https://images.squarespace-cdn.com/content/v1/55c902bfe4b04d5c0ca46e55/1689915011911-JVHK60CD56JCBI2ENJ1U/image-asset.jpeg

Hot Jets 2025

Loomis Lab (UIUC), January 8-10

Machine Learning biases in background subtraction to measure jet quenching

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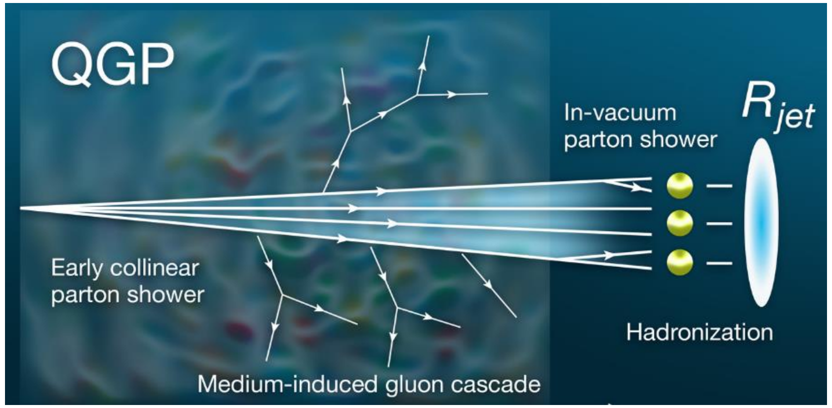
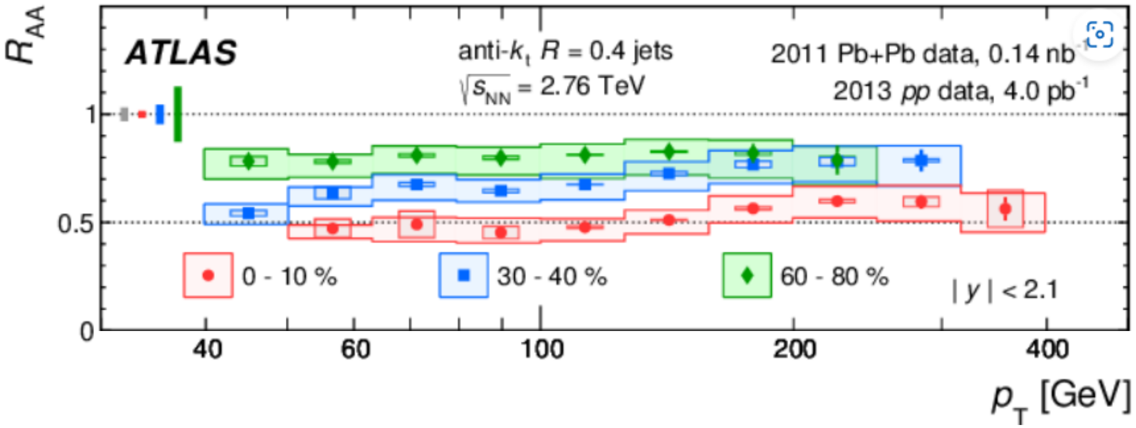
supported in part by
U.S. DEPARTMENT OF ENERGY | Office of Science
Award No. DE-FG02-92ER40713

Motivation: Measure Jet Quenching in QGP

- QGP: hot dense QCD colored medium
  - Generated in ultra-relativistic heavy ions collisions
- Rare, high-pT ("hard") scatterings form early in collisions
  - Traverse the QGP
  - Undergo interactions with the QGP (i.e. "quenching"
- Jets are experimental proxy of QGP:

  => Act like QGP femtoscopy of the QGP via gluon emission and scattering: "jet quenching"

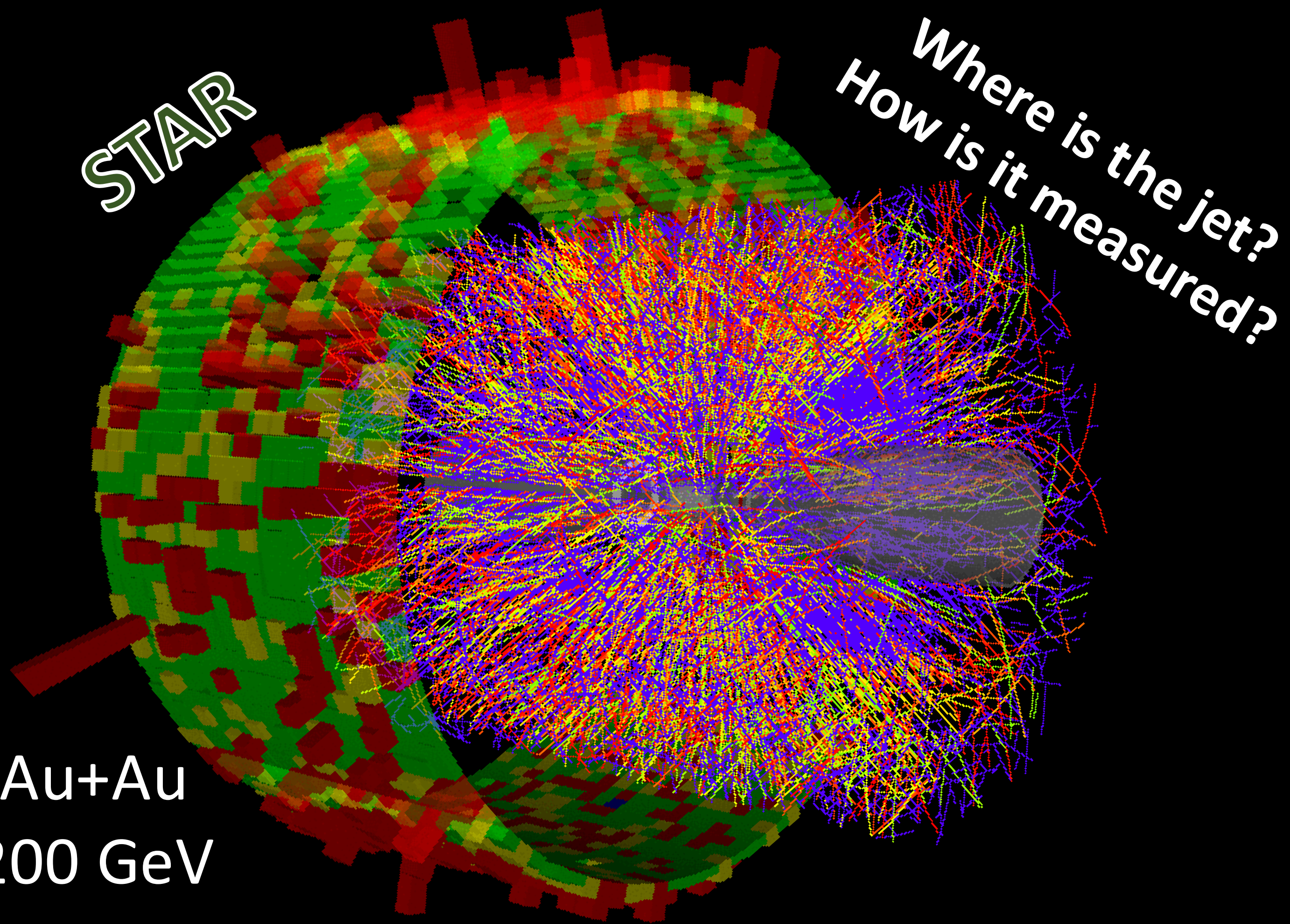




Inclusive R_{AA}^{jet} in central Au+Au at RHIC? – TBD…

https://science.osti.gov/-/media/np/nsac/pdf/reports/2024/2023-NSAC-LRP-Report_Final.pdf
10.1103/PhysRevLett.114.072302

Background in A+A is
very messy



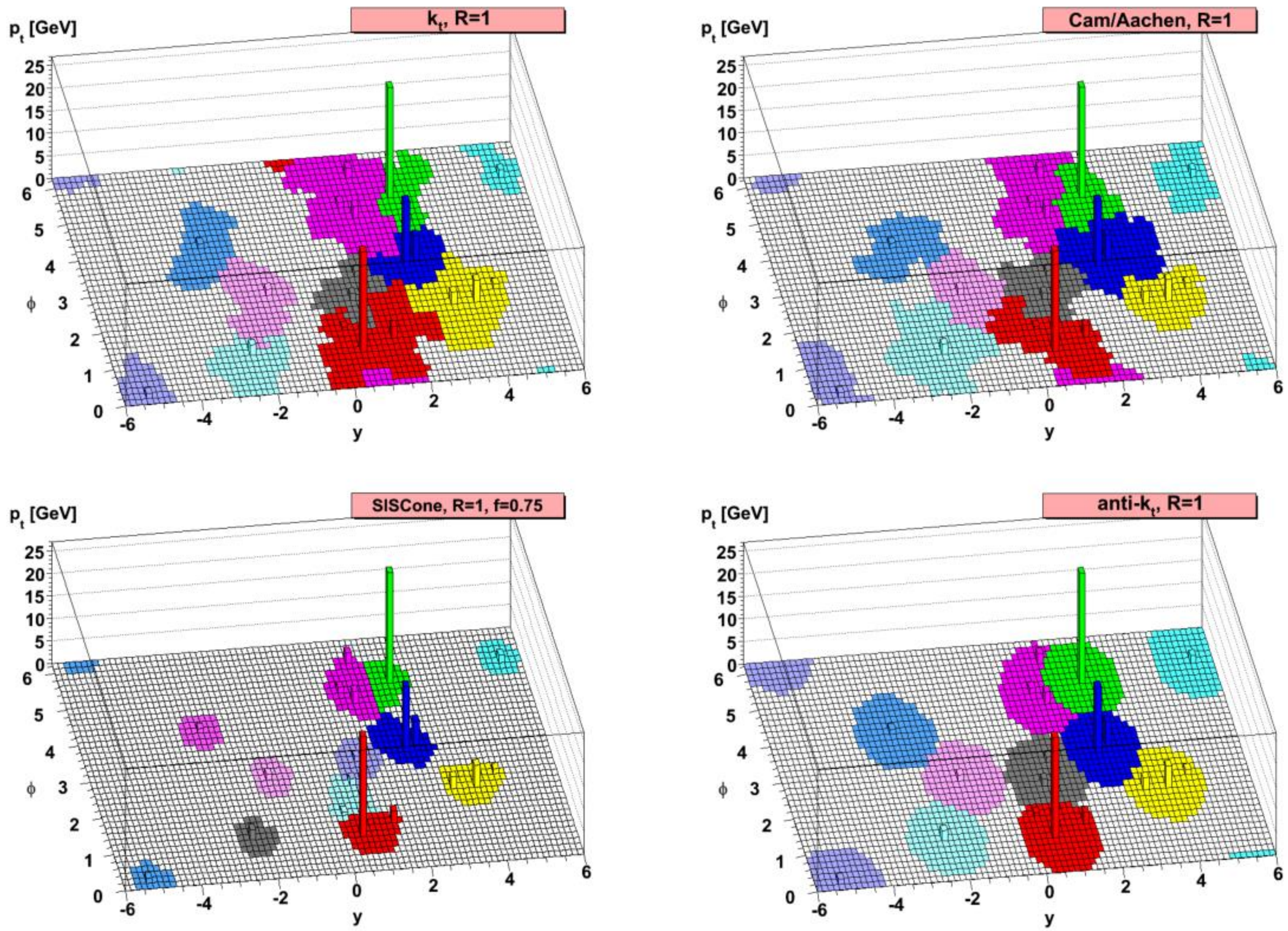
https://www.star.bnl.gov/public/comp/vis/OnLineEventDisplay/AuAu200Animated.gif

Jets – algorithmic clustering

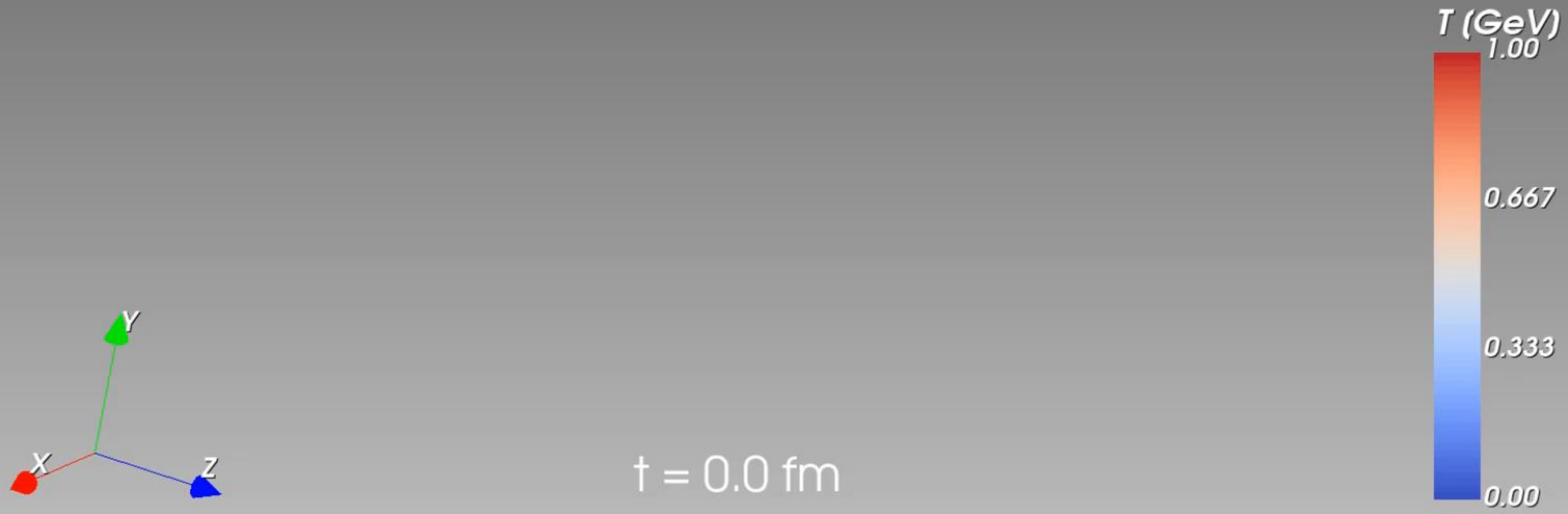
- anti-k_{T} algorithm
  - M. Cacciari and G. Salam (2008)
  - Infrared and collinear safe
  - Fast
- Also: add extra "ghost" (negligible p_{T}) particles & count to measure jet area

➔Result in area-based (AB) method to measure background:

- ➔ Use k_{T} algorithm to find median p_{T} density in jets (ρ_{bkg})
- ➔Correct anti-k_{T} jets as $p_{\mathrm{T}}^{\mathrm{corr}} \equiv p_{\mathrm{T}}^{\mathrm{jet}} - \rho_{\mathrm{bkg}} A_{\mathrm{jet}}$



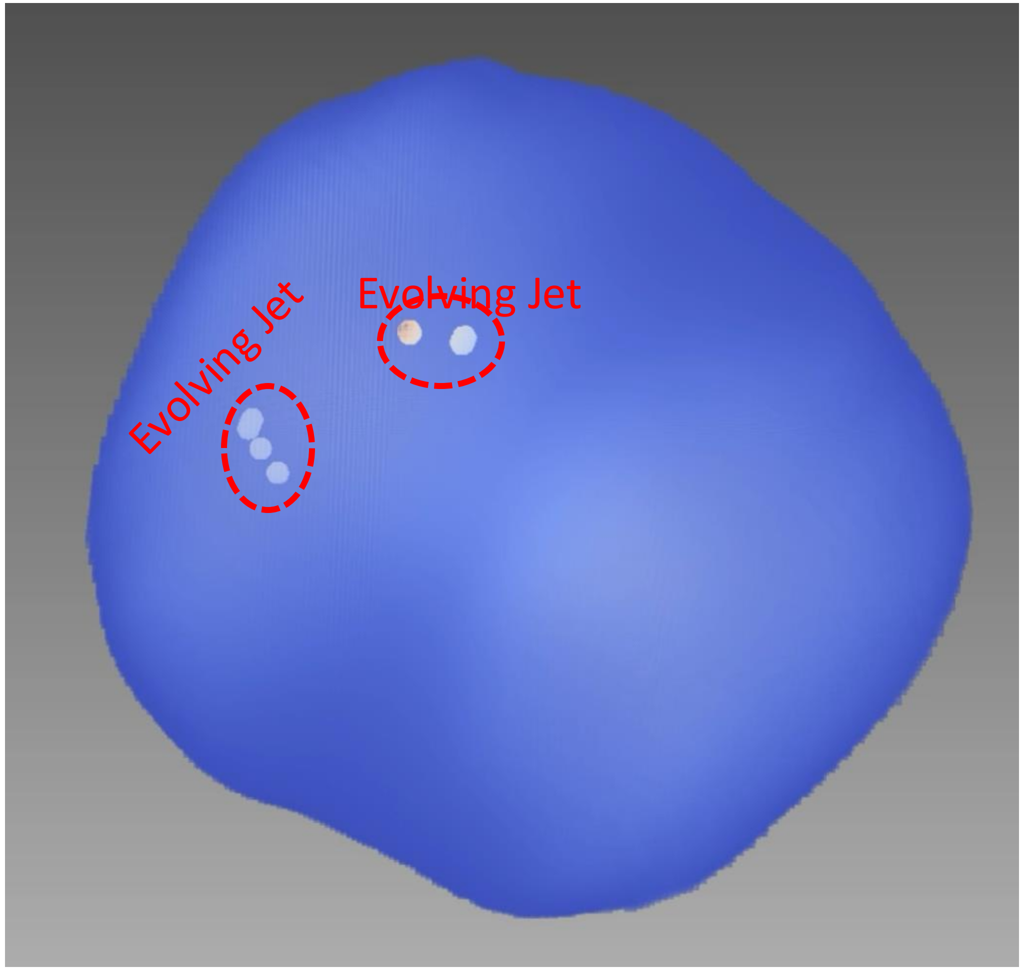
2 jets in an expanding QGP



J. Putschke (WSU) JETSCAPE/XSCAPE

This presentation: JETSCAPE Simulations

- Hydrodynamically flowing QGP
  - Au + Au
  - $\sqrt{s_{\rm NN}} = 200\ \mathrm{GeV}$
- Simulates jet evolution with quenching in QGP
- Provides kinematics of:
  - IP: Initiating Partons (hard scattered)
  - Particles from IP (make “truth” jets)
  - Particles from QGP (background)

