

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

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arXiv:2102.11337



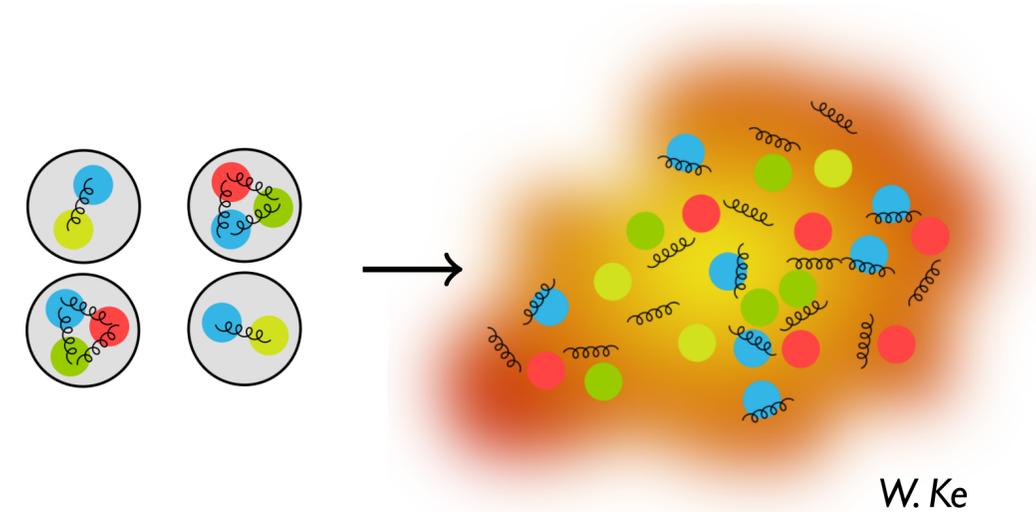
RHIP Seminar
University of Tennessee, Knoxville
Feb 23 2021



Jet quenching in the quark-gluon plasma

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

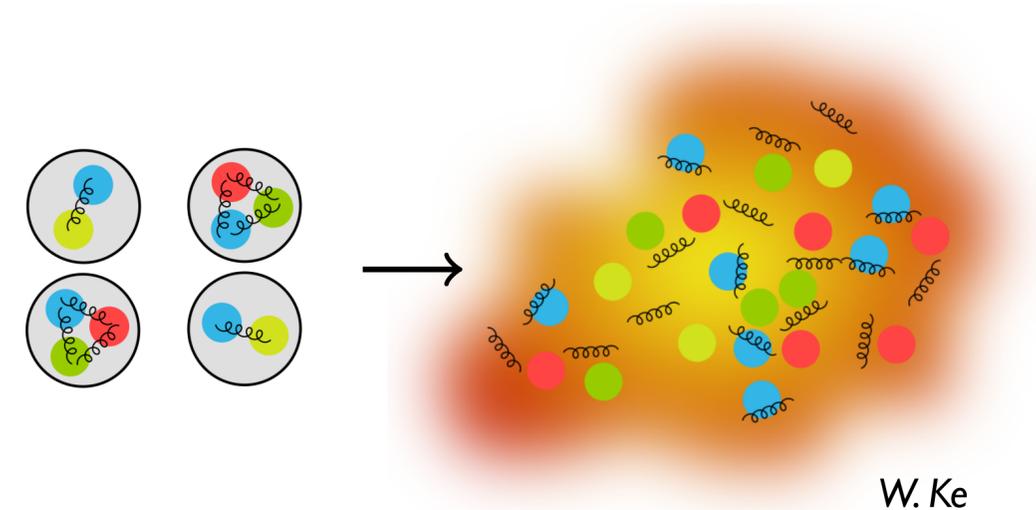
- What are the relevant degrees of freedom of the QGP?
 - Quasi-particles?
- How does a strongly-coupled system arise from QFT?
 - Compute bulk properties from first principles?



