Determining the jet transport coefficient $\hat{q}$ of the quark-gluon plasma using Bayesian parameter estimation

James Mulligan on behalf of the JETSCAPE Collaboration

Lawrence Berkeley National Laboratory

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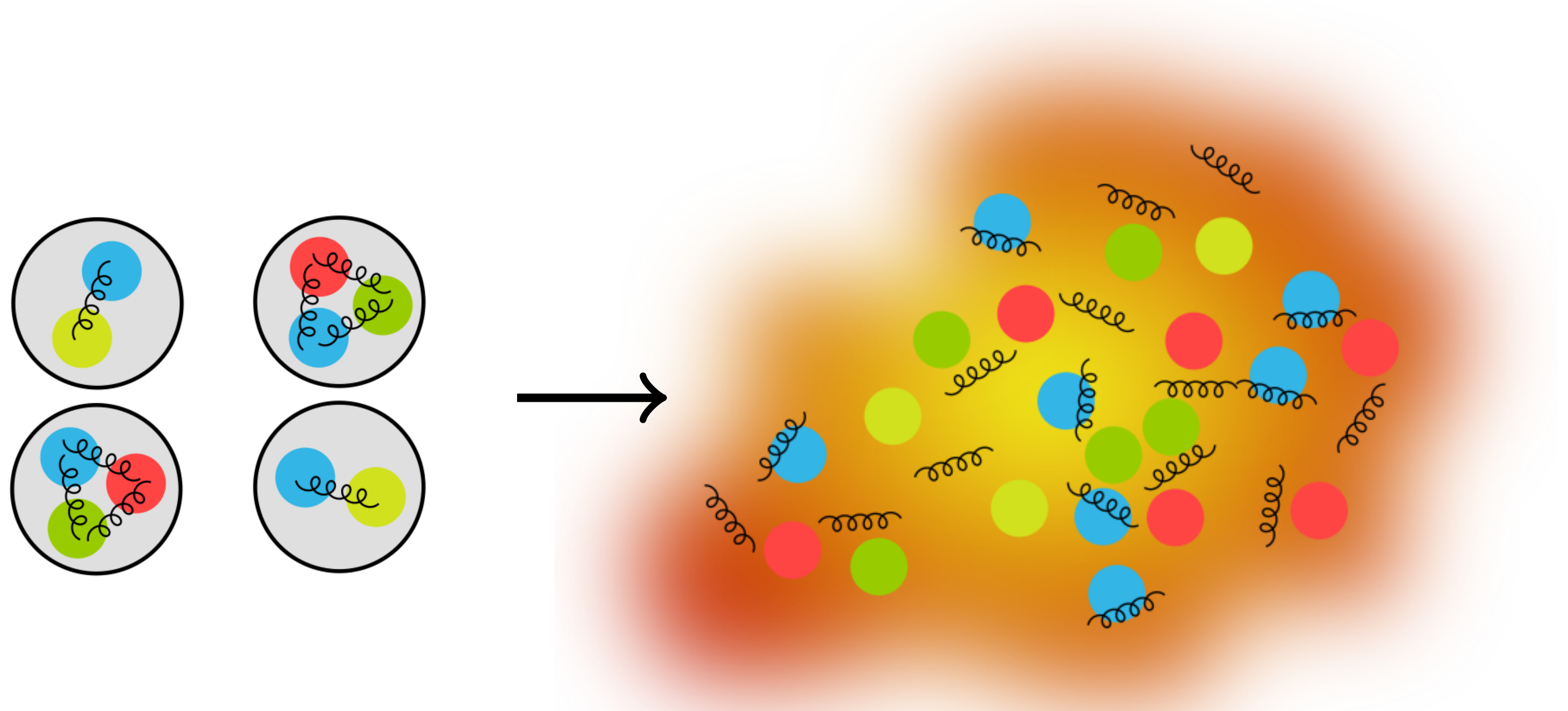
JETSCAPE

Jet quenching in the quark-gluon plasma

We would like to learn fundamental questions about the deconfined state of QCD

- What are the relevant degrees of freedom of the QGP?
  - Quasi-particles?
- How does a strongly-coupled system arise from QFT?
  - Compute bulk properties from first principles?



W. Ke

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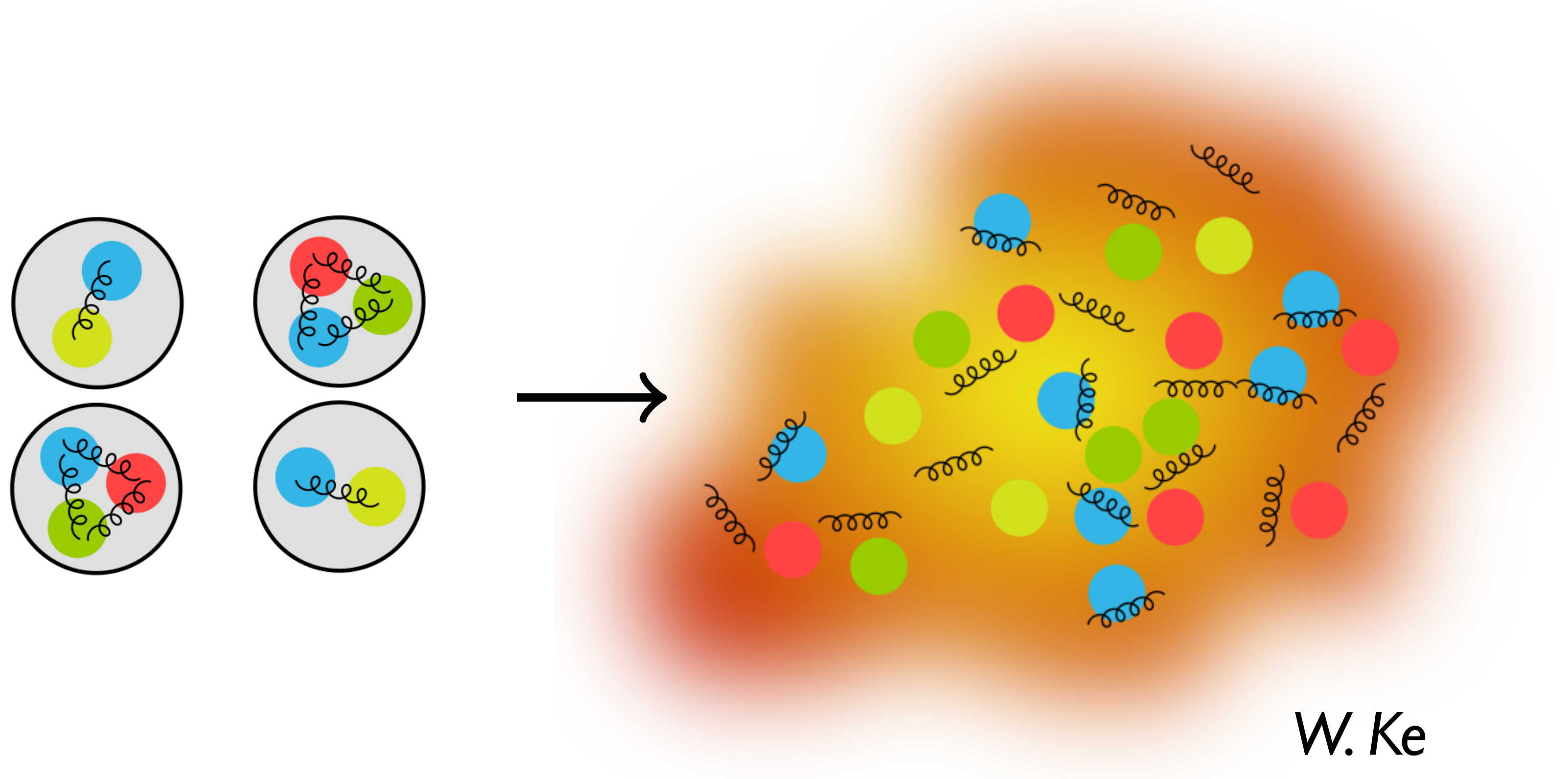

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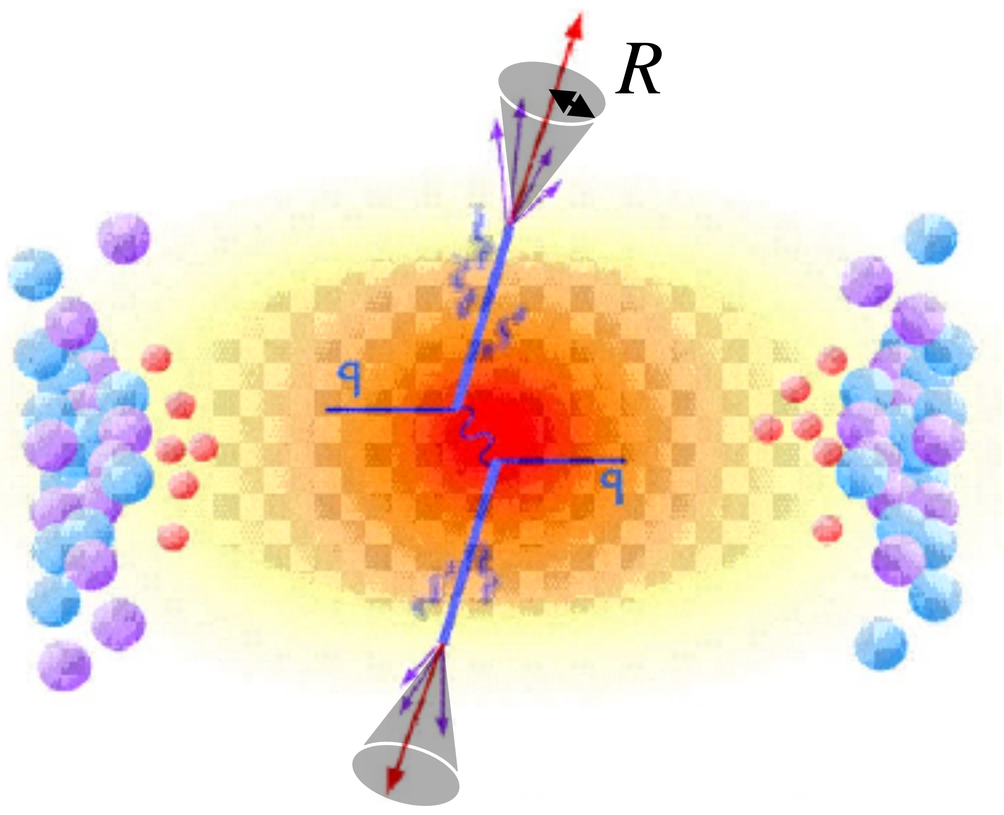
Jets offer a compelling tool

- Jets can probe from the smallest medium scales to the largest medium scales
- Jet evolution can be computed from first principles
- Jets are strongly sensitive to (some) medium properties: $\hat{q}$



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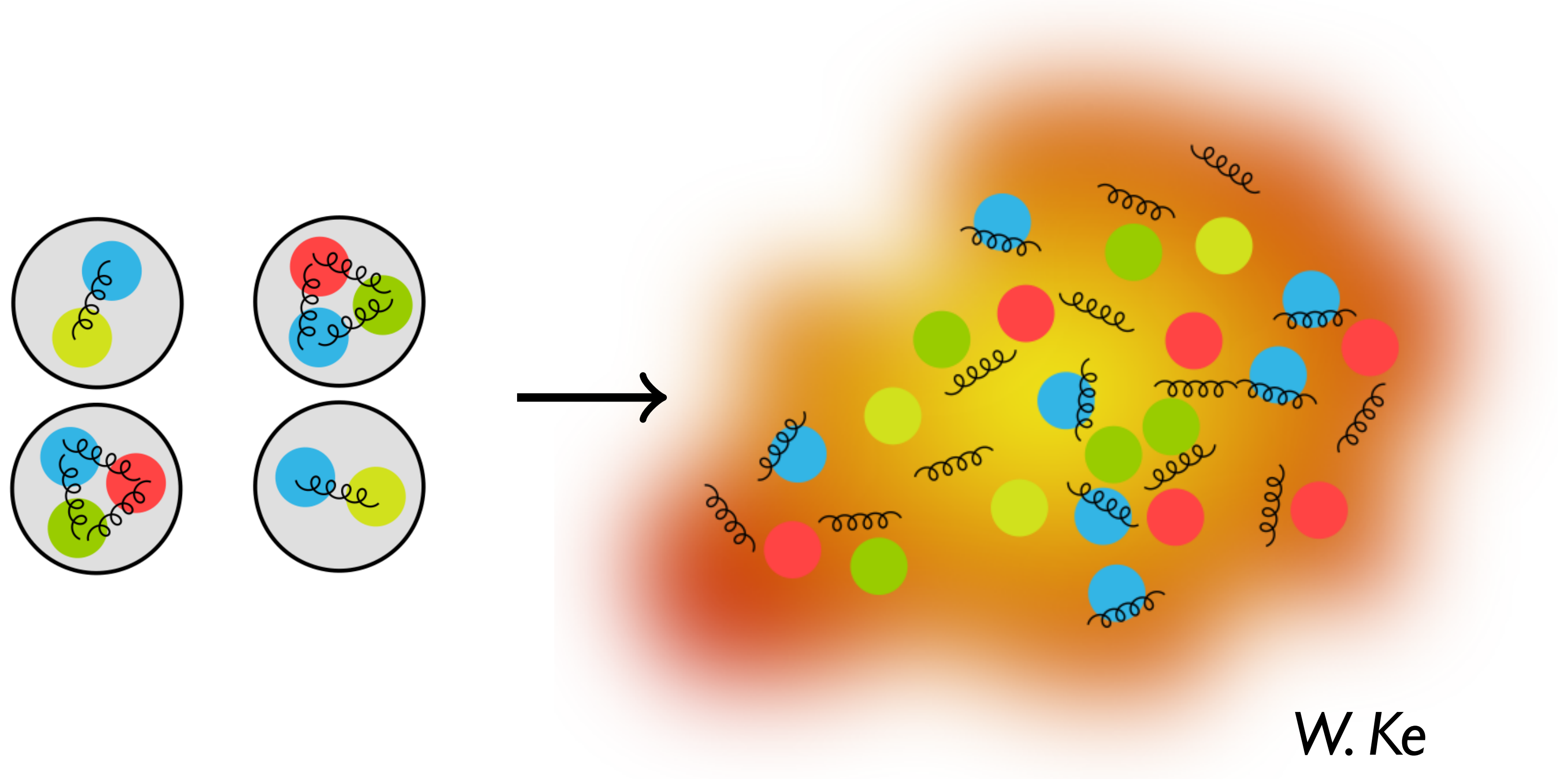