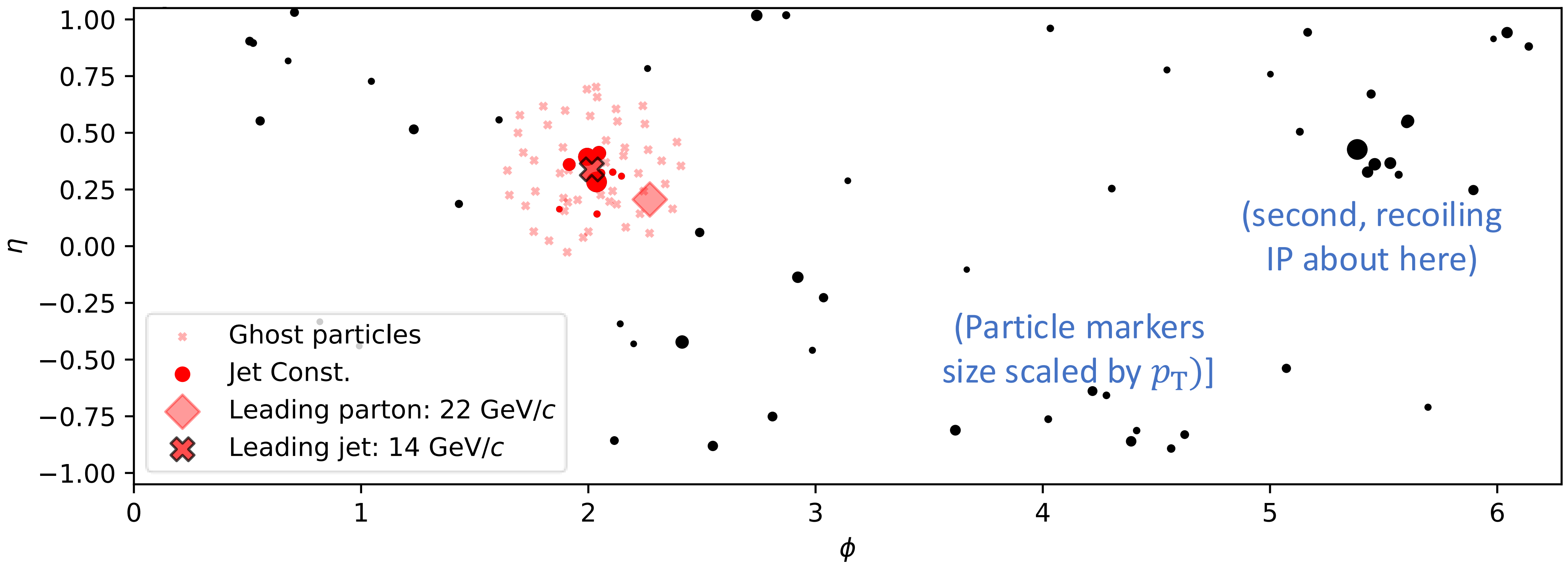


JETSCAPE simulation

Simulation Event Example

Anti-kT clustered jet nearest IP ("truth jet")

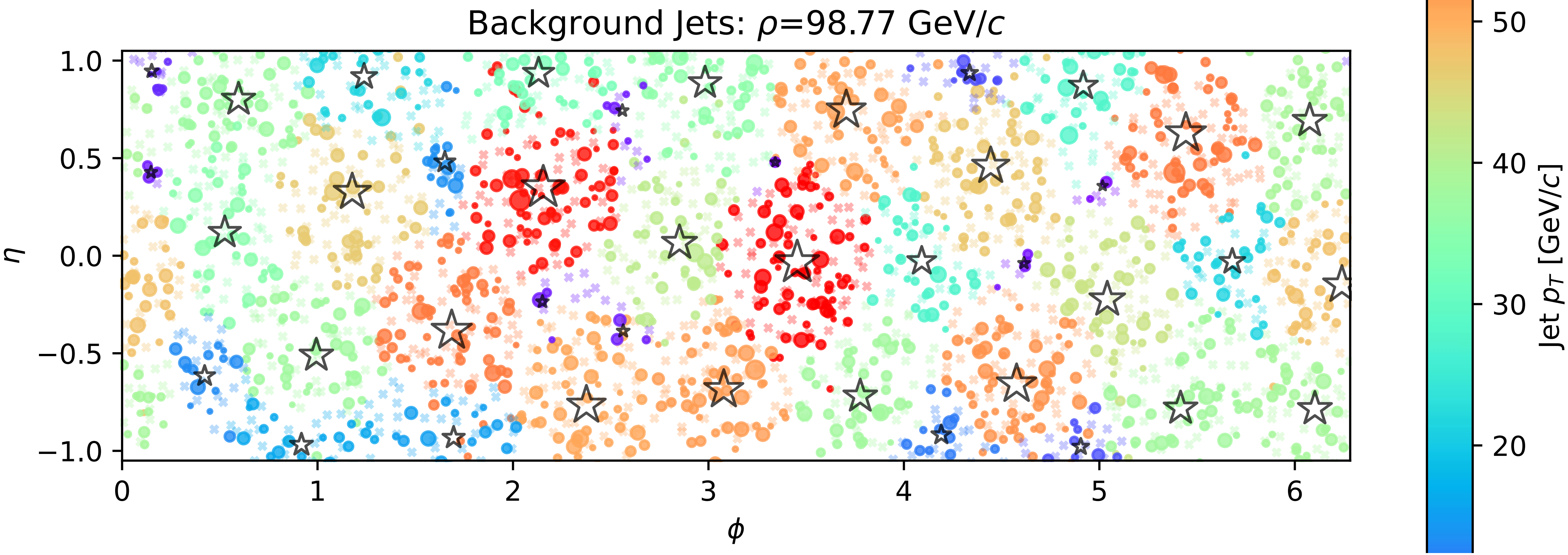
- Truth jet (R=0.4) from leading IP captures about 2/3's of IP's p_T; $p_\mathrm{T,jet}^\mathrm{truth} \approx 0.64\ p_\mathrm{T}^\mathrm{IP}$
- FastJet adds "ghost" particles (negligible p_T)
- Count ghost particles determines the jet area



JETSCAPE simulation

Simulation Event Example

anti-k_T clustering with background



Result: Area-Based ("AB") Method for p_{T} correction

Residual error $(\delta p_{\mathrm{T,jet}})$ dominated primarily by local ρ_{bkg} fluctuations

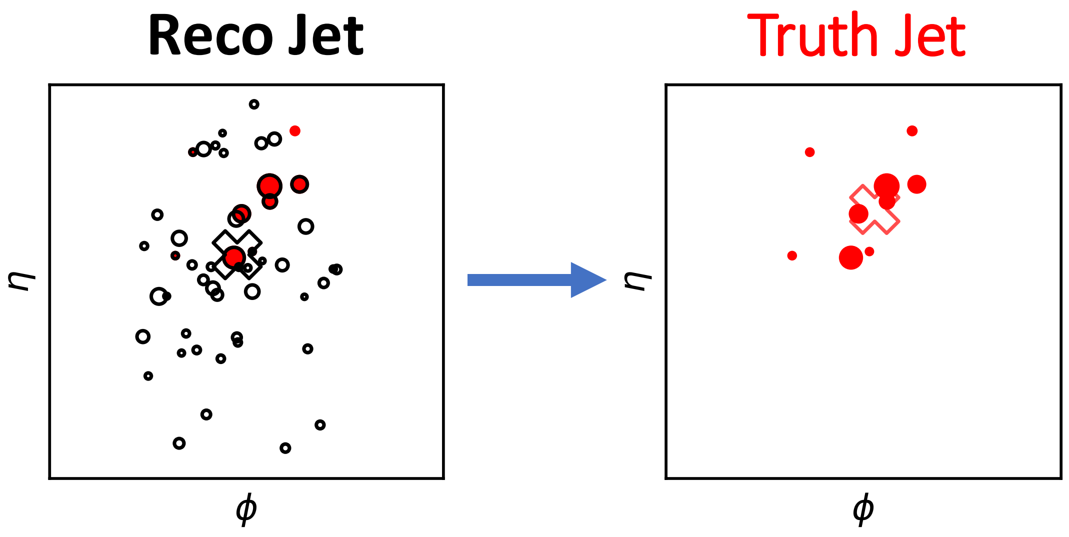
Pros:

- Fluctuations of ρ_{bkg} directly measured with lots of data
- Independent of jet substructure

Cons:

- Limited precision

  e.g., for $R = 0.4$ jets in 200 GeV Au+Au collisions:
  $\langle \delta p_{\mathrm{T,jet}} \rangle \sim 8\ \mathrm{GeV}/c$



remove pedestal

$$p_{\mathrm{T,jet}}^{\mathrm{reco}} \rightarrow \boxed{-A_{\mathrm{jet}}\rho_{\mathrm{bkg}}} \rightarrow p_{\mathrm{T,jet}}^{\mathrm{corr}}$$

metric for background correction

$$\delta p_{\mathrm{T,jet}} \equiv p_{\mathrm{T,jet}}^{\mathrm{corr}} - p_{\mathrm{T,jet}}^{\mathrm{truth}}$$

$$\mathrm{i.e.:}\ \delta p_{\mathrm{T,jet}} \equiv p_{\mathrm{T,jet}}^{\mathrm{reco}} - \rho_{\mathrm{bkg}} \mathrm{A}_{\mathrm{jet}} - p_{\mathrm{T,jet}}^{\mathrm{truth}}$$

Can we do better?

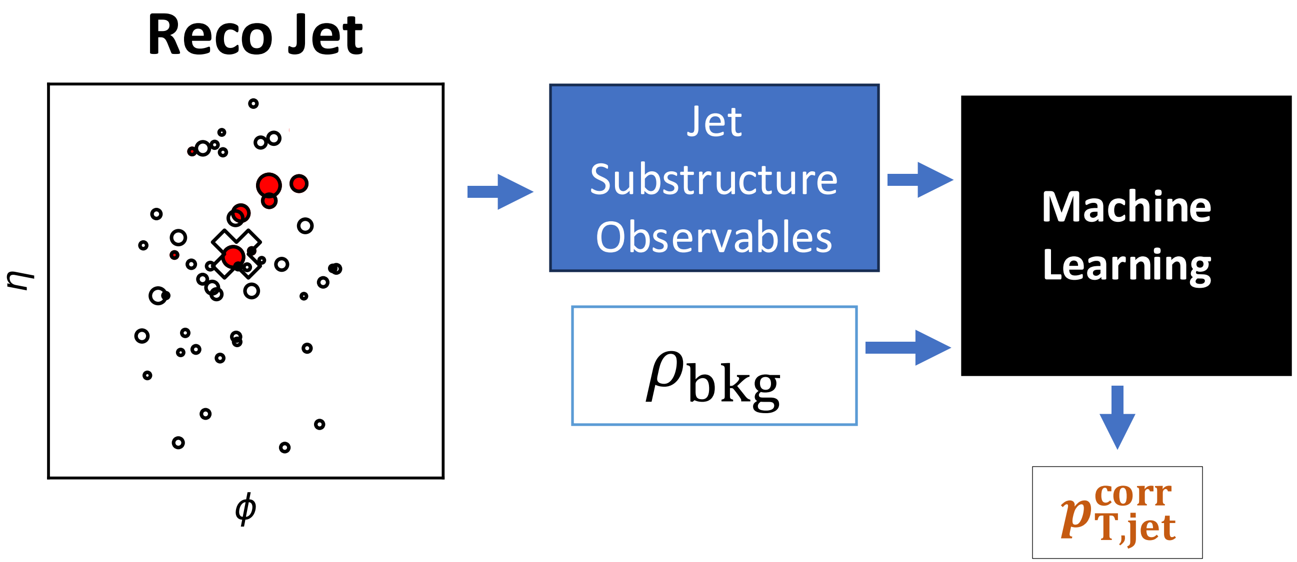
There are very good Monte Carlo simulators for vacuum jets:

- 40+ years of development using pQCD calculations and fine-tuned models for fragmentation and hadronization

⇒ In vacuum, we have very good models of truth jet substructure

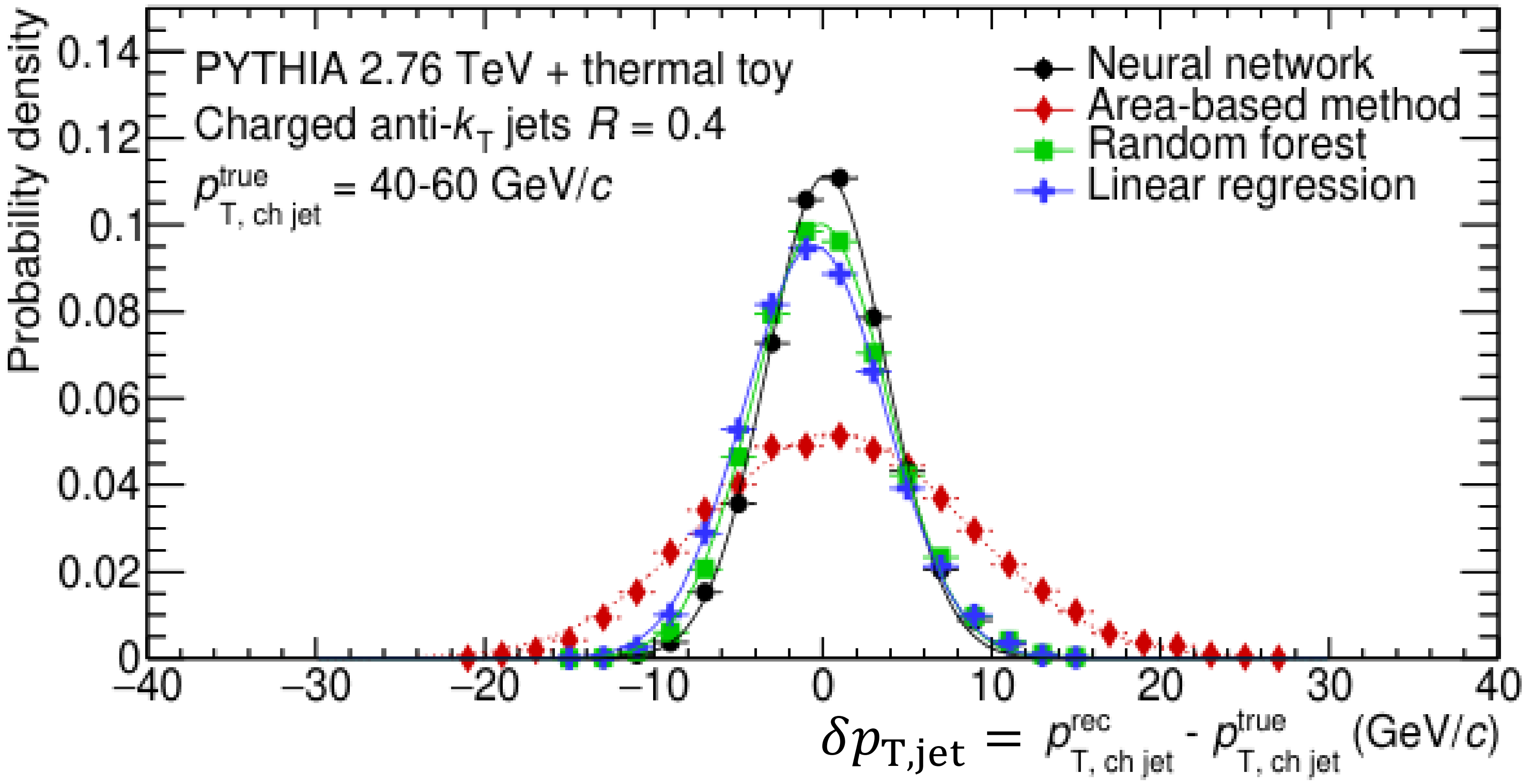
⇒ Embed into background, and measure reco jet substructure

⇒ Train machine learning (ML) to find truth jet $p_{\mathrm{T,jet}}^{\mathrm{true}}$



$$\delta p_{\mathrm{T,jet}} \equiv p_{\mathrm{T,jet}}^{\mathrm{corr}} - p_{\mathrm{T,jet}}^{\mathrm{truth}}$$

Studies show this works for vacuum jets!



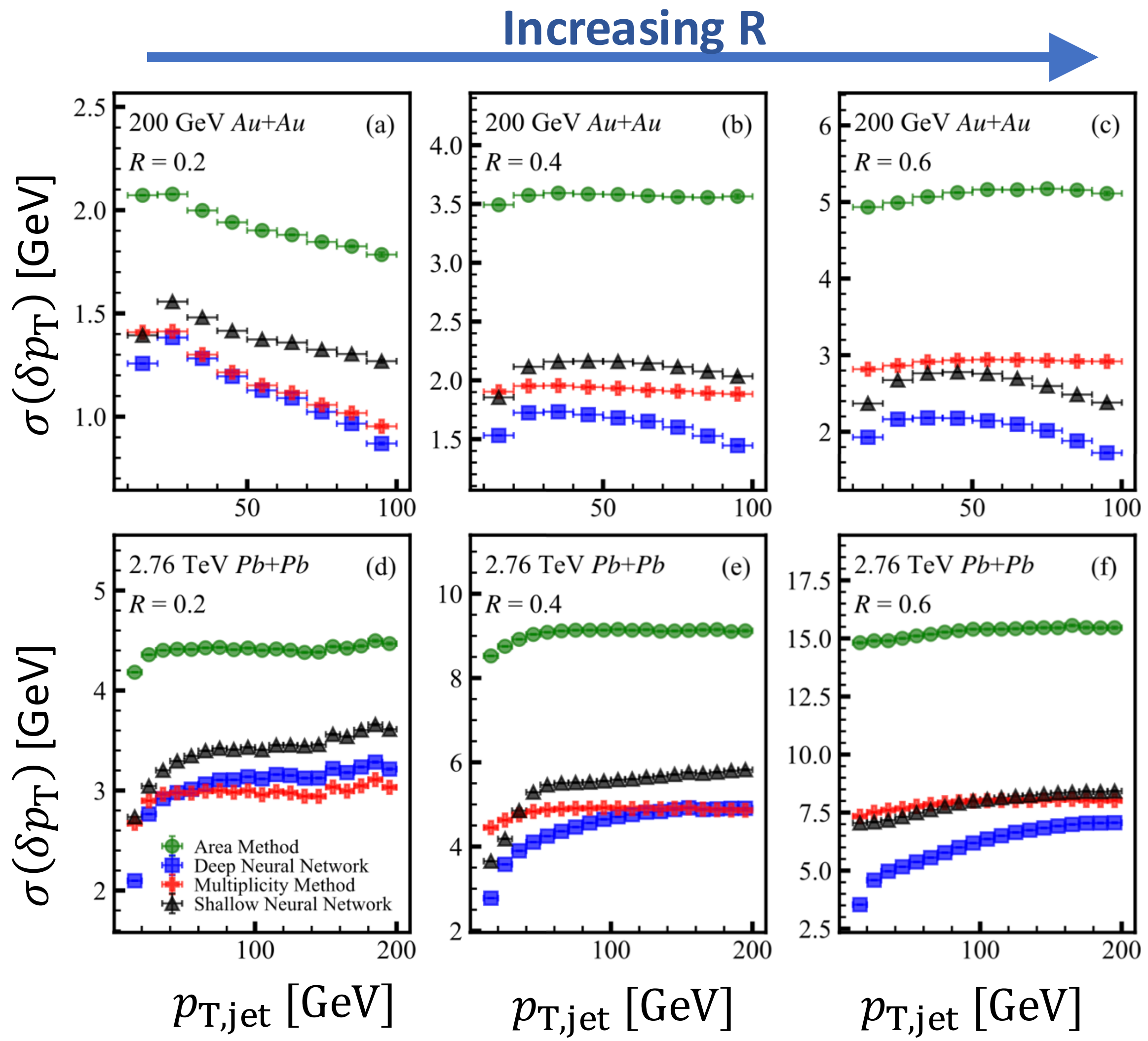
R. Haake and C. Loizides (2019), arXiv:1810.06324 [nucl-ex]

Improvements in $\delta p_{\mathrm{T,jet}}$ are more significant at larger jet R

- If we understand the fragmentation (and particularly in this study the multiplicity)

⇒ We get significant decrease in $\delta p_{\mathrm{T,jet}}$ at all jet resolution parameters

⇒ Gains become more important at larger jet R



Put another way, this is OK:

Machine Learning is trained on vacuum jets …

… ML results: smaller $\delta p_{\mathrm{T,jet}}$ distributions

But what about this?