Jet quenching in the quark-gluon plasma

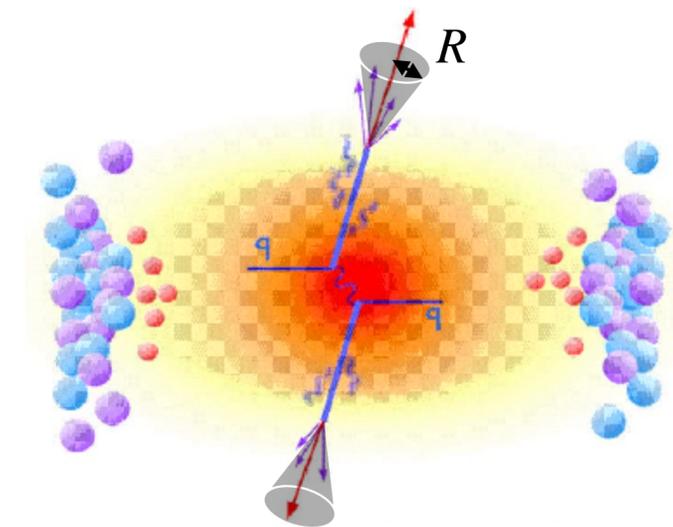
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Jets offer a compelling tool

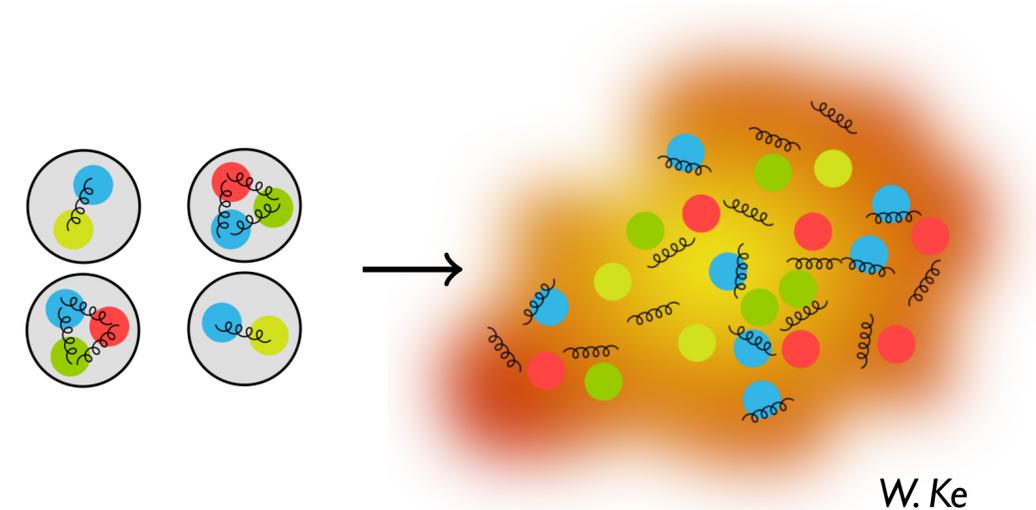
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- Jet evolution can be computed from first principles
- Jets are strongly sensitive to (some) medium properties: \hat{q}