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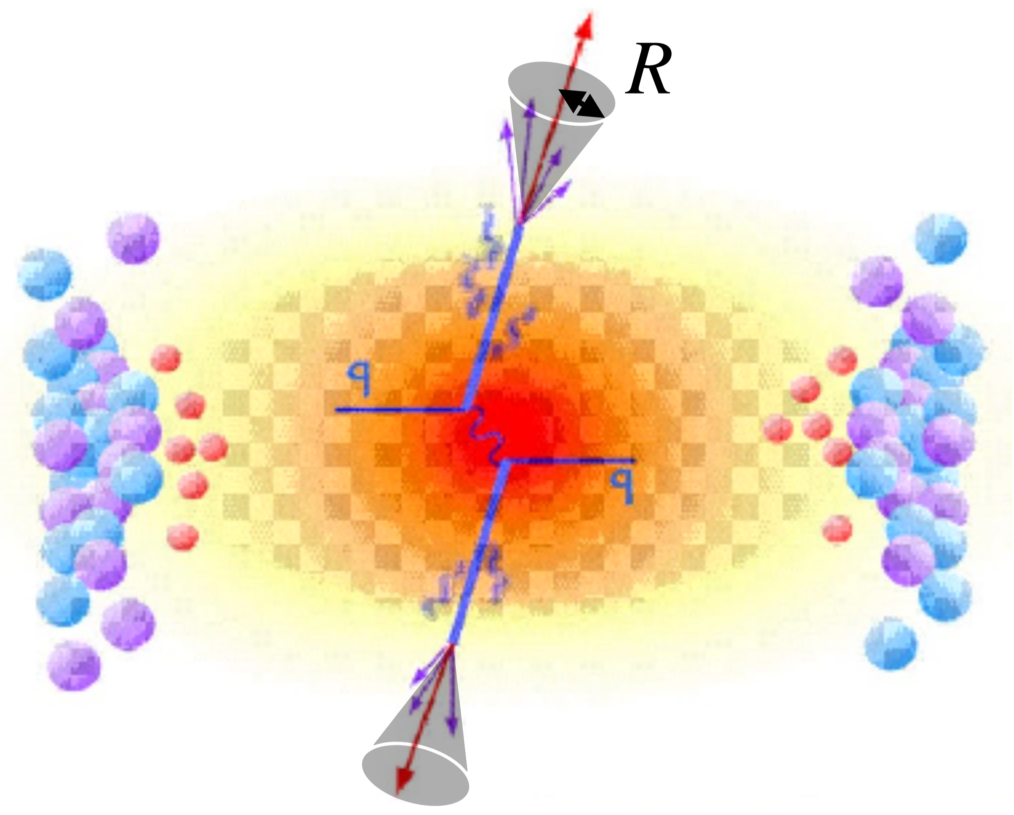
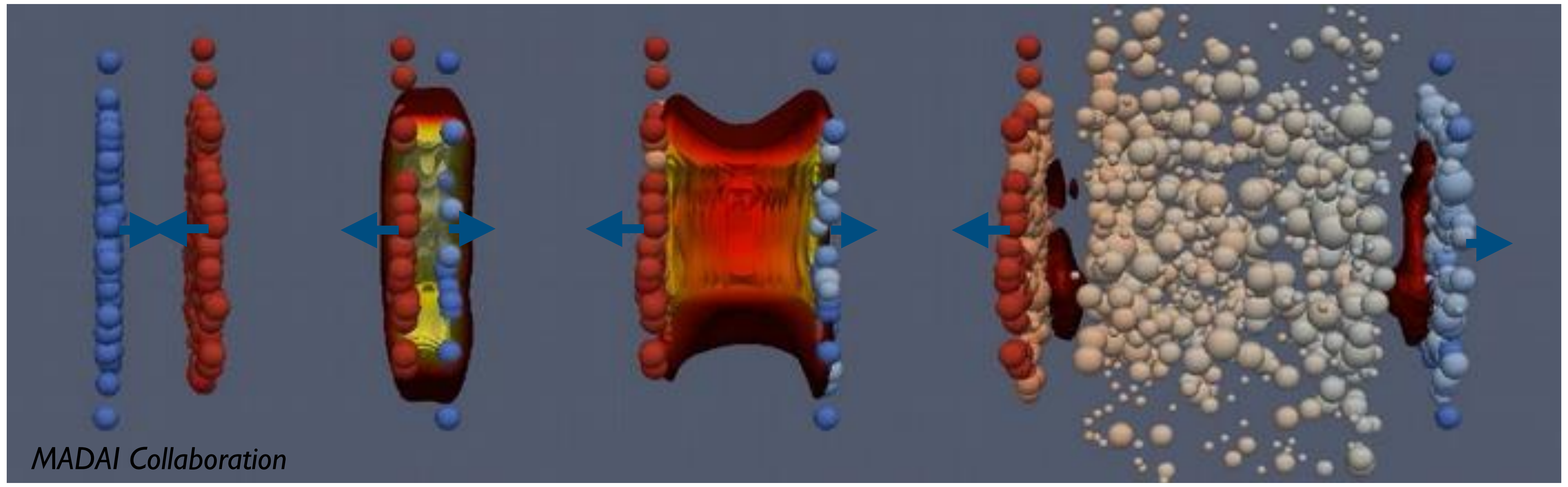


However, it is clear by now that this endeavor is not simple…

The need for global analysis

Jet evolution involves physics that is not known from first principles: initial state, hydrodynamic evolution, medium response, hadronic rescattering, hadronization



Fit models of the physics that are not known from first-principles

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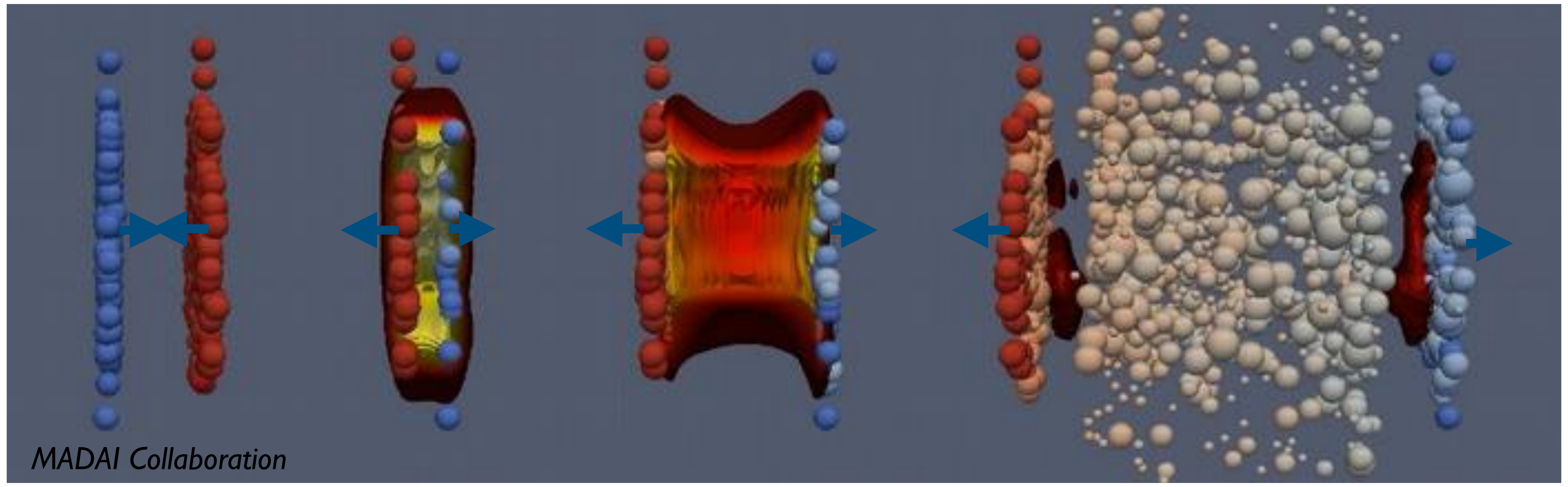
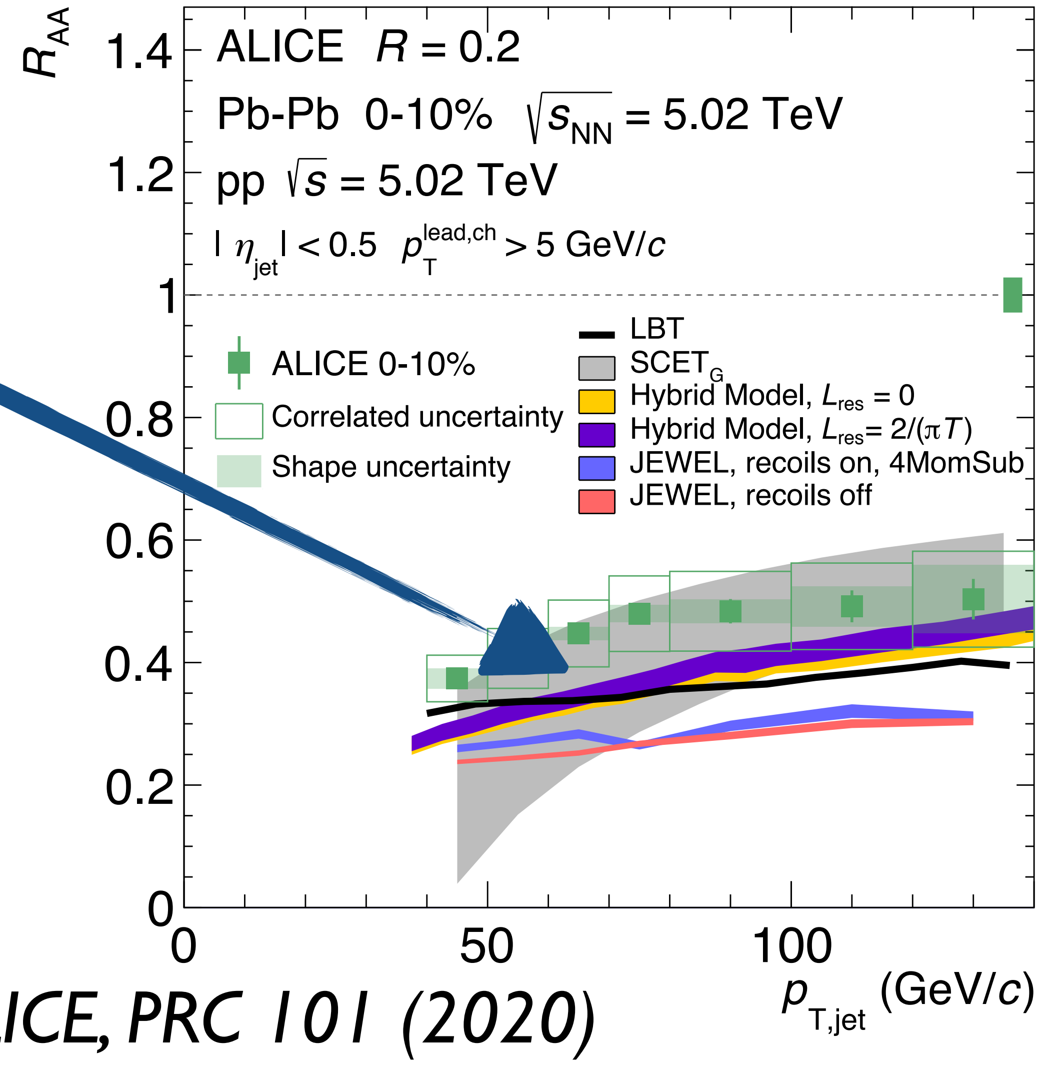


Fit models of the physics that are not known from first-principles

Jet evolution itself is complicated, and there is no (known) golden observable

Example: Models with different physics predict similar modification

$$R_{AA} = \frac{1}{\langle N_{coll} \rangle} \frac{dN^{PbPb}/dp_T}{dN^{pp}/dp_T}$$



ALICE, PRC 101 (2020)

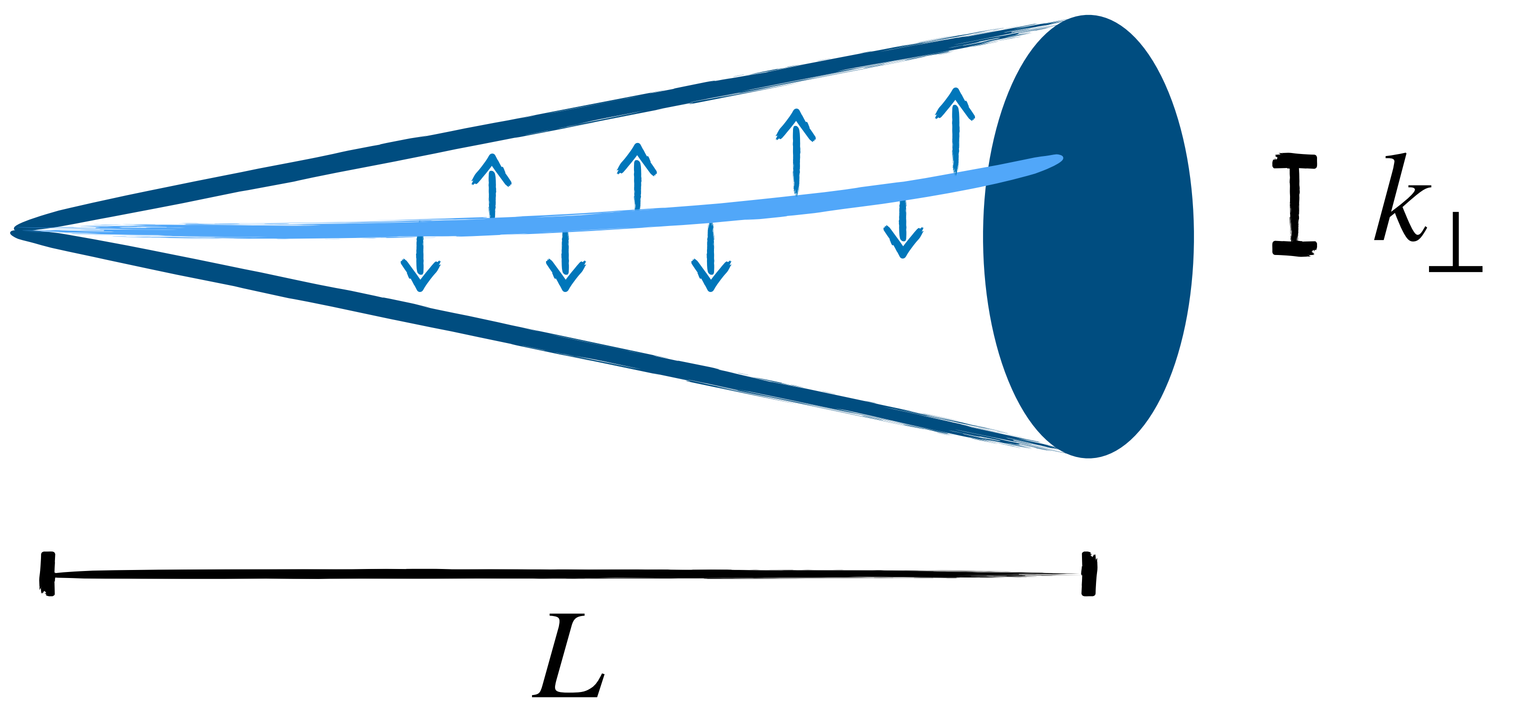
Disentangle simultaneous unknowns in jet quenching theory

- Strongly-coupled vs. weakly-coupled interaction
- Spacetime picture of parton shower
- Color coherence
- …

The jet transverse diffusion coefficient

As a parton propagates through the QGP, it will undergo momentum exchanges transverse to its direction of propagation:

$$\hat{q} \equiv \frac{\langle k_\perp^2 \rangle}{L} = \frac{1}{L} \int dk_\perp^2 \frac{dP\left(k_\perp^2\right)}{dk_\perp^2}$$



where $P\left(k_\perp^2\right)$ is a scattering kernel.