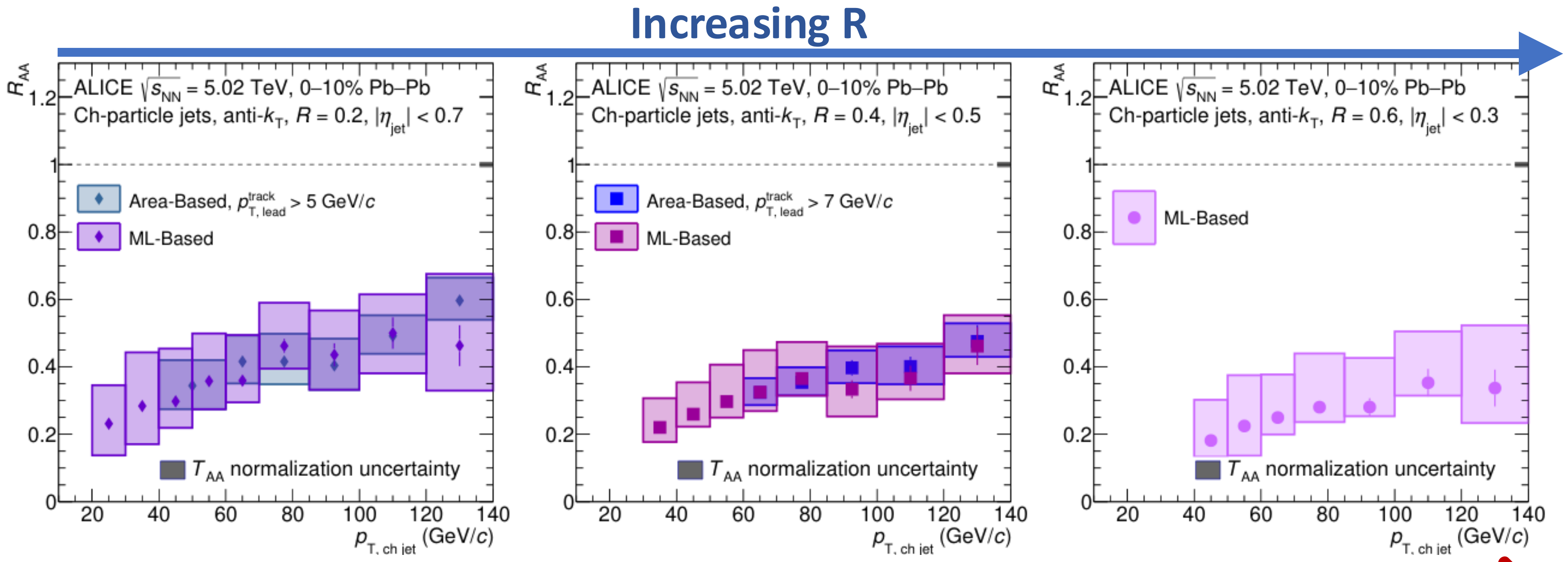
Machine Learning is trained on vacuum jets …

Vacuum Jet + Heavy Ion Background → **Machine Learning** ← Vacuum $p_{\mathrm{T,jet}}^{\mathrm{truth}}$

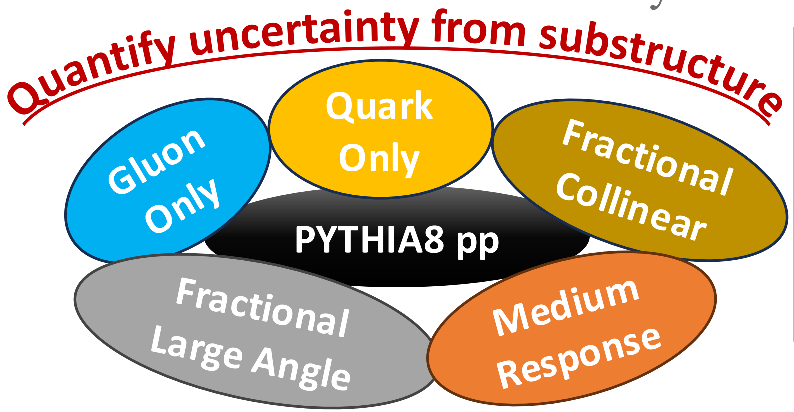
→ how is δp_{T} biased from quenching?

Quenched Jet In Heavy Ion Background → **Machine Learning** → Quenched $p_{\mathrm{T,jet}}^{\mathrm{corr}}$

Results: ALICE, Pb+Pb @ 5.02 TeV: Quantified uncertainty and published



Phys. Lett. B 849, 138412 (2024), arXiv:2303.00592 [nucl-ex]

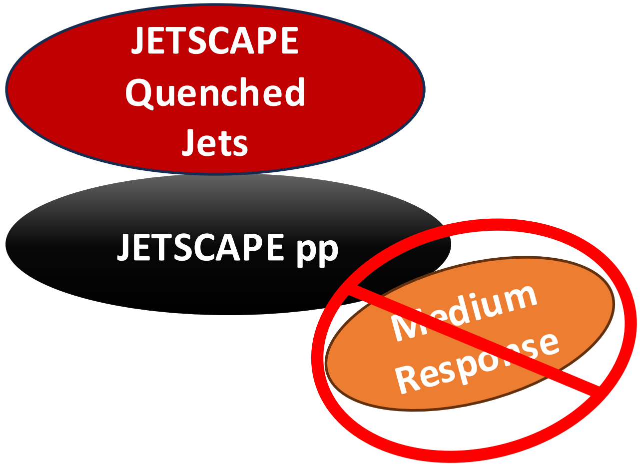


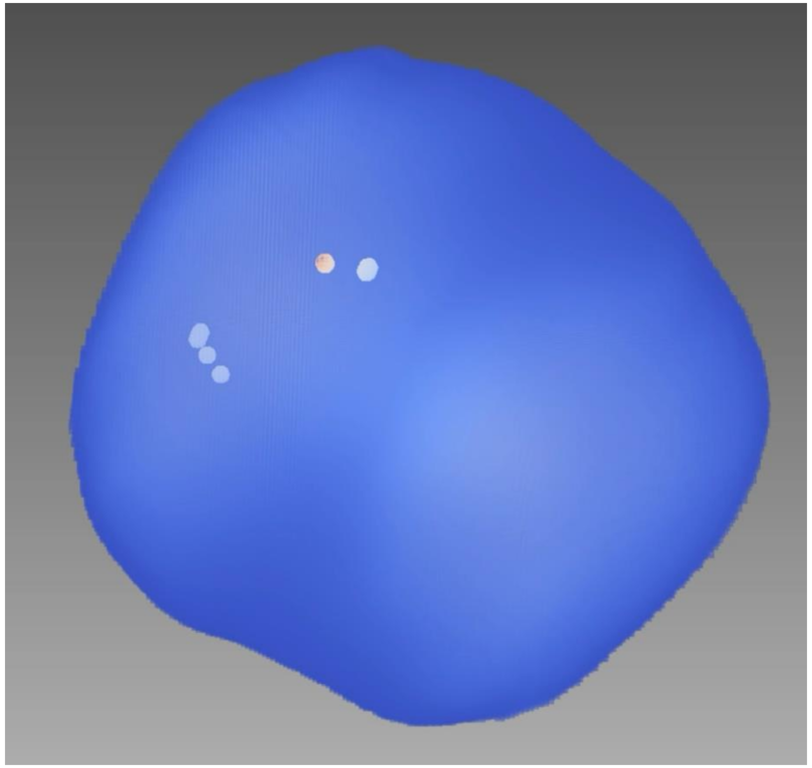
(from reference): *There are three points where the ML-based procedure is sensitive to jet fragmentation:*

- *measured input spectra*
- *the response matrix*
- *and the training*

This study: $\delta p_{\mathrm{T,jet}}$ evolution and bias (at RHIC kinematics)

JETSCAPE:
- Uses a virtuality dependent quenching mechanism
- Calibrated hydrodynamic QGP evaluation
- Quenching parameters fixed via Bayesian analysis
- Medium response not currently included (i.e. jet is quenched by medium, but medium isn't influence by jet)





D. Everett et al. (JETSCAPE), Phys. Rev. C 103, 054904 (2021), arXiv:2011.01430 [hep-ph]
A. Kumar et al. (JETSCAPE), Phys. Rev. C 107, 034911 (2023), arXiv:2204.01163 [hep-ph]

Evolution of quenching and result on ML bias

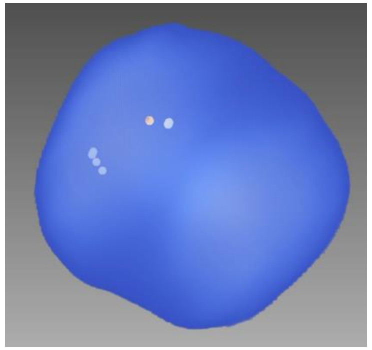
Want to see progression of effects:
no quenching → expected quenching → beyond expected quenching

- Path not taken (computationally expensive)
  - Run many hydro events while incrementing the jet interaction strength parameter $\hat{q}$
- Path actually taken (computationally "cheap"):
  - Quench jets in constant length "bricks" of QGP
  - Observe effects at incrementing brick lengths
  - Find brick length which approximates the quenching in hydro

Expensive Simulations: Hydro

Background from hydro evolved QGP

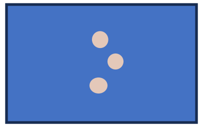
"hydro" jets -- jets quenched in the evolving QGP



200 GeV Au+Au Collisions

"Cheaply" Simulated Jets

"brick jets": Jets quenched in constant length bricks of QGP



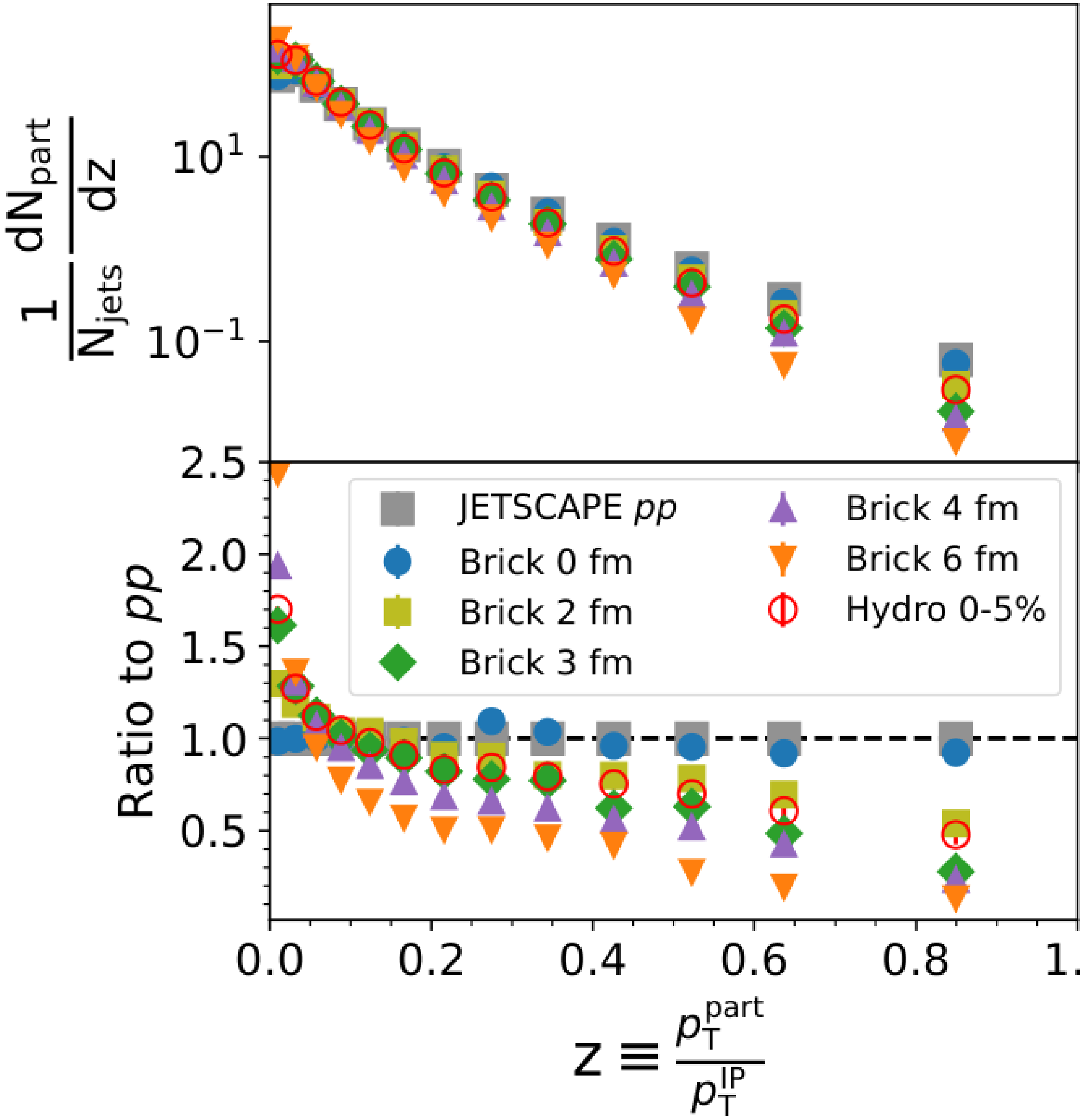
Also "cheap"

"pp jets": vacuum (not quenched) jets

What quenching looks like:

- Quenching induces gluon emission (essentially "gluon bremsstrahlung")
  - → makes more low-p_{T} constituents
- Inspect number of constituents in truth jet for:
  - pp jets
  - Jets quenched in QGP bricks
  - Jets quenched in QGP hydro

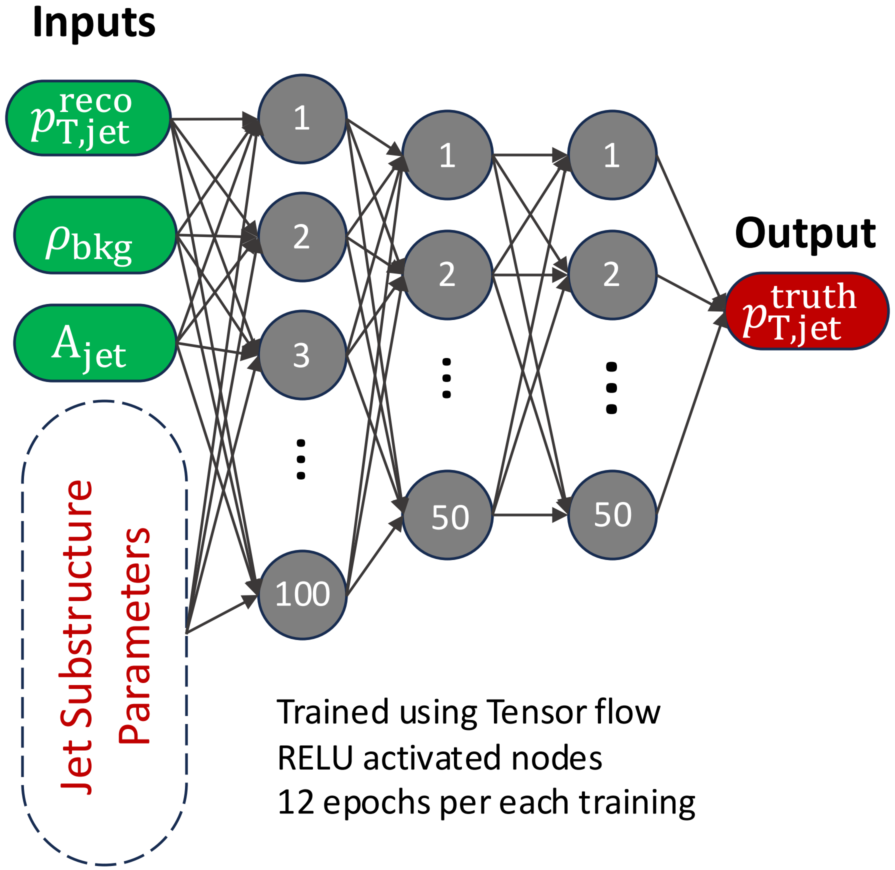
(In this metric) 3.5 fm QGP brick approximates the hydro quenching



Note: z defined as constituent p_{T} ratio to the jet initiating parton, rather than the jet p_{T}

Trained 5 Neural Networks

Data: *pp* jets embedded in hydro background



Trained using Tensor flow
RELU activated nodes
12 epochs per each training

Details
Paper: https://arxiv.org/abs/2412.15440
Code: https://github.com/david-stewart/jet_and_thermal

Parameters per neural network:

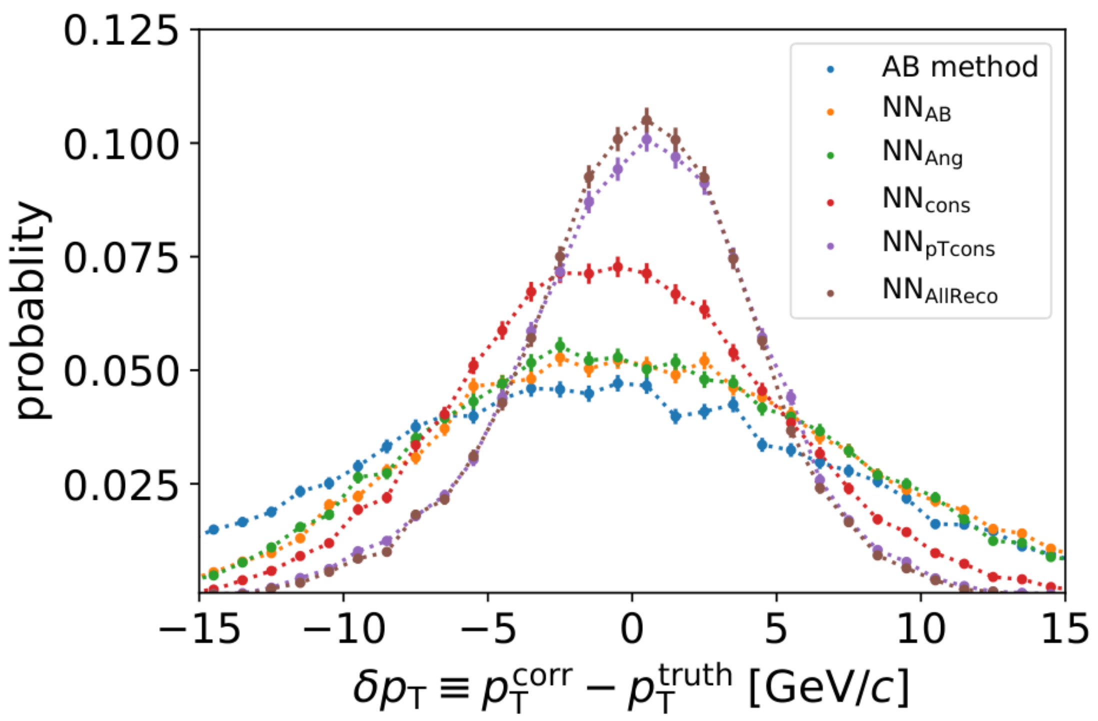
- $\mathrm{NN_{AB}}$: none (used to compare to AB method)
- $\mathrm{NN_{Ang}}$: Angularity: $\sum_{i=1}^{N} p_{\mathrm{T},i} \Delta R_i$
  (where ΔR is η-ϕ distance from constituent to jet axis)
- $\mathrm{NN_{Ncons}}$: Number of constituents (N)
- $\mathrm{NN_{pTcons}}$: p_{T} of highest 10 p_{T} constituents
- $\mathrm{NN_{AllReco}}$: All the parameters above together

Kinematic cuts:

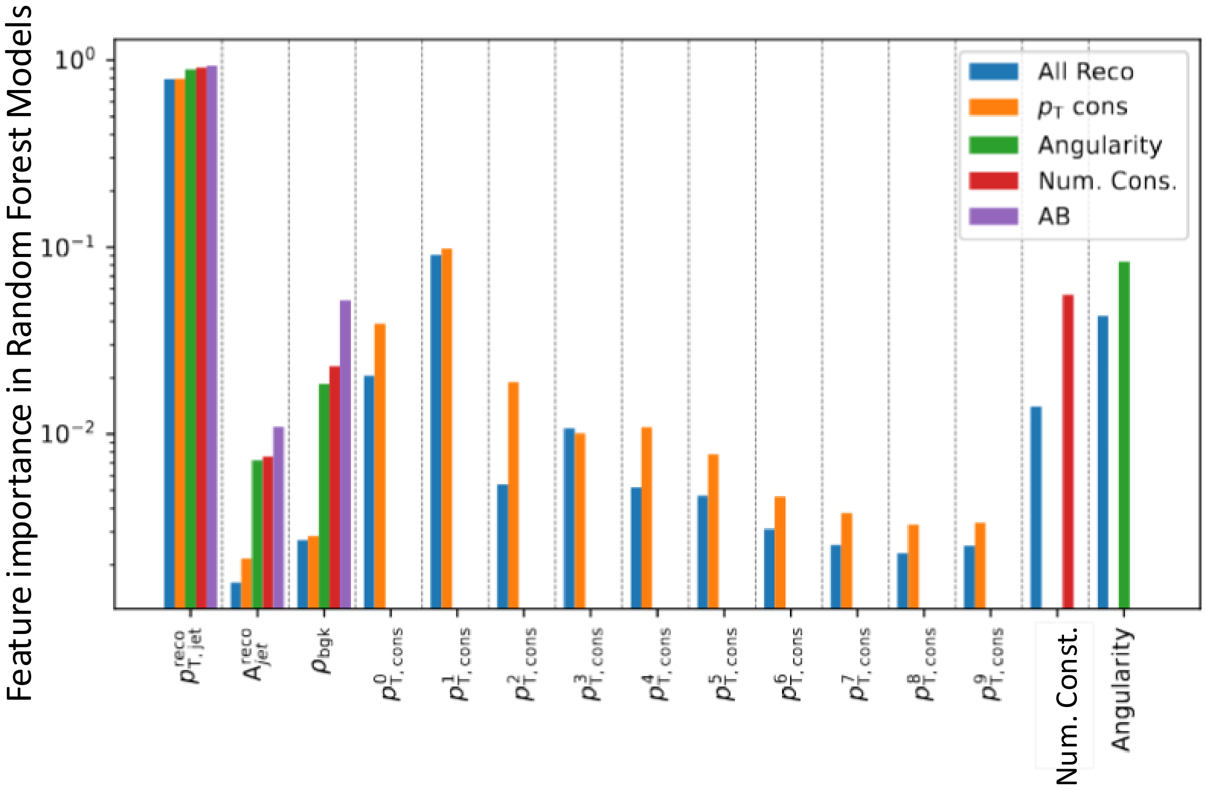
- At mid-rapidity (matches RHIC experiments)
- Only jet matched to high-p_{T} IP per event

NN on pp jets embedded in hydro background:

Machine learning finds strong discriminatory power from constituent p_T (particularly 2nd highest one)



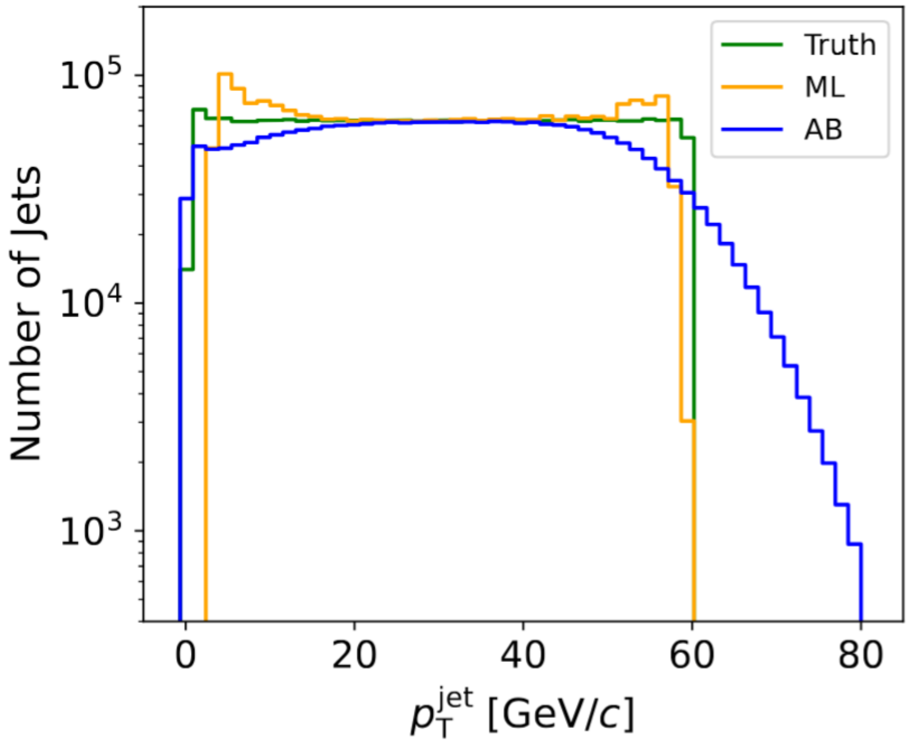
Residual error for jets from events with $\hat{p}_T \in [30,31]$ GeV/c



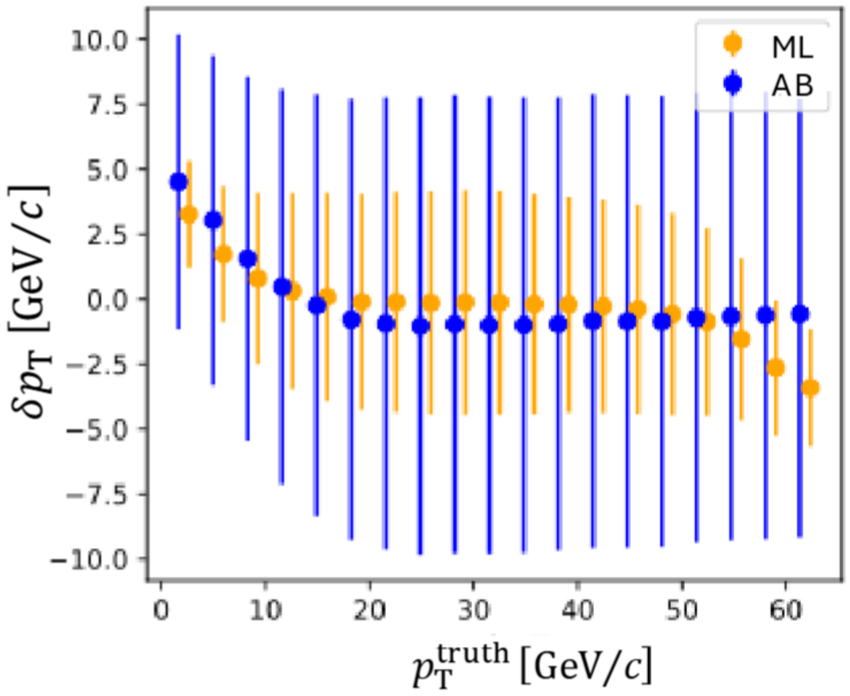
Same result found in the PYTHIA+thermal background for 2.76 TeV events
-> refer to R. Haake and C. Loizides (2019), arXiv:1810.06324 [nucl-ex]

TRAINING: $\mathrm{NN}_{\mathrm{AllReco}}$ on pp jets embedded in hydro background:

Distributions of $p_{\mathrm{T,jet}}$: truth and $p_{\mathrm{T,jet}}^{\mathrm{corr}}$ from $\mathrm{NN}_{\mathrm{AllReco}}$ and AB method



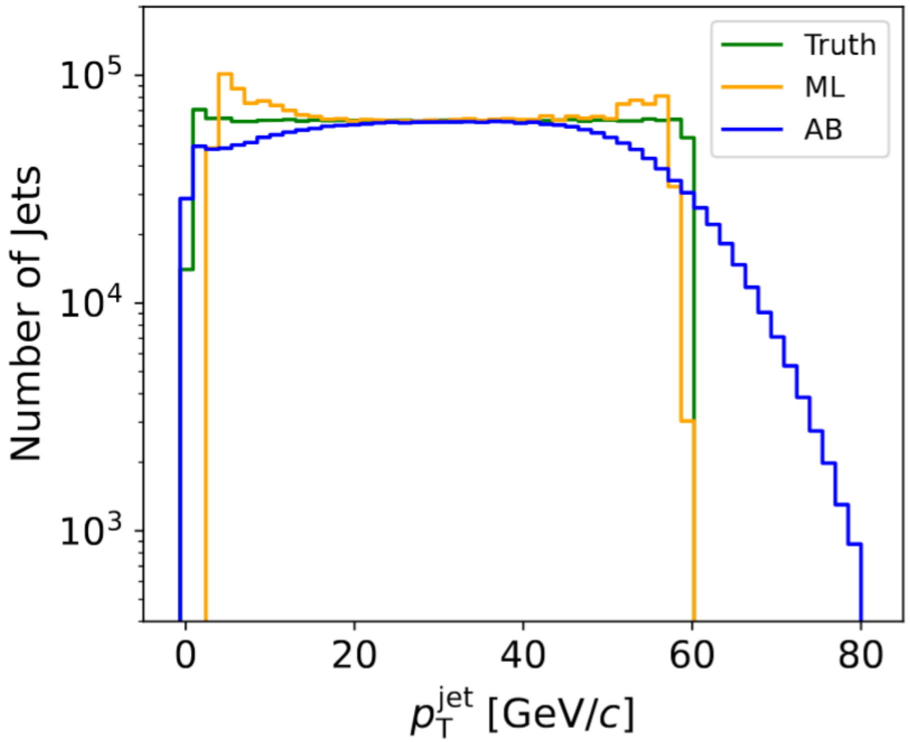
- Points: $\langle \delta p_{\mathrm{T,jet}} \rangle$
- Bars: $\sigma\left(\delta p_{\mathrm{T,jet}}\right)$



- Both the AB method and NN "know" : low $p_{\mathrm{T,jet}}^{\mathrm{reco}}$ jets are not from "$p_{\mathrm{T,jet}}^{\mathrm{truth}} < 0$ GeV/c jets" on upward background fluctuations
- Only NN "knows" that high $p_{\mathrm{T,jet}}^{\mathrm{reco}}$ jets do not result from "$p_{\mathrm{T,jet}}^{\mathrm{truth}} > 60$ GeV/c jets".
  (Warning: ML will always exploit boundary conditions if it can!)

$\mathrm{NN_{AllReco}}$ on pp jets embedded in hydro background:

Distributions of $p_{\mathrm{T,jet}}$: truth and $p_{\mathrm{T,jet}}^{\mathrm{corr}}$ from $\mathrm{NN_{AllReco}}$ and AB method



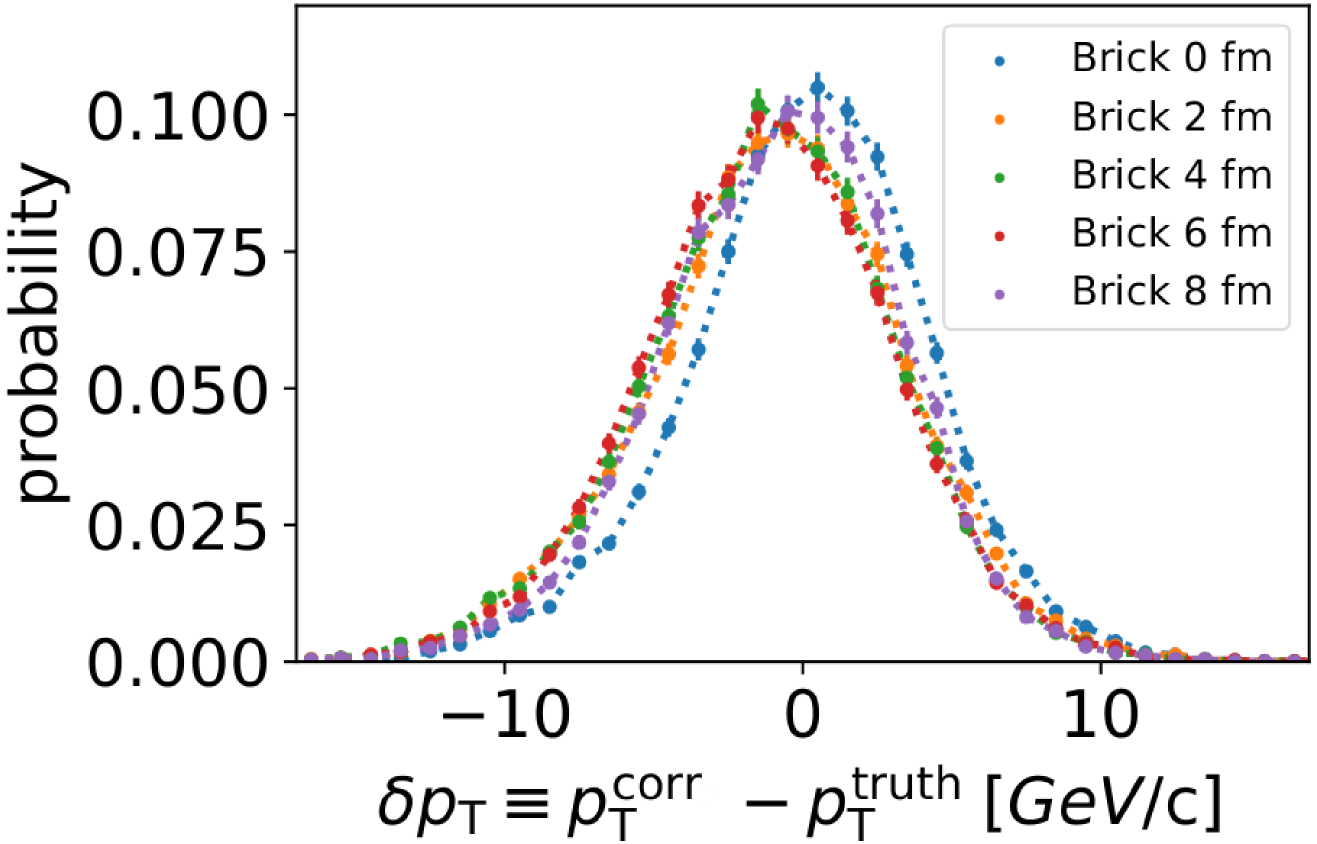
Neural Networks (NN) training note:

- Must use a uniform $p_{\mathrm{T,jet}}^{\mathrm{truth}}$ distribution for training; otherwise, ML will simply exploit the steeply falling spectrum and always guess upward fluctuations

- Both the AB method and NN "know" : low $p_{\mathrm{T,jet}}^{\mathrm{reco}}$ jets are not from "$p_{\mathrm{T,jet}}^{\mathrm{truth}} < 0\ \mathrm{GeV}/c$ jets" on upward background fluctuations
- Only NN "knows" that high $p_{\mathrm{T,jet}}^{\mathrm{reco}}$ jets do not result from "$p_{\mathrm{T,jet}}^{\mathrm{truth}} > 60\ \mathrm{GeV}/c$ jets".
  (Warning: ML will always exploit boundary conditions if it can!)

Evolution of δp_{T} for $\mathrm{NN}_{\mathrm{AllReco}}$ with incremental quenching:

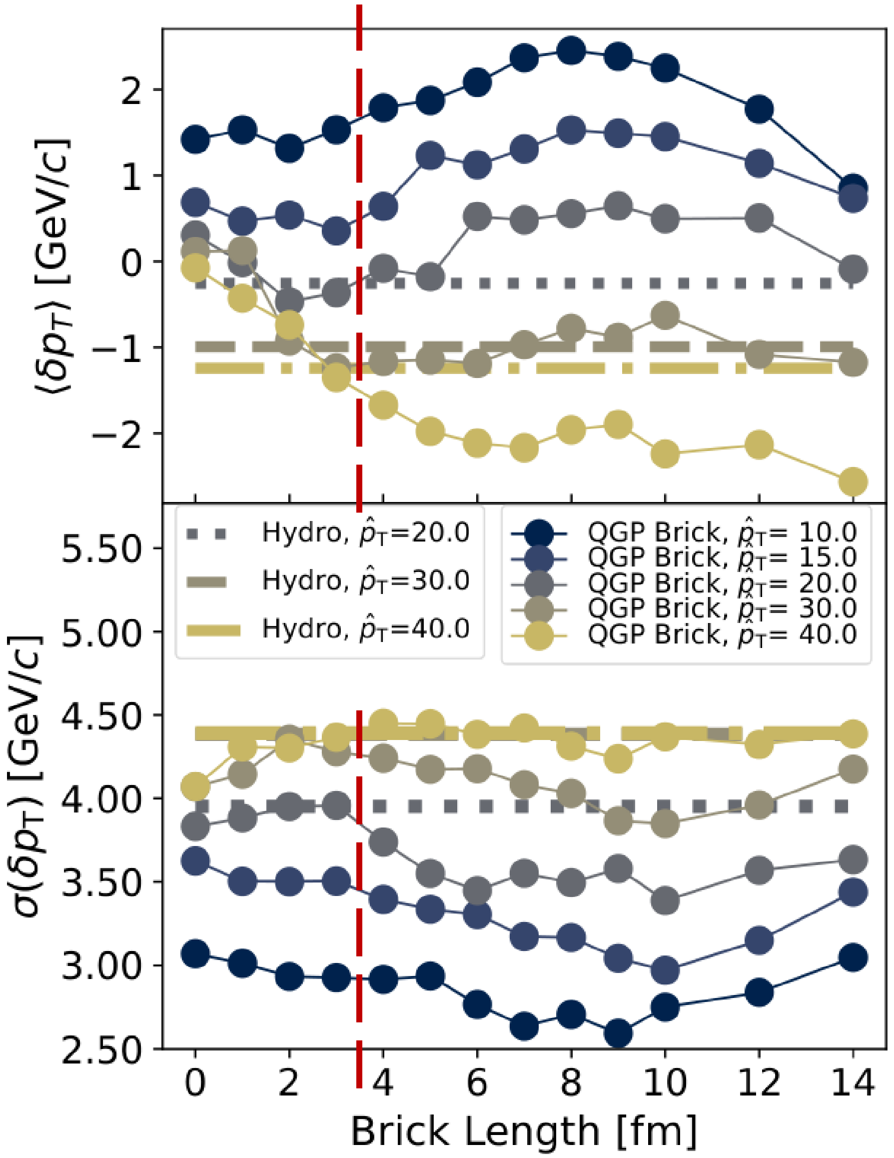
- The average value (the background pedestal) is biased ($\neq 0$)
  - We are not measuring background
- The NN correction values of $p_{\mathrm{T,jet}}^{\mathrm{corr}}$ systematically under-predicts the truth values with increasing quenching
- Biggest change w.r.t. first 2 fm of quenching



Values here for jets from events generated with $\hat{p}_{\mathrm{T}} \in [30,31]$ GeV/c

Summary of evolution of $\langle \delta p_{\mathrm{T,jet}} \rangle$ and $\sigma(\delta p_{\mathrm{T,jet}})$ w.r.t. quenching

