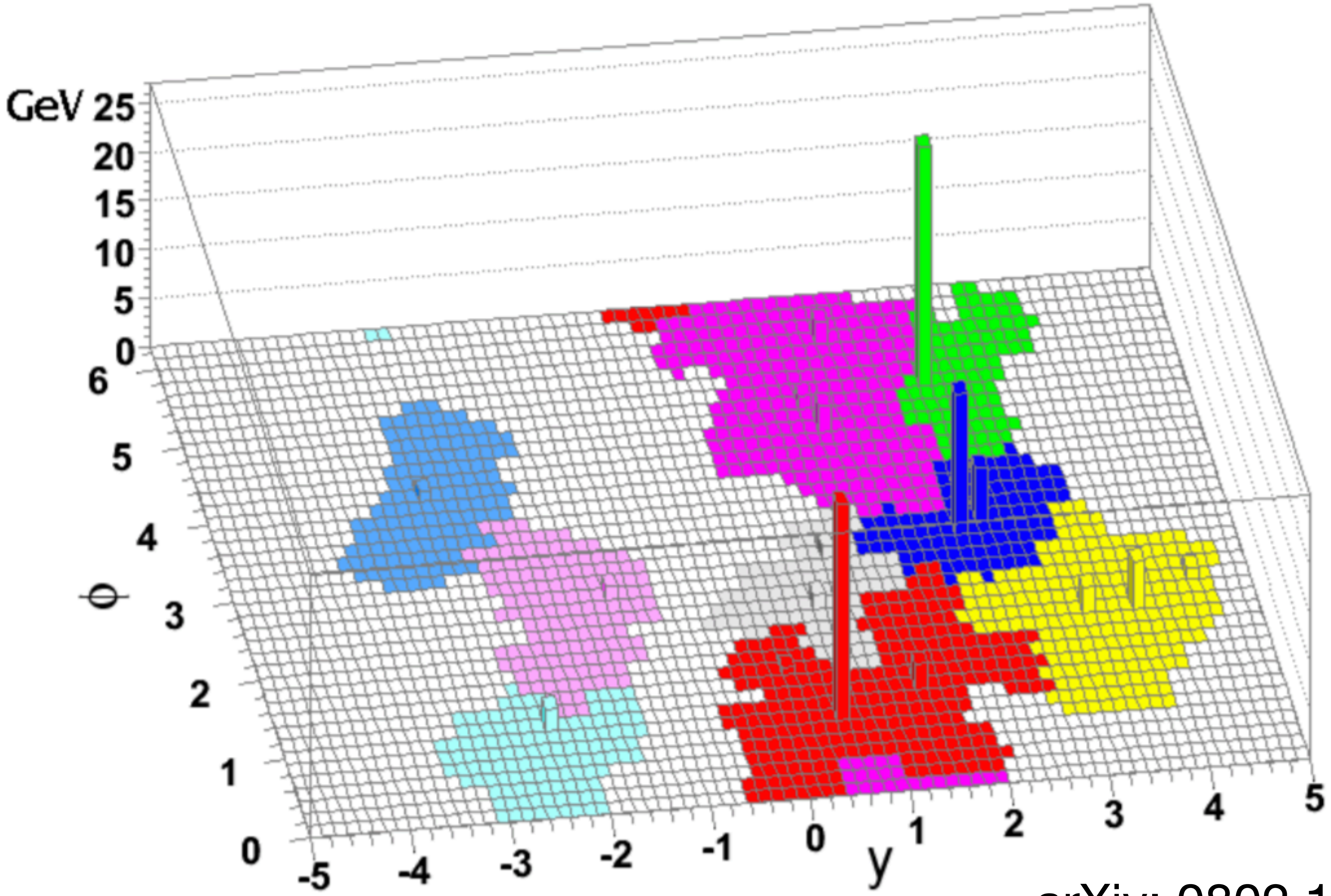
1. **Supervised Learning:** algorithm learns from a labeled set with the “true values”.



arXiv: 1150.05190

Ex: Distinguishing QCD jets and W jets with jet images

2. **Unsupervised Learning:** algorithm finds structure in data without knowing the desired outcome.



arXiv: 0802.1188

Ex: Jet Clustering Algorithms

(Brief) intro to machine learning

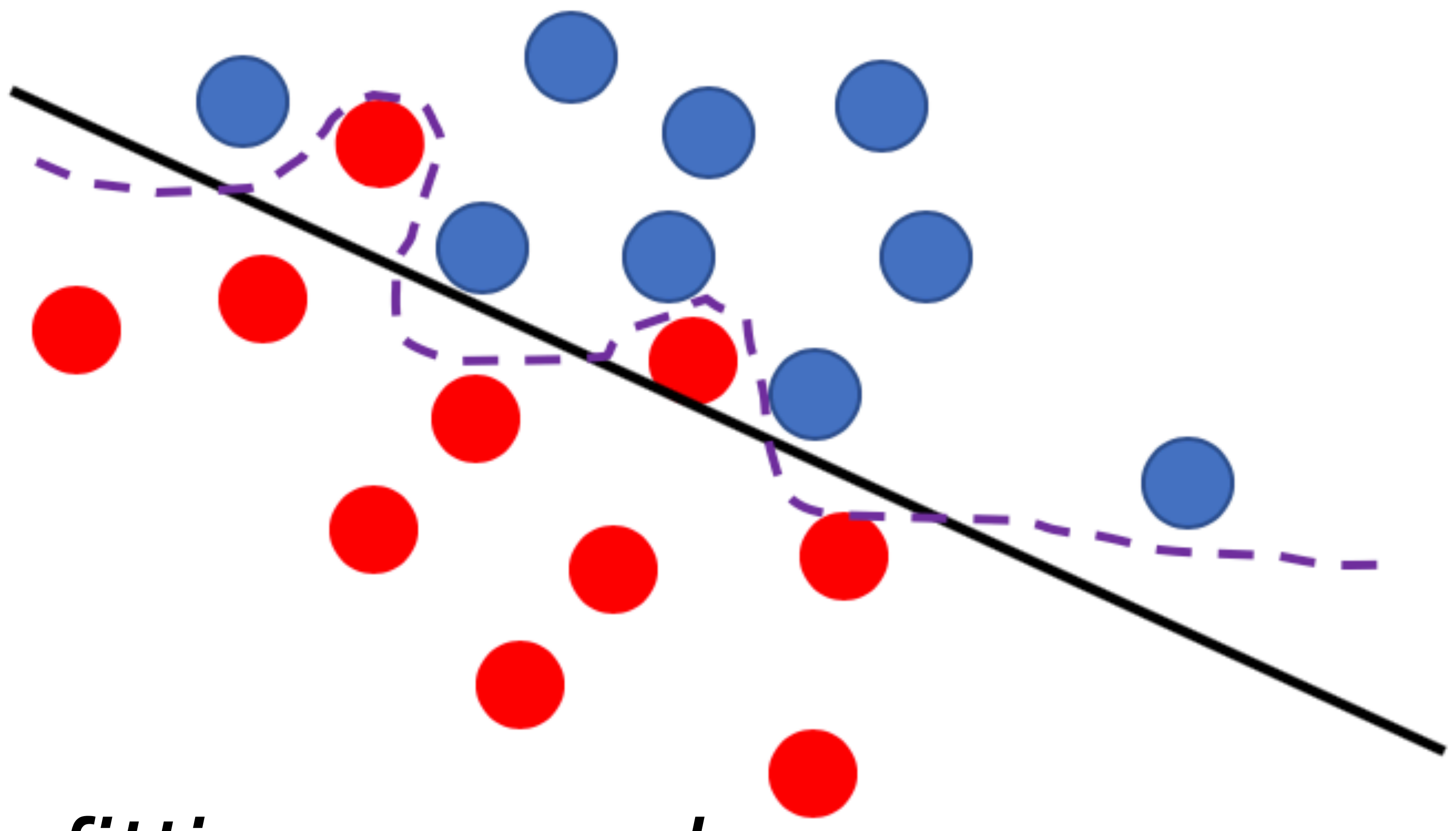
Words of caution!

Put garbage in, get garbage out

→Choices for input variables should be intentional, ML can't replace domain knowledge

→Avoid correlated variables in training.

→Keep model simple, prevents overfitting.



Overfitting example

Don't want to be finding cloudy days when you should be finding tanks!

Machine learning background estimator

Use machine learning (ML) to create a mapping to correct the jet for the background!

Jet Properties

(Including constituent properties)

$\xrightarrow{\textbf{ML}}$

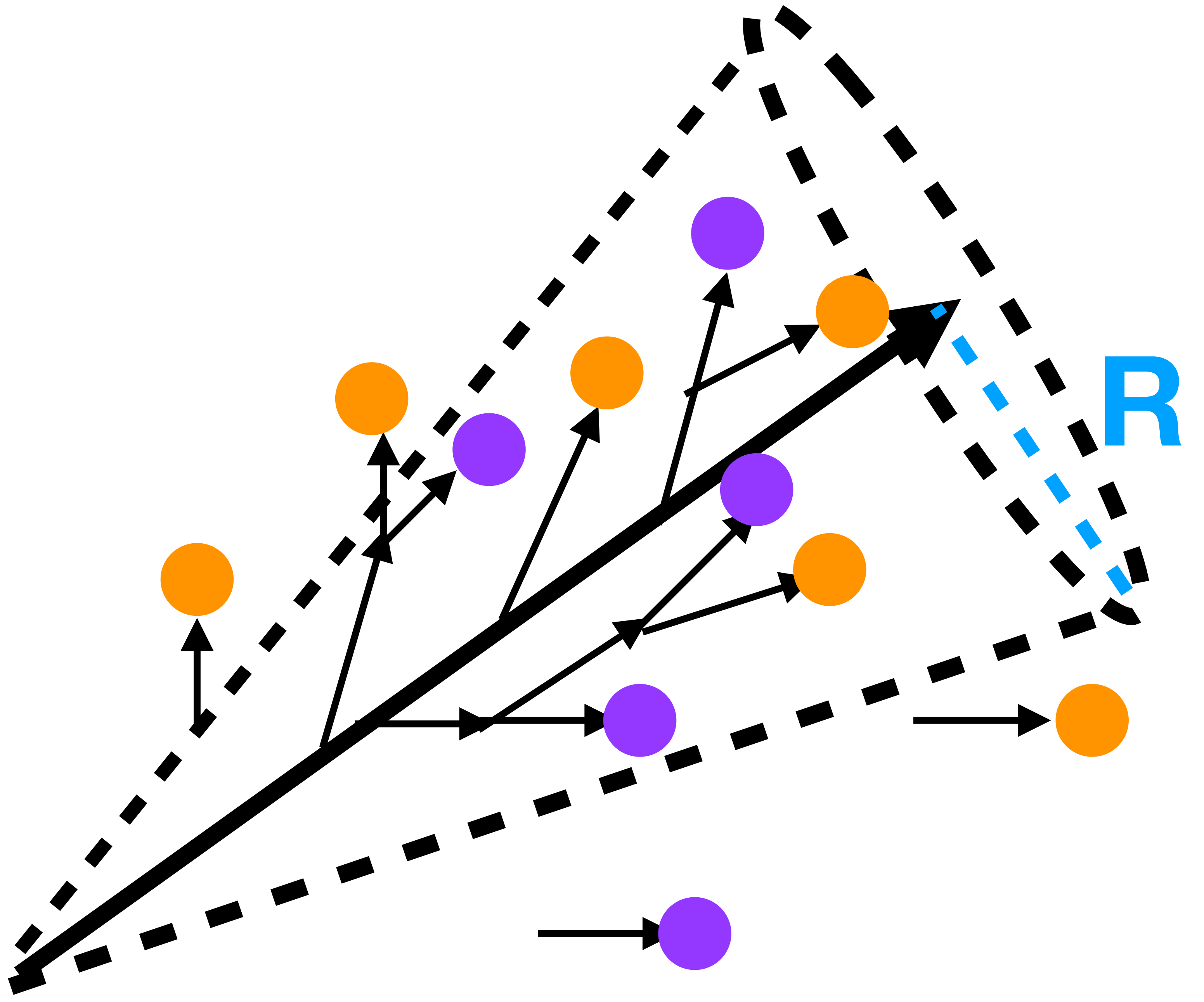
Corrected Jet p_{T}

$\longrightarrow$

Unfold for fluctuations and detector effects

Does this method reduce residual fluctuations, allowing the measurement to be pushed to lower p_{T} with reduced systematic uncertainties?

Does using constituent information in training introduce a fragmentation bias?



R.Haake, C. Loizides Phys. Rev. C 99, 064904 (2019)

Process

Training (PYTHIA fragmentation)

Train on “hybrid event” created by embedding PYTHIA jets into Pb-Pb Background

ML Estimator

Testing

Apply ML estimator to hybrid events not used in training.

Can either be Pb-Pb data or thermal toy background.

Key is that this background is *realistic.*

ML for this analysis

Regression task where the regression target is the detector level jet p_{T}.

Supervised learning, we provide the PYTHIA true p_{T} in training.

Training sample 10%, testing sample 90%.

Implemented in *scikit-learn*. Default parameters used unless otherwise specified.

Shallow Neural Network

Shallow, 3 layers with [100, 100, 50] nodes

ADAM optimizer, stochastic gradient descent algorithm.

Nodes/neurons activated by a ReLU activation function.

Linear Regression

Normalization set to true by default.

Random Forest

Ensemble of 30 decision trees.

Maximum number of features set to 15.

Features for training

Feature	Score	Feature	Score
Jet p_T (no corr.)	**0.1355**	$p^1_{T,const}$	0.0012
Jet mass	0.0007	$p^2_{T,const}$	**0.0039**
Jet Area	0.0005	$p^3_{T,const}$	0.0015
Jet p_T (area based corr.)	**0.7876**	$p^4_{T,const}$	0.0011
LeSub	0.0004	$p^5_{T,const}$	0.0009
Radial moment	0.0005	$p^6_{T,const}$	0.0009
Momentum dispersion	0.0007	$p^7_{T,const}$	0.0008
Number of constituents	0.0008	$p^8_{T,const}$	0.0007
Mean of constituent p_Ts	**0.0585**	$p^9_{T,const}$	0.0006
Median of Constituent p_Ts	0.0023	$p^{10}_{T,const}$	0.0007

Ask ourselves two questions before selecting a feature:

1. How important is the feature to the model? → Feature Scores

2. How correlated is the feature with other features?

Iteratively remove unimportant or highly correlated features, we are prioritizing a simple model!

R.Haake, C. Loizides Phys. Rev. C 99, 064904 (2019)

Features for training

Final List: Prioritizing a simple model!

Jet p_{T} (area-based corrected)

Number of Constituents within Jet

Jet Angularity

p_{T} of 8 Leading Constituents

Ask ourselves two questions before selecting a feature:

1. How important is the feature to the model? → Feature Scores

2. How correlated is the feature with other features?

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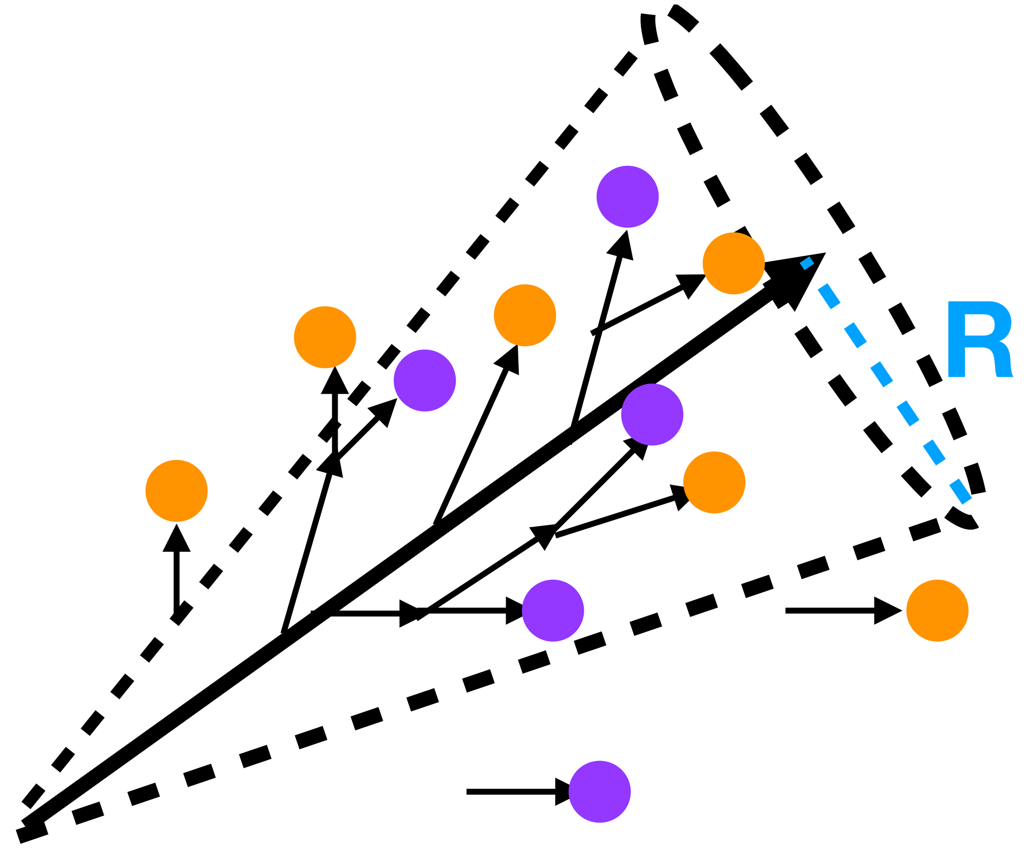
Charged vs. full jets



Today we will show charged and full jet results!