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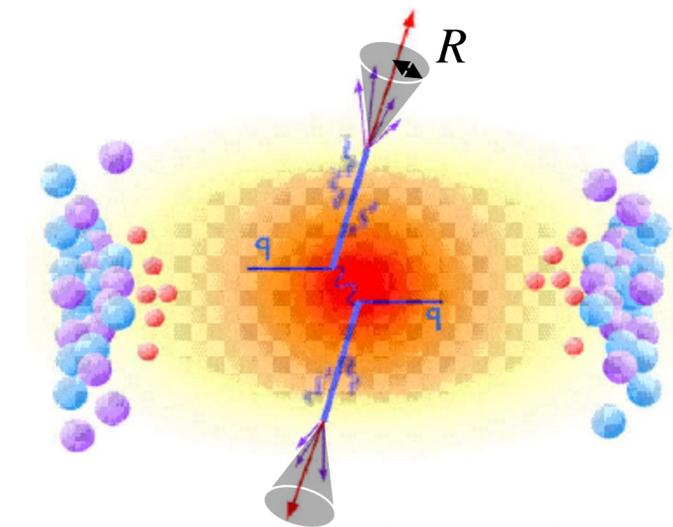
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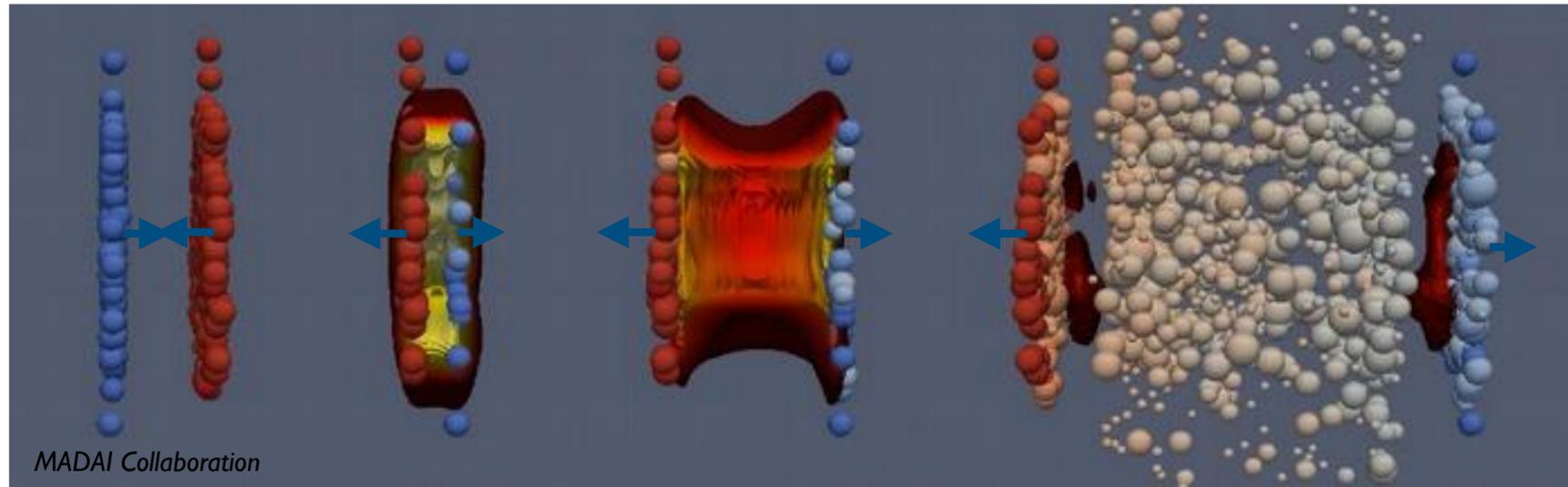
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However, it is clear by now that this endeavor is not simple...