The accumulated $\langle k_\perp^2 \rangle$ can arise from various microscopic interactions:

- Single hard emission
- Multiple soft scattering
- Smooth drag

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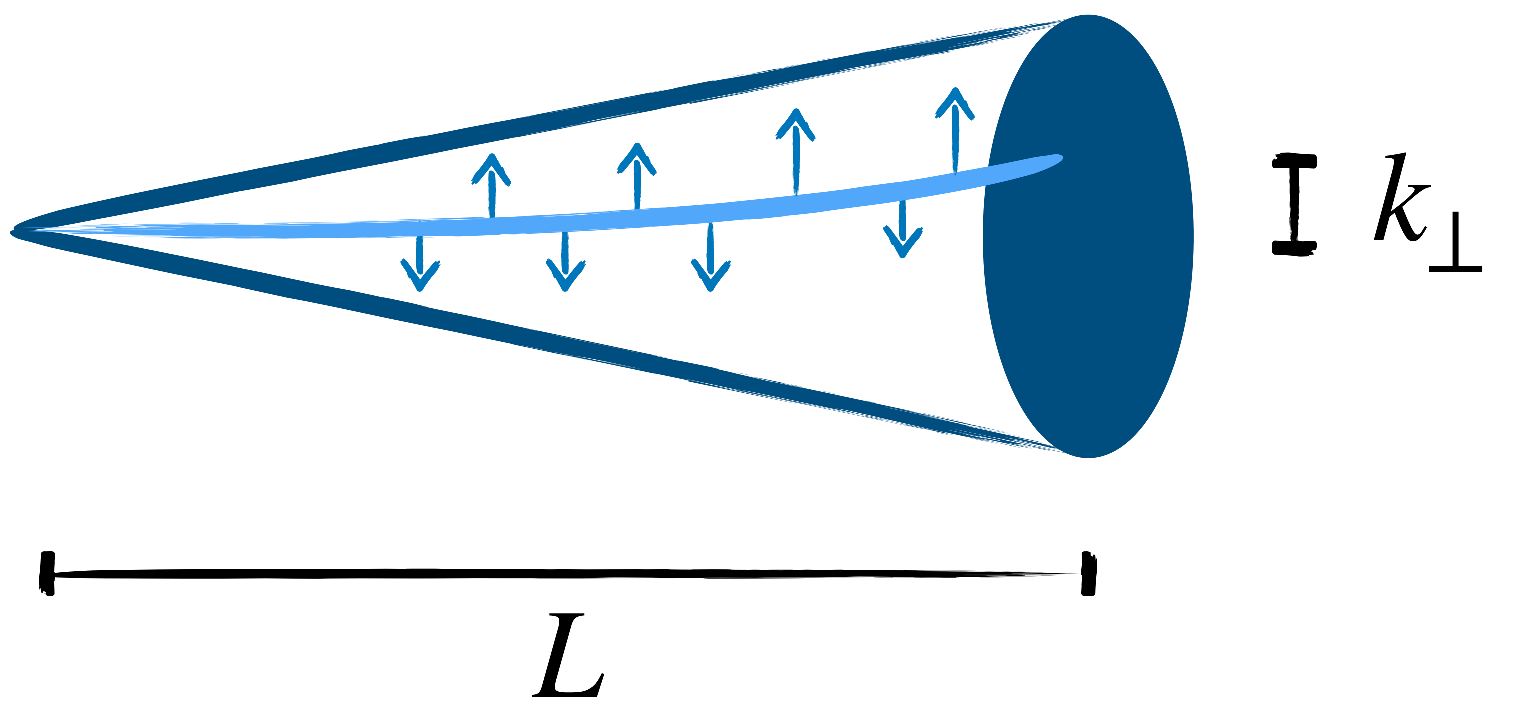

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$\hat{q}$ is one of the most important quantities characterizing jet quenching

- Out-of-cone transport — "energy loss"
  In BDMPS: $\Delta E \sim \hat{q} L^2$
- Broadening
  In BDMPS: $\Delta \varphi \sim \sqrt{\hat{q} L}$

Parameterizing $\hat{q}$

Under certain assumptions, $\hat{q}$ can be calculated

e.g. HTL formula — perturbative elastic scattering

However, we will instead **parameterize** $\hat{q}$ in JETSCAPE with a more general form:

$$\frac{\hat{q}\left(E,T\right)|_{A,B,C,D}}{T^3} = 42C_R\frac{\zeta(3)}{\pi}\left(\frac{4\pi}{9}\right)^2\left\{\frac{A\left[\ln\left(\frac{E}{\Lambda}\right)-\ln(B)\right]}{\left[\ln\left(\frac{E}{\Lambda}\right)\right]^2}+\frac{C\left[\ln\left(\frac{E}{T}\right)-\ln(D)\right]}{\left[\ln\left(\frac{ET}{\Lambda^2}\right)\right]^2}\right\}$$

Parton energy

Local temperature

High-virtuality inspired

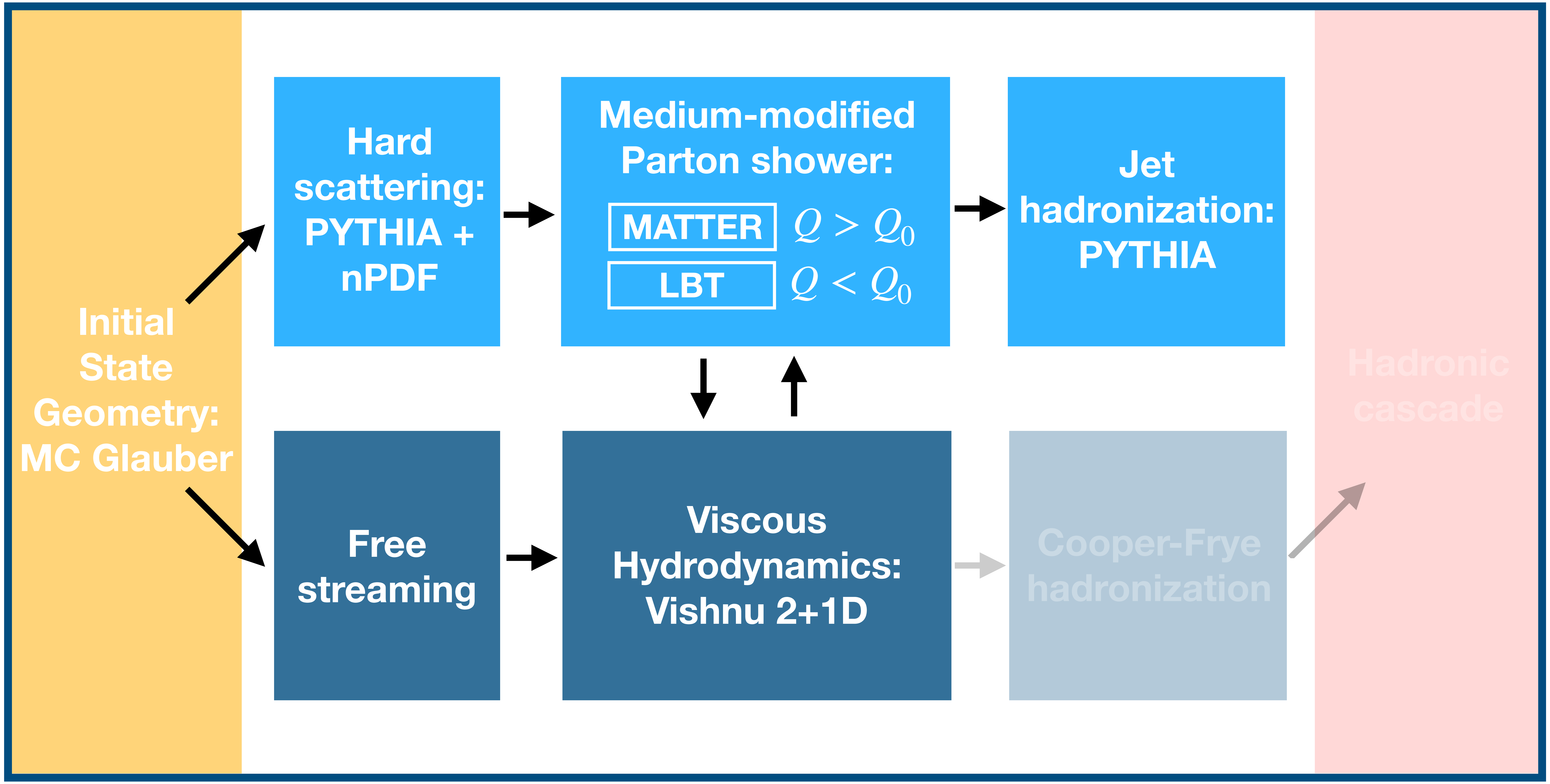
T-independent

HTL-inspired

elastic scattering off temperature T

Modular event generator framework for heavy-ion collisions

JETSCAPE 1903.07706



MATTER

- High-virtuality, radiation-dominated regime

LBT

- Low-virtuality, scattering-dominated regime

Bayesian parameter estimation

$$\hat{q}(E,T)\Big|_{\theta=\{A,B,C,D\}}$$

$$P(\theta|D) \sim P(D|\theta)P(\theta)$$

Posterior Likelihood Prior

The **prior** is our initial knowledge of the parameters

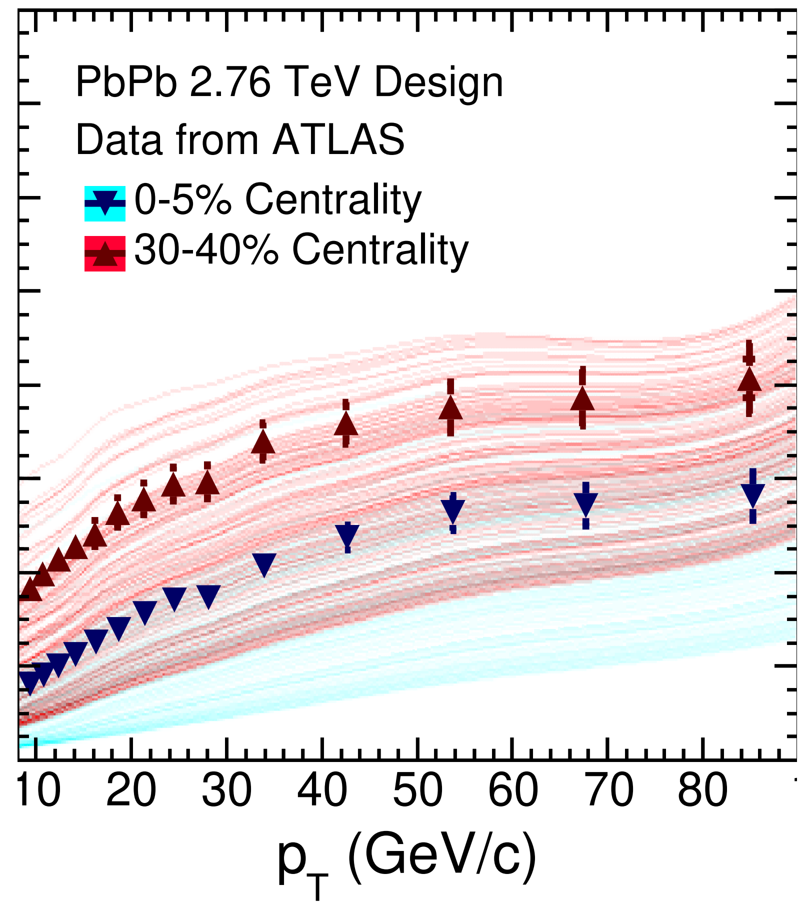
The **likelihood** characterizes how likely we would be to observe the given data, given a set of parameters θ

$$P(D|\theta) \sim \exp\left[-\left(\Delta_i \Sigma_{ij}^{-1} \Delta_j\right)^2\right]$$ where $\Delta_i = R^{\theta}_{\mathrm{AA,i}} - R^{\mathrm{data}}_{\mathrm{AA}}$

Σ is the covariance matrix

The **posterior** is the probability distribution of $\hat{q}$, given the data

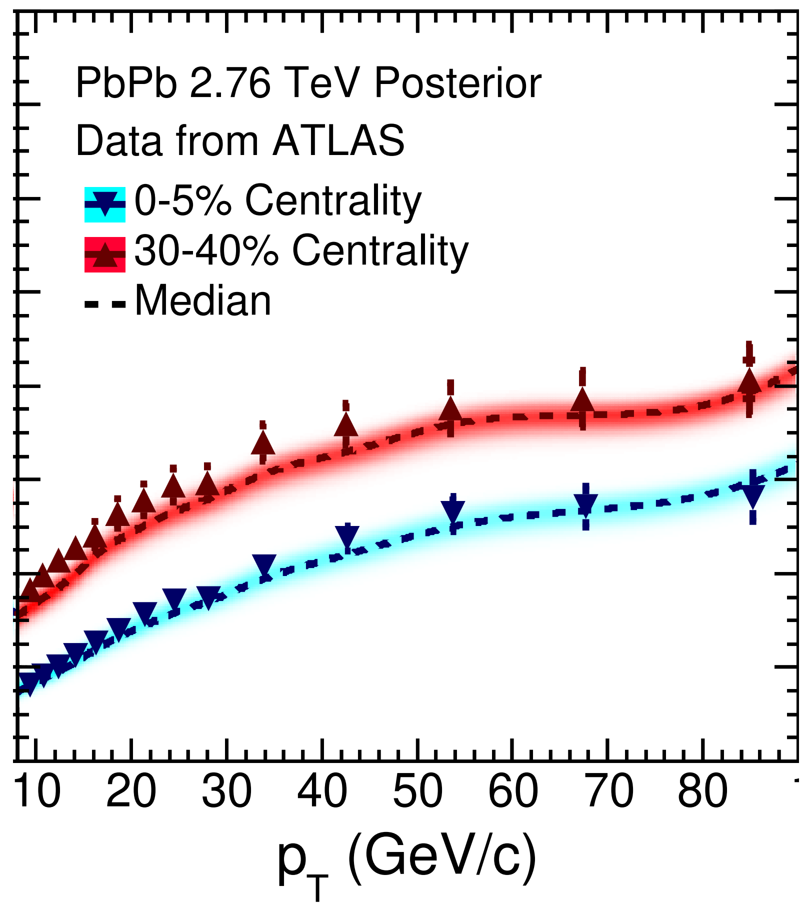
We sample the posterior using Markov Chain Monte Carlo (MCMC)