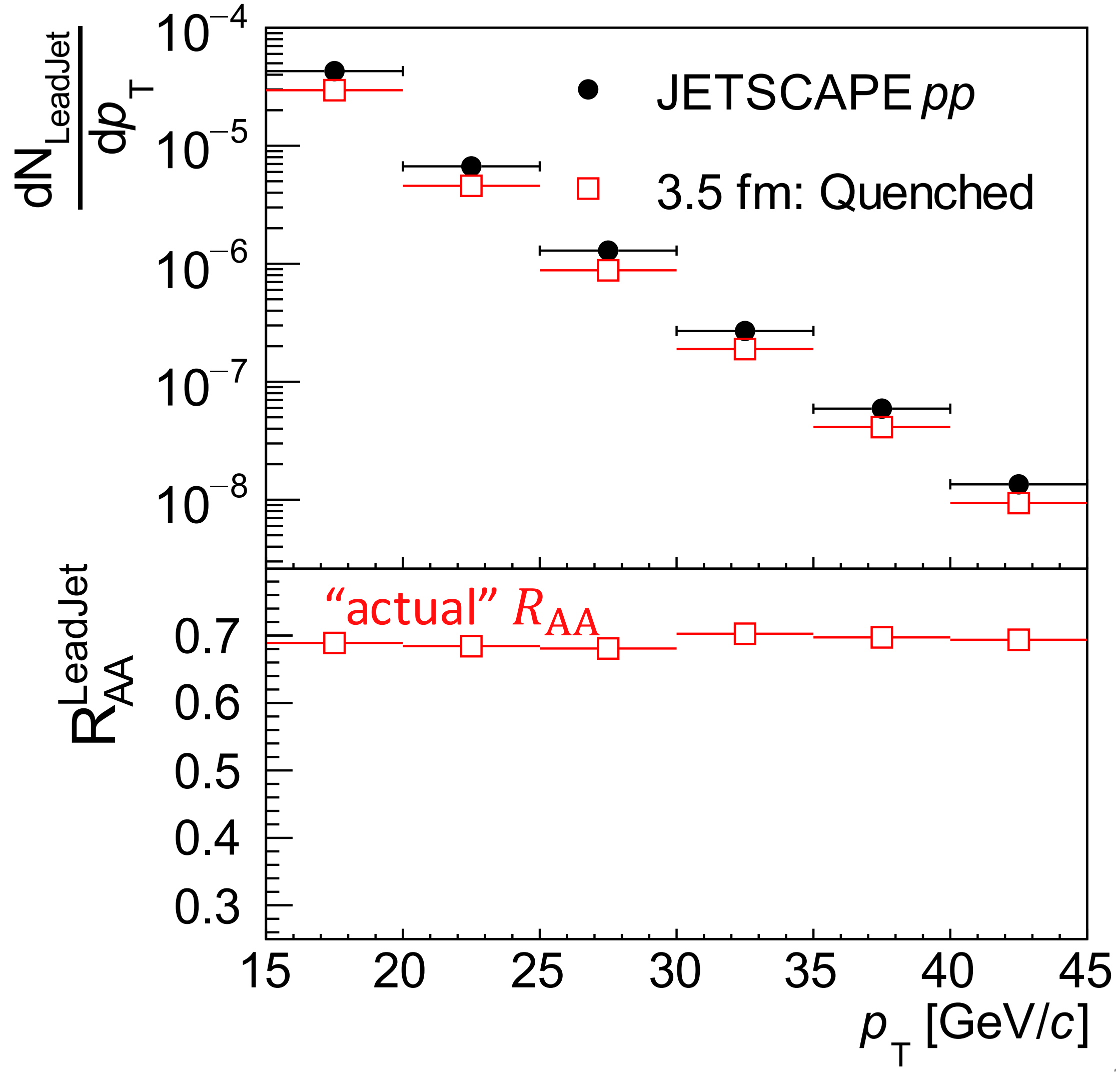
- $\langle \delta p_{\mathrm{T,jet}} \rangle$ and $\sigma(\delta p_{\mathrm{T,jet}})$ plotted for jets at a range of p_{T}
- Values for hydro quenched jets (horizontal lines) are again consistent with those of $\sim$3.5 fm brick quenched jets
- Values are both p_{T} and quenching dependent, but (except for high-p_{T} $\langle \delta p_{\mathrm{T,jet}} \rangle$) monotonic w.r.t. quenching



Values here for jets from events generated with $\hat{p}_{\mathrm{T}} \in [30,31]\ \mathrm{GeV}/c$

Perform an R_{AA} “measurement” with each NN:

- Generate a full spectrum of jets quenched in 3.5 fm of QGP:
  $p_{\mathrm{T,jet}}^{\mathrm{quenched}}$
- Embed $p_{\mathrm{T,jet}}^{\mathrm{truth}}$ into hydro backgrounds and cluster:
  $p_{\mathrm{T,jet}}^{\mathrm{reco}}$
- Use same steps as an experimental analysis to “measure” $p_{\mathrm{T,jet}}^{\mathrm{quenched}}$ from $p_{\mathrm{T,jet}}^{\mathrm{reco}}$ (and ρ_{bkg})
- Compare the measured R_{AA} to the actual R_{AA}
- Results indicate how biases in $\delta p_{\mathrm{T,jet}}$ propagate

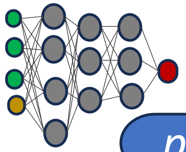


Our simulated analysis:

There are three points where the ML-based procedure is sensitive to jet fragmentation:

- **A** *measured input spectra*
- **B** *the response matrix*
- **C** *and the training*

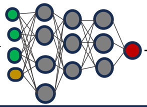
C **Train NN:** *pp* jets embedded in "measured" (hydro) background

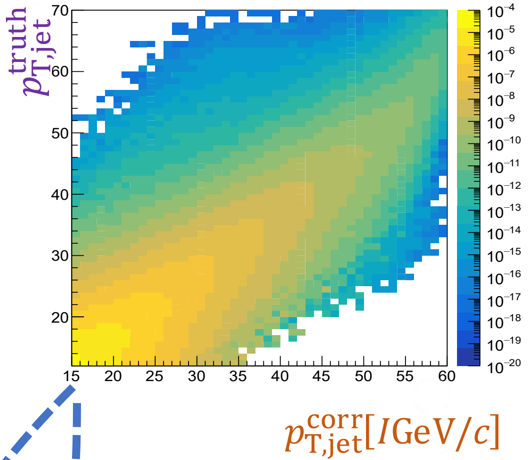


pp jets

Perform leading jet R_{AA} "calculation":

B **Make response matrix:**

- Embed *pp* jets into measured (hydro) background
- Cluster and find $p_{\mathrm{T,jet}}^{\mathrm{reco}}$ and matched to the embedded $p_{\mathrm{T,jet}}^{\mathrm{truth}}$
- Correct: $p_{\mathrm{T,jet}}^{\mathrm{reco}} \rightarrow$  $\rightarrow p_{\mathrm{T,jet}}^{\mathrm{corr}}$

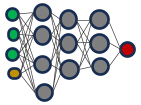


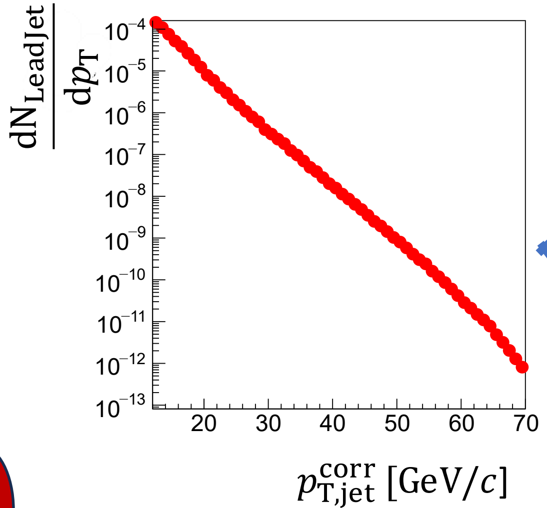
$p_{\mathrm{T,jet}}^{\mathrm{corr}}[IGeV/c]$

pp jets

A

Measure "data"
(jets quenched in 3.5 fm brick embedded into hydro background) and background correct with NNs:

$p_{\mathrm{T,jet}}^{\mathrm{reco}} \rightarrow$  $\rightarrow p_{\mathrm{T,jet}}^{\mathrm{corr}}$



$\delta p_{\mathrm{T,jet}}$ *biases*

Unfold measured $p_{\mathrm{T,jet}}^{\mathrm{corr}}$:

Bayesian Unfold.

RooUnfold
unfolding framework and algorithms

△ 3.5 fm: $\mathrm{NN}_{\mathrm{RecoAll}}$ Unfolded

Single Bin Efficiency

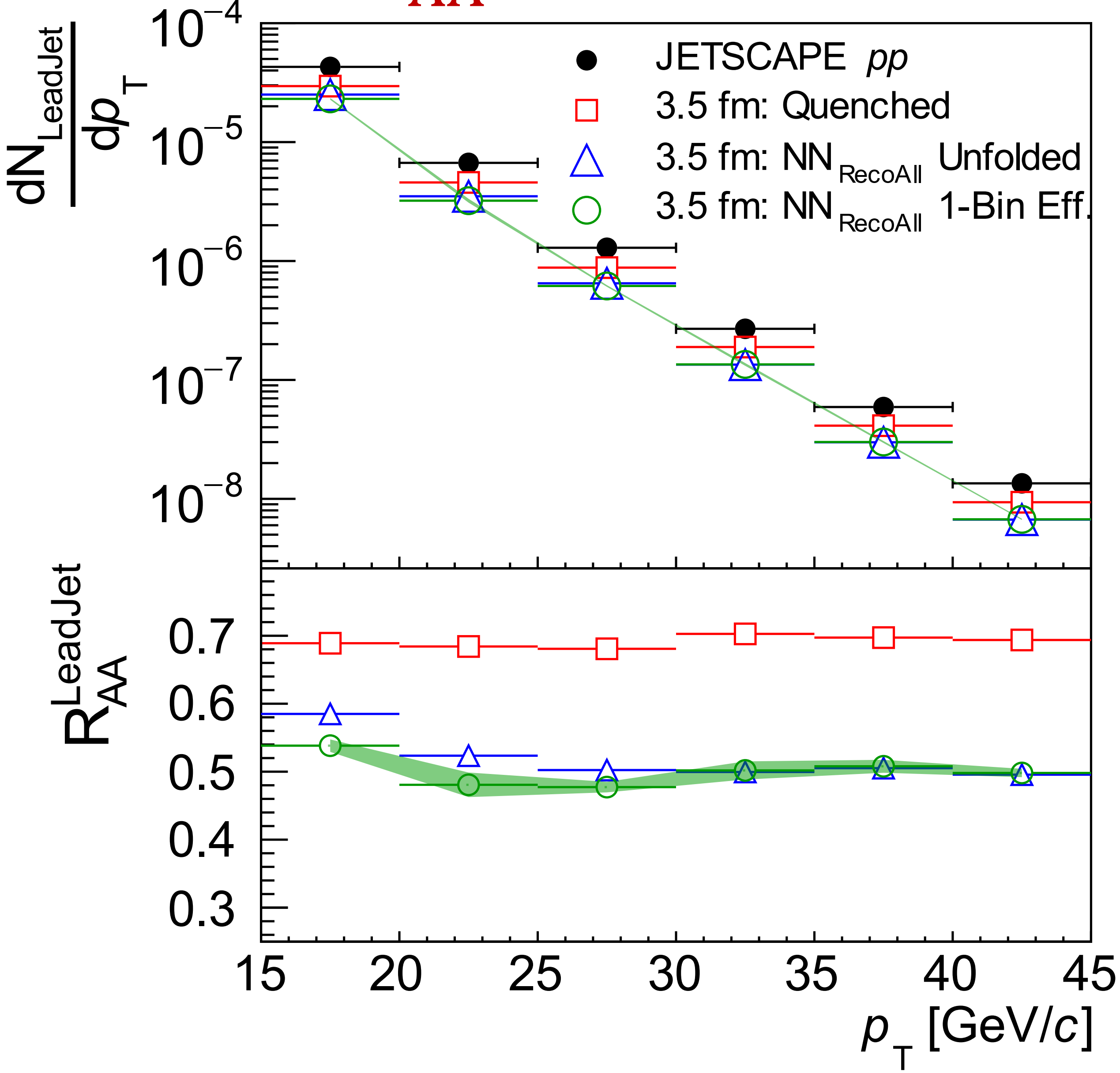
$$\left.\frac{p_{\mathrm{T,jet}}^{\mathrm{corr}}}{p_{\mathrm{T,jet}}^{\mathrm{truth}}}\right|_{i-bin}$$

○ 3.5 fm: $\mathrm{NN}_{\mathrm{RecoAll}}$ 1-Bin Eff.

Correction Biases

Result: Significantly biased $R_{AA}^{LeadJet}$

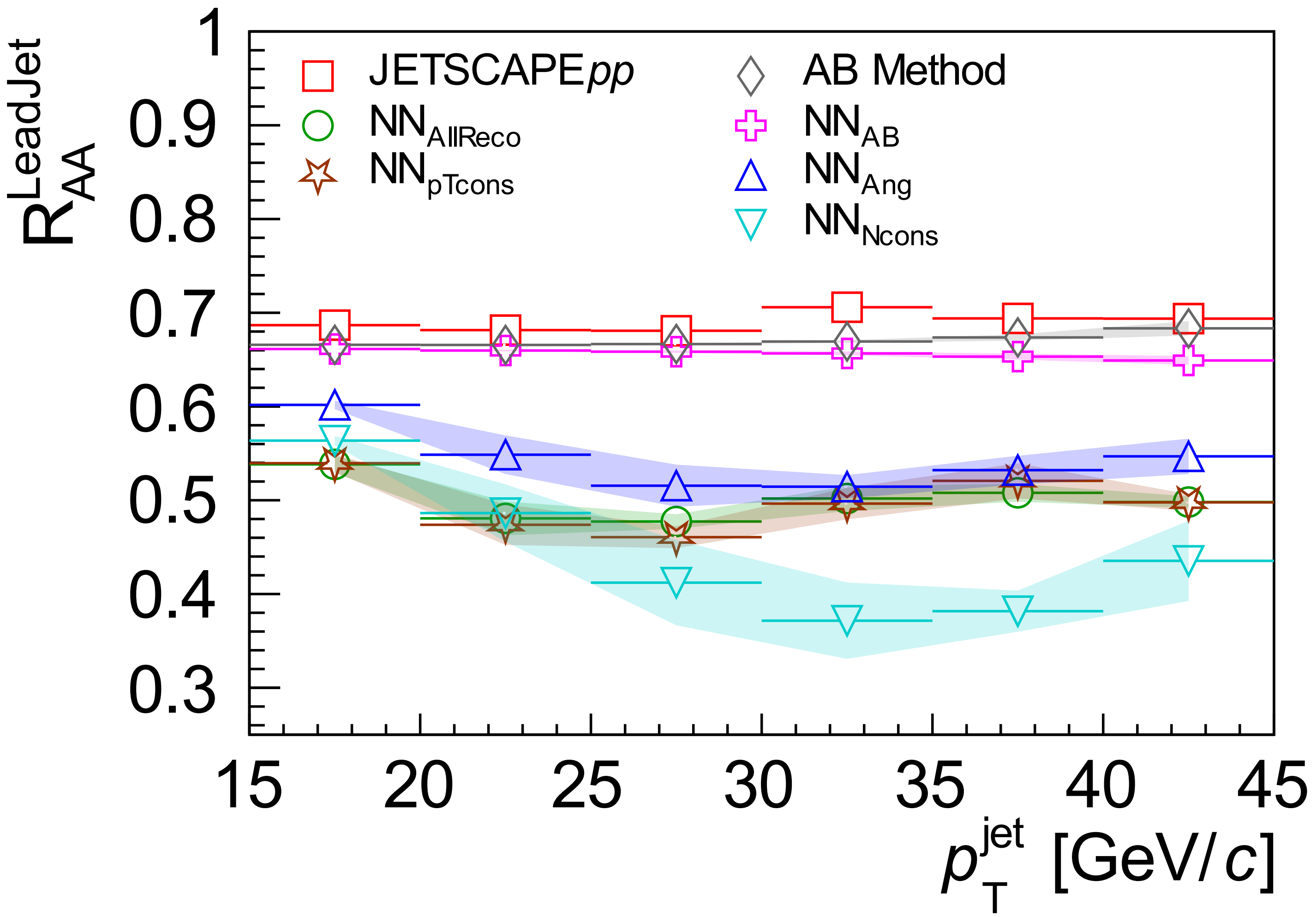
Perform leading jet R_{AA} "calculation":



Perform leading jet R_{AA} "calculation":

Results for $R_{\mathrm{AA}}^{\mathrm{LeadJet}}$ using all NN's (as well as AB method)

- The AB method is accurate
  (use the method for both background correction and construction of $\mathcal{M}(p_{\mathrm{T,jet}}^{\mathrm{truth}}, p_{\mathrm{T,jet}}^{\mathrm{reco}})|_{\mathrm{pp}}$)
- $\mathrm{NN_{AB}}$ uses only ρ_{bkg}, A_{jet}, and $p_{\mathrm{T,jet}}^{\mathrm{reco}}$ is equally accurate as AB method
- All other NNs generate significant bias in $R_{\mathrm{AA}}^{\mathrm{LeadJet}}$



ML: Where to go from here? – Using jet substructure

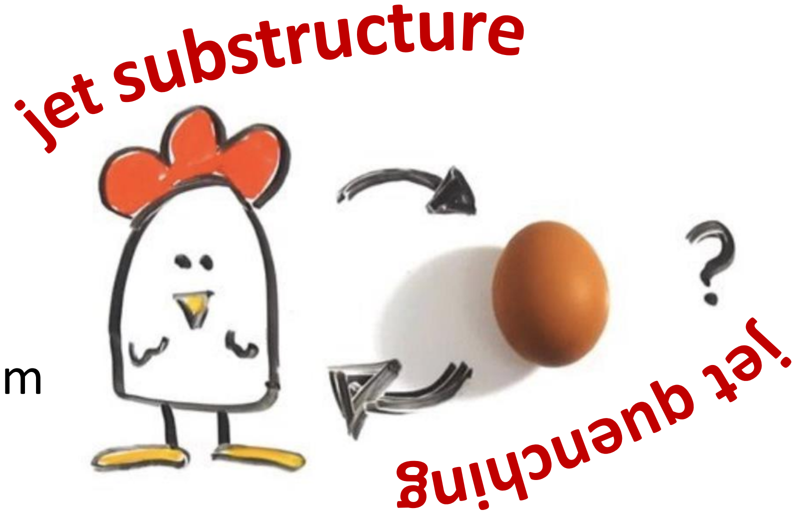
If we wish to use jet substructure to correct for background in quenched jets, we must use either/or:

a) Know that we have different substructure scenarios which bound the effects on the results
(How to report most probably results?)

b) For each substructure observable used, be able to generate representative data for ML training:

- This would probably mean already knowing the quenching present to match/qualify the training data