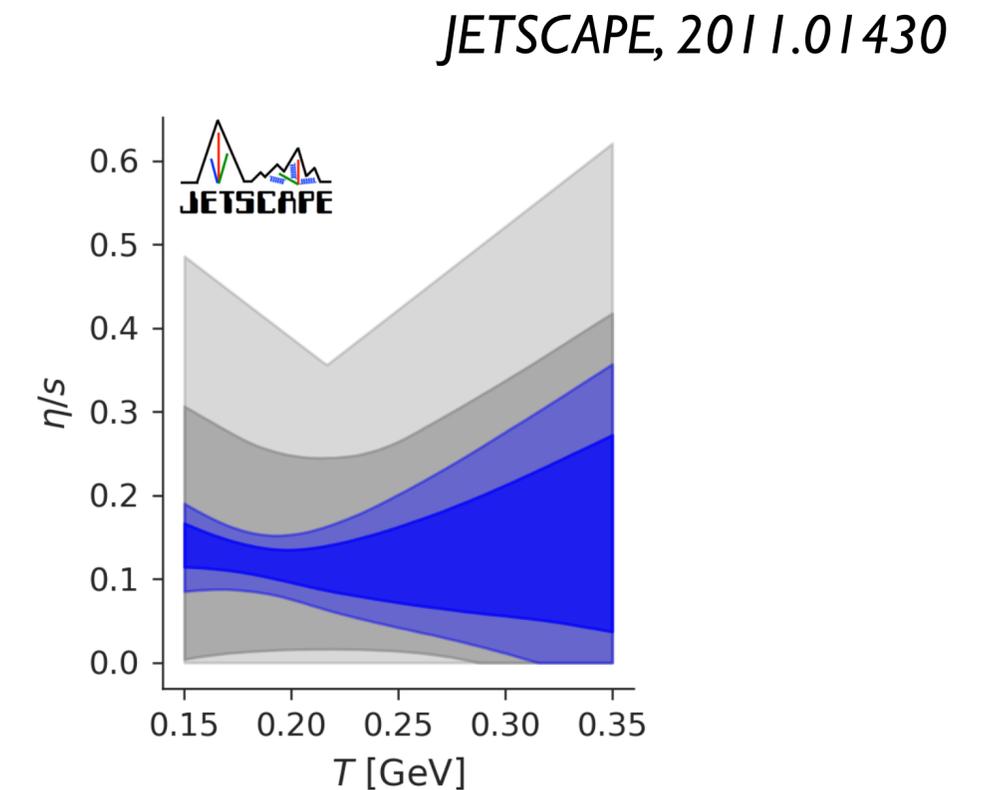
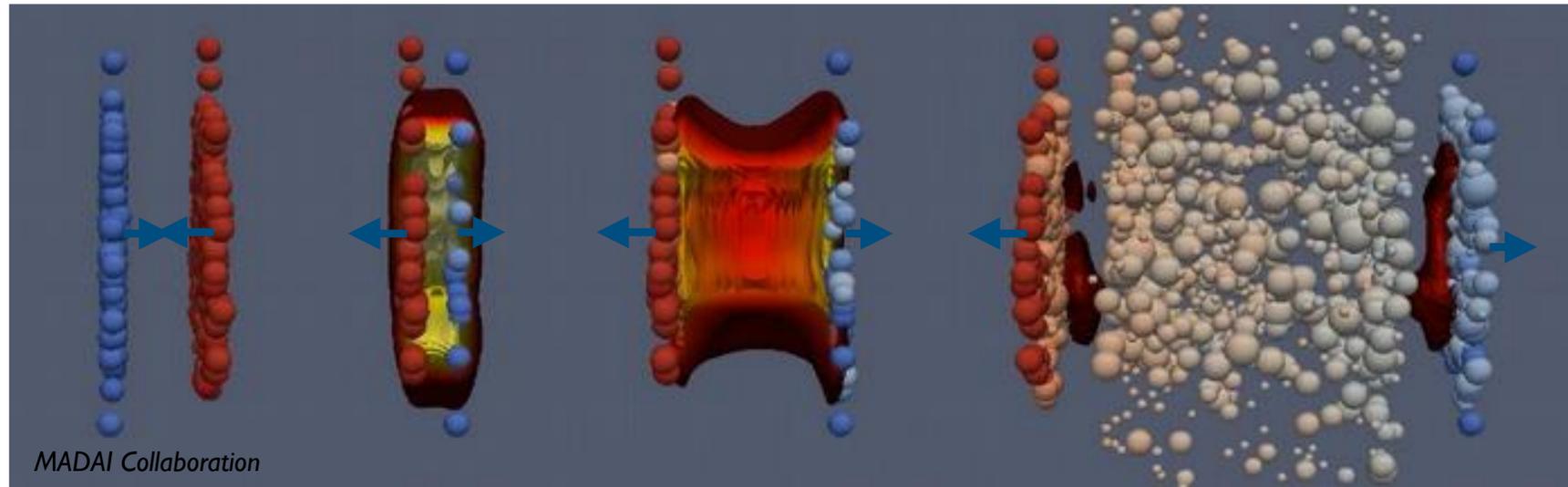
Challenge #1

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



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Global analysis is needed to fit models of the physics that are not known from first-principles