Prior

↓

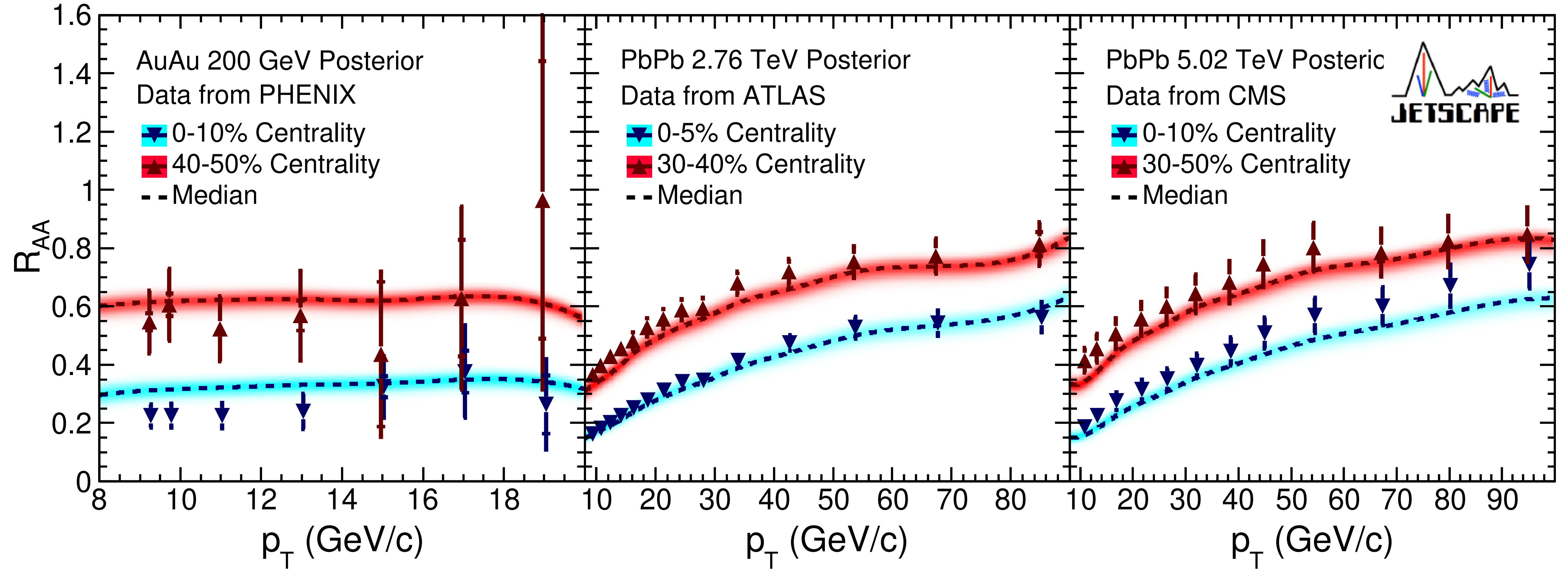
Posterior



2102.11337

Results

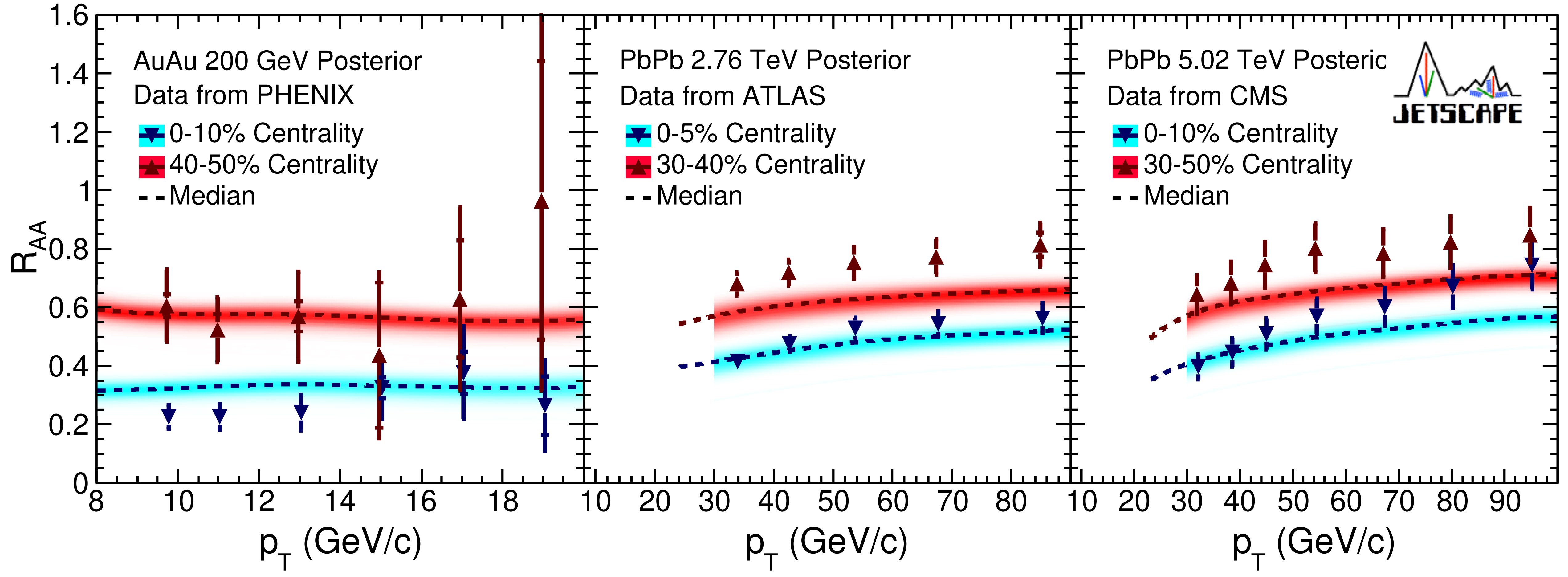
LBT model



LBT describes the data reasonably well

Some small systematic deviations

MATTER model



MATTER describes the data slightly less well

MATTER expected to be valid only at sufficiently high p_T; fit restricted

Results

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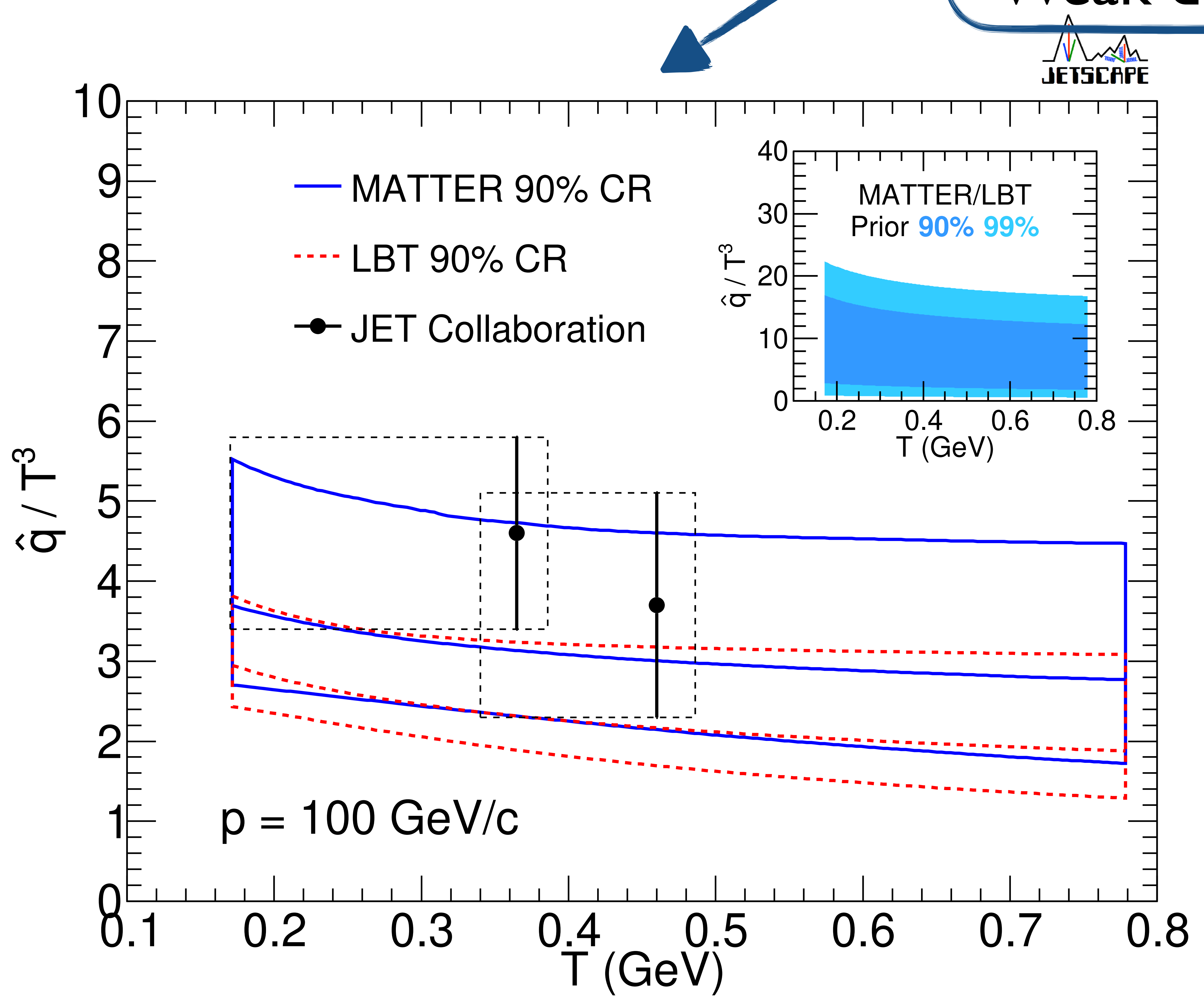
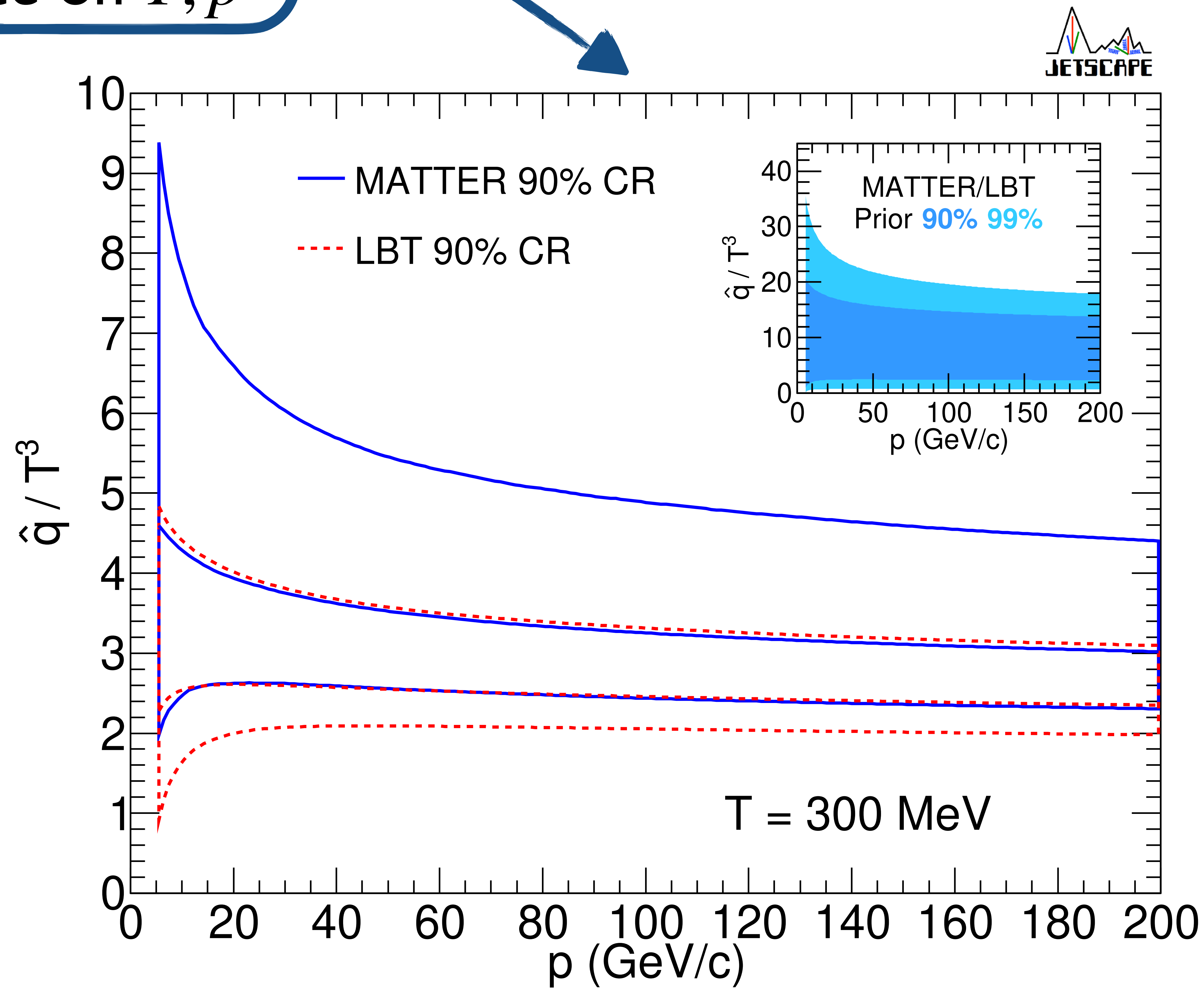
From these extracted parameters, we plot the extracted $\hat{q}$

Weak dependence on T, p





Consistent T-dependence with JET Collaboration

Smaller median: elastic scattering, multiple gluon emission

See also: JET Collaboration, PRC 90 (2014)
Andrés, Armesto, Luzum, Salgado, Zurita (2016)
Ke, Wang (2020)

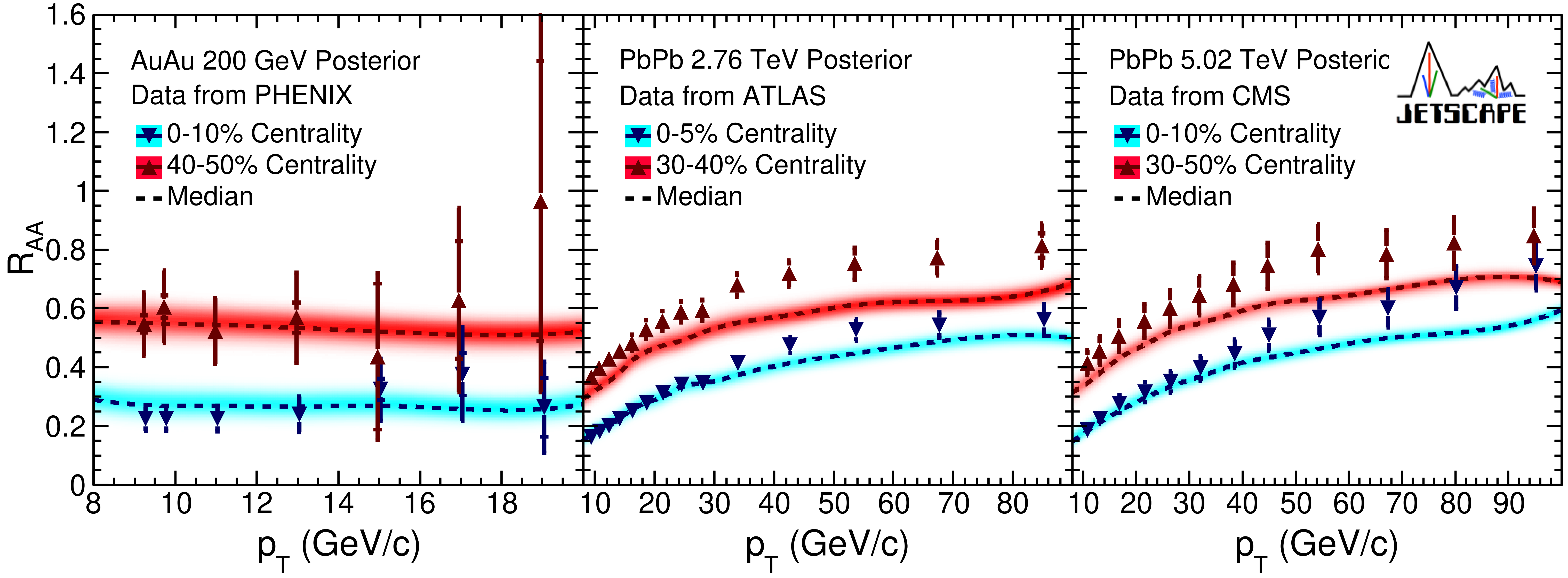
Multi-stage model

2102.11337

Theoretical arguments suggest that a multi-stage model is more well-founded:

MATTER — high-virtuality, $Q > Q_0$
LBT — low-virtuality, $Q < Q_0$

→ Include additional parameter, Q_0, to the fit



No evidence that multi-stage model improves agreement with data

- Caveat: p_T range not restricted as in MATTER only case

Multi-stage model

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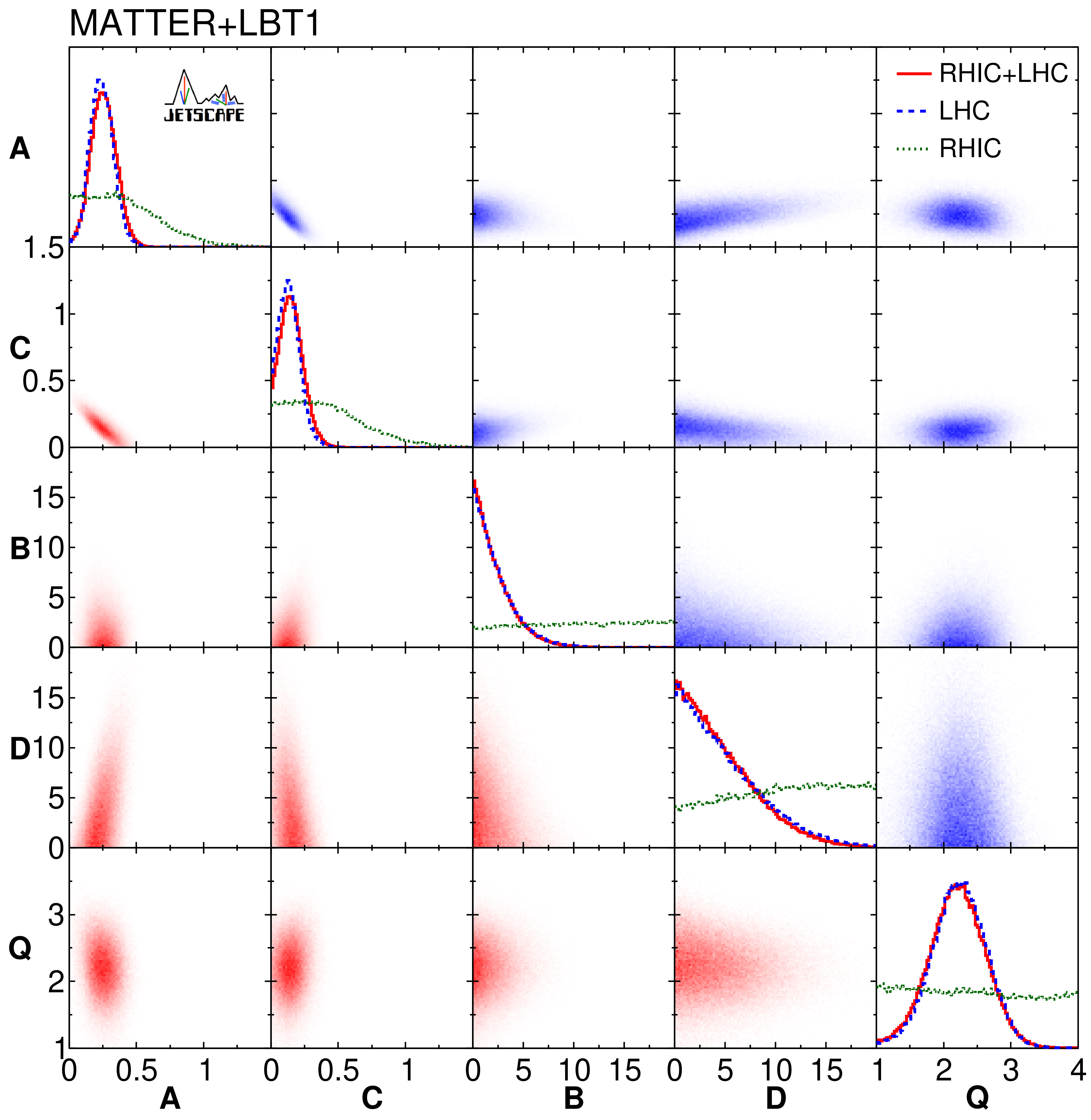


We also test the impact of RHIC vs. LHC data

Fit dominated by LHC data

Due to choice of input data: $p_{\mathrm{T}} > 8\ \mathrm{GeV}/c$

Summary

We extracted the jet transport coefficient $\hat{q}(E,T)$ of the quark-gluon plasma using Bayesian parameter estimation with inclusive hadron R_{AA} data

- Extracted as continuous function of E, T — data significantly constrains prior distributions
- Several JETSCAPE models considered: MATTER, LBT, MATTER+LBT

Summary

We extracted the jet transport coefficient $\hat{q}(E,T)$ of the quark-gluon plasma using Bayesian parameter estimation with inclusive hadron R_{AA} data

- Extracted as continuous function of E, T — data significantly constrains prior distributions
- Several JETSCAPE models considered: MATTER, LBT, MATTER+LBT

Global analysis will be key to uncovering the nature of deconfined QCD matter

- Extension to additional medium properties: τ_{init}, medium response, quasi-particles, …
- Extension to additional observables — jet R_{AA}, substructure, correlations, HF, EW, …
  - **Need theory input:** improved modeling and parameterizations, multi-stage paradigm, …
  - **Need experiment input:** (i) corrections, (ii) uncertainty correlations on HEPData
- Provide experimental guidance — observables, systems, centrality to best constrain models

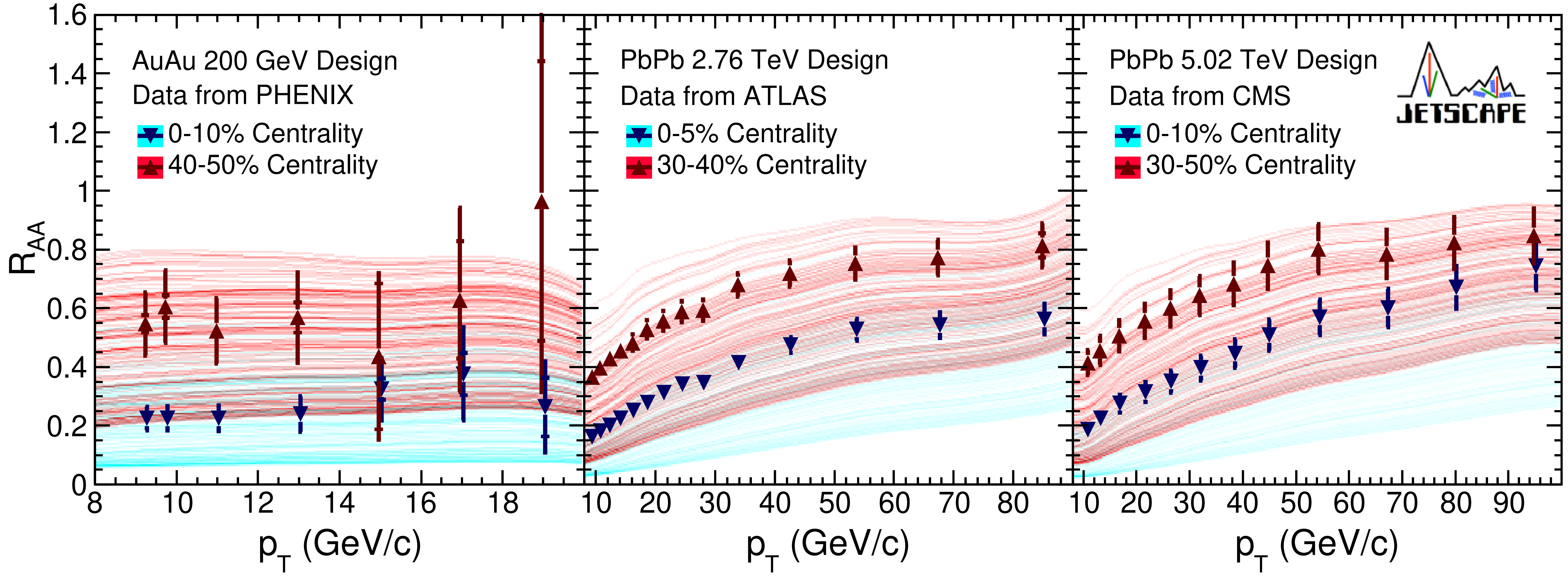
Backup

Experimental data

PHENIX PRC 87 (2013)
CMS EPJC 72 (2012)
ATLAS JHEP 09 (2015)

Inclusive hadron R_{AA}

- Multiple centrality, $\sqrt{s_{\mathrm{NN}}}$ to vary T

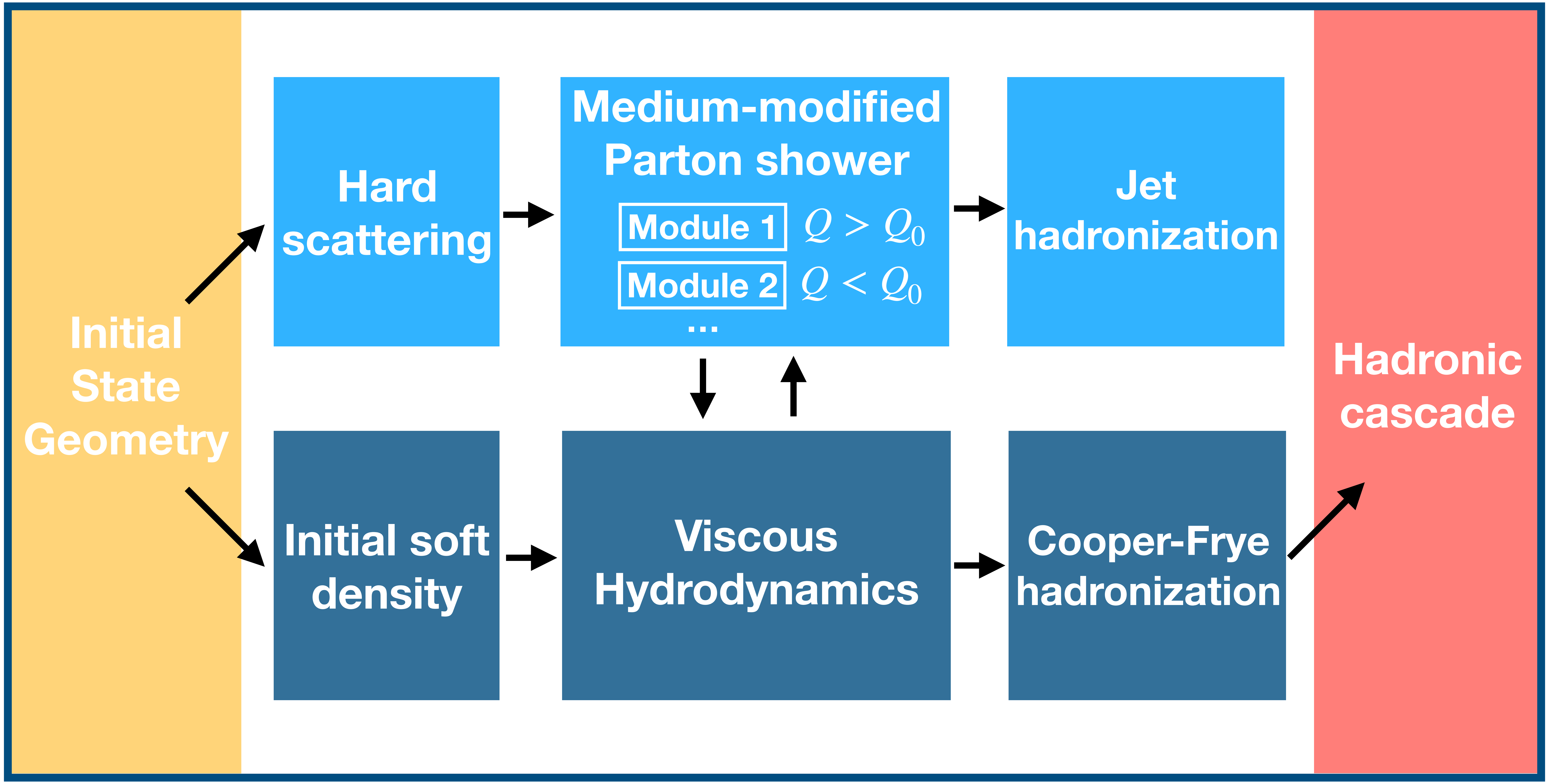


We decompose the experimental covariance matrix into several sources, with varying degree of information reported by experiment

Note: Please report **signed** systematic uncertainty breakdowns in HEPData
(or full covariances matrices)

0.0 - 0.1	0.31931 ±0.066862 stat ±11.376551075580494% sys,unfolding ∓14.473809748383616% sys,trkeff ±3.9122415926653775% sys,generator
0.1 - 0.13	5.7953 ±0.44877 stat ±4.27125329701226% sys,unfolding ±1.7492371459259304% sys,trkeff ∓0.9203612018695351% sys,generator

Jet quenching in JETSCAPE



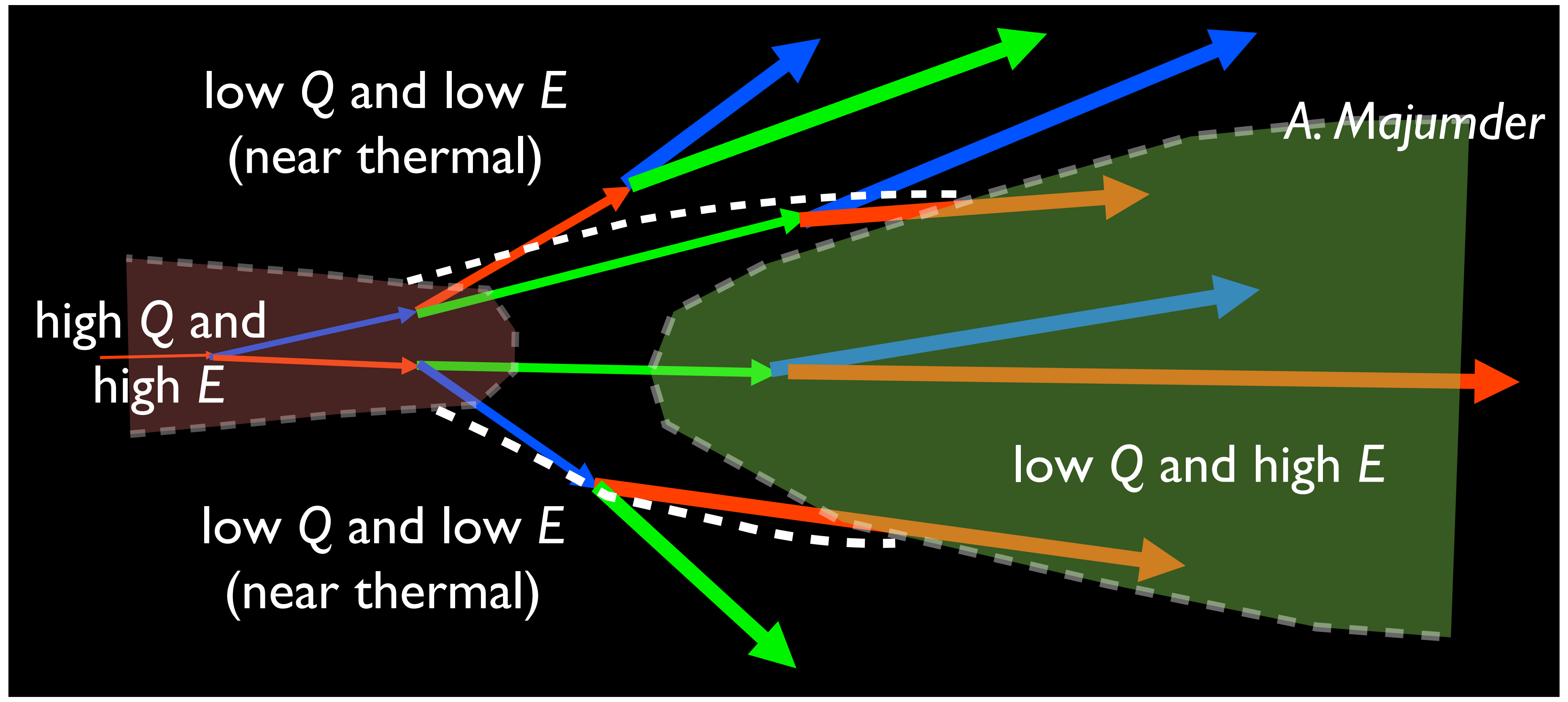
MATTER

Majumder PRC 88 (2013)
Cao, Majumder PRC 101 (2020)