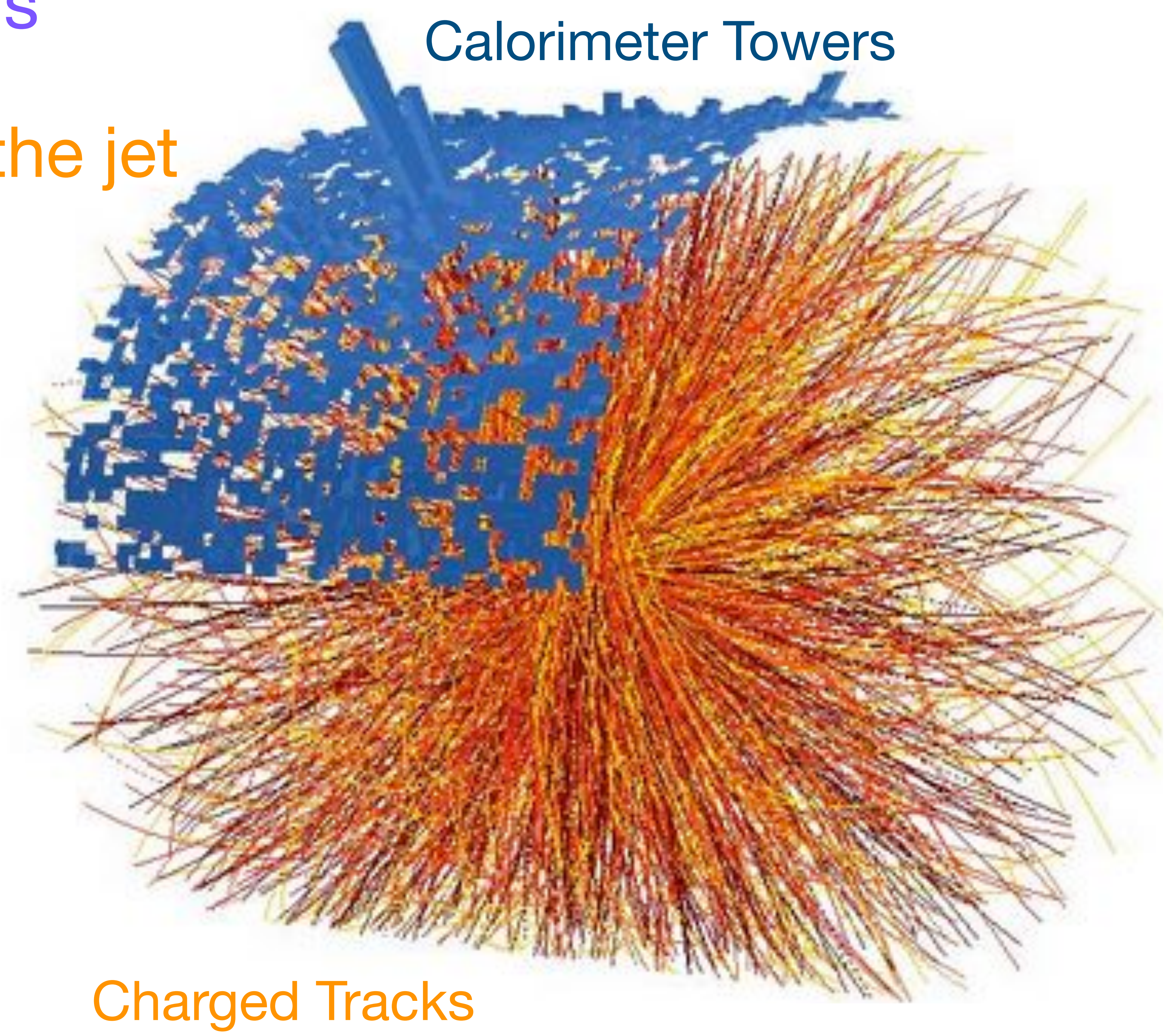
Charged particle jets → contain the charged component of the jet

→ measured with tracking detectors

Full jets → contain charged and neutral components of the jet

→ measured with electromagnetic calorimeter

→ limited to fiducial phi acceptance



Full jets show greater alignment with the traditional definition of a jet.

Experimentally challenging as we are using constituents from two different detector components.

Features for training

Final List: Prioritizing a simple model!

Jet p_{T} (area-based corrected)

Number of Constituents within Jet

Jet Angularity

p_{T} **of 12 Leading Constituents**

Ask ourselves two questions before selecting a feature:

1. How important is the feature to the model? → Feature Scores

2. How correlated is the feature with other features?

For full jets we need more constituents in training to reflect increase in constituents in the jet. Constituents are now both charged and neutral.

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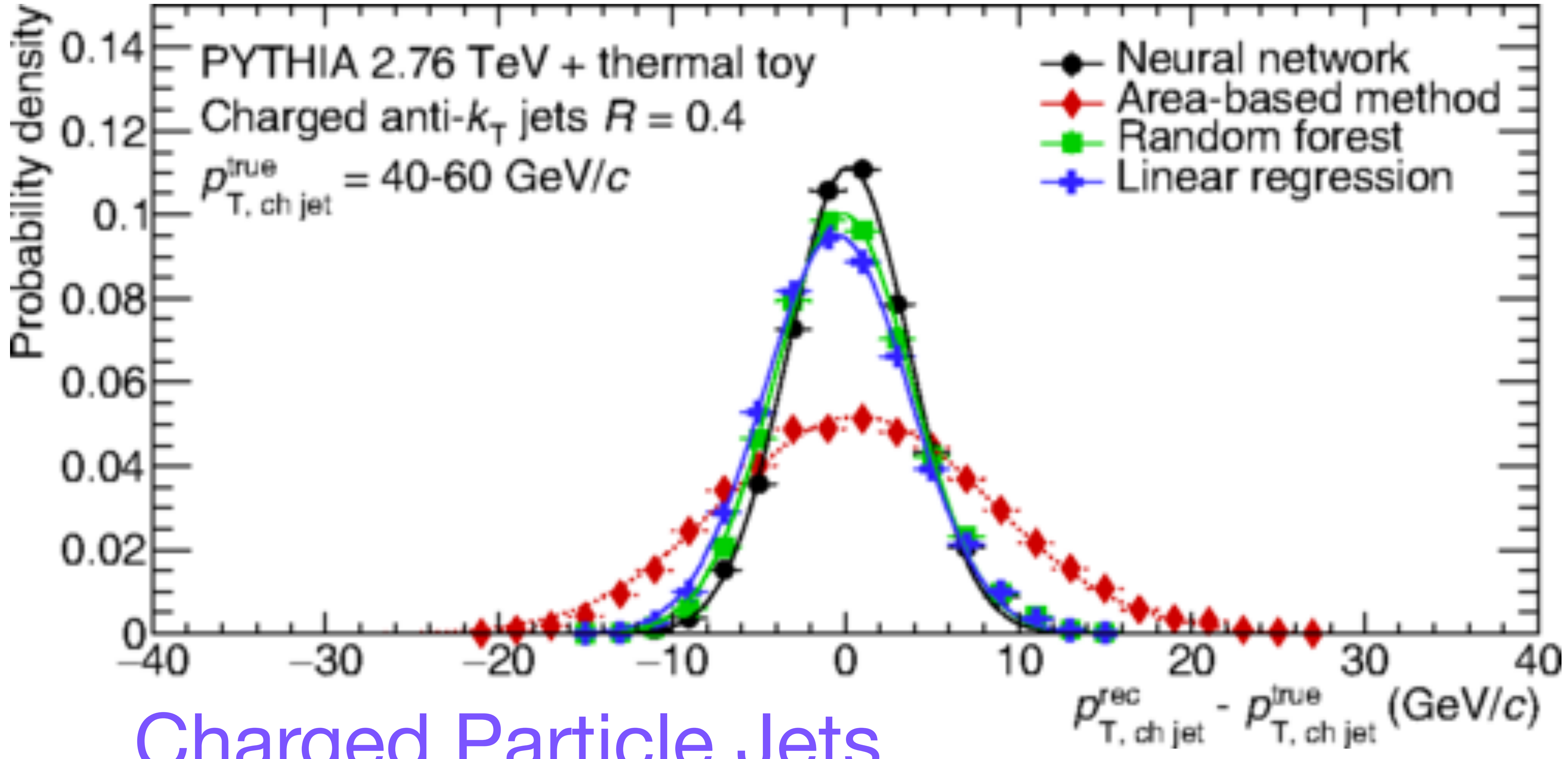
Evaluating the performance

$$\delta p_{\mathrm{T}} = p_{\mathrm{T,rec}} - p_{\mathrm{T,true}}$$

Are we getting back to the "truth" (matched PYTHIA detector level jet)?

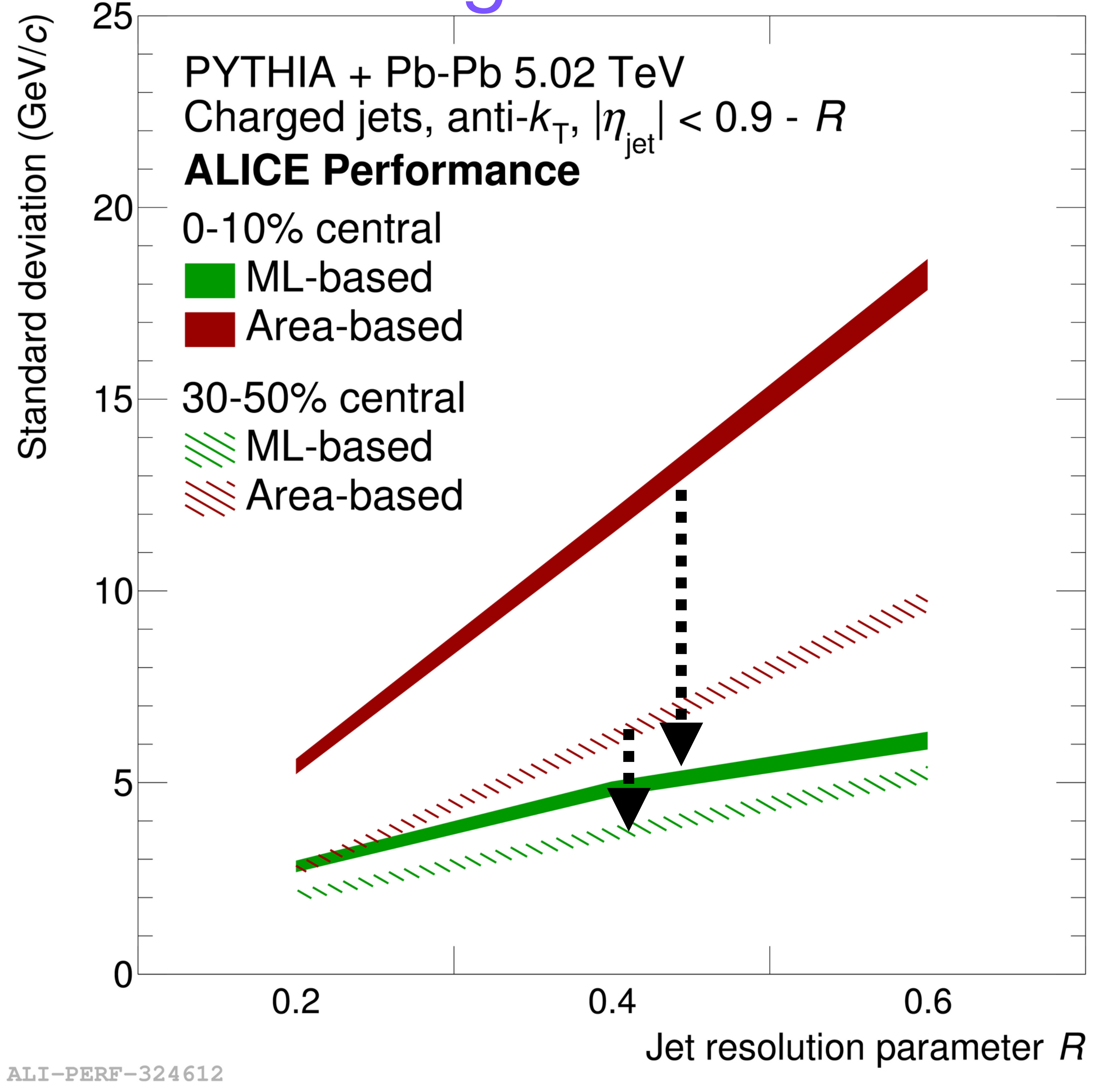
Narrow δp_{T} → Reduced residual fluctuations

Phys. Rev. C 99, 064904 (2019)



Charged Particle Jets

Charged Particle Jets



Residual fluctuations significantly reduced!

Evaluating the performance

$$\delta p_{\mathrm{T}} = p_{\mathrm{T,rec}} - p_{\mathrm{T,true}}$$

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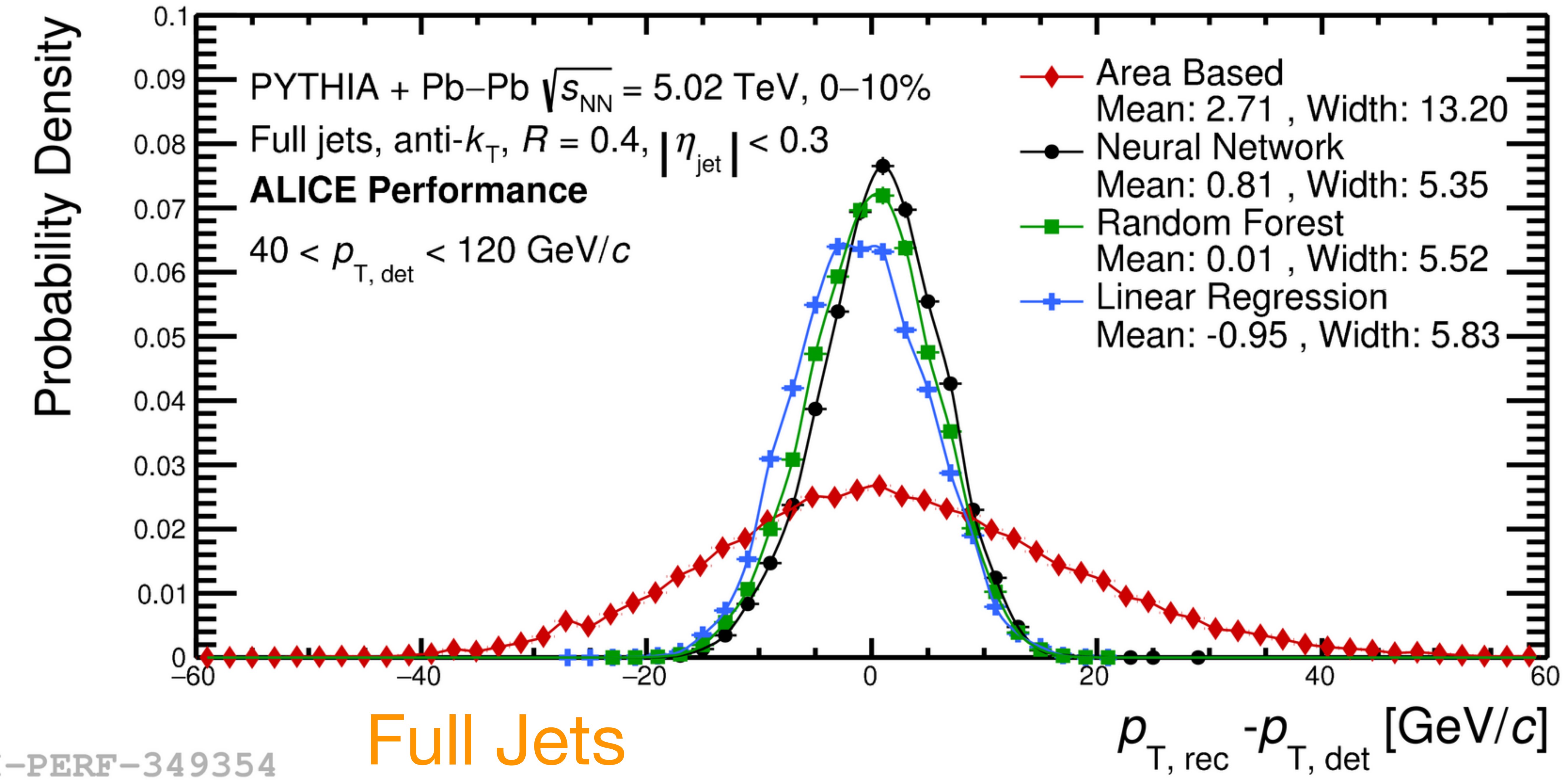
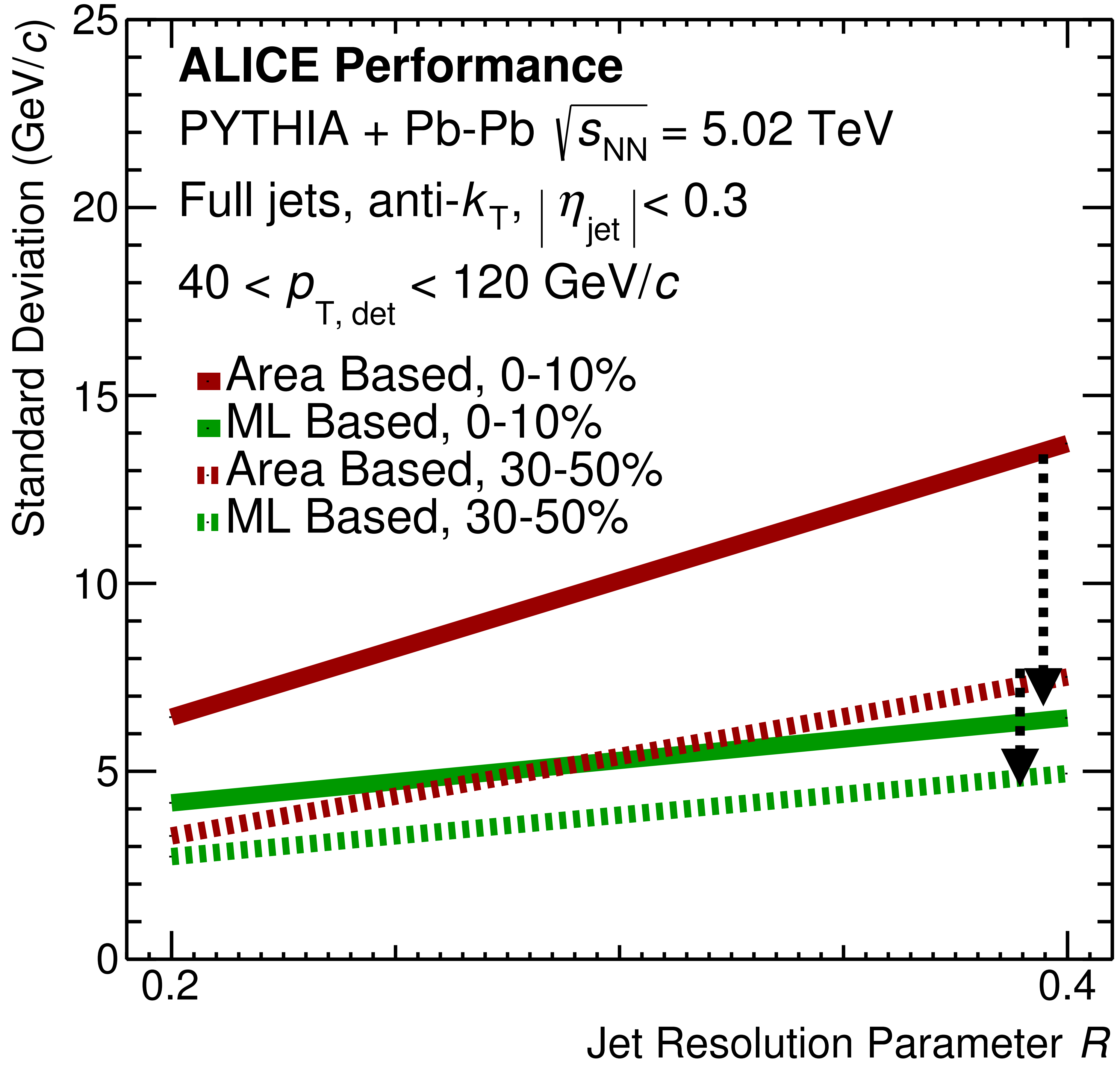
Narrow δp_{T} → Reduced residual fluctuations