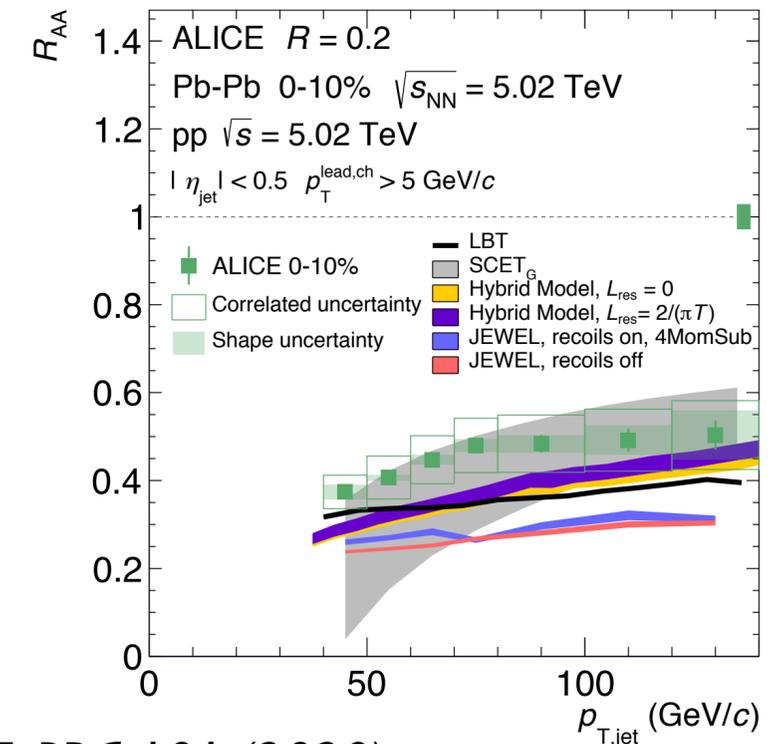
Challenge #2

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

Simultaneous unknowns in jet quenching theory:

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

Jet R_{AA} , for example, is strongly modified — but models with different physics predict similar values



ALICE, PRC 101 (2020)

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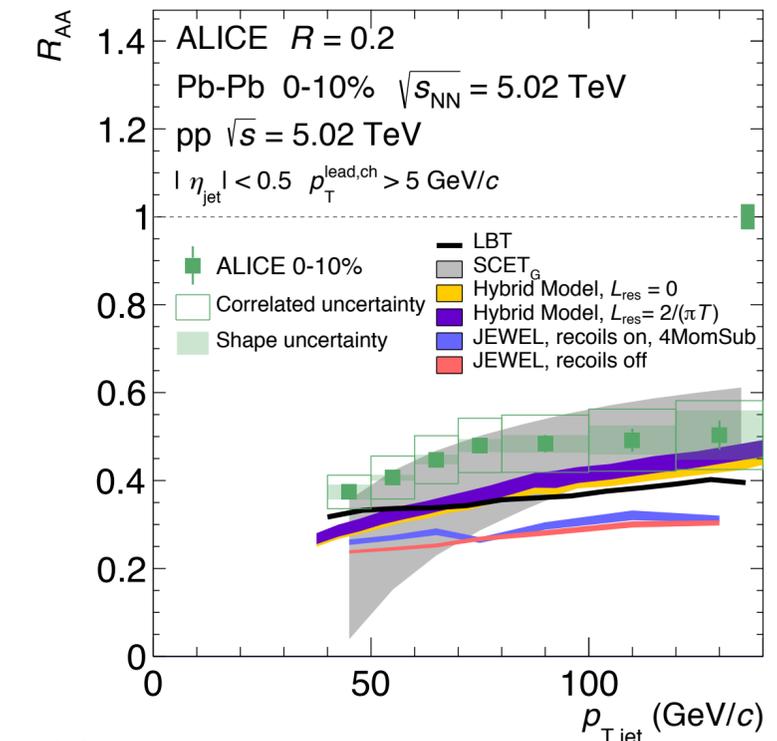
Jet R_{AA} , for example, is strongly modified — but models with different physics predict similar values



Need global analysis of multiple jet observables to:

1. Distinguish theoretical approaches
2. Precisely determine medium properties

→ **This talk**



ALICE, PRC 101 (2020)

Outline

\hat{q} and JETSCAPE

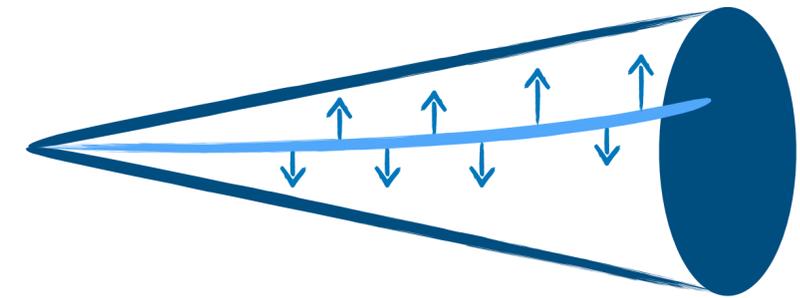
Bayesian parameter estimation

Results

The jet transverse diffusion coefficient

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

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



where $P(k_{\perp}^2)$ is a scattering kernel.