Medium-modified splitting function

$$P_a(z, Q^2) = P_a^{\text{vac}}(z) + P_a^{\text{med}}(z, Q^2)$$

High-virtuality, radiation-dominated regime: $Q \gg \sqrt{\hat{q}E}$



LBT

Cao, Luo, Qin, Wang PRC 94 (2016)
PLB 777 (2018)

Elastic and inelastic scatterings — linearized Boltzmann transport of jet partons

- Inelastic scatterings generate gluon radiation
- Broadening due to elastic scattering

Low-virtuality, scattering-dominated regime

See also:
JEWEL
Martini
Q-PYTHIA
Hybrid Model
…

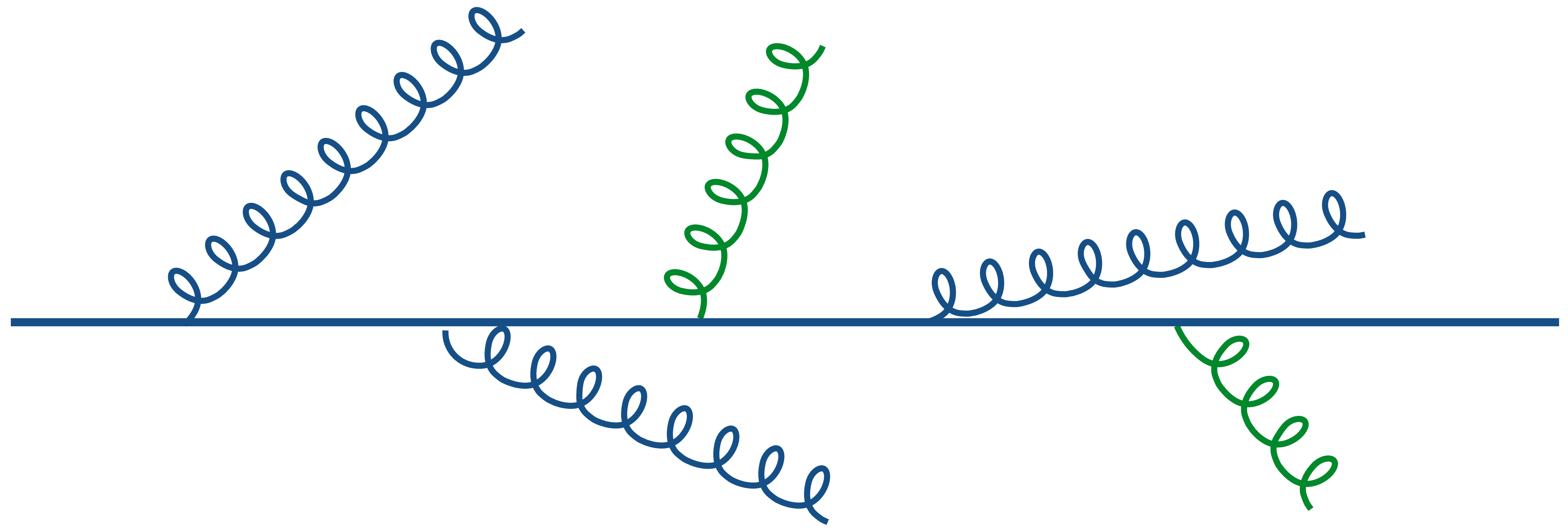
Leading hadrons

While $\hat{q}$ is important for all jet observables, it is not the **only** important physics

- Re-scattering of soft emissions
- Medium response

→ Relevant to reconstructed jets

For leading hadron p_{T}, however, $\hat{q}$ is the dominant physics



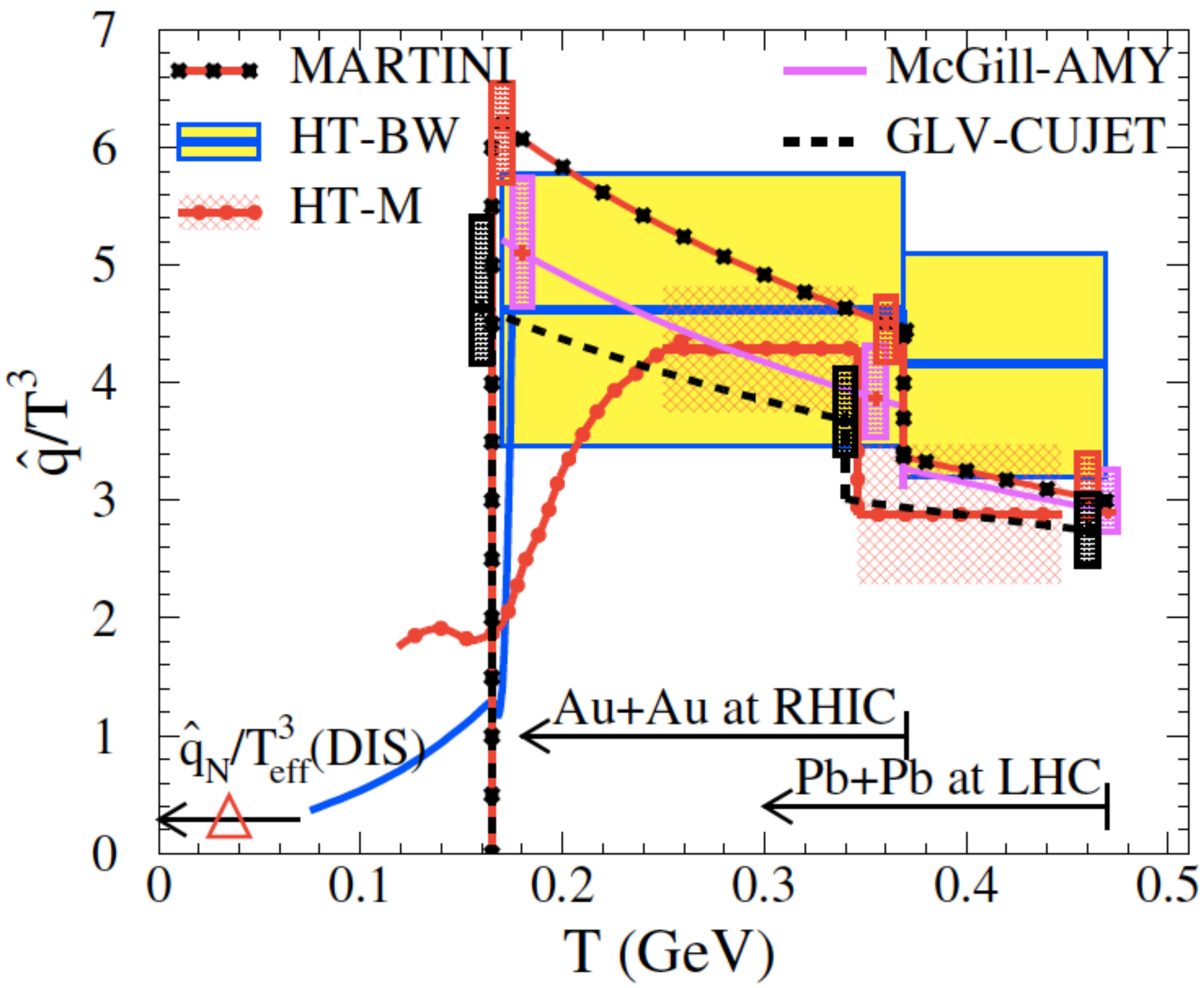
We only need to know what is radiated away from the leading parton

— not what happens to those radiations

JET Collaboration

JET Collaboration, PRC 90 (2014)

Previous work: Separate fits of $\hat{q}$ at RHIC and LHC for various pQCD models



Improvements in this talk:

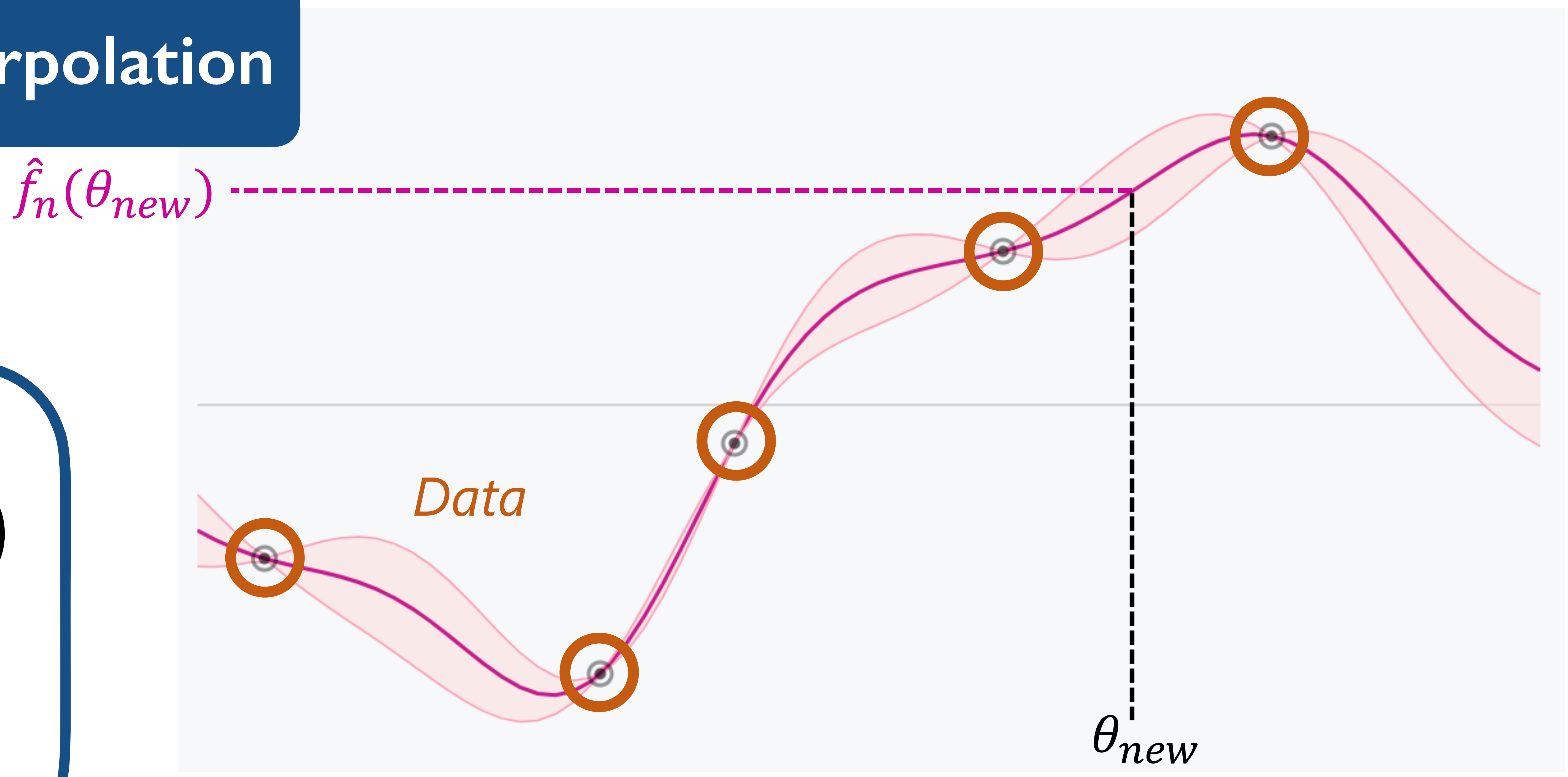
- Extraction of $\hat{q}$ as a continuous function of T, E
- Bayesian statistics — correct approach
- Improved theoretical models

See also:
Andrés, Armesto, Luzum, Salgado, Zurita (2016)
Ke, Wang (2020)

Gaussian Process Emulators

In order to evaluate the likelihood across the parameter space θ, we need to know the R_{AA} predicted by JETSCAPE at **prohibitively many** different θ

Solution: Non-parametric interpolation



This allows us to train an interpolator using $\mathcal{O}\left(10 \times \dim\theta\right)$ JETSCAPE model calculations

with quantification of interpolation uncertainty

Simon Mak

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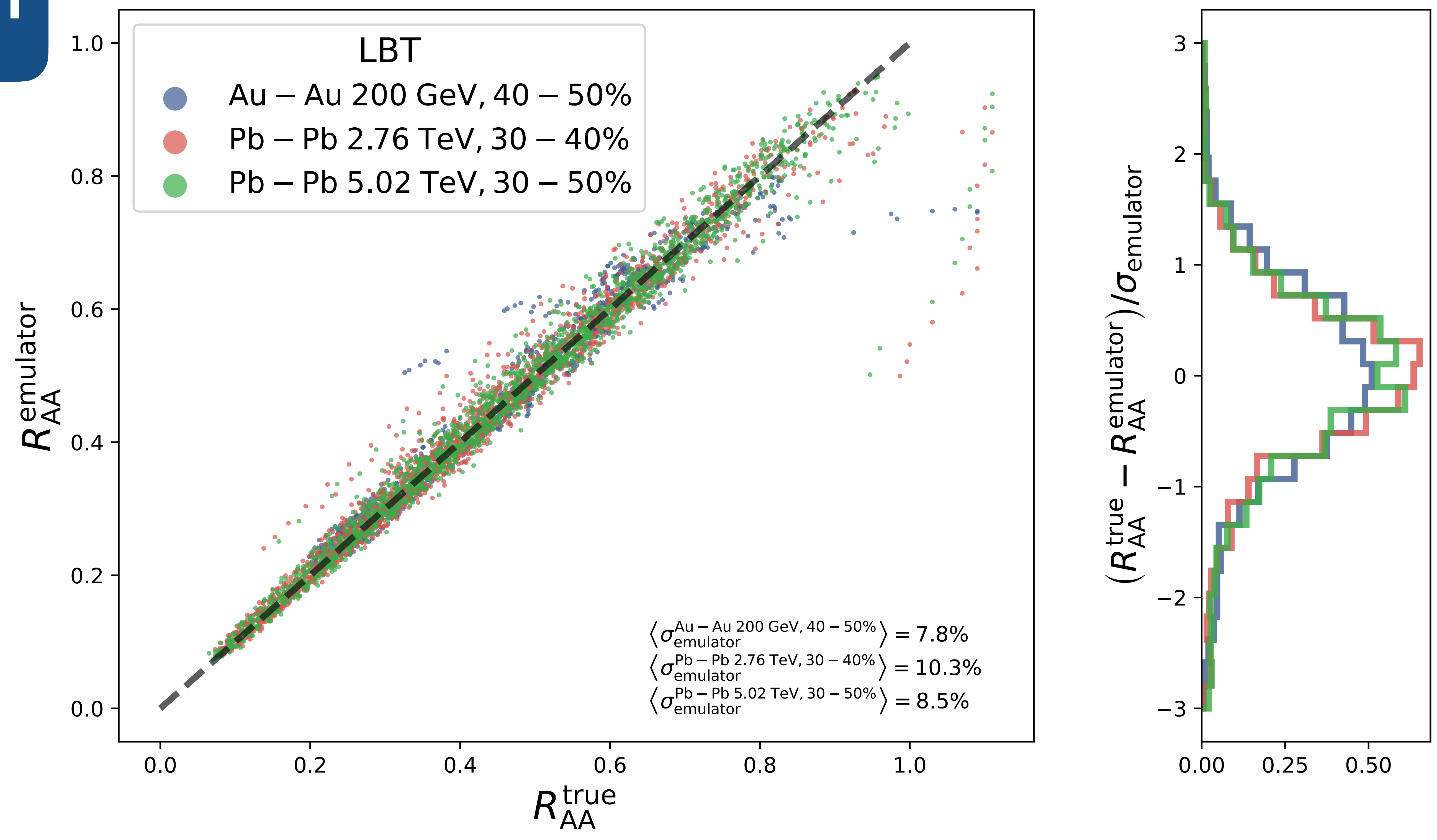