ALI-PERF-349354

Full Jets

Full Jets

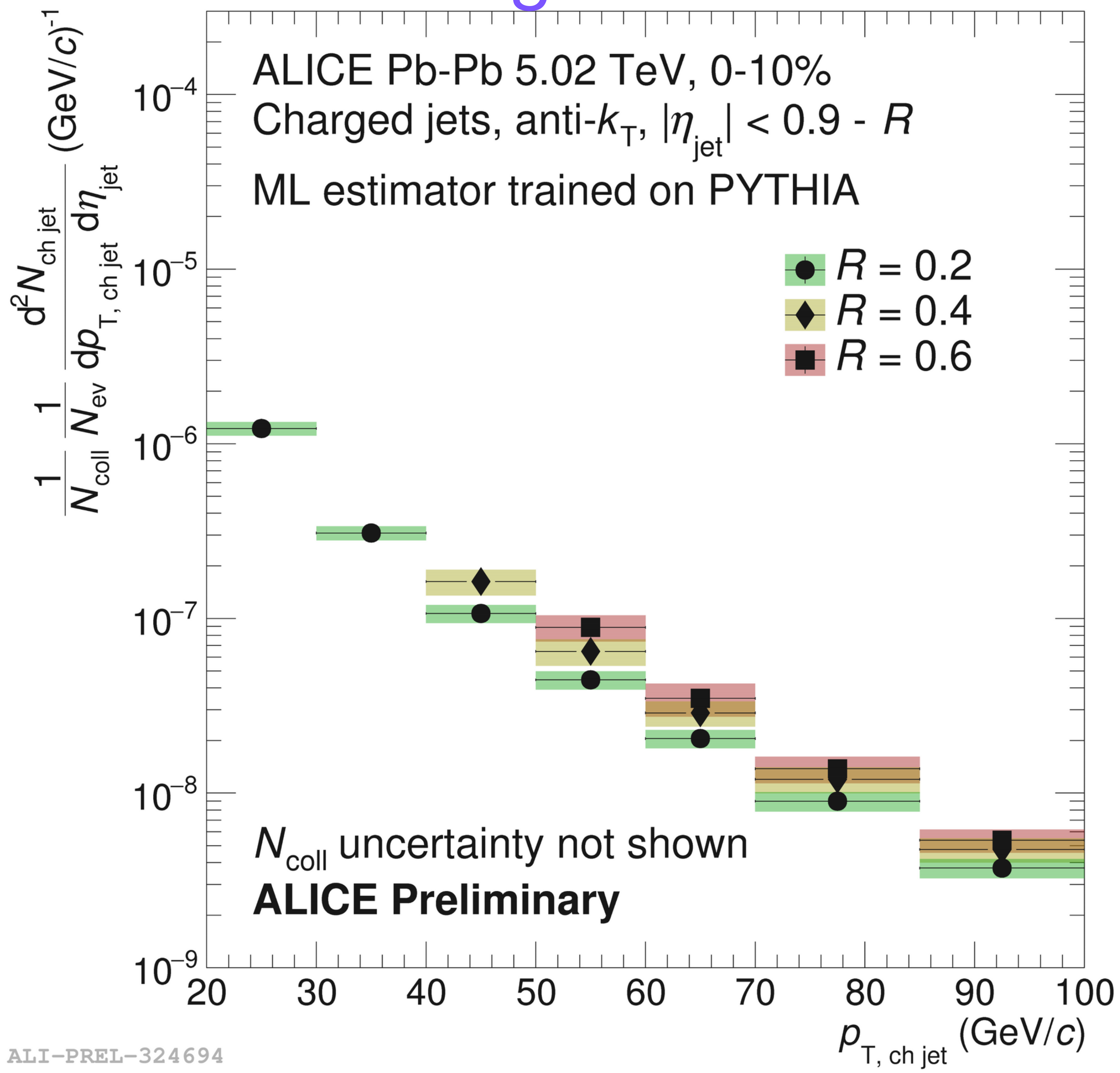


ALI-PERF-339976

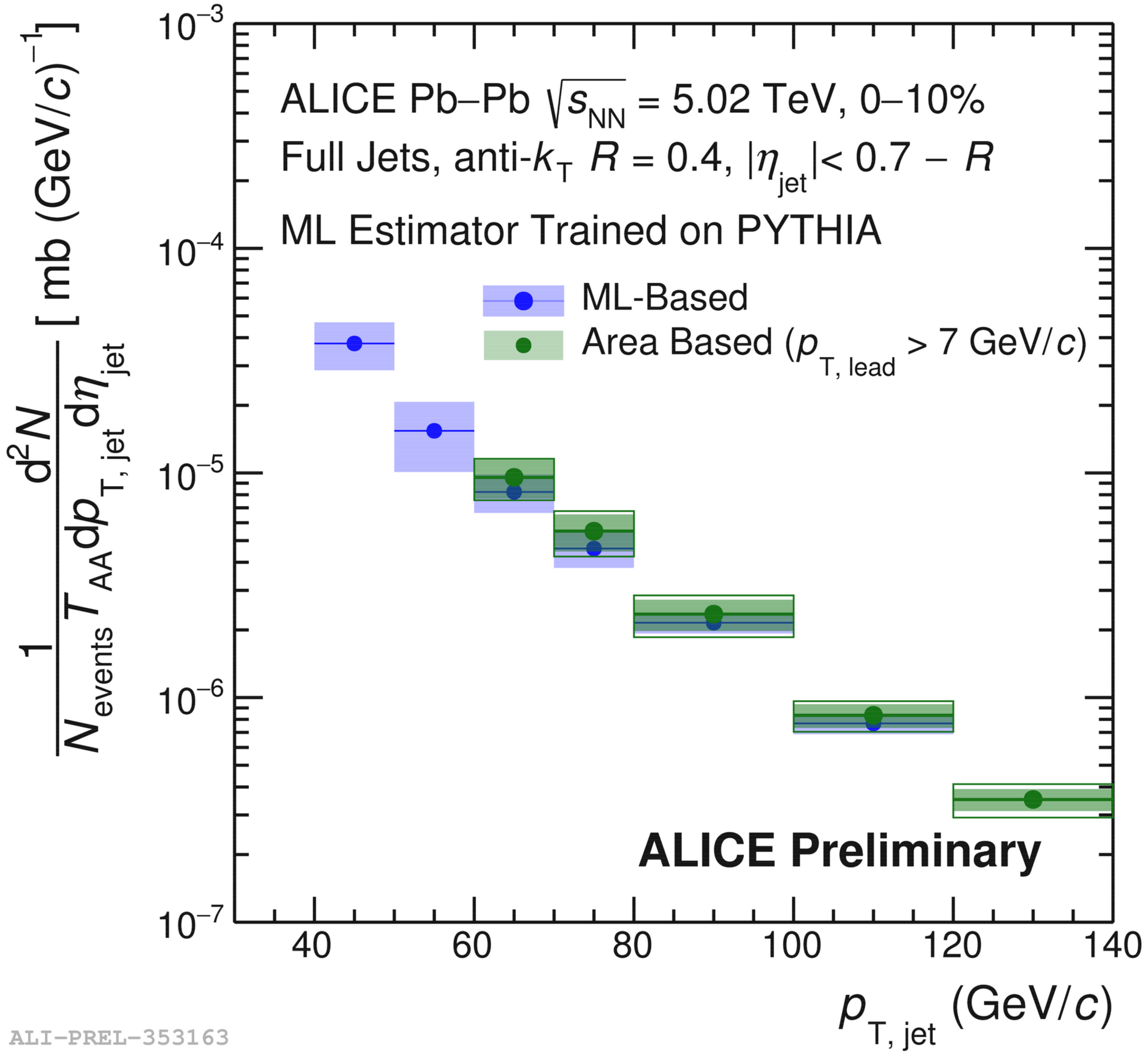
Residual fluctuations significantly reduced!

Results - inclusive jet spectra

Charged Particle Jets



Full Jets



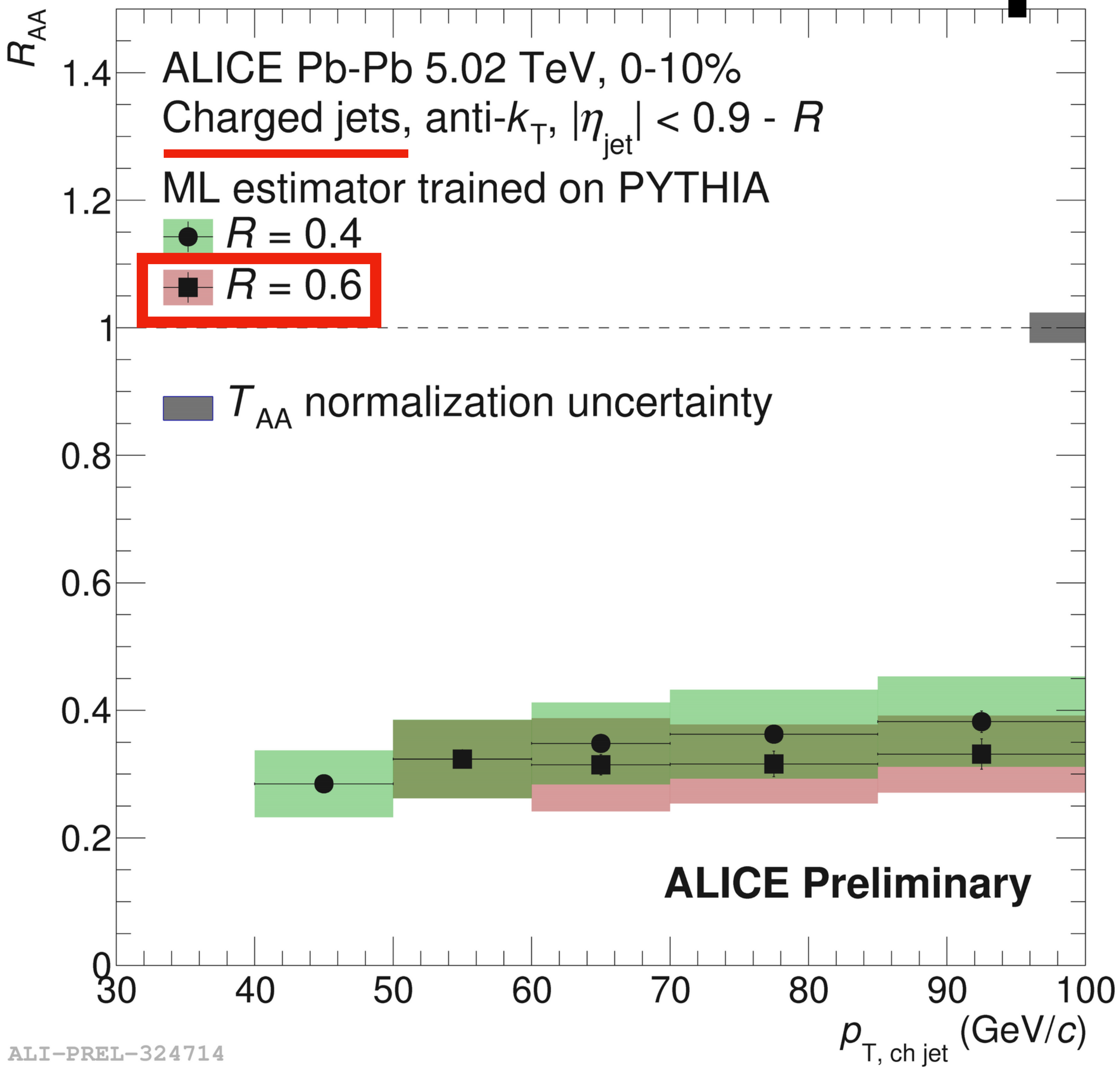
Unfolding systematics dominate at lower p_T.

Tracking efficiency systematics dominate at high p_T.

	Lower p_T Cutoff (GeV/c)	
R	Charged Particle Jets	Full Jets
0.2	20	40
0.3	50	60
0.4	40	40
0.6	50	N/A

Able to extend measurements to lower p_T and larger *R*!

What does experiment say?



ALICE uses a machine learning based background correction.

Able to extend measurements of the R_{AA} to low p_T and large *R*.

Advantageous to extend method to full jets!

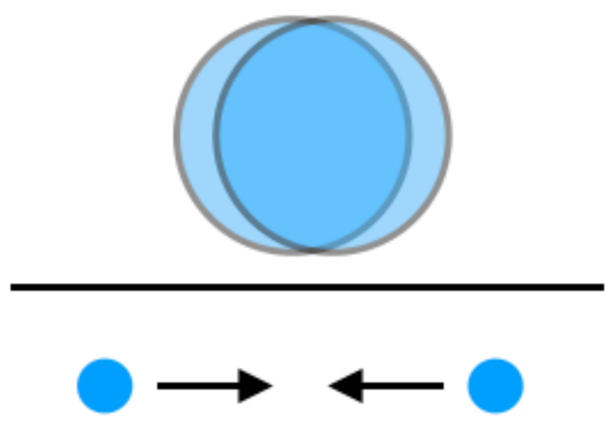
ALICE: Low p_T, Large *R*, Charged Particle Jets

Phys. Rev. C 99, 064904

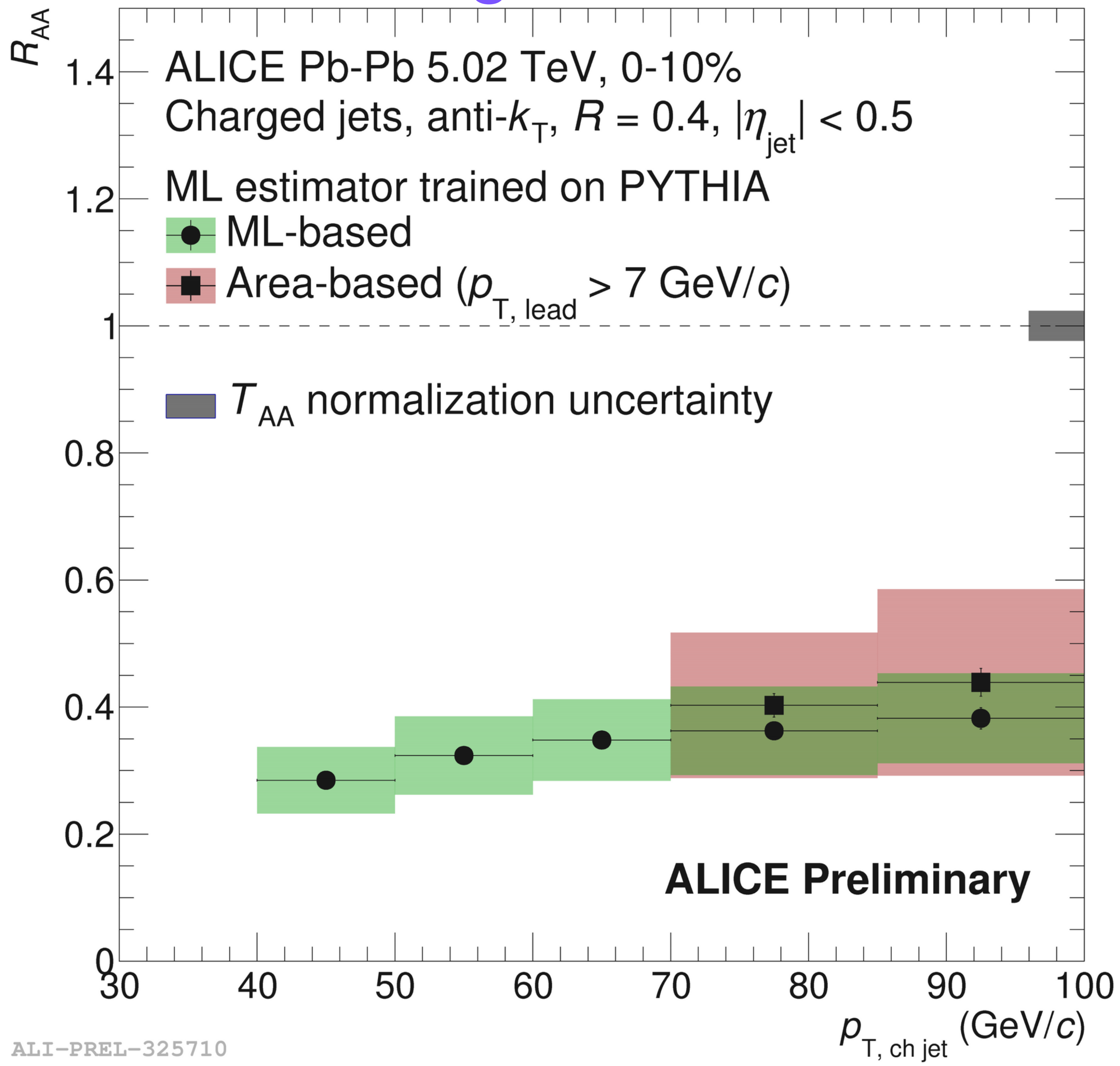
HP Talk on ML R_{AA}

Results - jet R_{AA}

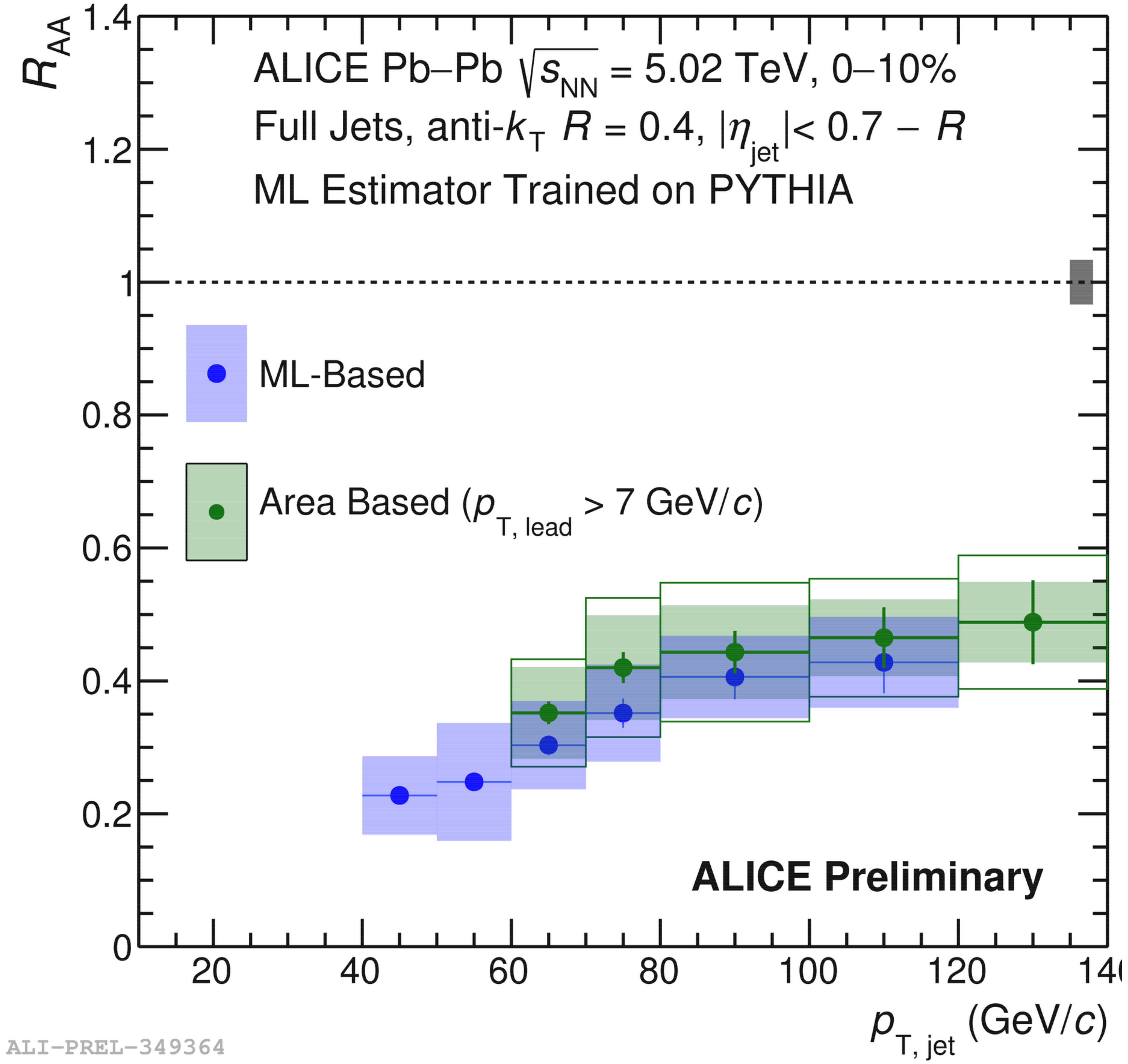
$$R_{AA} = \frac{\text{[image]}}{\text{[image]}} = \frac{\frac{1}{N_{\text{event}}}\frac{d^2N_{\text{jet}}^{\text{PbPb}}}{dp_{\text{T}}dy}\Big|_{\text{cent}}}{\langle T_{\text{AA}}\rangle \frac{d^2\sigma_{\text{jet}}^{\text{pp}}}{dp_{T}dy}}$$