- Could be a virtuous research cycle – but is not a trivial problem

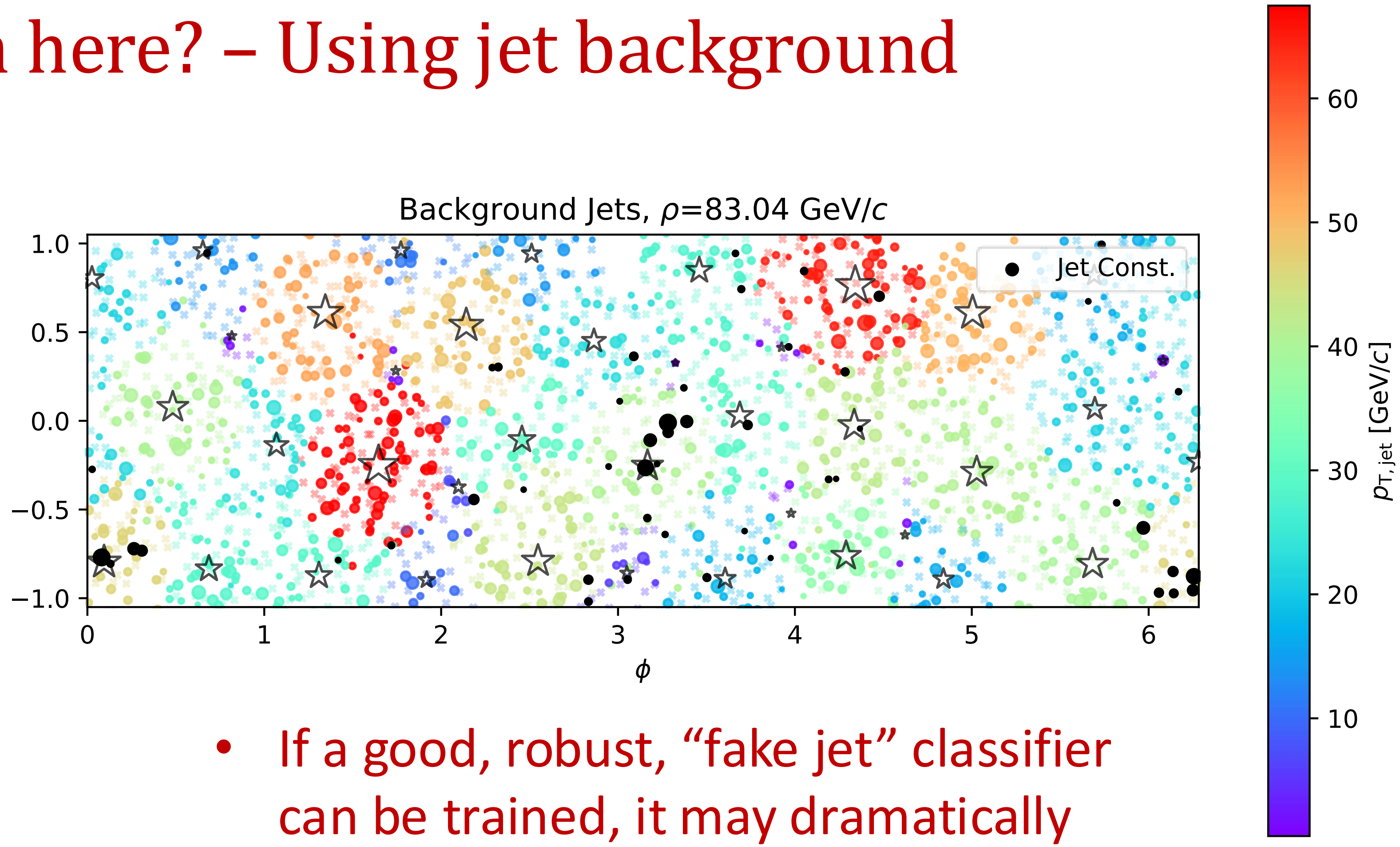


https://www.workroomfashionmash.com/isgreenthenewblackblog/the-chicken-or-the-egg

ML: Where to go from here? – Using jet background

We have quite a lot of jet background data (min bias) events, so that we can train ML to recognize ”background” (or “fake”) jets to distinguish from those with real jet constituents

- Quite a lot of interesting work in ML for detecting/classifying anomalies → might be mostly independent of jet substructure.
- Might find a p_{T} cutoff at which we can declare an actual jet “fully quenched”/indistinguishable from background.



- If a good, robust, “fake jet” classifier can be trained, it may dramatically decrease the fake to real jet ratio at low $p_{\mathrm{T,jet}}$ and therefore allow measurements at lower $p_{\mathrm{T,jet}}$

Thank You

Special thanks to Hannah Bossi, Chun Shen, Raymond James, and Helen Caines for conversation, expertise, insight, and help

Extra Slides

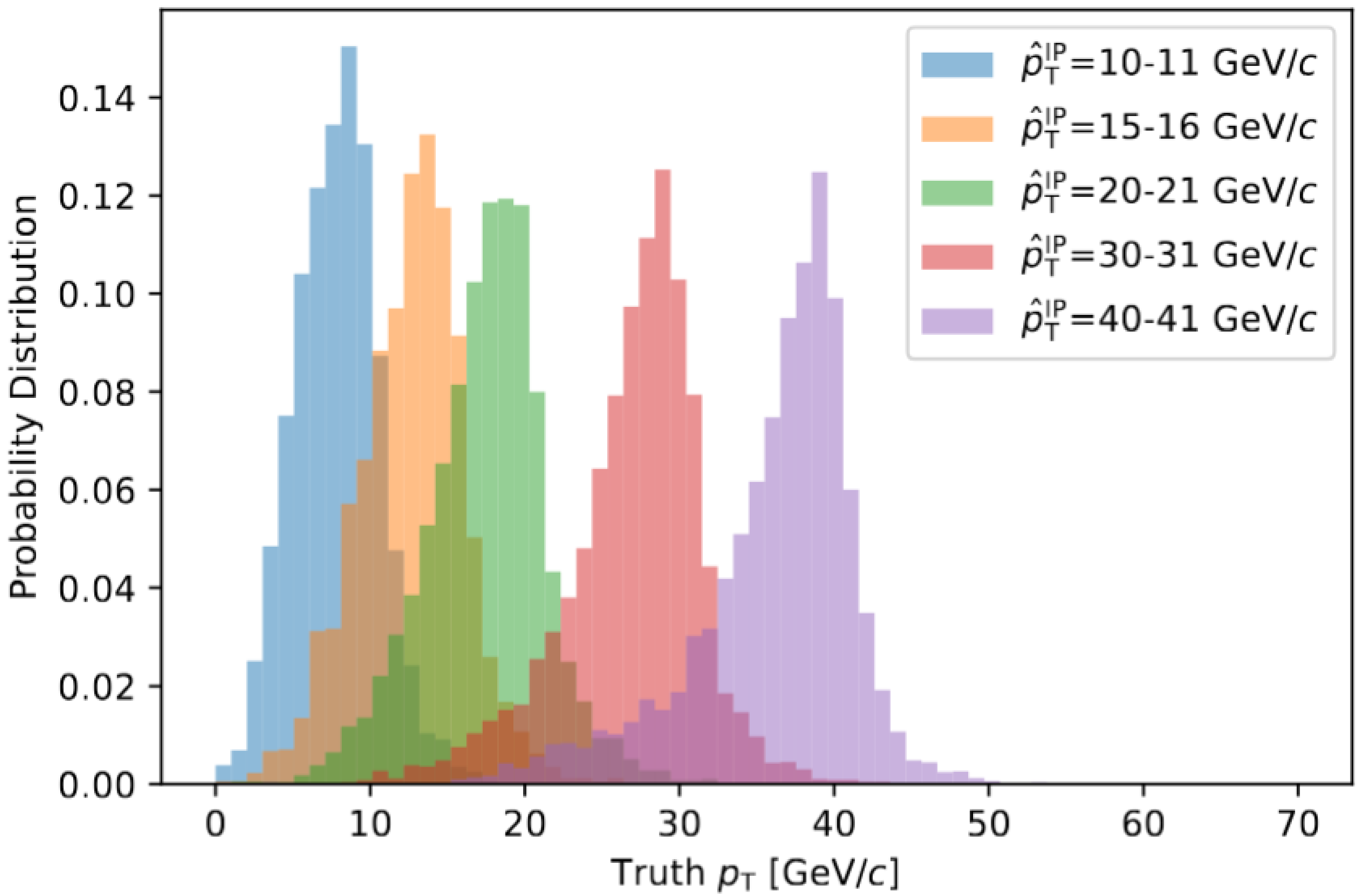


FIG. A.2. Distribution of $p_{\mathrm{T,jet}}^{\mathrm{truth}}$ per JETSCAPE $\hat{p}_{\mathrm{T}}$ parameter selection for the non-quenched datasets.

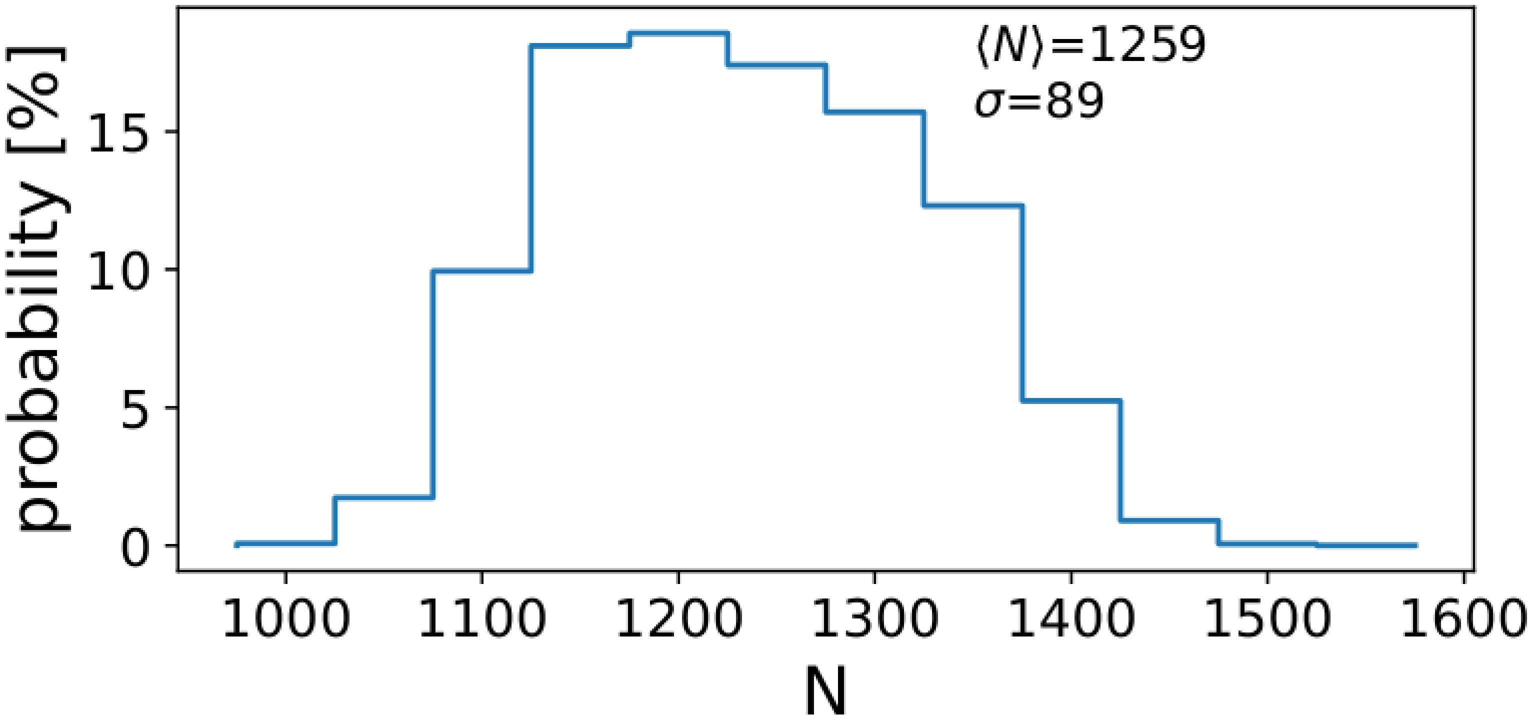


FIG. 2. Distribution of the numbers of background particles per event.

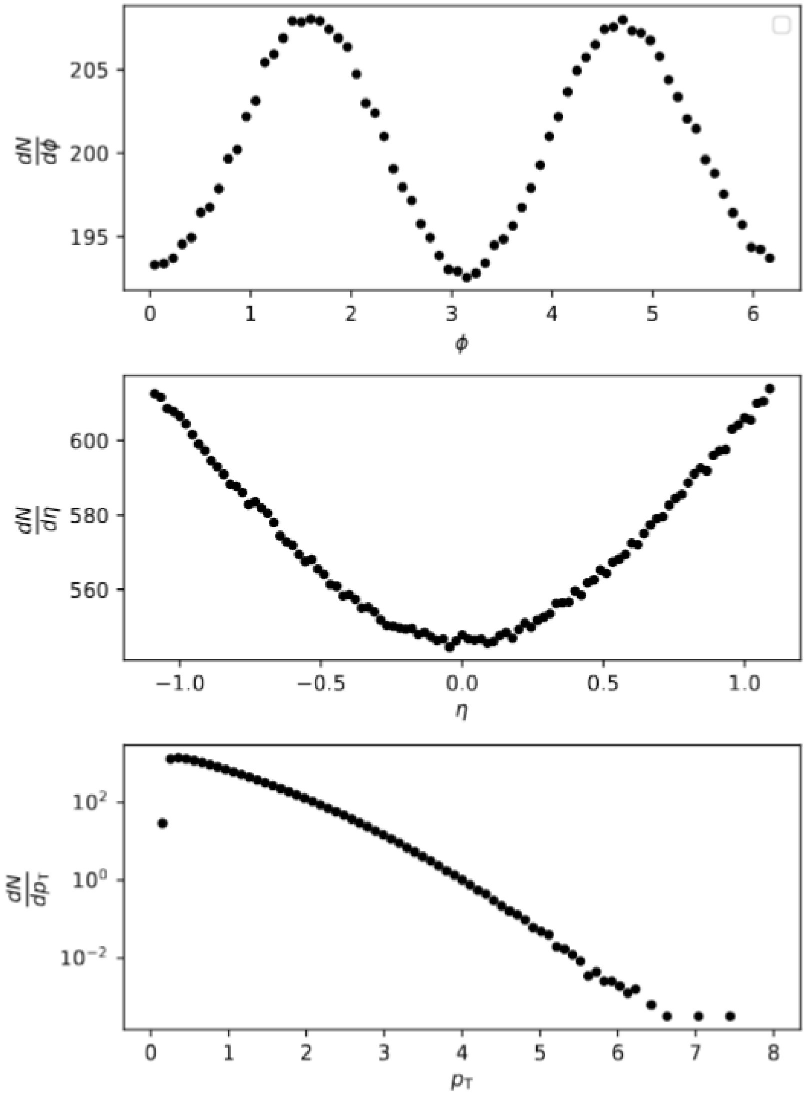


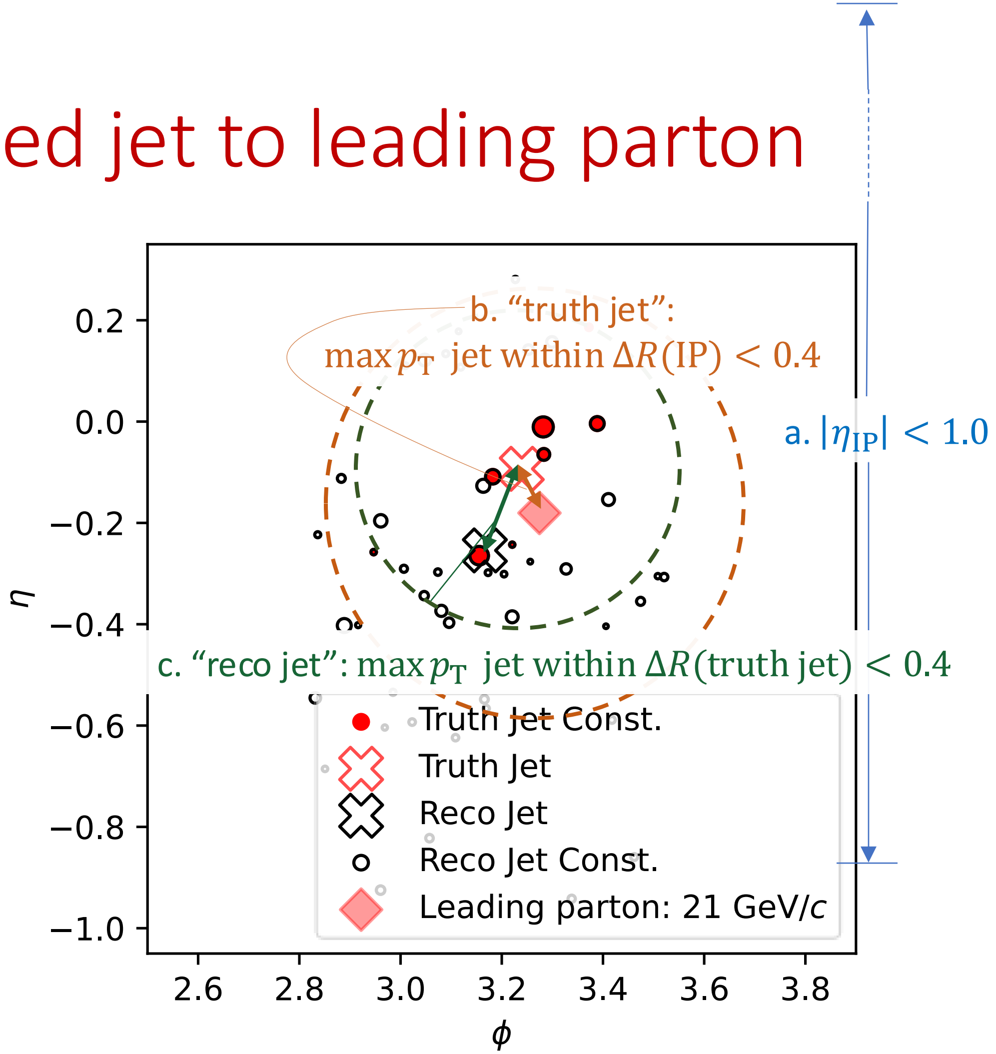
FIG. A.1. Distributions of ϕ, η, and p_T densities of background particles, averaged over all background events. The v^2 flow shown is a result of JETSCAPE aligning all impact parameters along the x-axis.