Results

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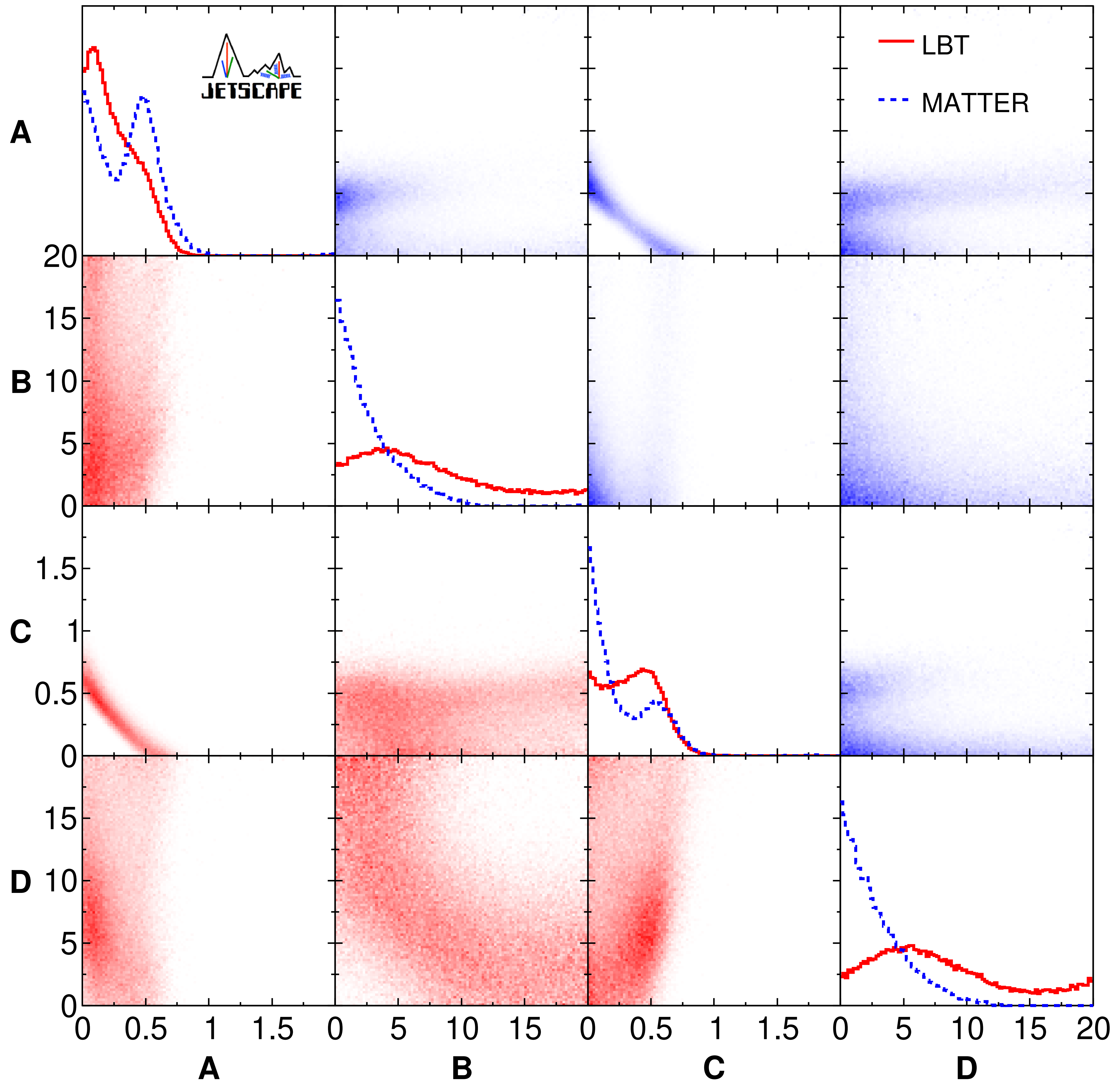

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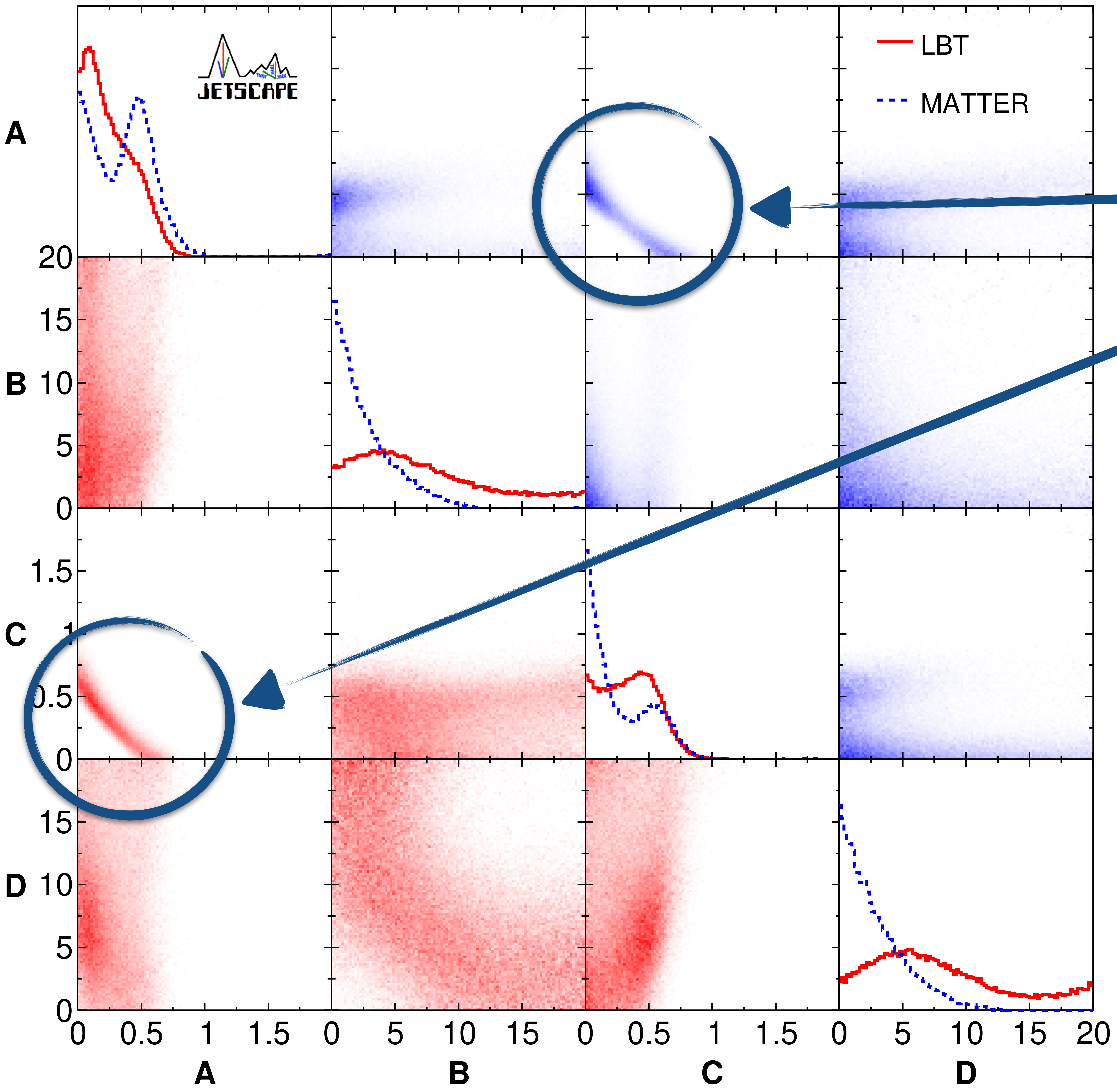


The extracted parameters are substantially different for MATTER vs. LBT

MATTER: large A, small C

LBT: small A, large C

Consistent with the original motivation of the $\hat{q}$ parameterization:

$$\frac{\hat{q}\left(E,T\right)|_{A,B,C,D}}{T^3} = 42C_R\frac{\zeta(3)}{\pi}\left(\frac{4\pi}{9}\right)^2\left\{\frac{A\left[\ln\left(\frac{E}{\Lambda}\right)-\ln(B)\right]}{\left[\ln\left(\frac{E}{\Lambda}\right)\right]^2}+\frac{C\left[\ln\left(\frac{E}{T}\right)-\ln(D)\right]}{\left[\ln\left(\frac{ET}{\Lambda^2}\right)\right]^2}\right\}$$

High-virtuality inspired

T-independent

HTL-inspired

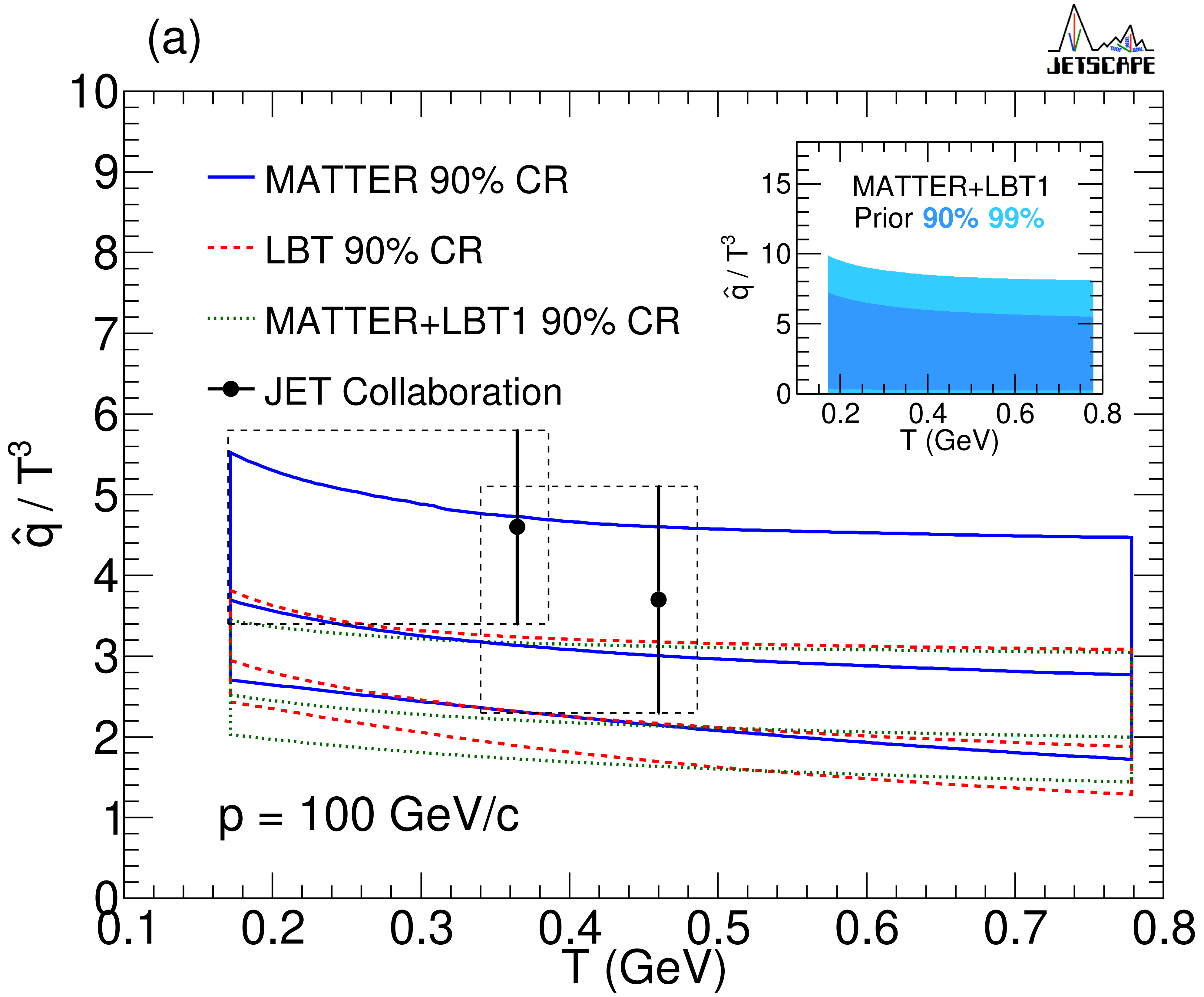
elastic scattering off temperature T

Multi-stage model

2102.11337

Extracted $\hat{q}$ of MATTER+LBT is smaller than MATTER,LBT alone

Due to additional quenching at low virtuality (compared to MATTER) or high virtuality (compared to LBT alone)

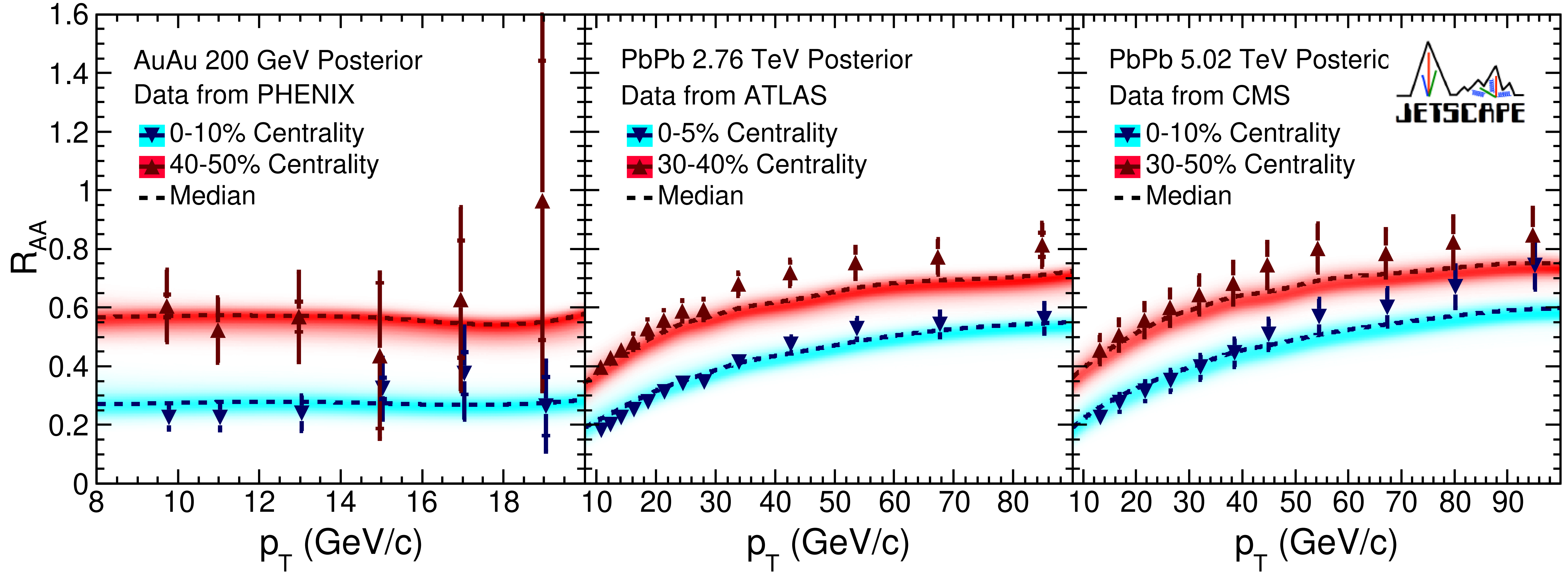


Multi-stage model

2102.11337

We also explored an alternate multi-stage parameterization, in which we replace the "high-virtuality" term with $E \to Q$

$$\frac{\hat{q}\left(Q,E,T\right)|_{Q_0,A,C,D}}{T^3} = 42C_R\frac{\zeta(3)}{\pi}\left(\frac{4\pi}{9}\right)^2\left\{\frac{A\left[\ln\left(\frac{Q}{\Lambda}\right)-\ln\left(\frac{Q_0}{\Lambda}\right)\right]}{\left[\ln\left(\frac{Q}{\Lambda}\right)\right]^2}\theta(Q-Q_0)+\frac{C\left[\ln\left(\frac{E}{T}\right)-\ln(D)\right]}{\left[\ln\left(\frac{ET}{\Lambda^2}\right)\right]^2}\right\}$$