Charged Particle Jets



Full Jets

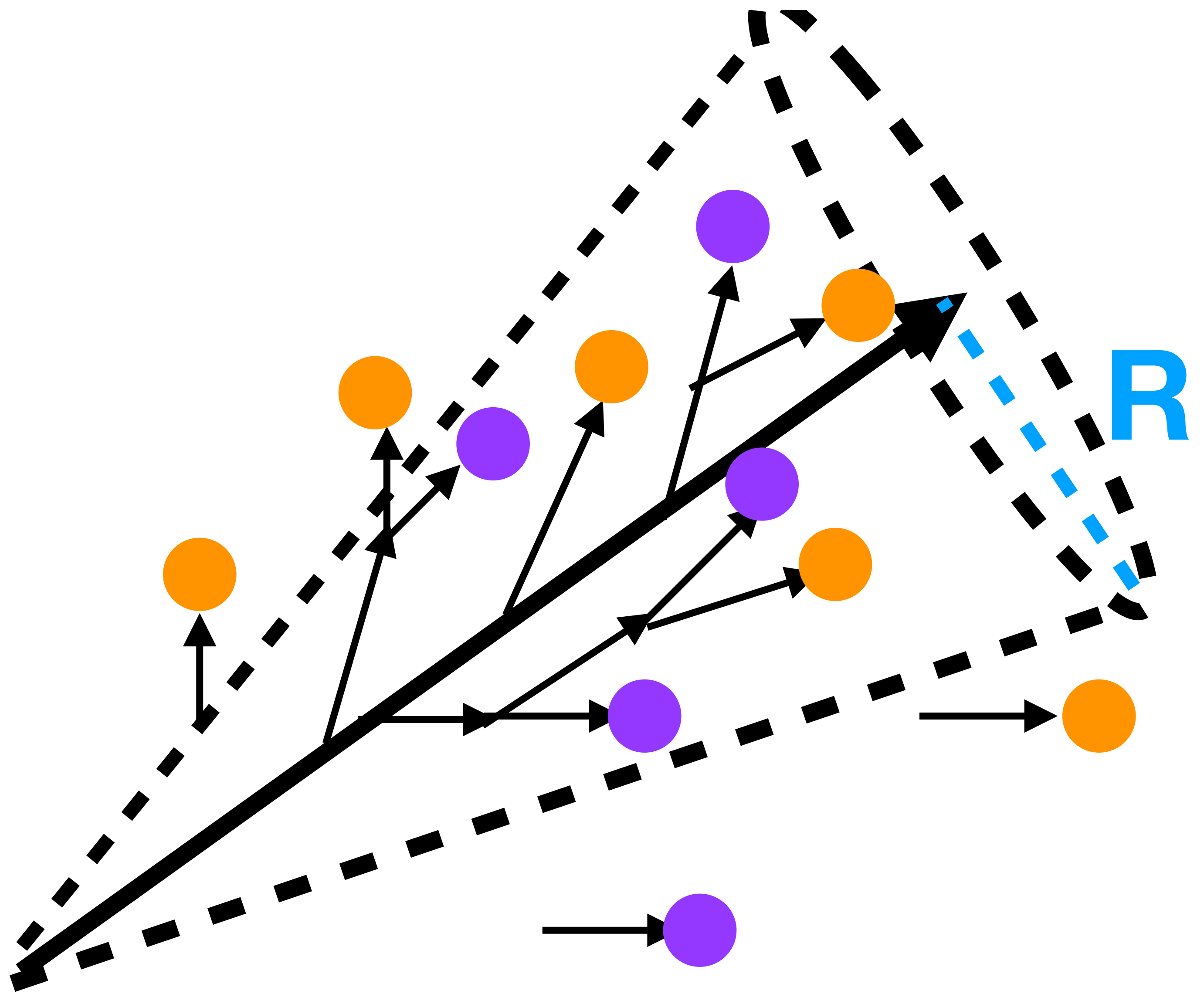


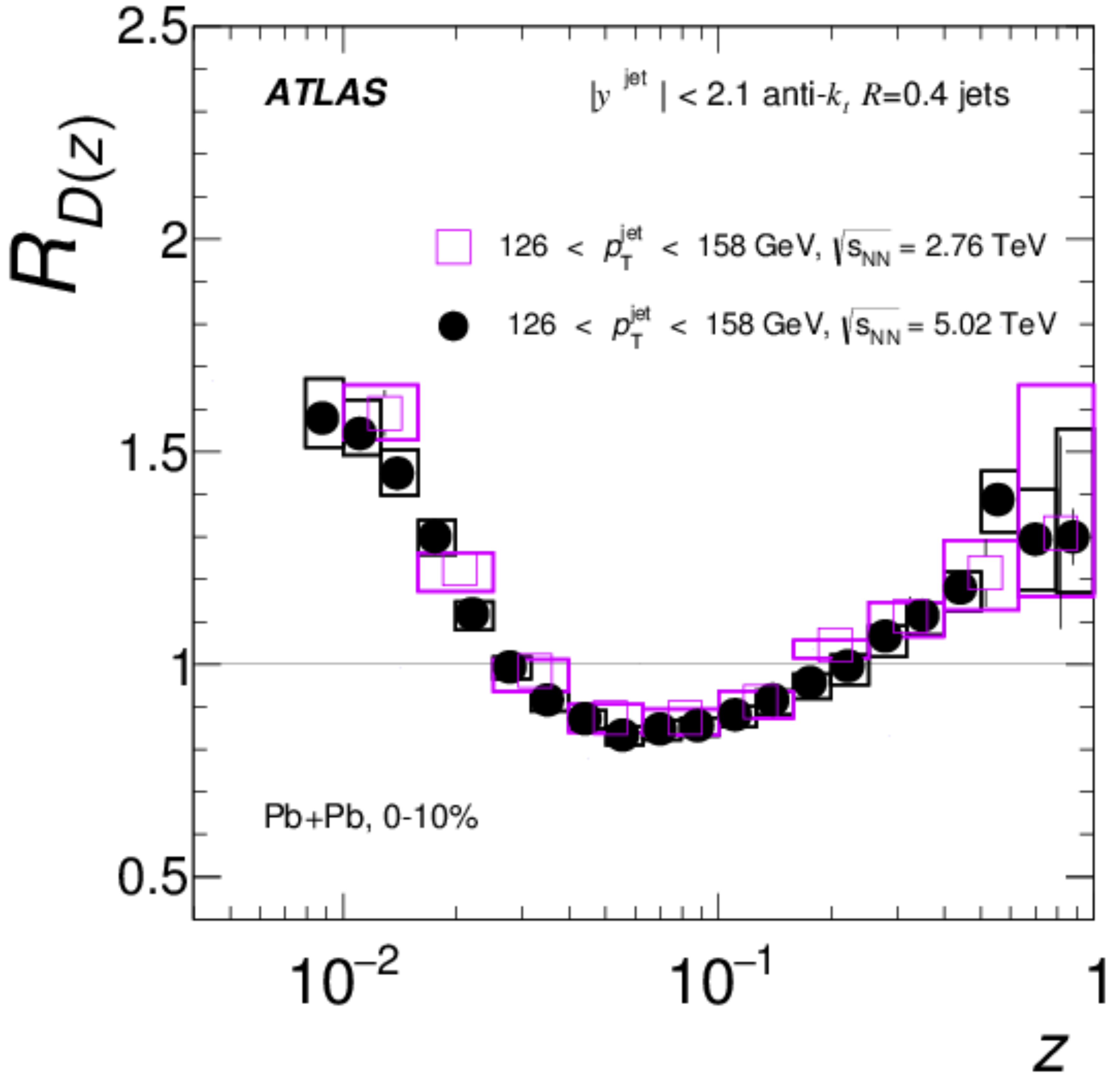
See significant jet suppression down to 40 GeV/c!

Systematic uncertainties are reduced.

Fragmentation bias

Learning on constituents introduces a fragmentation bias.





Phys. Rev. C 98, 024908 (2018)

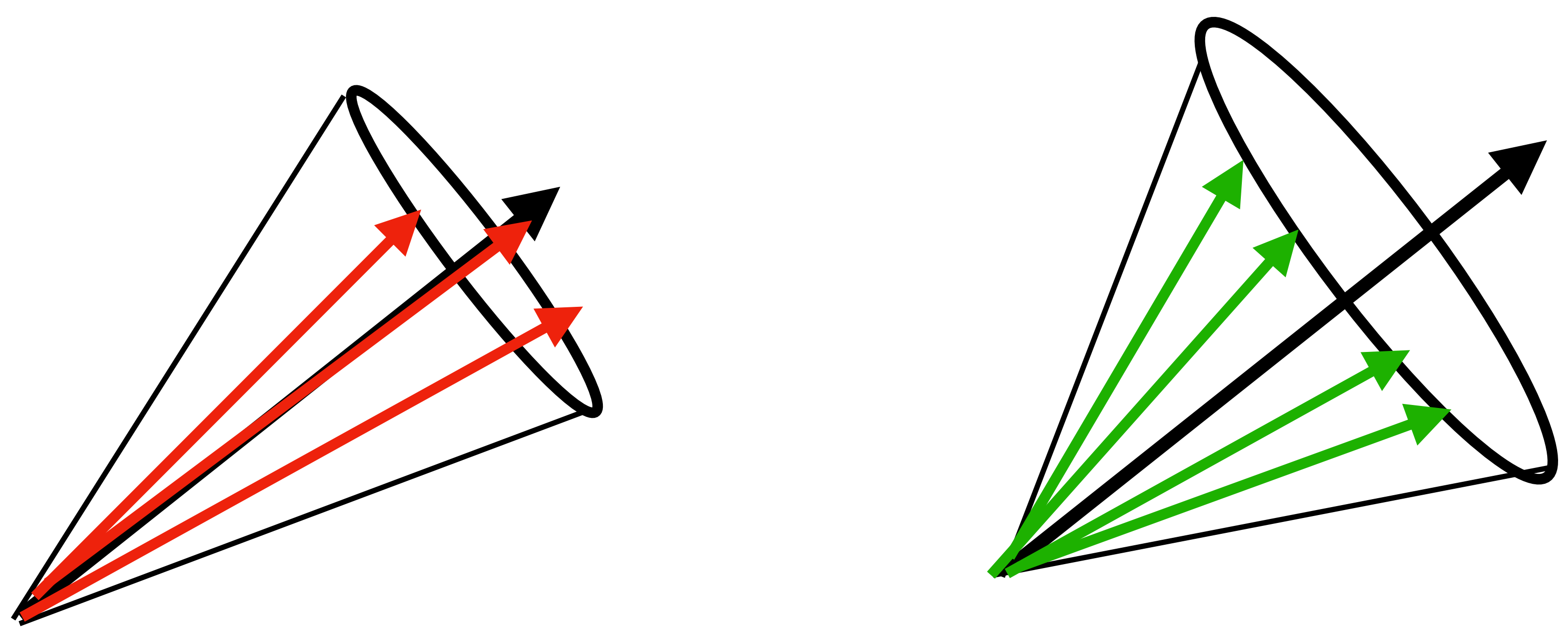
We learn on a PYTHIA fragmentation.

We know that fragmentation in heavy-ion collisions is modified by the presence of the medium.

We want to investigate how this impacts the final result we get with ML!

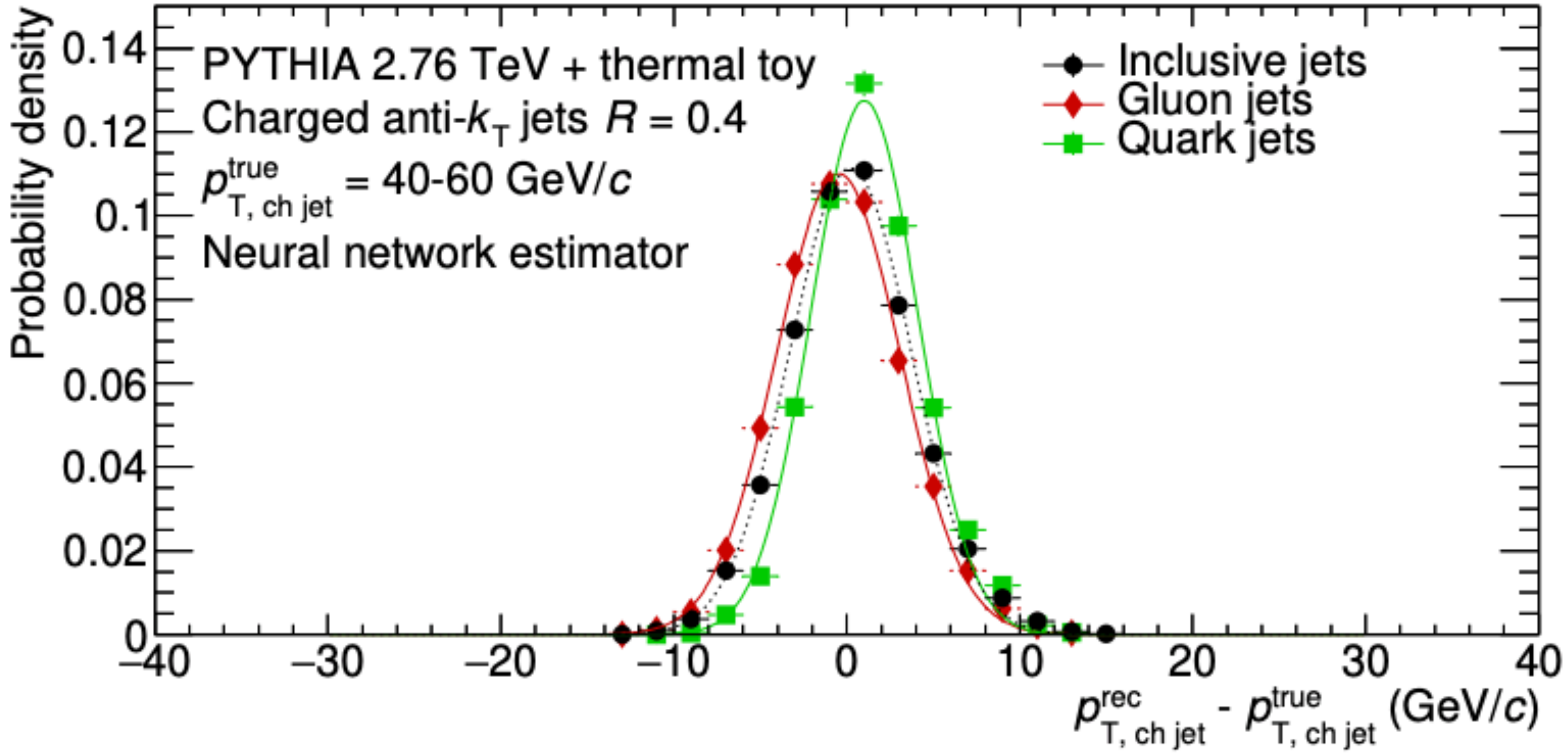
Quark vs. Gluons

Investigate fragmentation dependence by checking model performance on jets with different fragmentation.



Quark jets have less constituents with a harder fragmentation→ narrower.

Gluon jets have more constituents with a more even distribution in energy → wider.



See a small bias relative to the inclusive case!