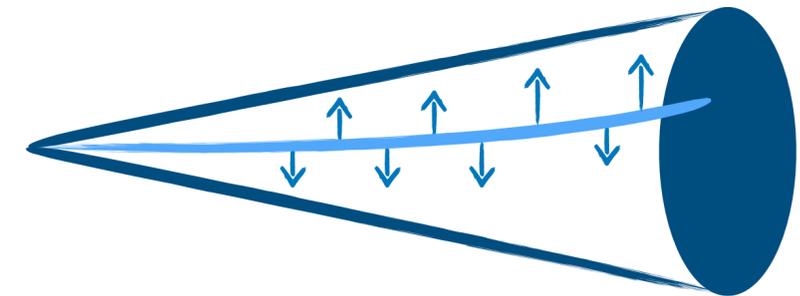
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- Single hard emission
- Multiple soft scattering
- Smooth drag

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

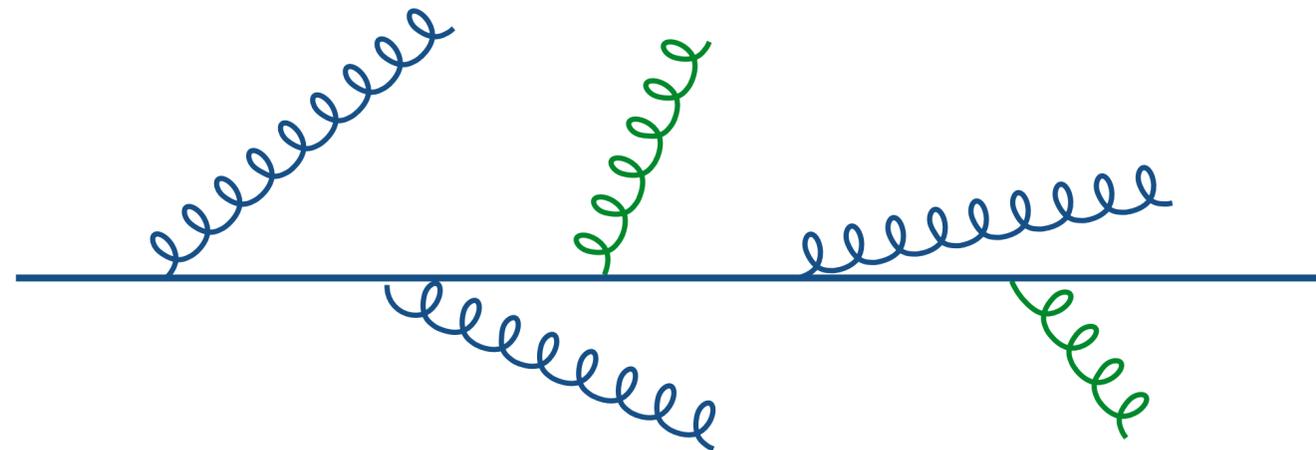
- Out-of-cone transport — “energy loss”
In BDMPS: $\Delta E \sim \hat{q}L^2$
- Broadening
In BDMPS: $\Delta\varphi \sim \sqrt{\hat{q}L}$

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

Calculating \hat{q}

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

For example, assuming perturbative, small-angle elastic scattering off a thermal medium:

HTL formula

$$\hat{q}(T, E) = C_R \frac{42\zeta(3)}{\pi} \alpha_S^2 T^3 \ln \left[\frac{\mu^2}{6\pi\alpha_S T^2} \right]$$

Local temperature Parton energy Parton-medium interaction scale

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Local temperature Parton energy Parton-medium interaction scale

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

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

High-virtuality inspired HTL-inspired
 T -independent elastic scattering off temperature T