Improved fit

Will require additional observables to make more definitive statement about multi-stage model

Principal component analysis

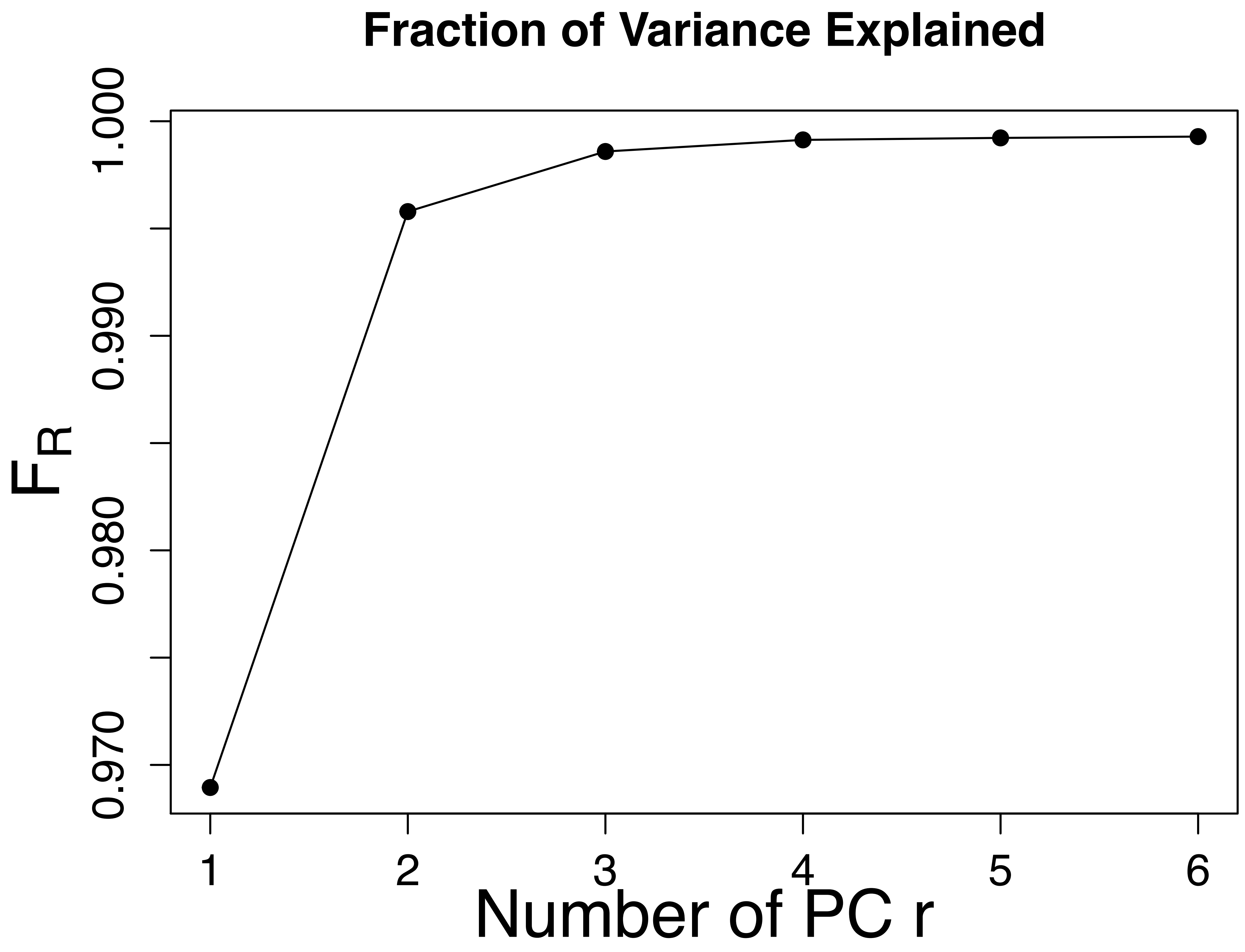
We have 66 data points

- R_{AA} for various $\sqrt{s_{NN}}$, centrality, p_T

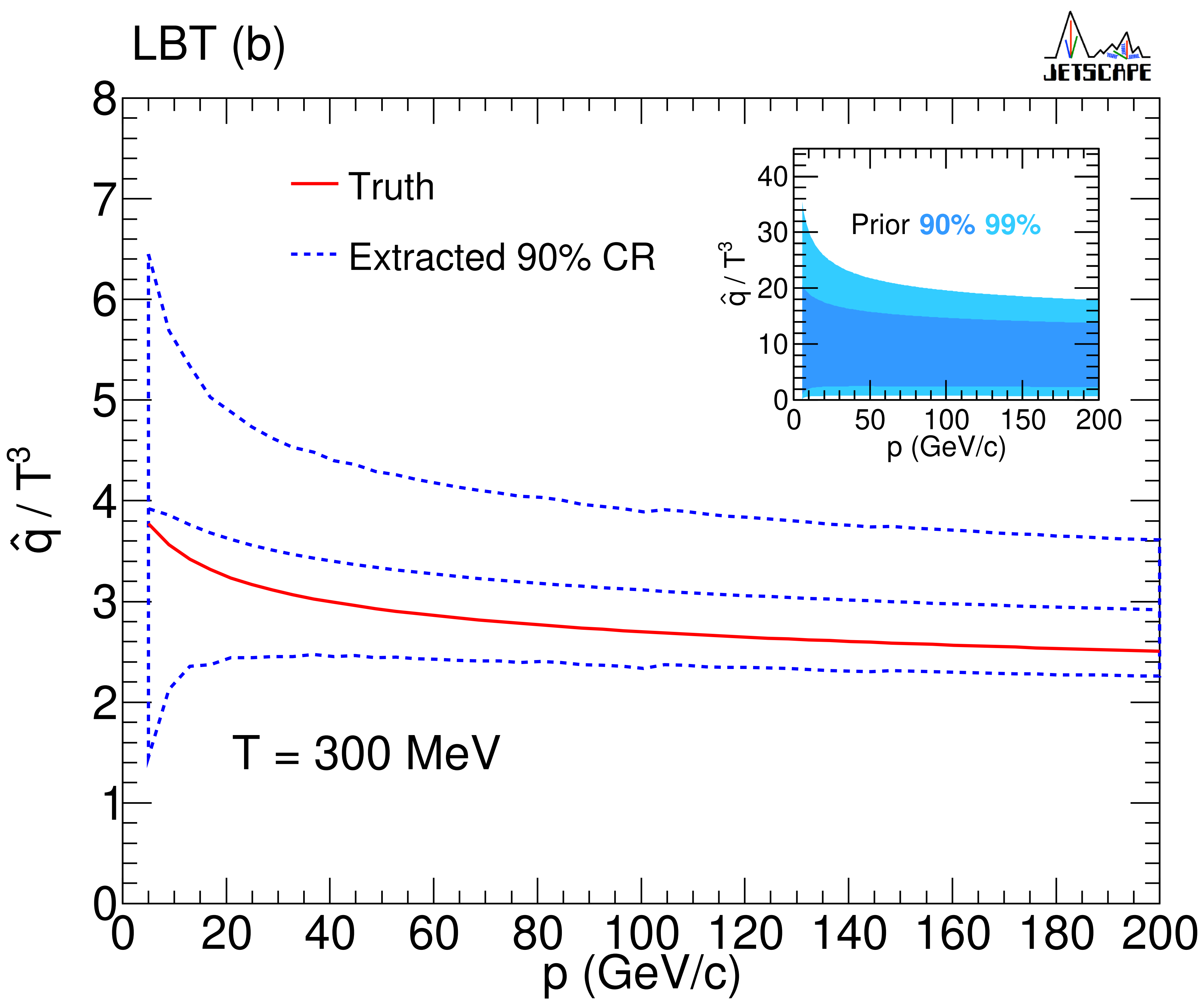
For each $\sqrt{s_{NN}}$, we perform PCA:

- Instead of fitting a single GPE to this 66-dimensional space, we determine the most important linear combinations of centrality, p_T
- Keep e.g. 3 components

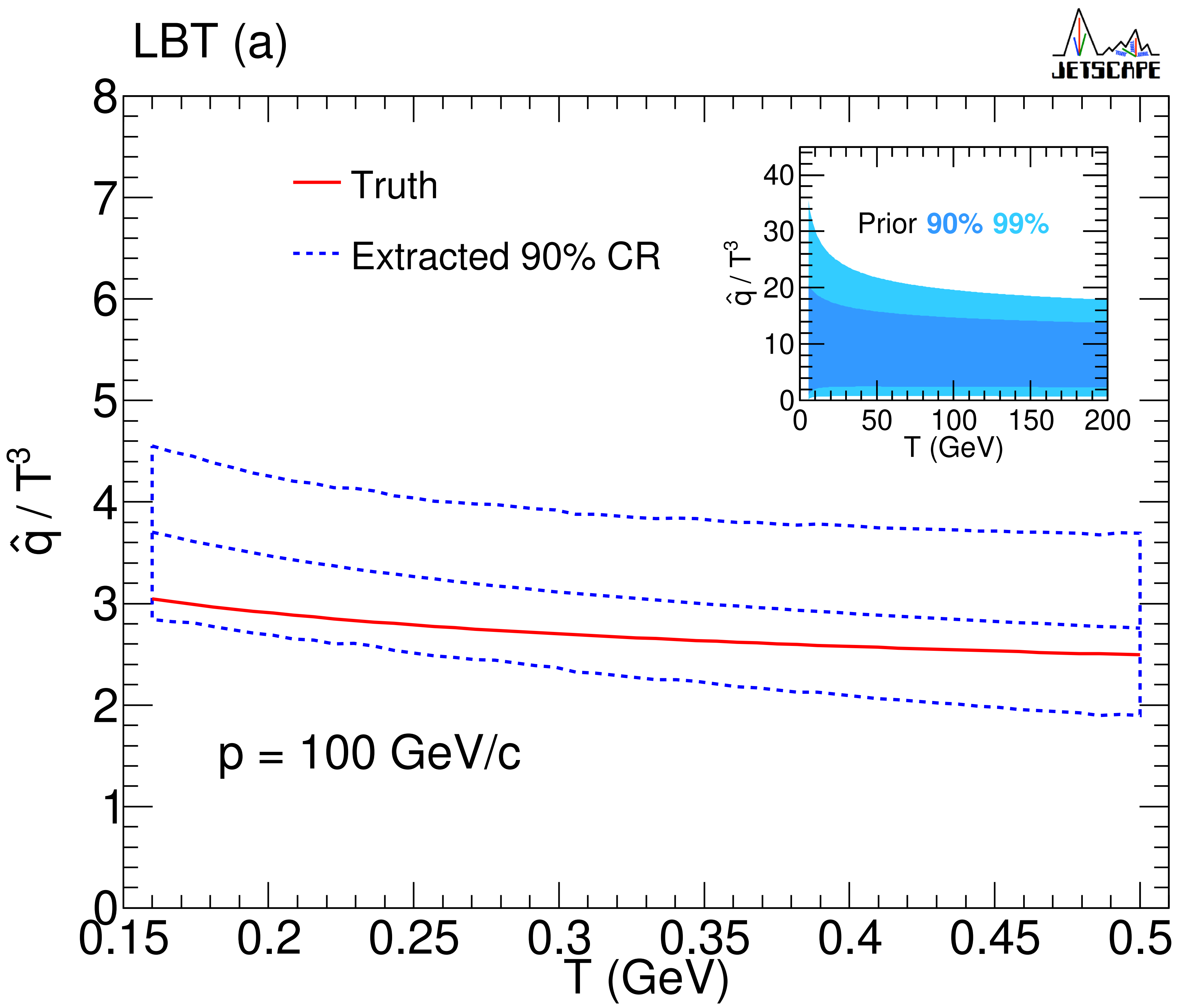
For each PC, train an independent GPE



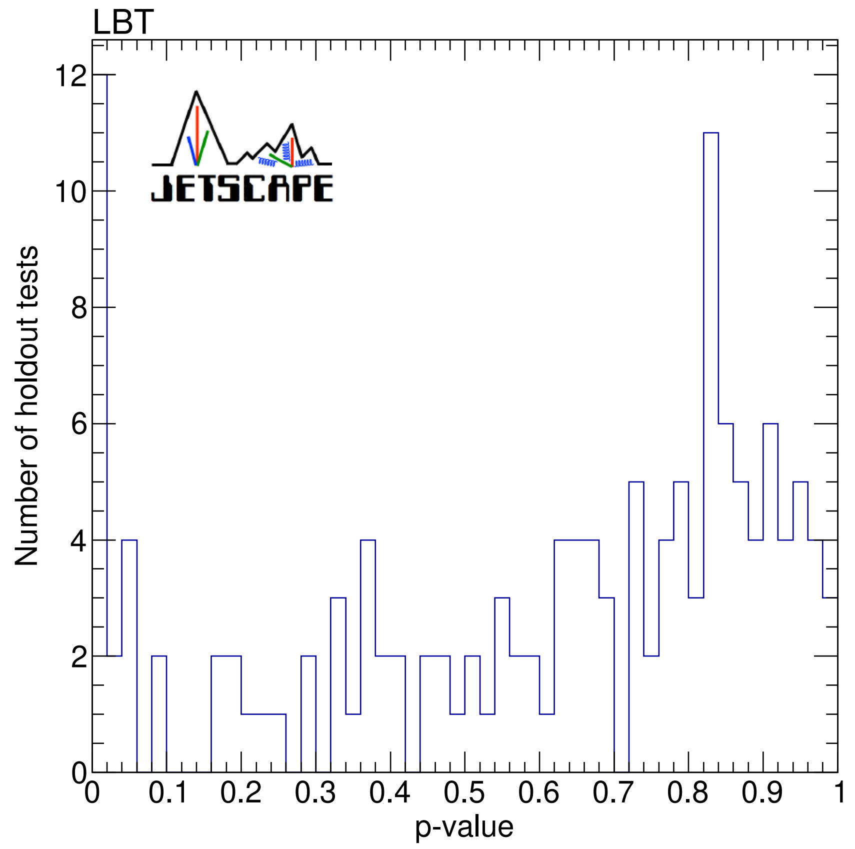
Closure



LBT (b)
Truth
Extracted 90% CR
Prior 90% 99%
T = 300 MeV
p (GeV/c)



LBT (a)
Truth
Extracted 90% CR
Prior 90% 99%
p = 100 GeV/c
T (GeV)



LBT
Number of holdout tests
p-value