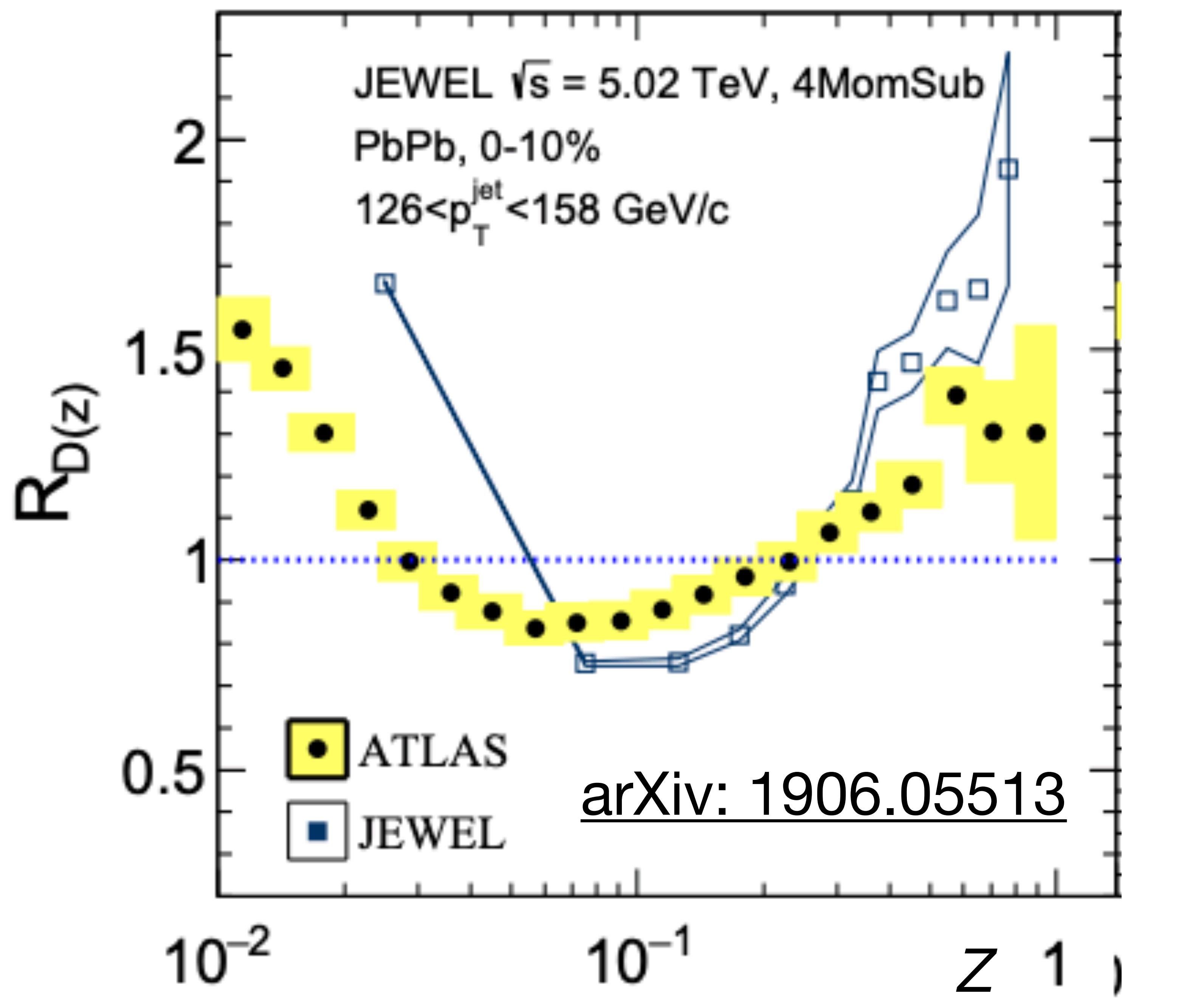
Using JEWEL

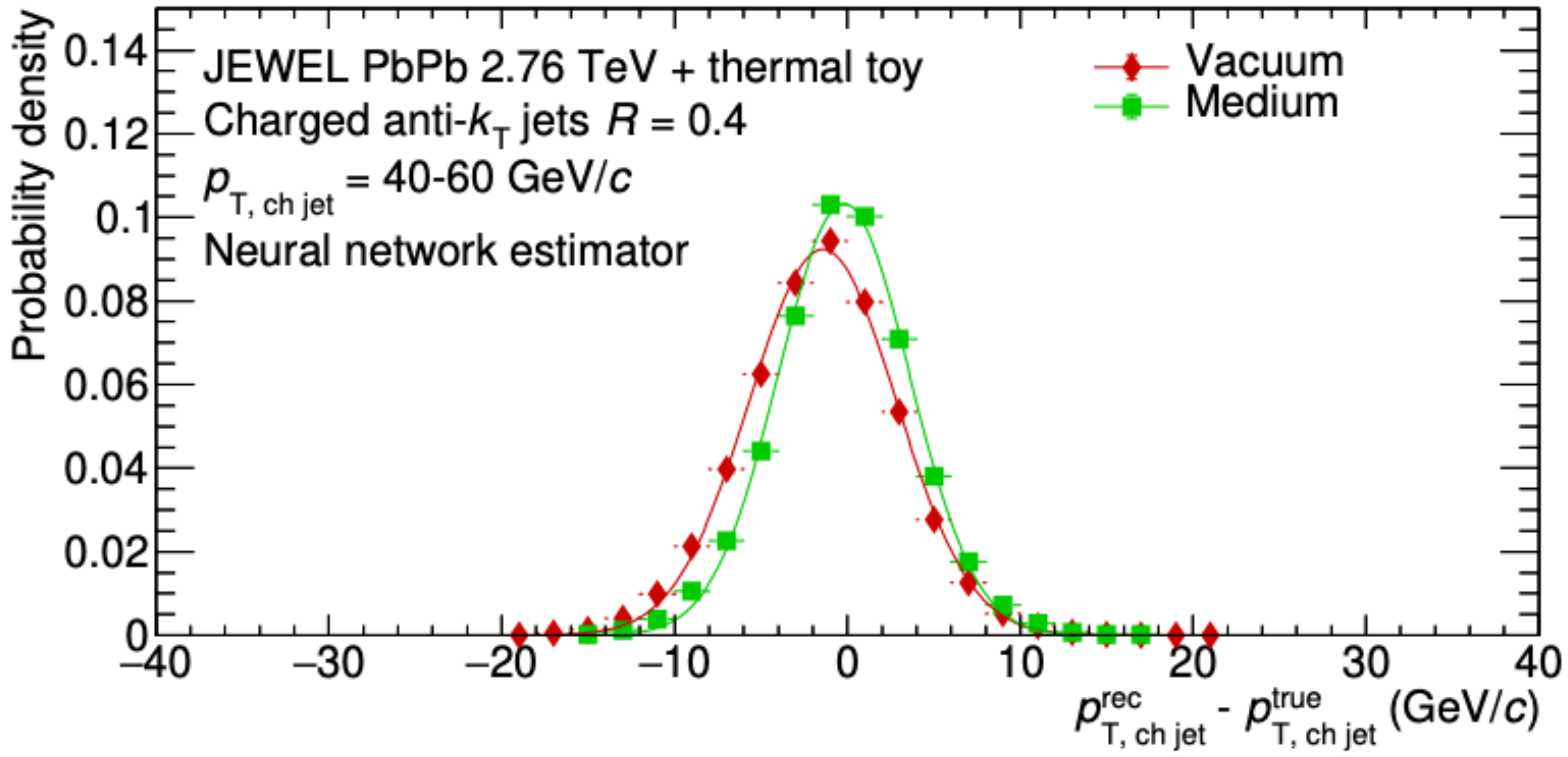
Investigate fragmentation dependence by checking model performance on jets with different fragmentation.

Use JEWEL, a quenched MC designed to mimic heavy ion quenching effects.

Vacuum JEWEL ~ PYTHIA (nominal case)

Bias similar to Q/G observed.



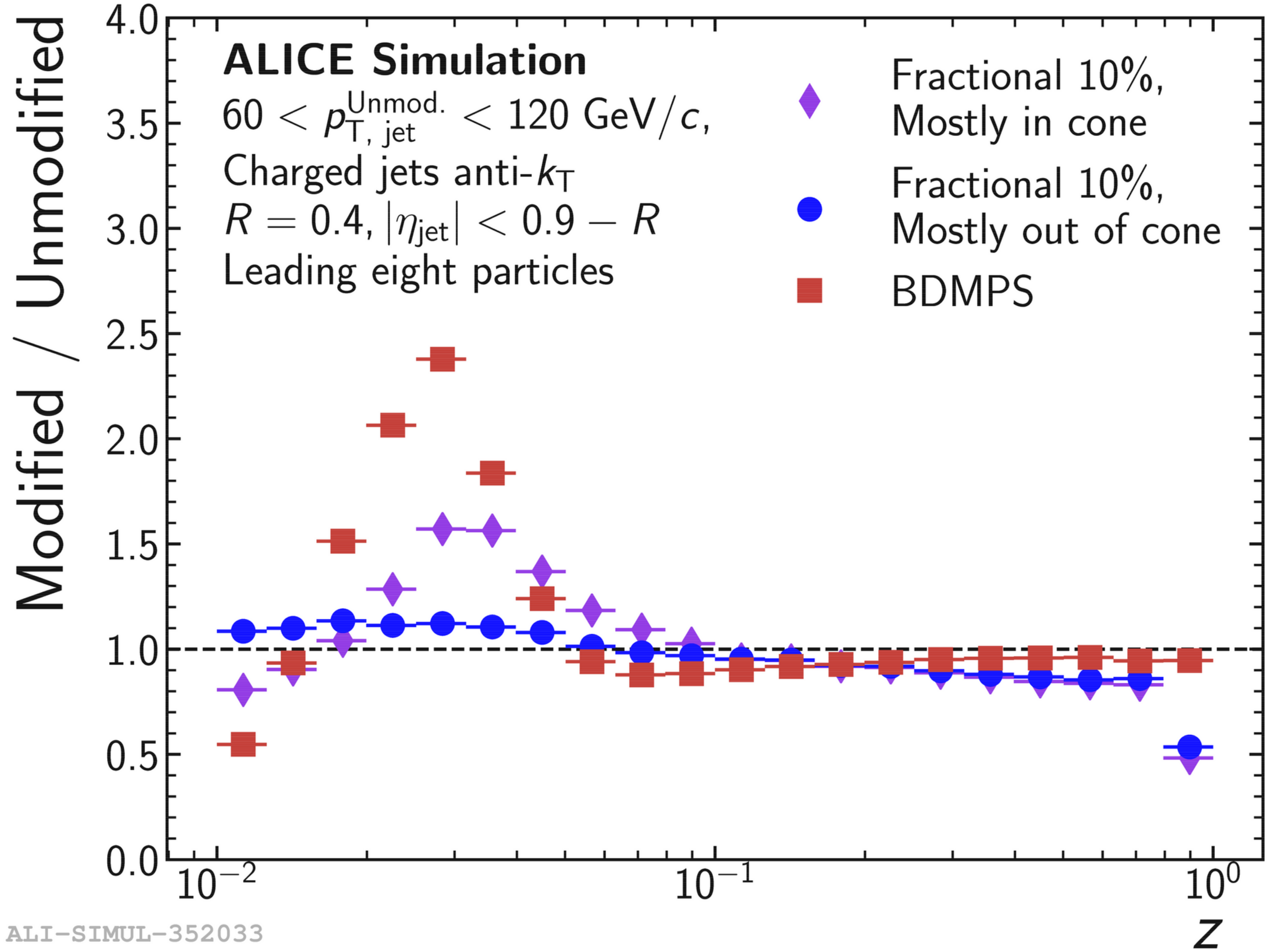


Toy model studies

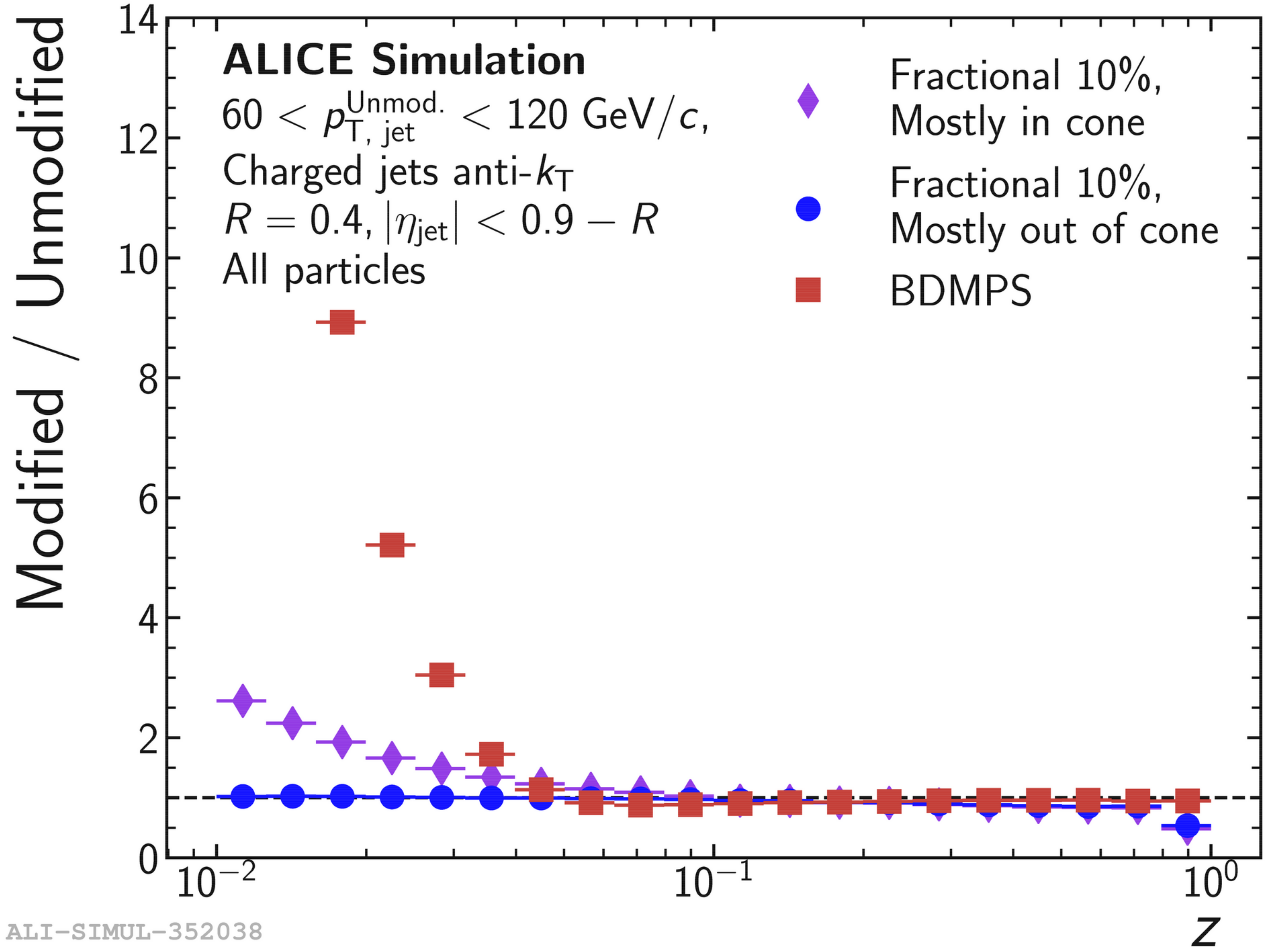
We also study a toy model with three different ways to alter constituents of the jet, changing the fragmentation.