Simulations cuts: Use only matched jet to leading parton

a. Highest-p_T IP: $|\eta| \le 1$

b. Highest p_T jet from truth constituents within $\Delta R \le 0.4$ from IP is “truth jet”

c. Highest p_T jet from truth+bkg constituents within $\Delta R \le 0.3$ of truth jet is “reco jet”

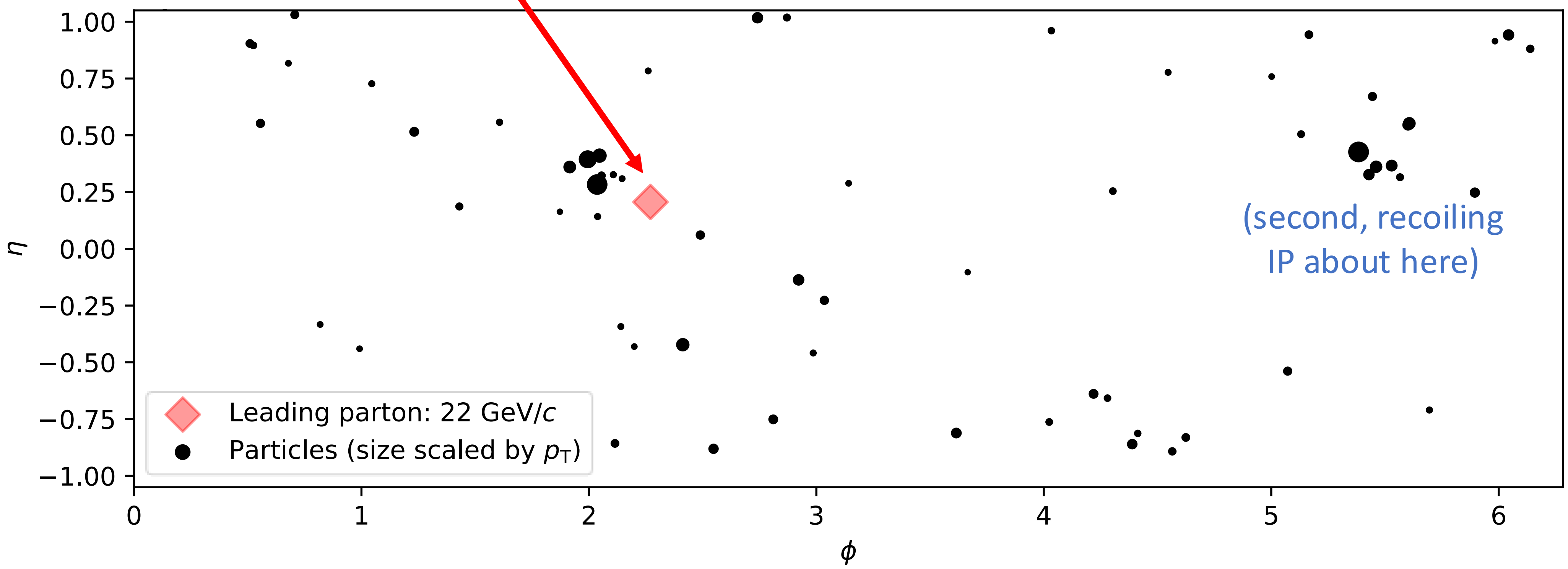


Details
Paper: https://arxiv.org/abs/2412.15440
Code: https://github.com/david-stewart/jet_and_thermal)

JETSCAPE simulation

IP with resulting hadrons

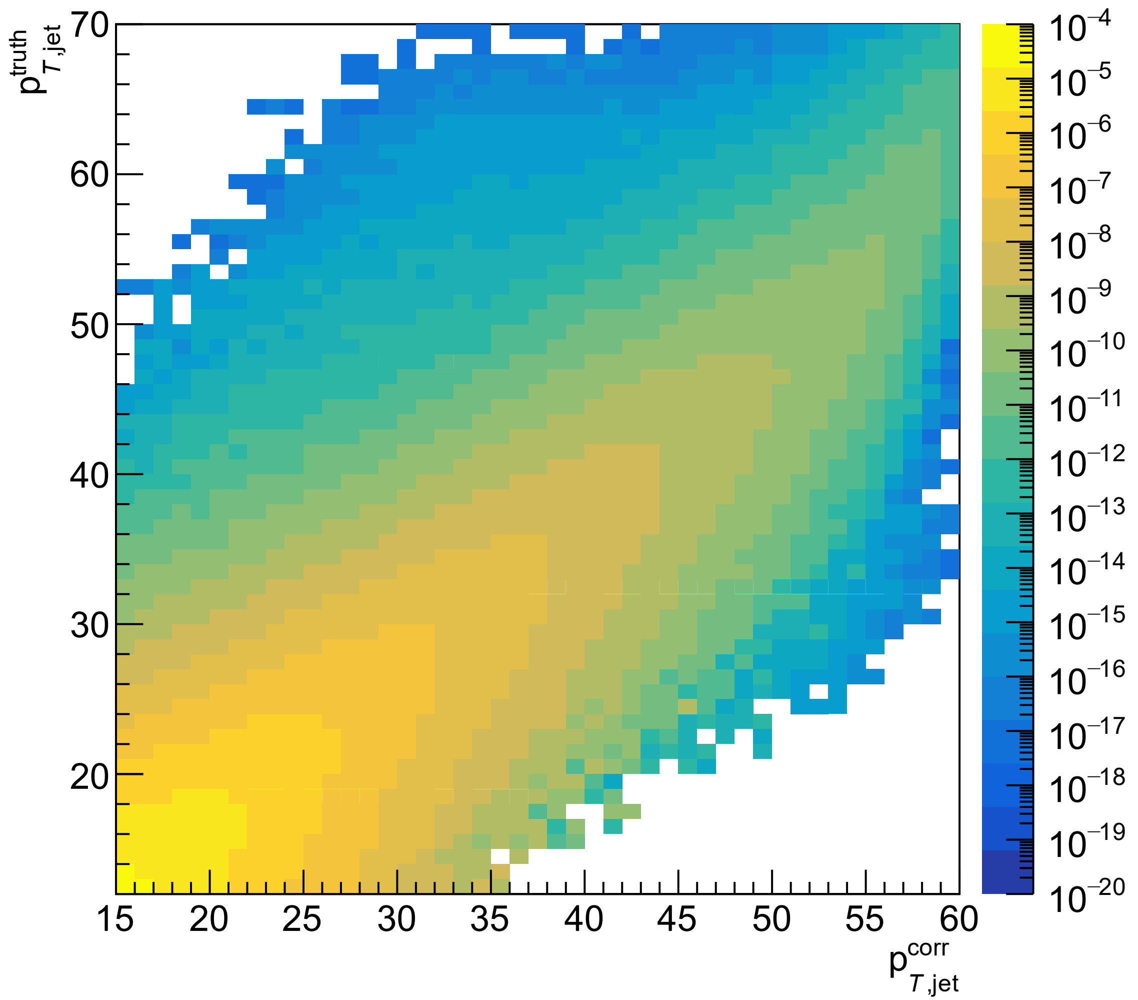
- Highest p_{T} ("leading") parton at $p_{\mathrm{T}}^{\mathrm{IP}} = 22\ \mathrm{GeV}/c$
- Resulting hadrons from initial scattering



(second, recoiling IP about here)

How could $\delta p_{\mathrm{T,jet}}$ biases propagate in actual measurement?

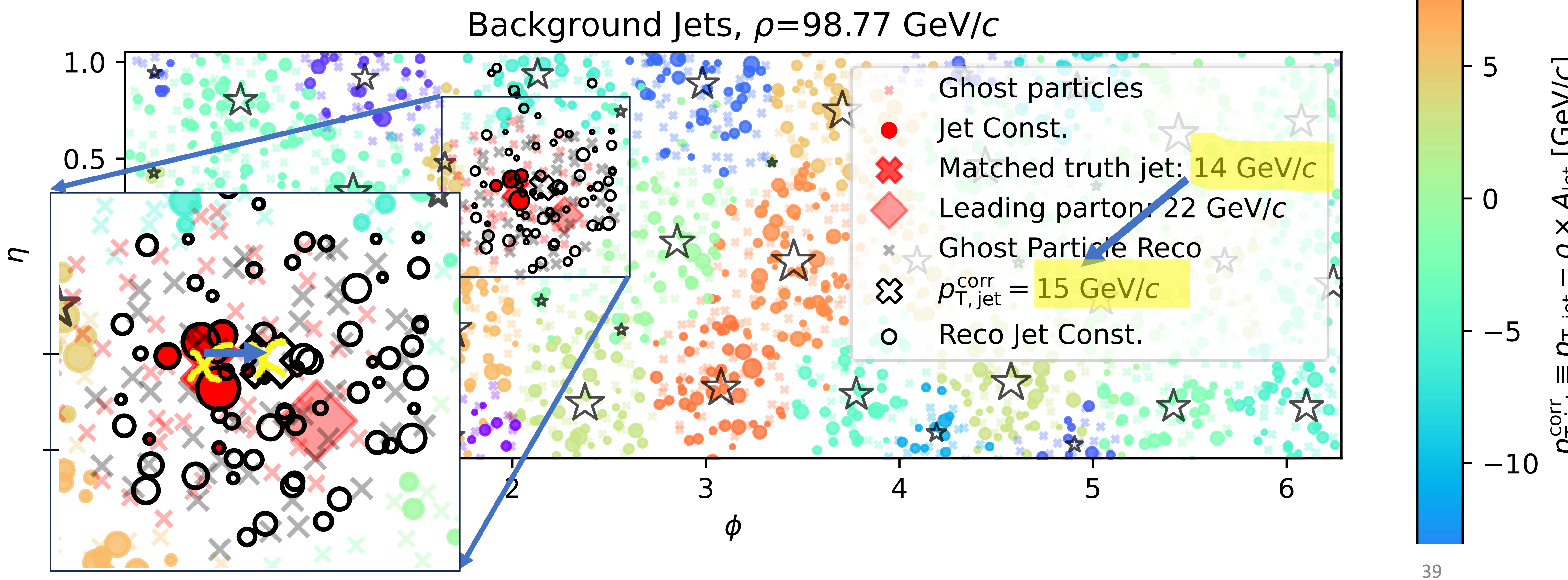
- Embed the quenched spectra in hydro background, cluster, and background correct (using NN's) to $p_{\mathrm{T,jet}}^{\mathrm{reco}}$
- Embed a pp spectra into hydro background, cluster, and background correct (using NN's) to $p_{\mathrm{T,jet}}^{\mathrm{reco}}$
  - Use the collection of $\{p_{\mathrm{T,jet}}^{\mathrm{truth}}, p_{\mathrm{T,jet}}^{\mathrm{reco}}\}$ to generate a response matrix $\mathcal{M}\left(p_{\mathrm{T,jet}}^{\mathrm{truth}}, p_{\mathrm{T,jet}}^{\mathrm{reco}}\right)|_{\mathrm{pp}}$ (in experiment to correct for detector efficiency)
  - Save unmatched $p_{\mathrm{T,jet}}^{\mathrm{truth}}$ as misses and unmatched $p_{\mathrm{T,jet}}^{\mathrm{reco}}$ as fakes



JETSCAPE simulation

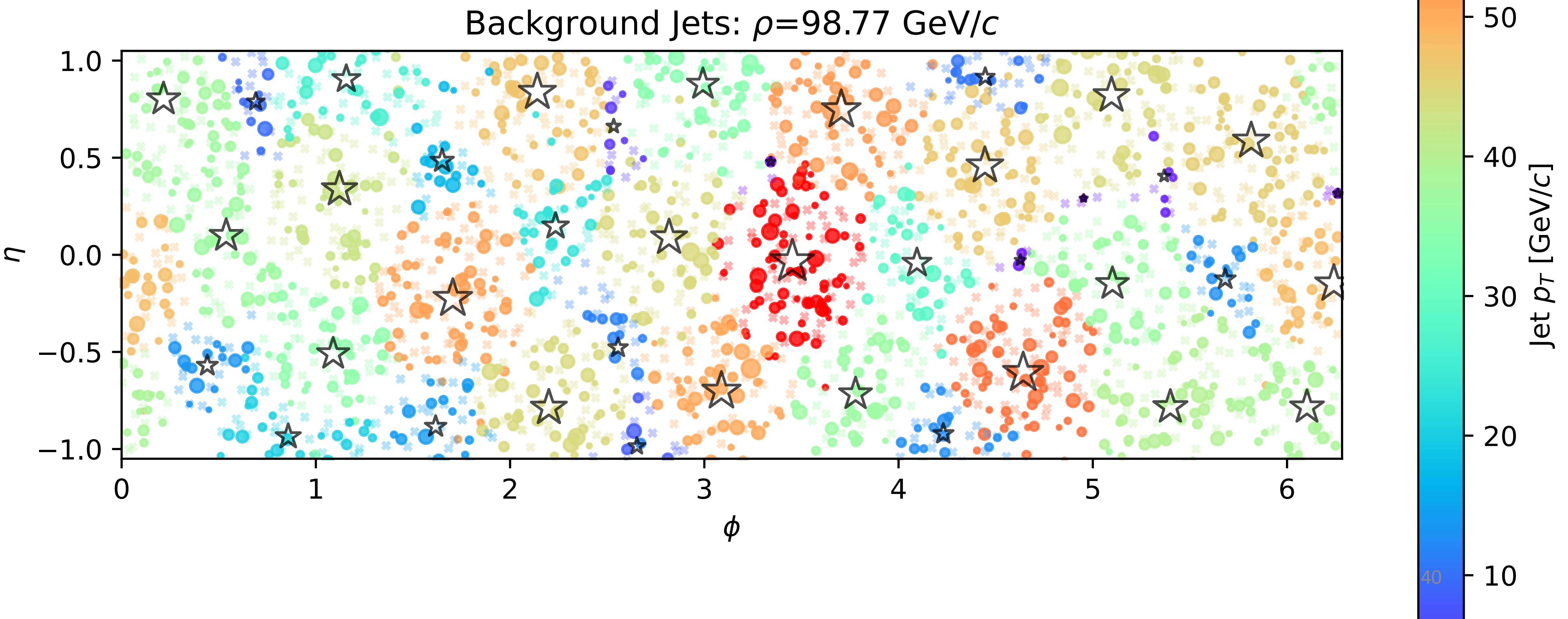
Simulation Event Example

Jet measurement: $p_{\mathrm{T,jet}}^{\mathrm{corr}} = p_{\mathrm{T,jet}}^{\mathrm{reco}} - \rho A_{\mathrm{jet}}$



JETSCAPE simulation

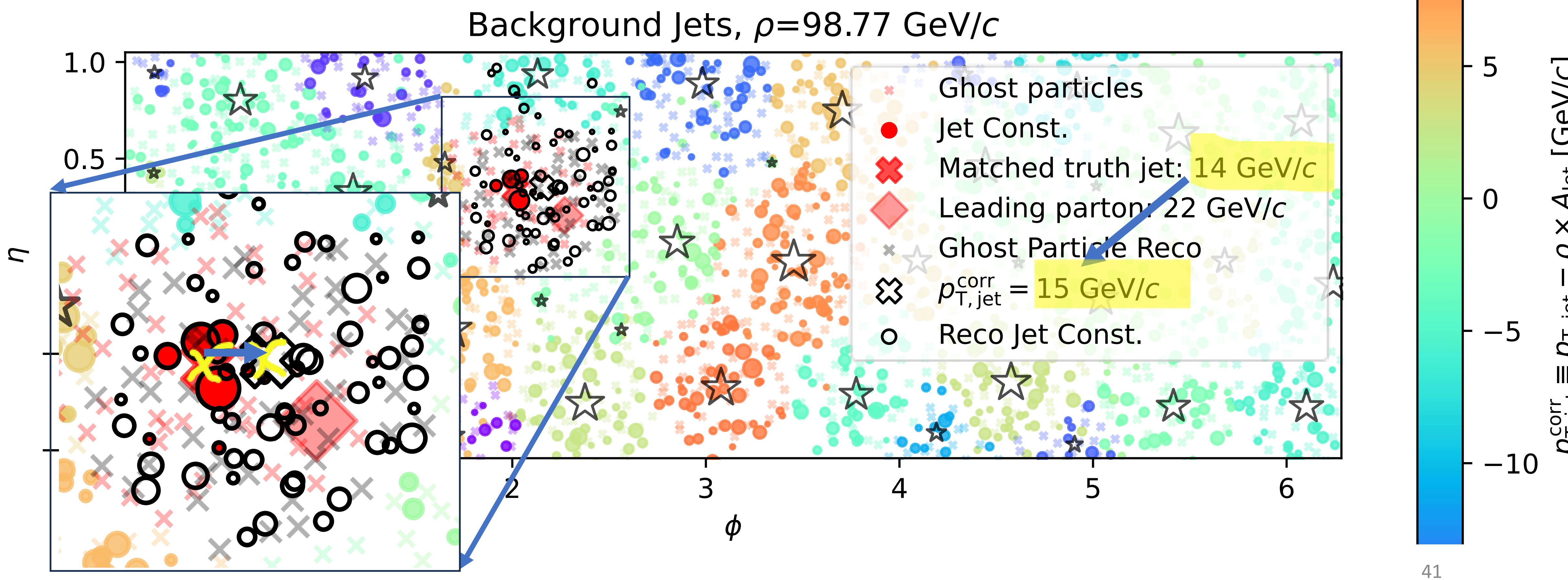
Background Particles Only:
anti-k_T clustering finds many “fake” jets



JETSCAPE simulation

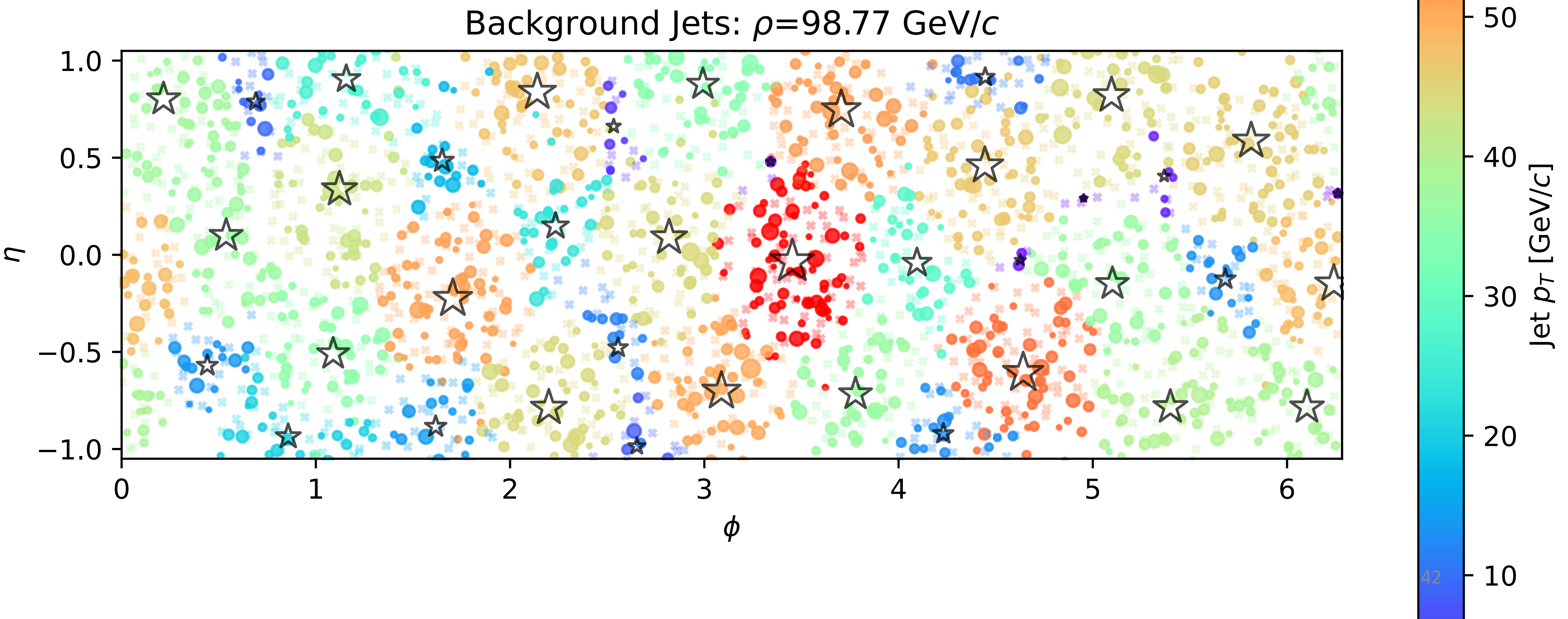
Simulation Event Example

Jet measurement: $p_{\mathrm{T,jet}}^{\mathrm{corr}} = p_{\mathrm{T,jet}}^{\mathrm{reco}} - \rho A_{\mathrm{jet}}$