Modification to the fragmentation function

Leading 8 particles



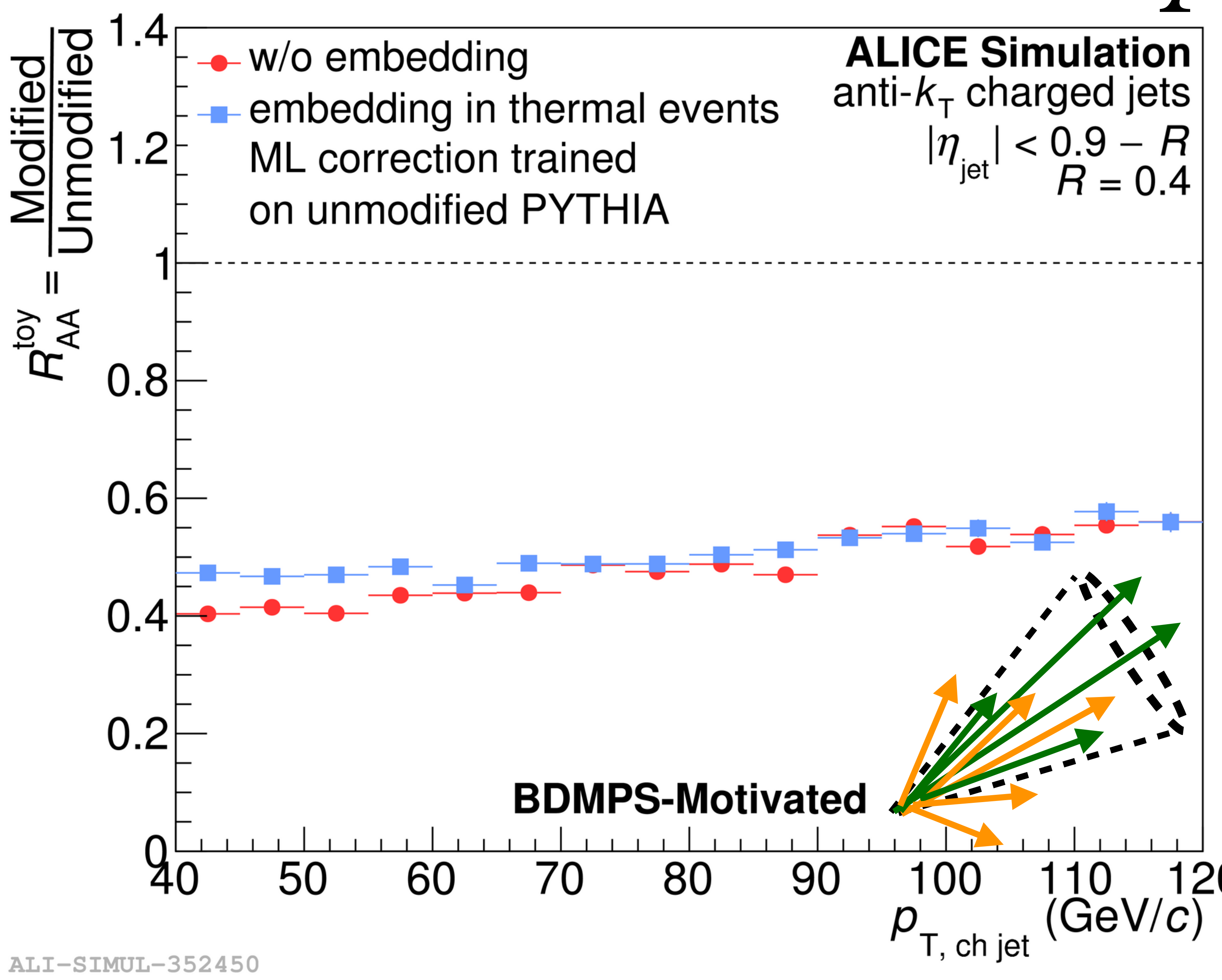
Inclusive particles

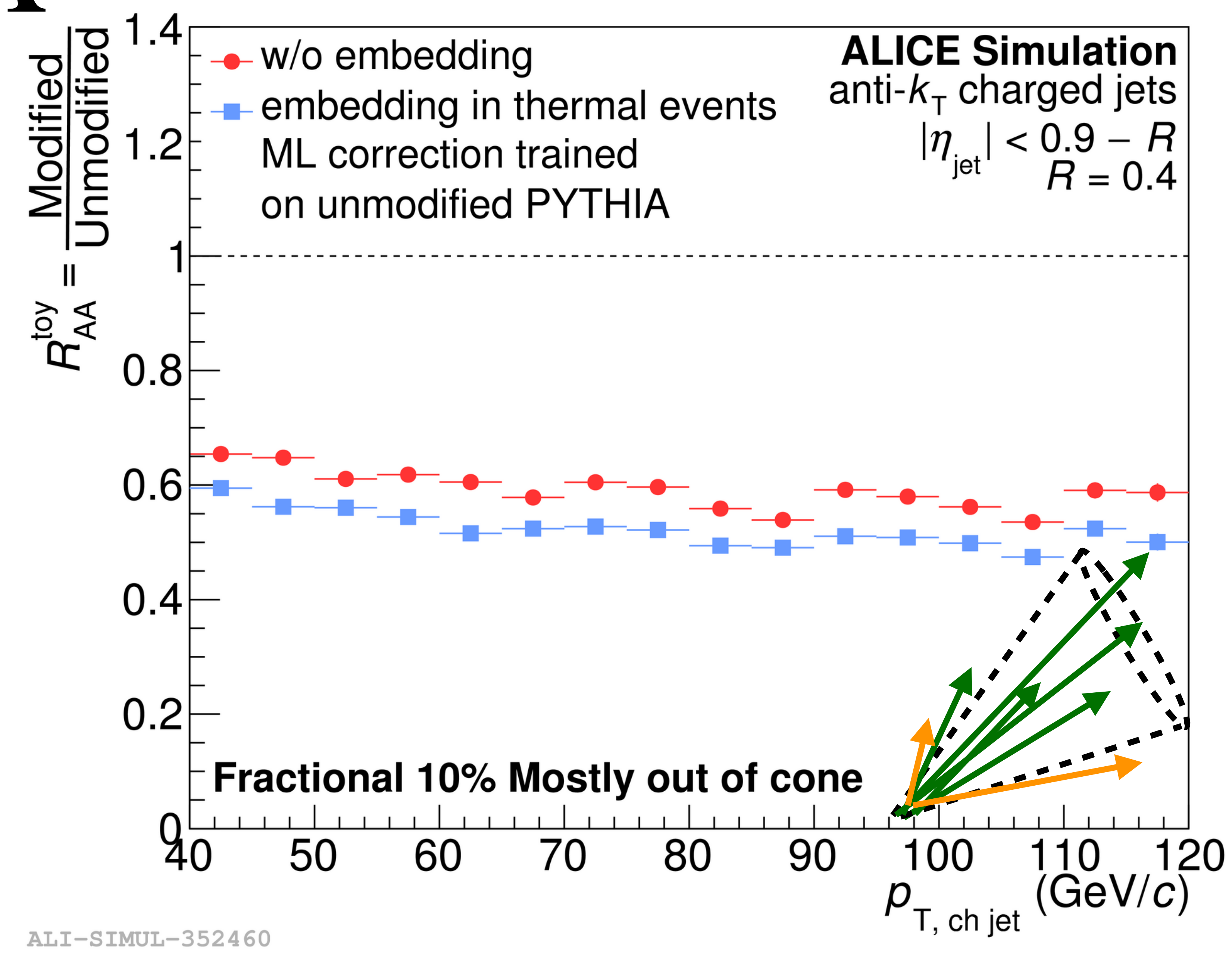


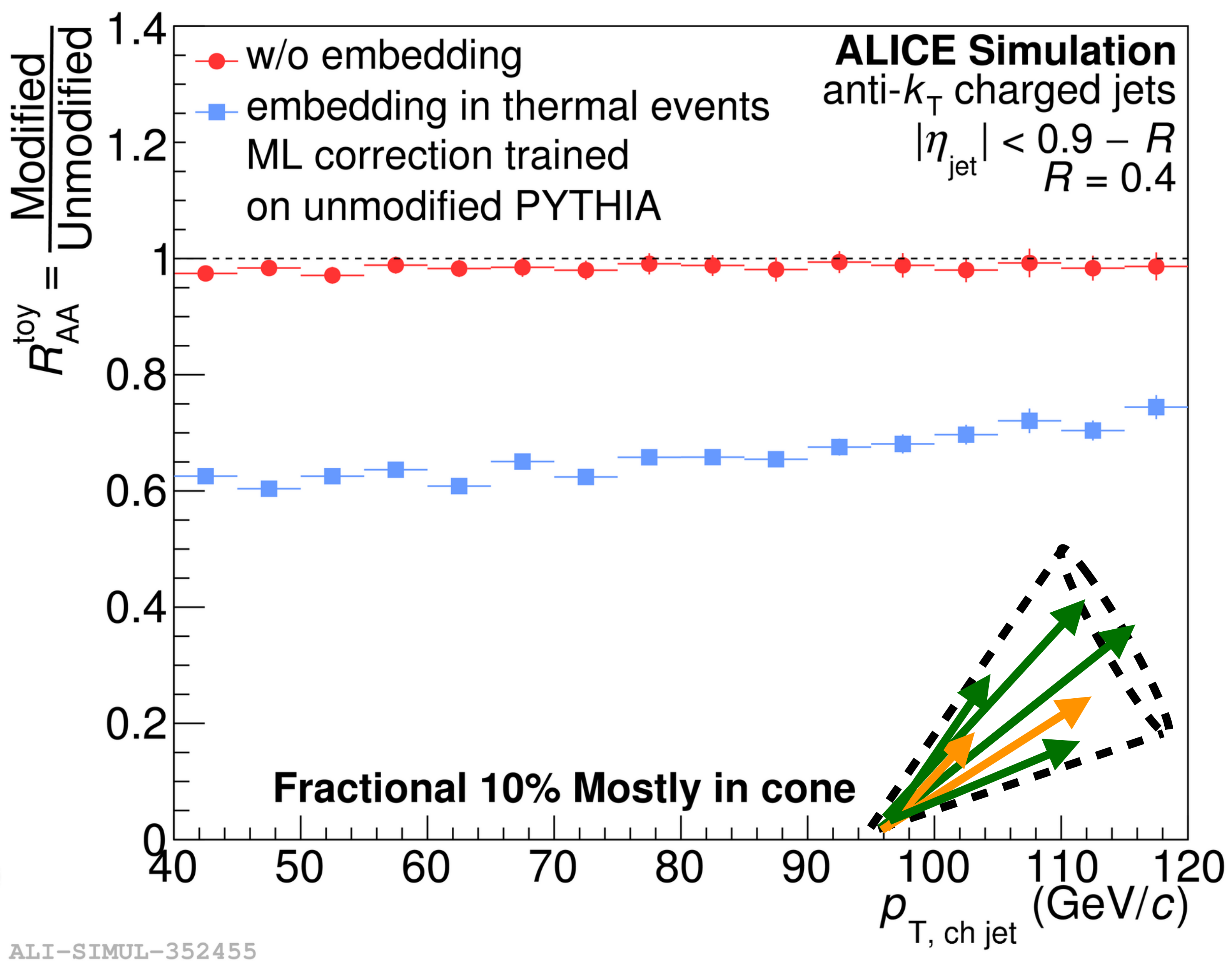
Toy model modifications indeed modify the fragmentation, some modifications are more extreme than others.

8 leading particles are what we chose to train on.

Looking at R_{AA}^{toy}







1. Modify PYTHIA jets

2. Apply ML trained on unmodified PYTHIA

3. Look at $R_{AA}^{toy} = \frac{\textbf{Modified}}{\textbf{Unmodified}}$

Here, we focus on the difference between PYTHIA and Embedded (ML).

Largest difference for the mostly in cone case.

Let's unpack this!

Looking deeper into $R_{\mathrm{AA}}^{\mathrm{toy}}$

1. Modify PYTHIA jets

2. Apply ML trained on unmodified PYTHIA

3. Look at $R_{\mathrm{AA}}^{\mathrm{toy}} = \frac{\textbf{Modified}}{\textbf{Unmodified}}$

ML has the same target $p_{\mathrm{T,mod}}^{\mathrm{PYTHIA}} = p_{\mathrm{T,unmod}}^{\mathrm{PYTHIA}}$

→ Whenever energy is lost out of cone $p_{\mathrm{T,mod}}^{\mathrm{PYTHIA}} \neq p_{\mathrm{T,unmod}}^{\mathrm{PYTHIA}}$

Every constituent has lost 10% of its energy in cone.

The ML is trained using only leading 8 constituents for the unmodified case, unable to recover energy lost in cone.

→ ML is picking up on energy loss, just energy lost in cone.

Would we see similar biases training on the modified toy?

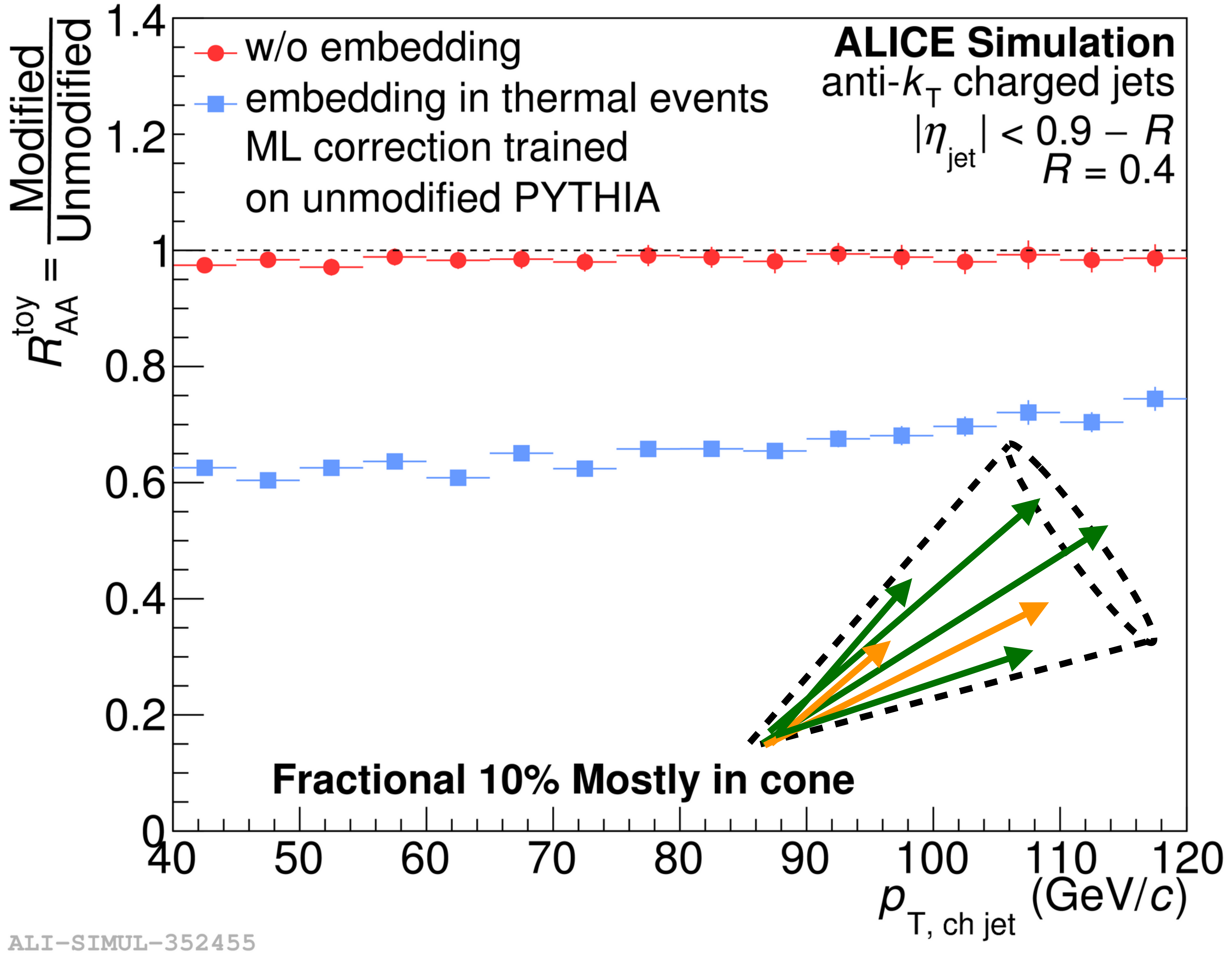
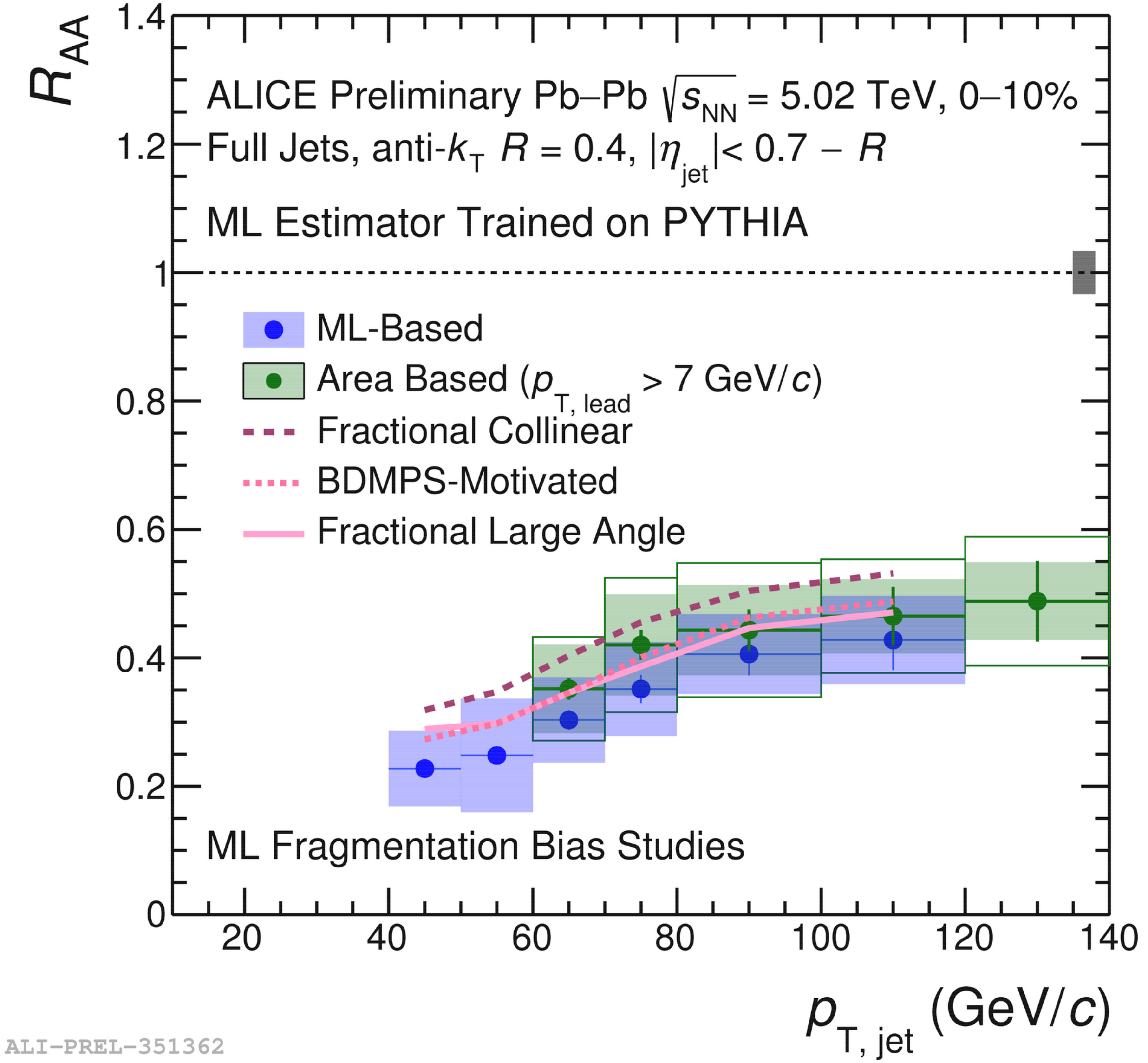


Illustration of potential bias

Train on the modified toy model and apply to data; measure bias.

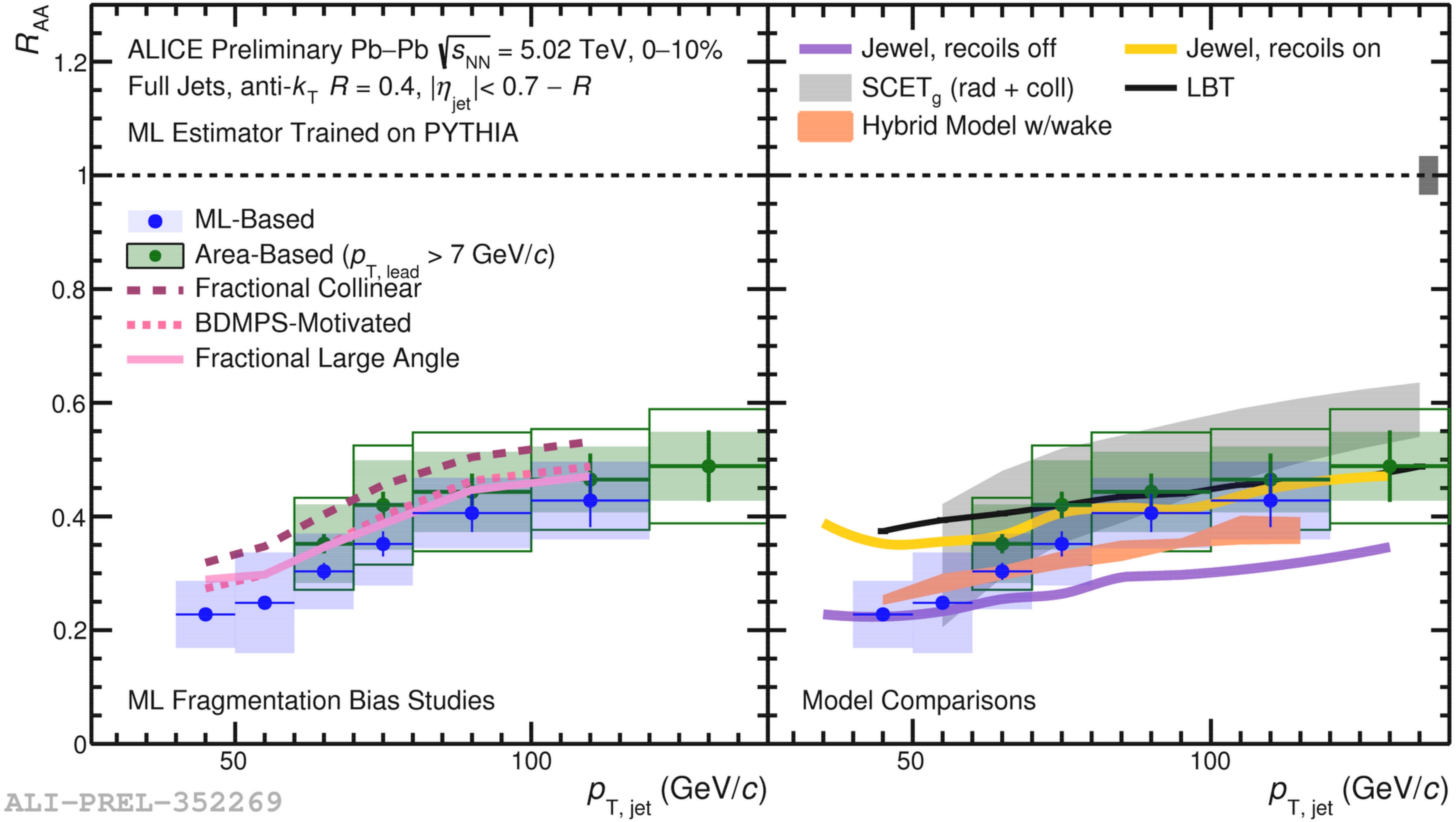
Method is relatively robust to the explored biases!

Lower p_T is a largely unexplored region. Machine learning provides us with an opportunity to study this.



Comparing to models

Keeping previous studies in mind, let's compare to models!



Aiming to constrain models at low p_T with new measurement technique!

JEWEL: Scattering and radiative energy loss, with/without recoiling medium.
JHEP 1707 (2017) 141

SCETg: Interactions with medium mediated by Glauber gluon exchange.
JHEP 07 (2019) 148

Hybrid Model: medium response via wake. AdS/CFT non-pert. regime.
Phys. Rev. Lett. 124, 052301

LBT: hydrodynamic medium, jet-medium interactions, recoils.
Phys. Rev. C 99 (2019) 054911

Conclusions

Low p_{T} and large *R* are less studied regions with inclusive jet probes in HI collisions due to difficulties created by the large fluctuating background from the underlying event.

These measurements are useful in separating out different energy loss effects.

We present a novel machine learning based background correction, which allows for the extension to lower p_{T} and larger *R* than previously possible in ALICE.

See significant jet suppression down to p_{T} accessible by RHIC.

We study the fragmentation bias introduced by training the neural network on the constituents from PYTHIA

$\rightarrow$ do this using a toy model with three different modifications

$\rightarrow$ estimating the effect of these modifications on the R_{AA}

What's next?

Where do we go from here?

Our toy models are only simple tests, how do we get closer to the true case?

→ Train on a quenched MC: JEWEL, JETSCAPE, etc.

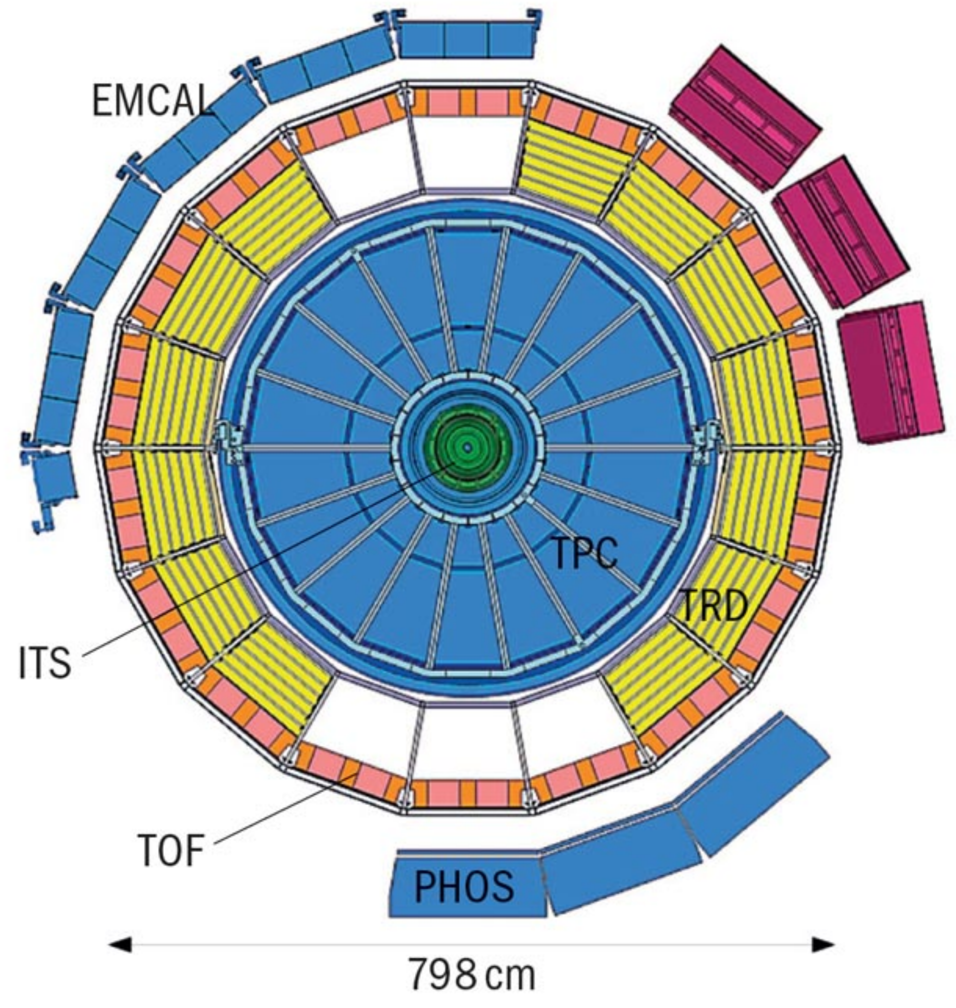
Compare low p_T results with sPHENIX and STAR!

How far can we go in R with ALICE?

Charged particle jets: Limited to R = 0.9 max from eta acceptance of TPC.

Full jets: Limited to R = 0.7 max from eta acceptance of EMCAL.

Let's see how far we can go!



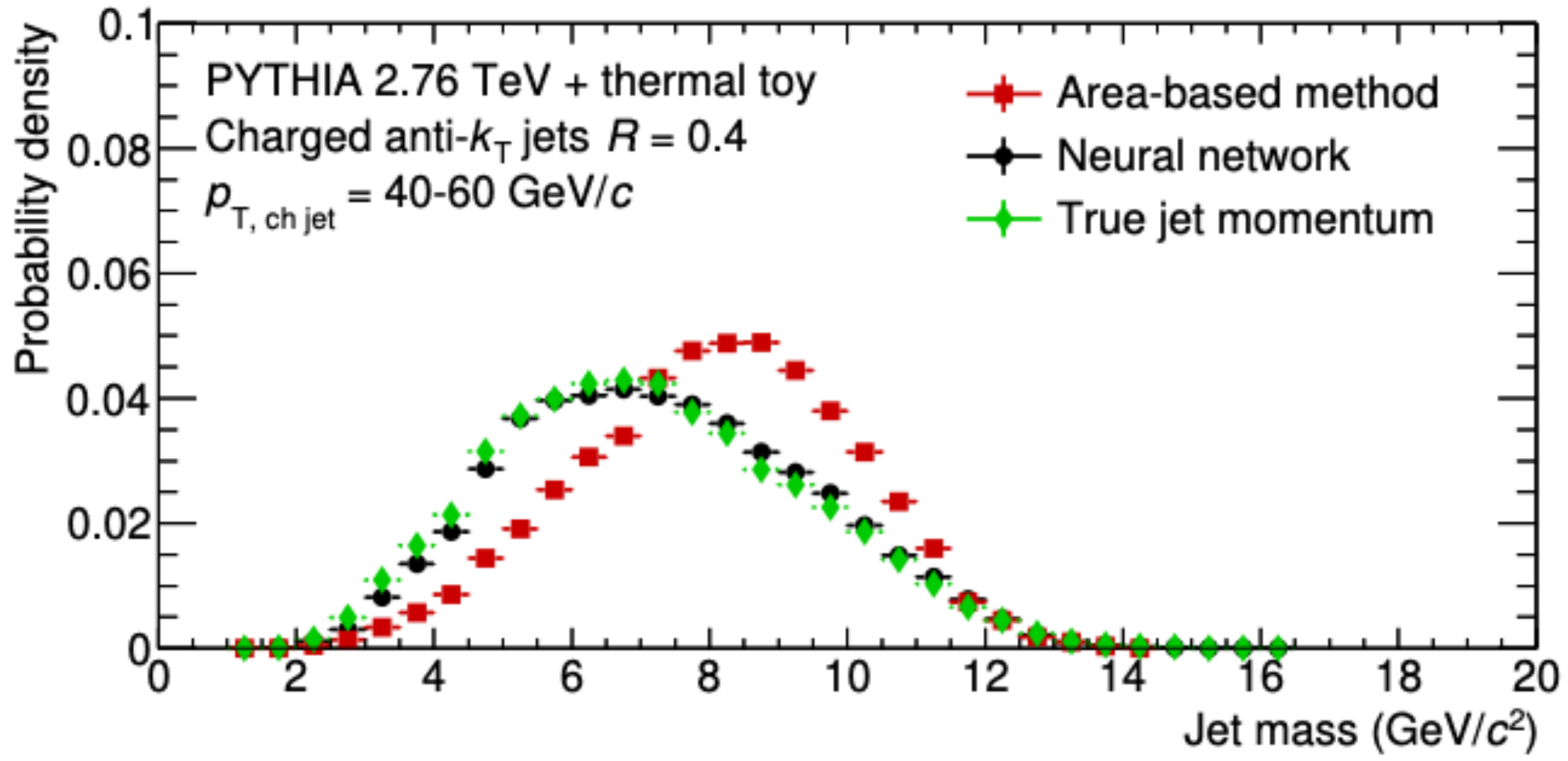
There are also many other methods of reconstructing jet p_T how do these compare?

Eur. Phys. J. C75 (2) (2015) 59

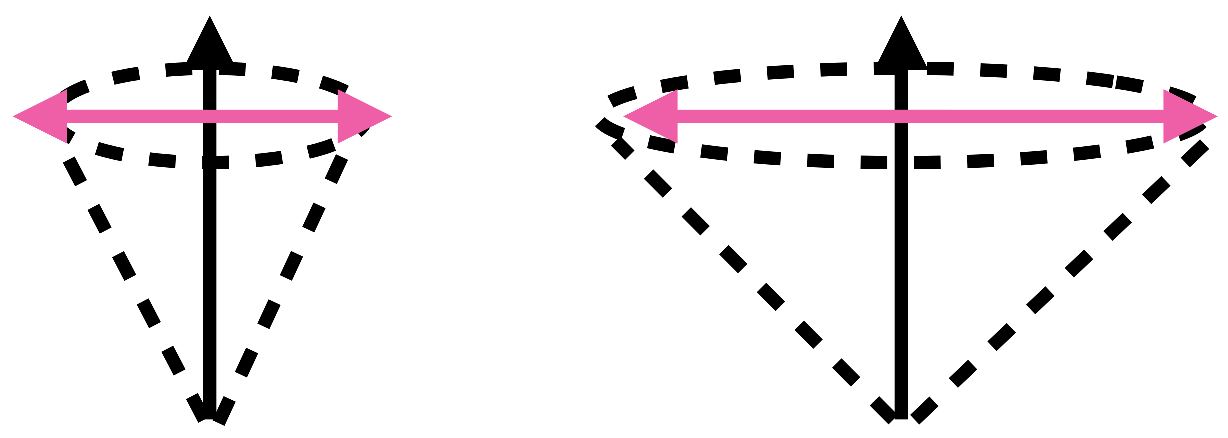
Phys. Rev. D 100 114023 (2019)

What variables can we use ML for?

Jet mass is a good candidate for ML → binned in p_T!



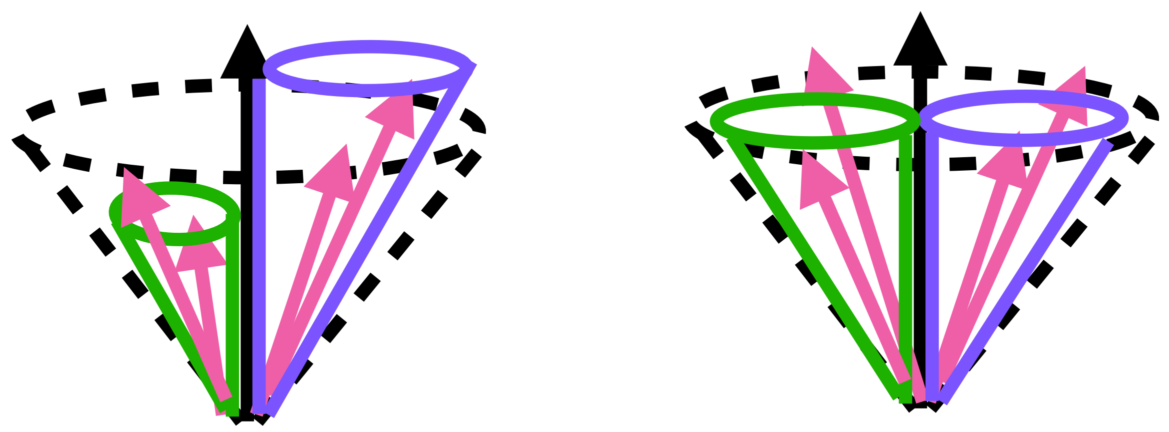
Jet Mass



Already see good performance!

Next frontier: Could we use ML for substructure??

Jet Splittings



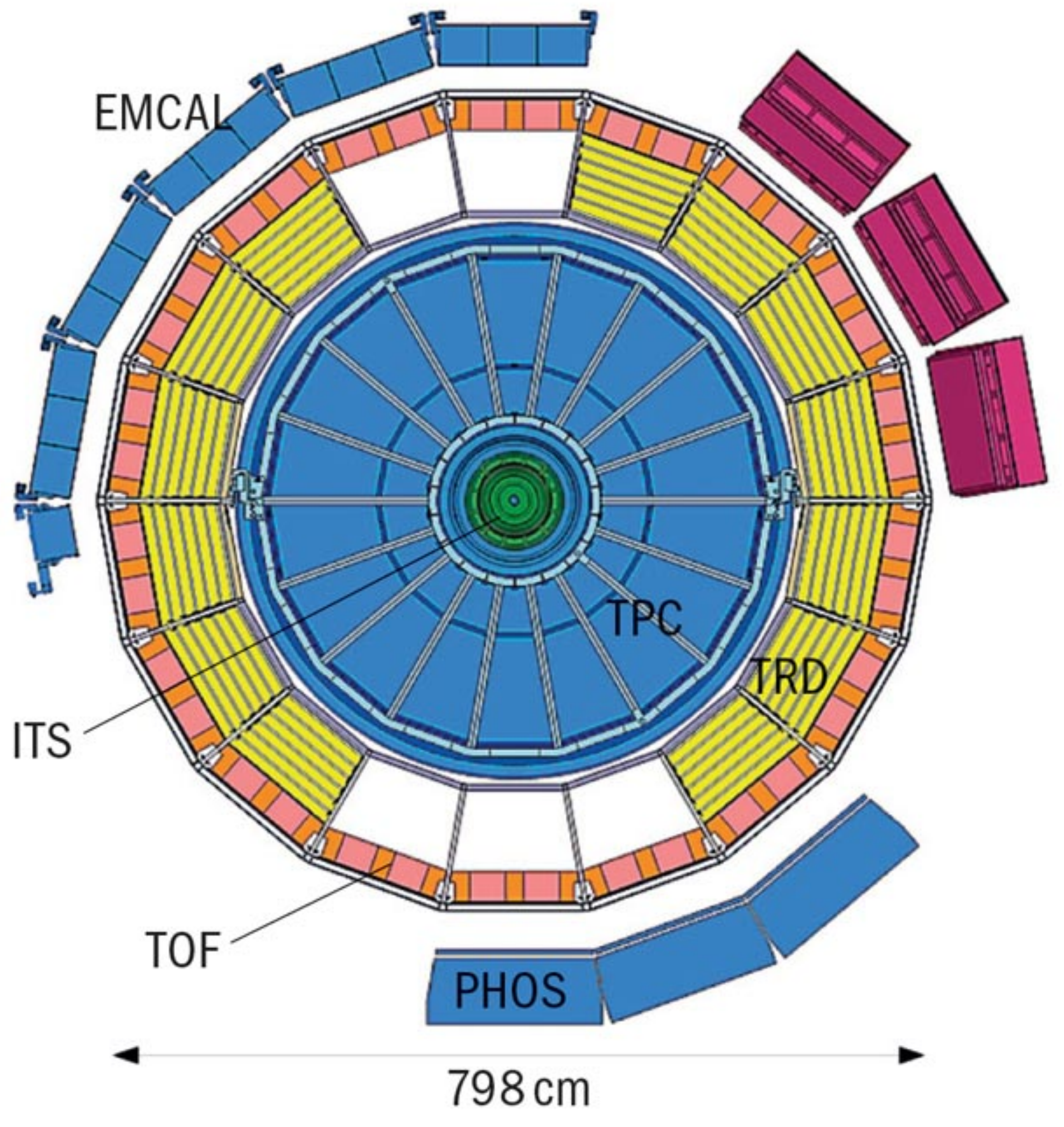
Stay tuned! Thanks!

Backup

Analysis details

Inclusive Pb—Pb jet sample at $\sqrt{s_{\mathrm{NN}}}$ = 5.02 TeV $L \sim 250\ \mu b^{-1}$
with the ALICE detector in 2015.

anti-k_{T} jets with various resolution parameters *R* and centralities



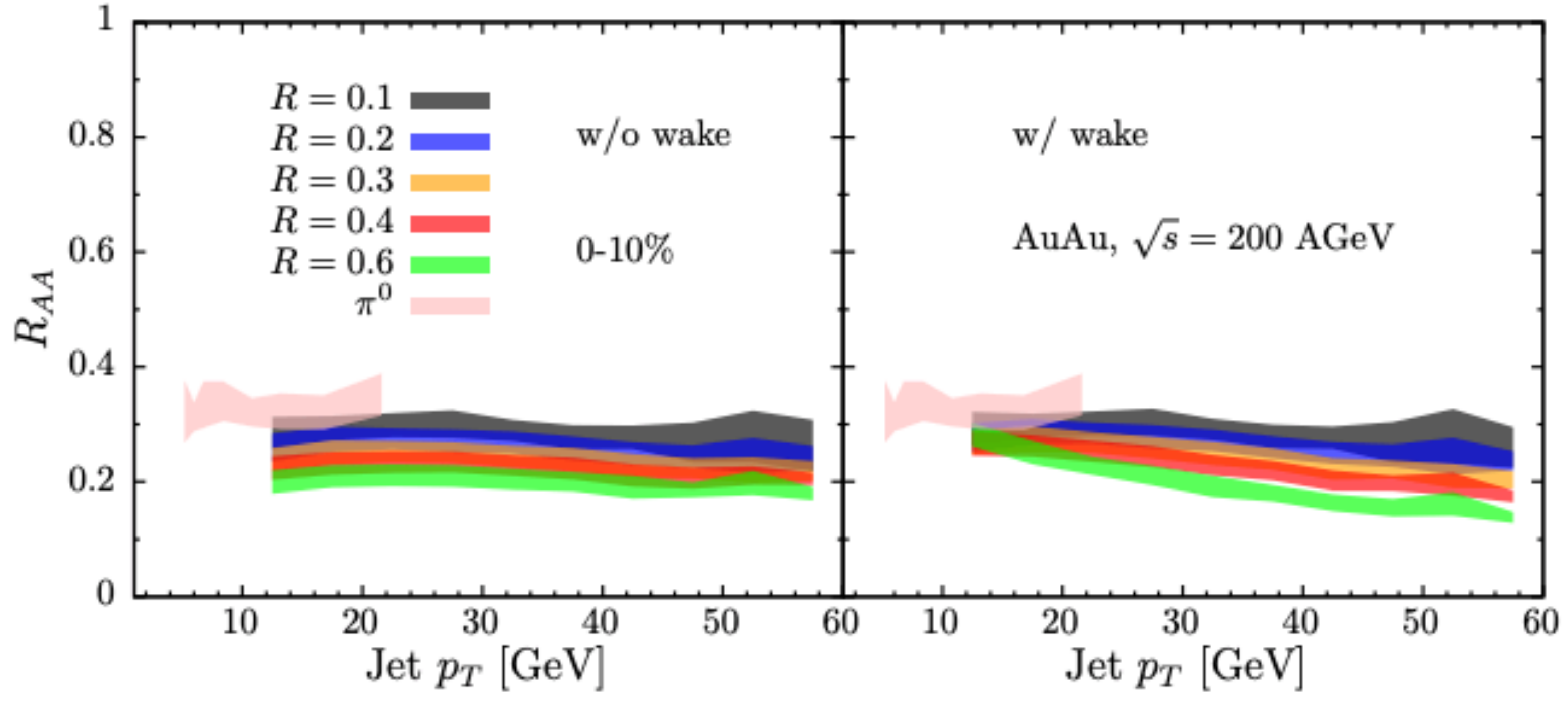
Charged particle jets → contain the charged component of the jet
→ measured with tracking detectors

Full jets → contain charged and neutral components of the jet
→ measured with electromagnetic calorimeter
→ limited to fiducial phi acceptance