JETSCAPE simulation

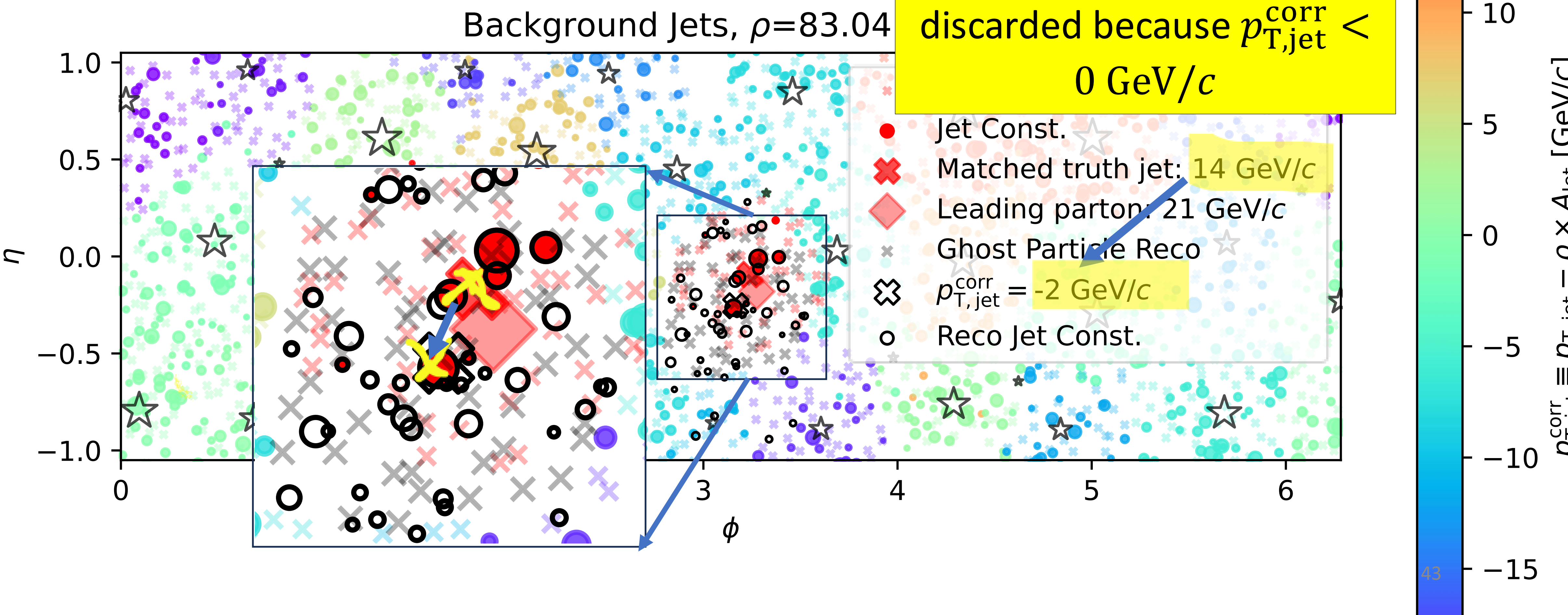
Background Particles Only:
anti-k_{T} clustering finds many "fake" jets



JETSCAPE simulation

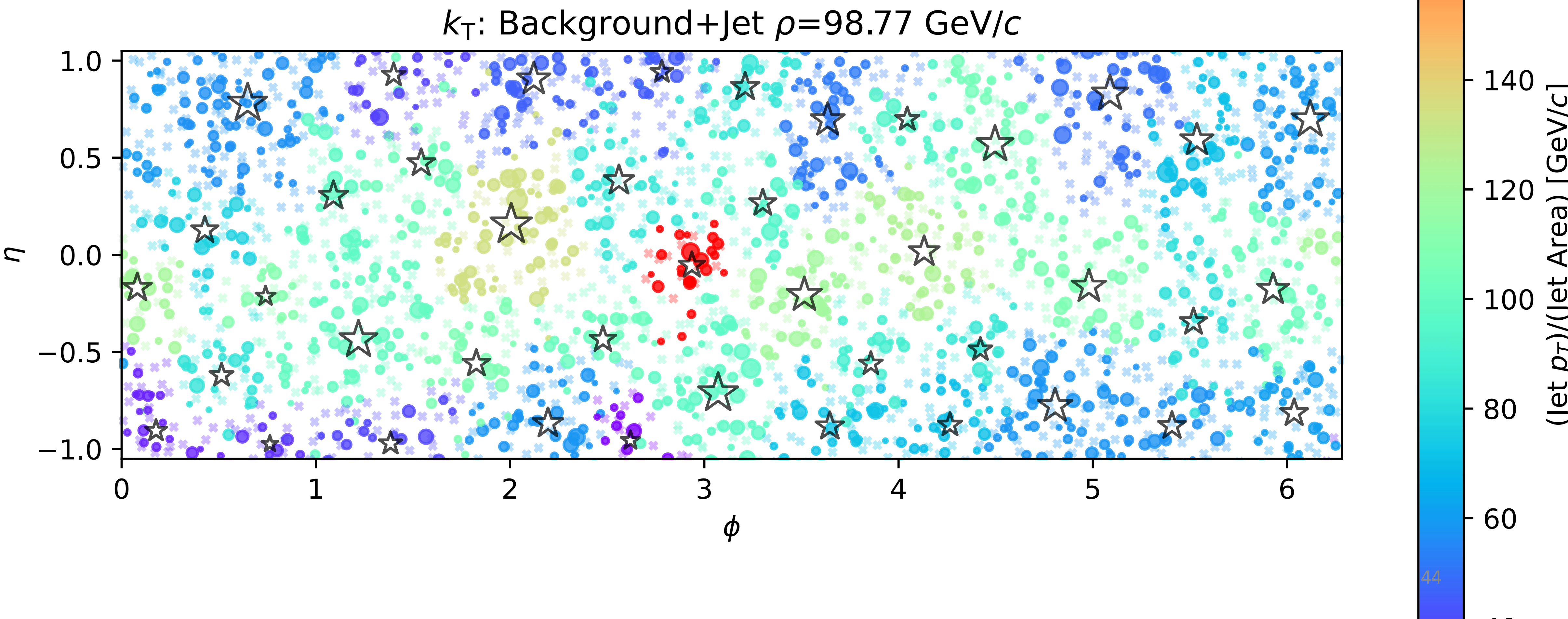
Another example:

This jet is on a downward fluctuation of background particles – in analysis this is discarded because $p_{\mathrm{T,jet}}^{\mathrm{corr}} < 0\ \mathrm{GeV}/c$



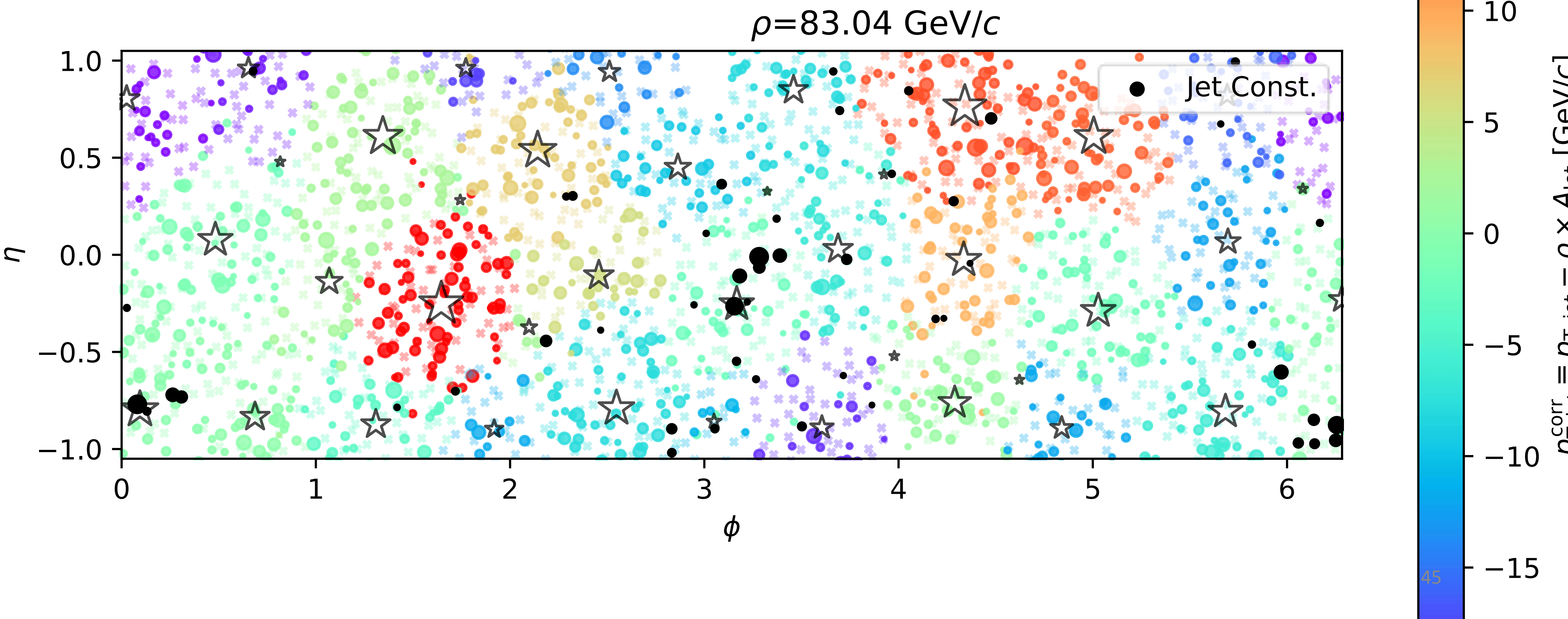
JETSCAPE simulation

ρ_{bkg} from k_{T} jets: median ($p_{\mathrm{T}}^{\mathrm{jet}}/A\_\mathrm{jet}$)
(cluster all particles, exclude 2 highest values)



JETSCAPE simulation

Measured jets, anti-k_T: $p_T^{\mathrm{corr}} \equiv p_T^{\mathrm{reco}} - \rho_{\mathrm{bkg}} A_{\mathrm{jet}}$



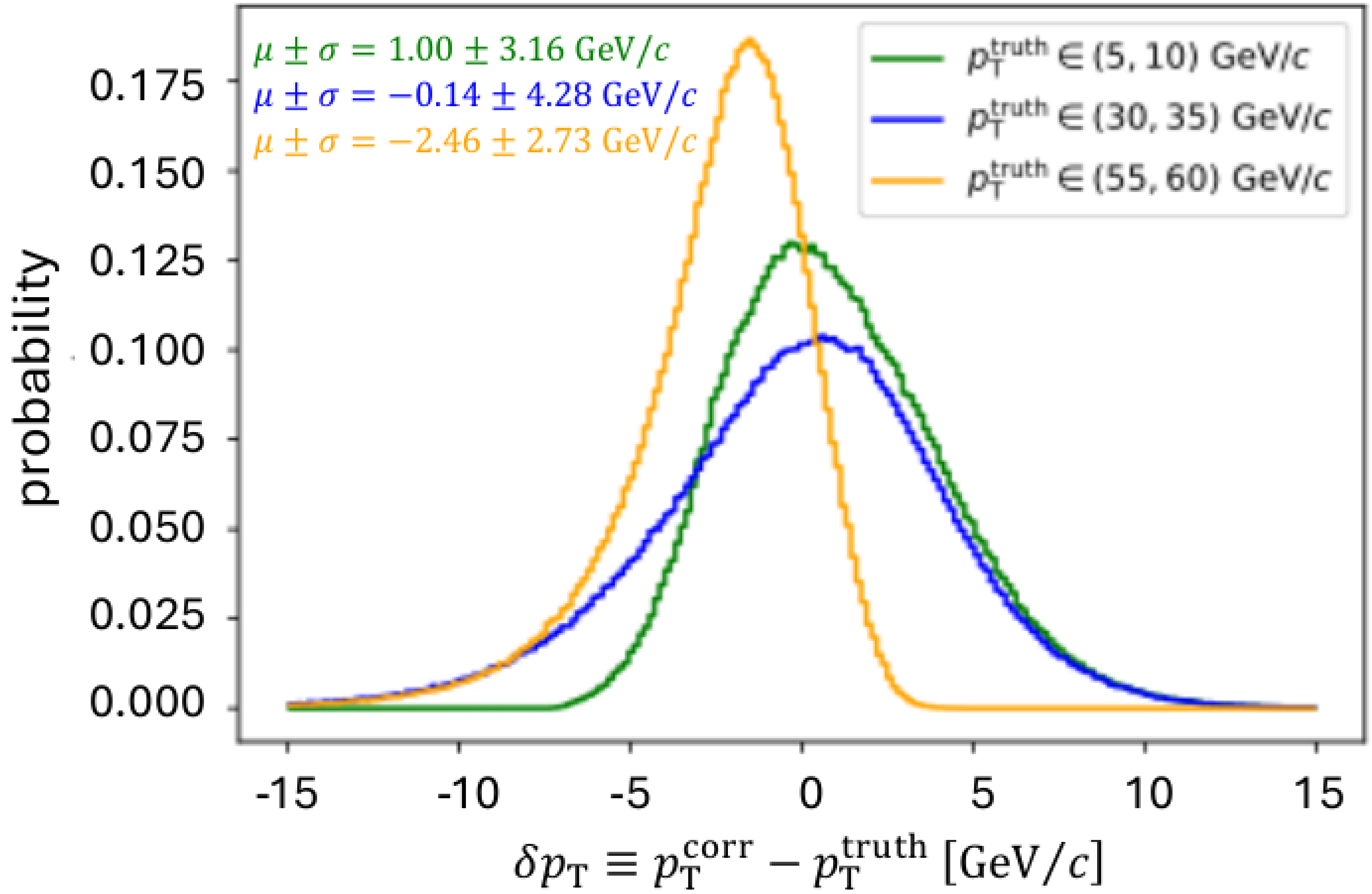
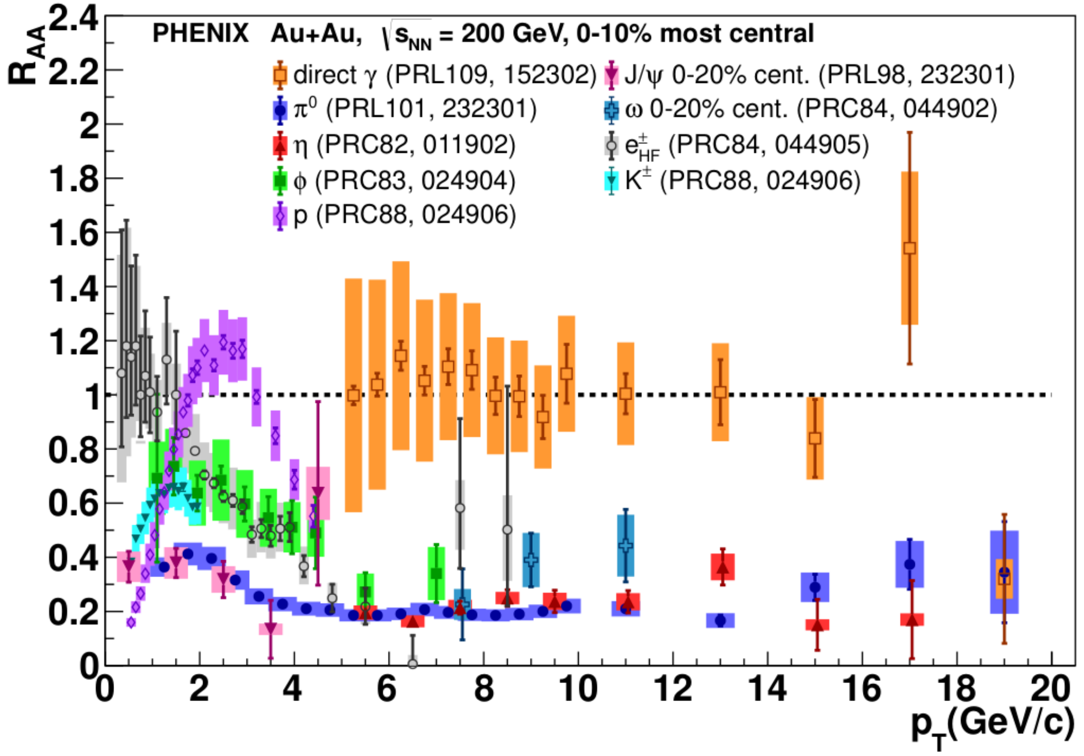


FIG. 4. The probability distribution of the residual error, $\delta p_{T,jet} \equiv p_{T,jet}^{corr} - p_{T,jet}^{truth}$, with $p_{T,jet}^{corr}$ from $NN_{AllReco}$ for events with three ranges of $p_{T,jet}^{truth}$. Also listed are the mean and standard deviation of $\delta p_{T,jet}$ for each range.



T. Sakaguchi, Overview of latest results from PHENIX. HardProbes2018. **PoS:**, 035 (2019).

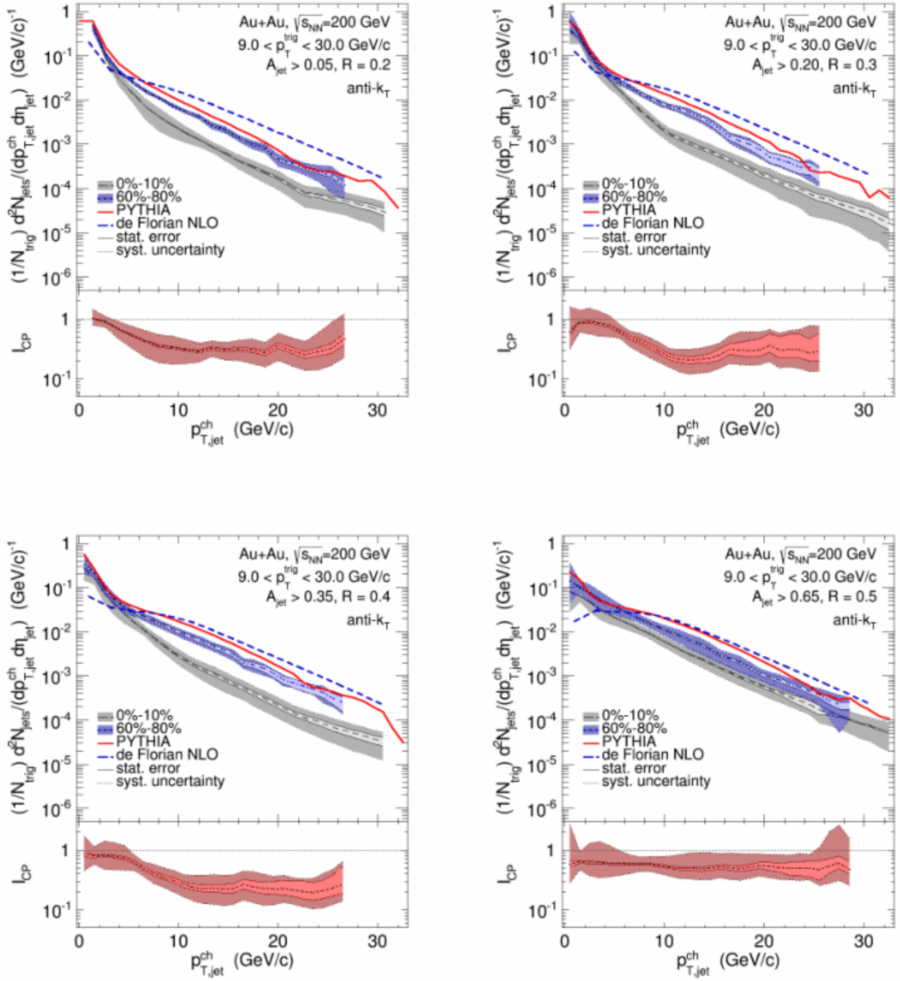


FIG. 19. (Color online) Fully corrected distributions of $Y\left(p_{\mathrm{T,jet}}^{\mathrm{ch}}\right)$ (upper panels) and its ratio I_{CP} (lower panels) for central and peripheral Au+Au collisions at $\sqrt{s_{\mathrm{NN}}}$ = 200 GeV, for anti-k_{T} jets with R = 0.2, 0.3, 0.4 and 0.5. The upper panels also show $Y\left(p_{\mathrm{T,jet}}^{\mathrm{ch}}\right)$ for p+p collisions at $\sqrt{s}$ = 200 GeV, calculated using PYTHIA at the charged-particle level and NLO pQCD transformed to the charged-particle level (Sect. X). The uncertainty of the NLO calculation is not shown.

10.1103/PhysRevC.96.024905