Other Theory Predictions

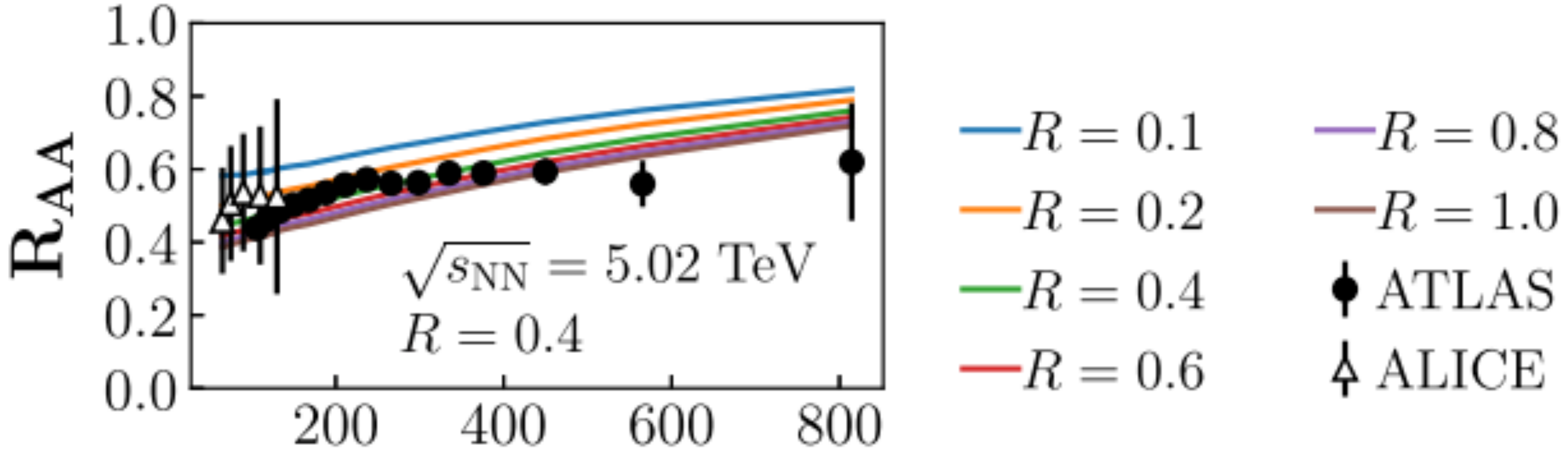
Hybrid Model @ RHIC Energies

See Daniel Pablos's Talk at HP



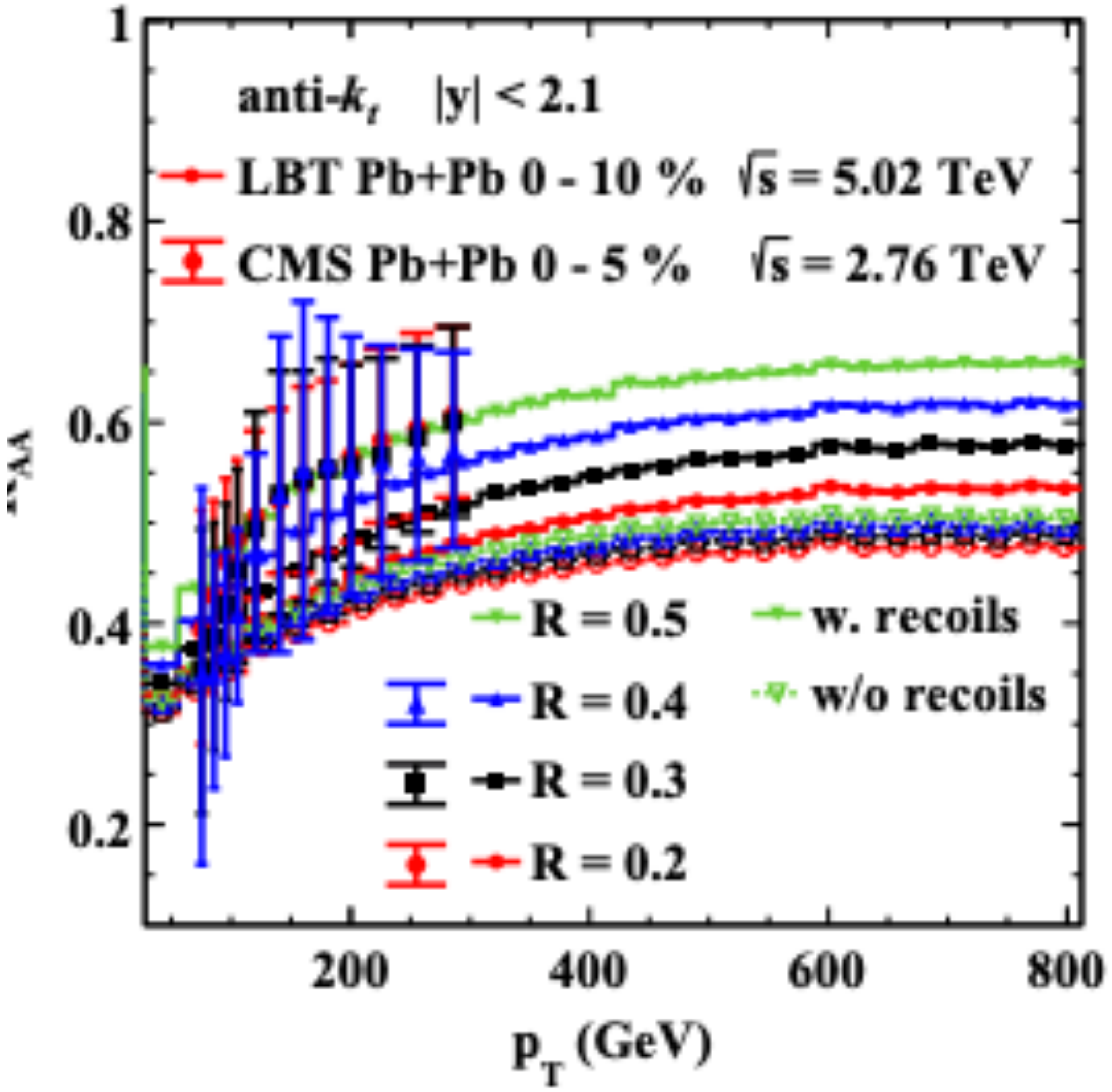
Factorization

Phys. Lett 122 (2019) 252301

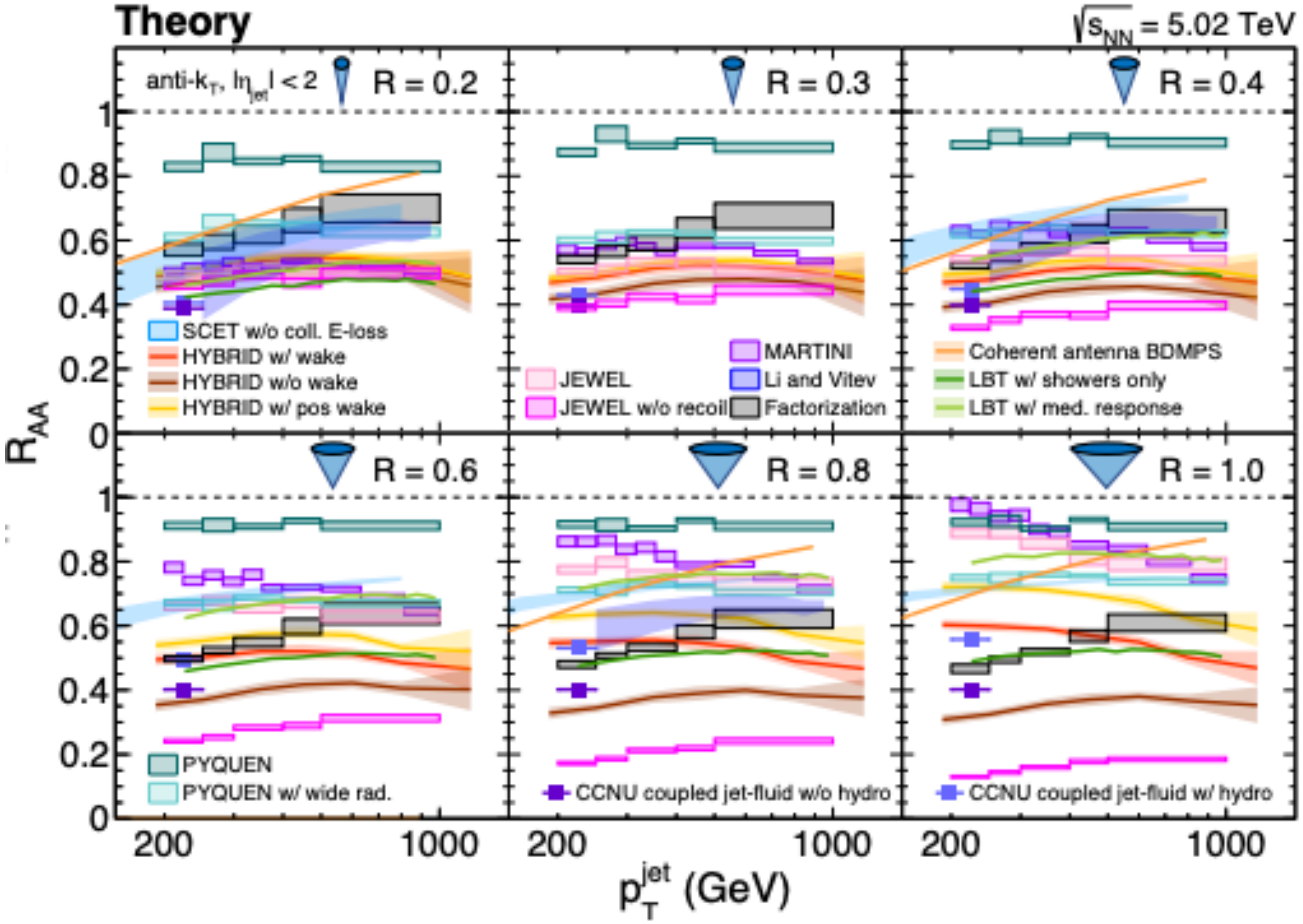


LBT

arXiv: 1809.02525

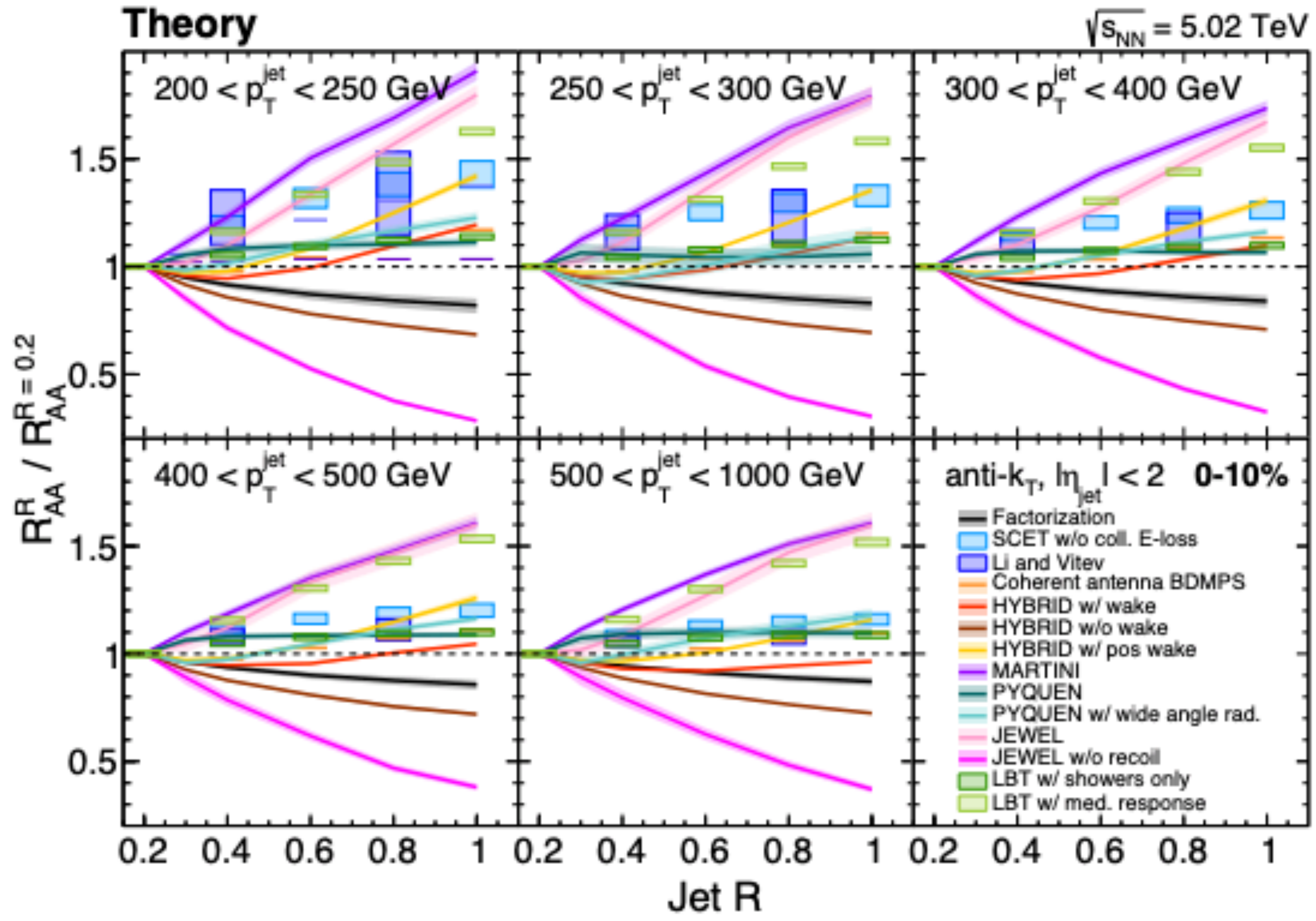


Inclusive jet R_{AA}: theory summary



From Molly Taylor's talk at QM 2019

R dependence from theory: A Summary



From Molly Taylor's talk at QM 2019

Comparing theory underlying mechanisms

With Medium Response

JEWEL (recoils on): Medium recoil without re-scattering.

Hybrid Model: Medium response via wake.

CCNU: Medium recoil and back reaction with re-scattering.

LBT: Medium recoil

Without Medium Response

JEWEL (recoils off)

SCETg

Factorization

BDMPS Toy Model Modification

$$P(\theta_g, \omega) = \alpha\omega\theta_q^3\sqrt{\frac{2\omega}{\hat{q}}}Le^{\frac{-\theta_q^2\omega^2}{\sqrt{2\omega\hat{q}}}}$$

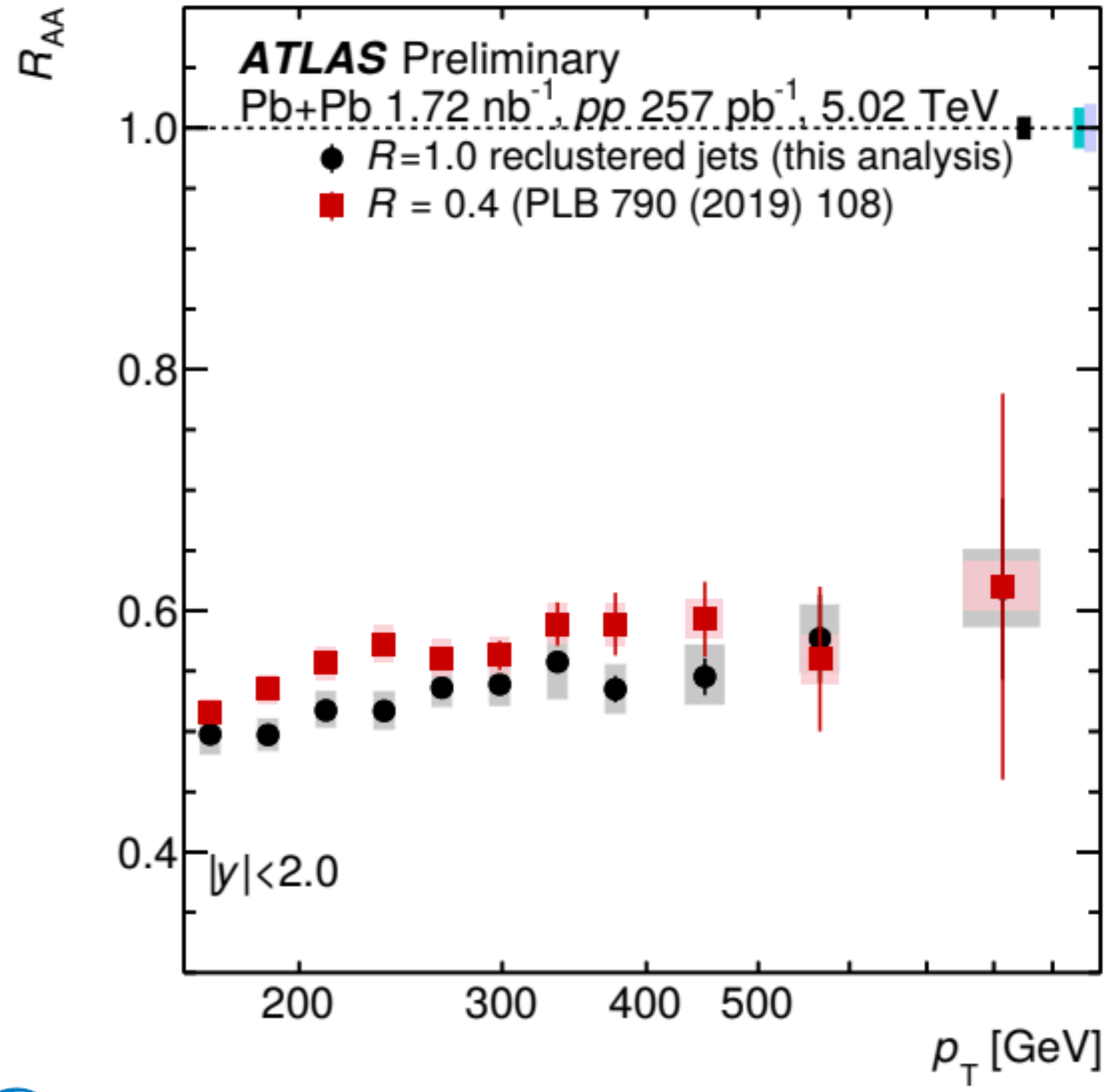
JHEP 0109 (2001) 033

Modify the constituents of the jet by sampling the BDMPS gluon emission spectrum in the emission angle and energy.

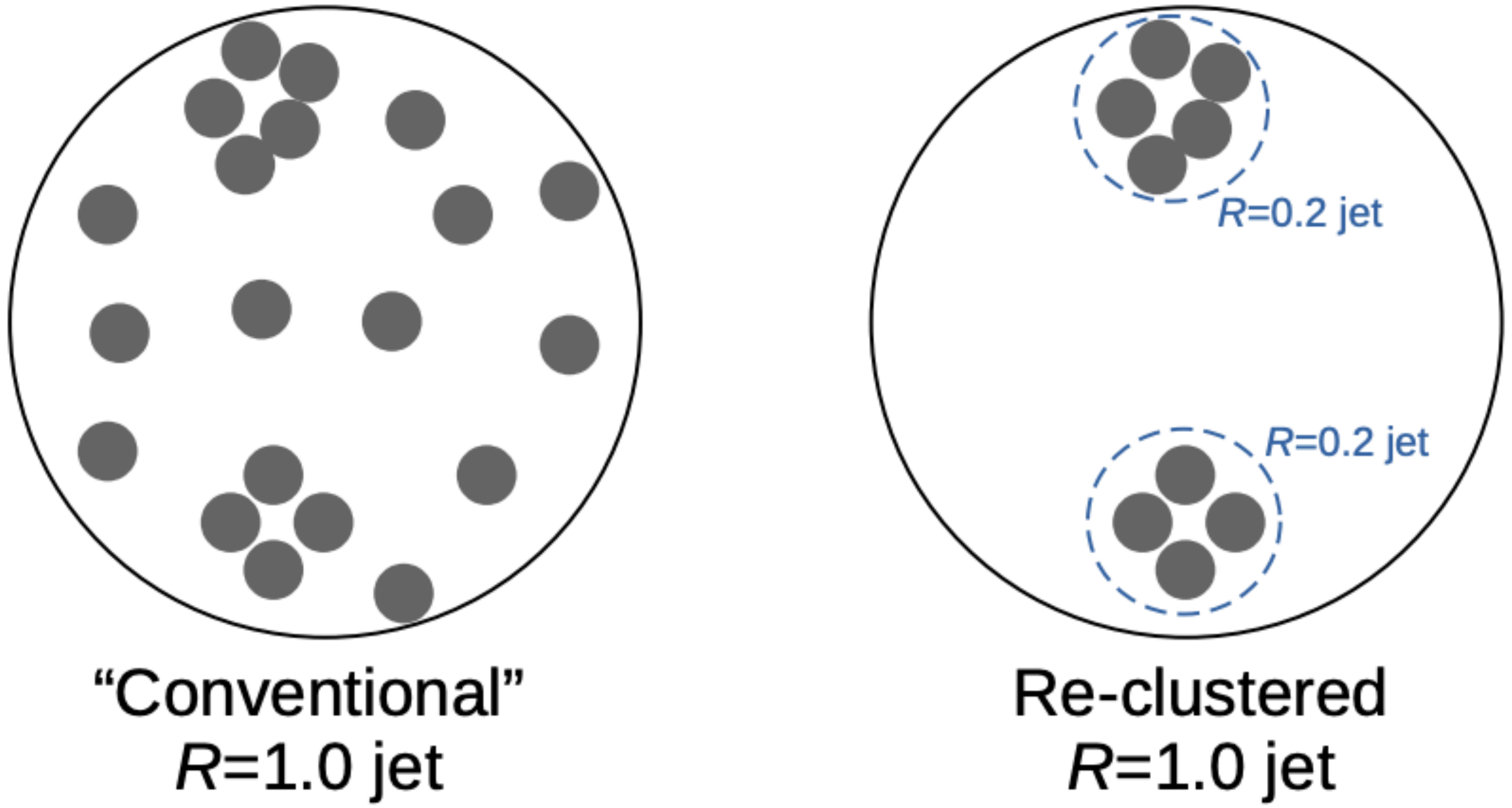
For this study we use values of $\hat{q}$ = 2 and L = 7 fm and p_{loss} = 1.0 .

Motivation behind this is to emit from a probability distribution dictated by quenching theory.

What does experiment say?



Strategy 2: Make R = 1.0 jets using R = 0.2 subjets.



Small increase in R_{AA} with respect to R = 0.4.

ATLAS: High p_T, Large R, Full Jets

ATLAS-CONF-2019-056

HP Talk by Anne Sickles