MATTER

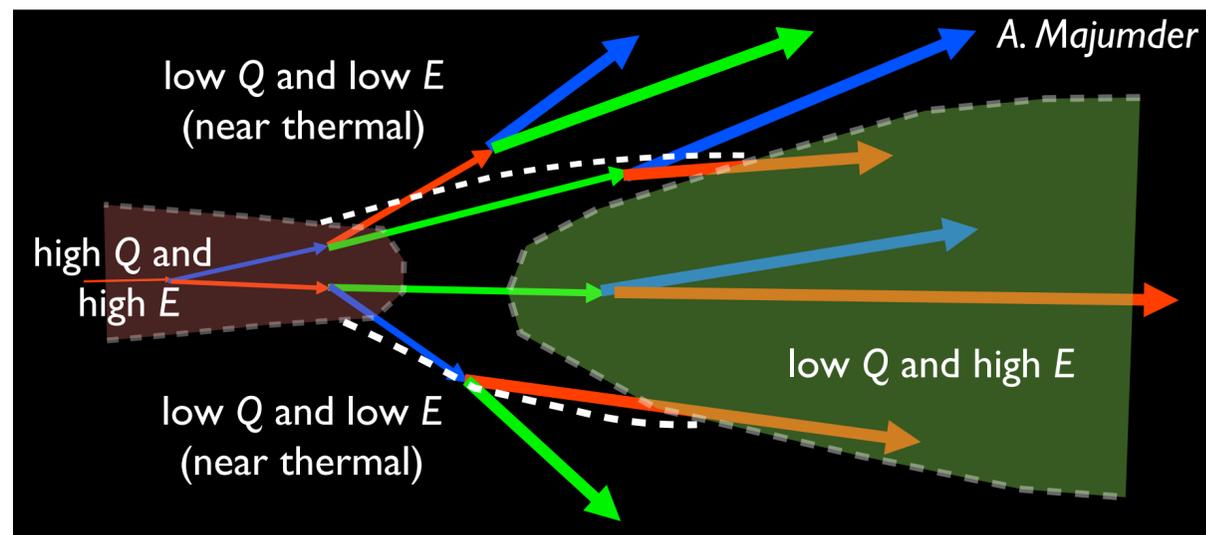
Majumder PRC 88 (2013)
Cao, Majumder PRC 101 (2020)

Medium-modified splitting function

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

Virtuality-ordered shower modified
to contain spacetime information

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



MATTER

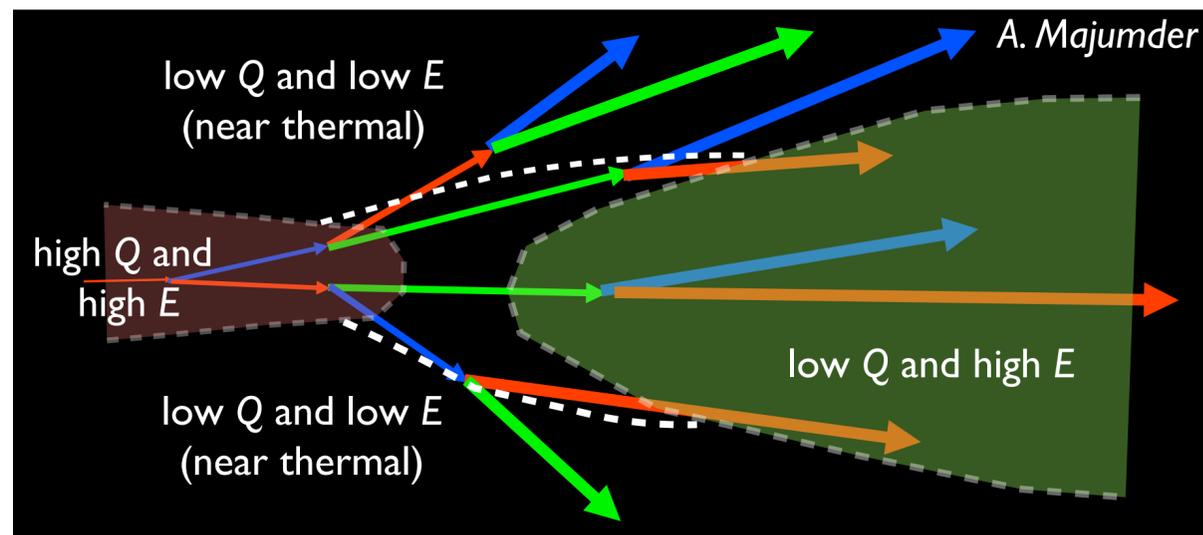
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LBT

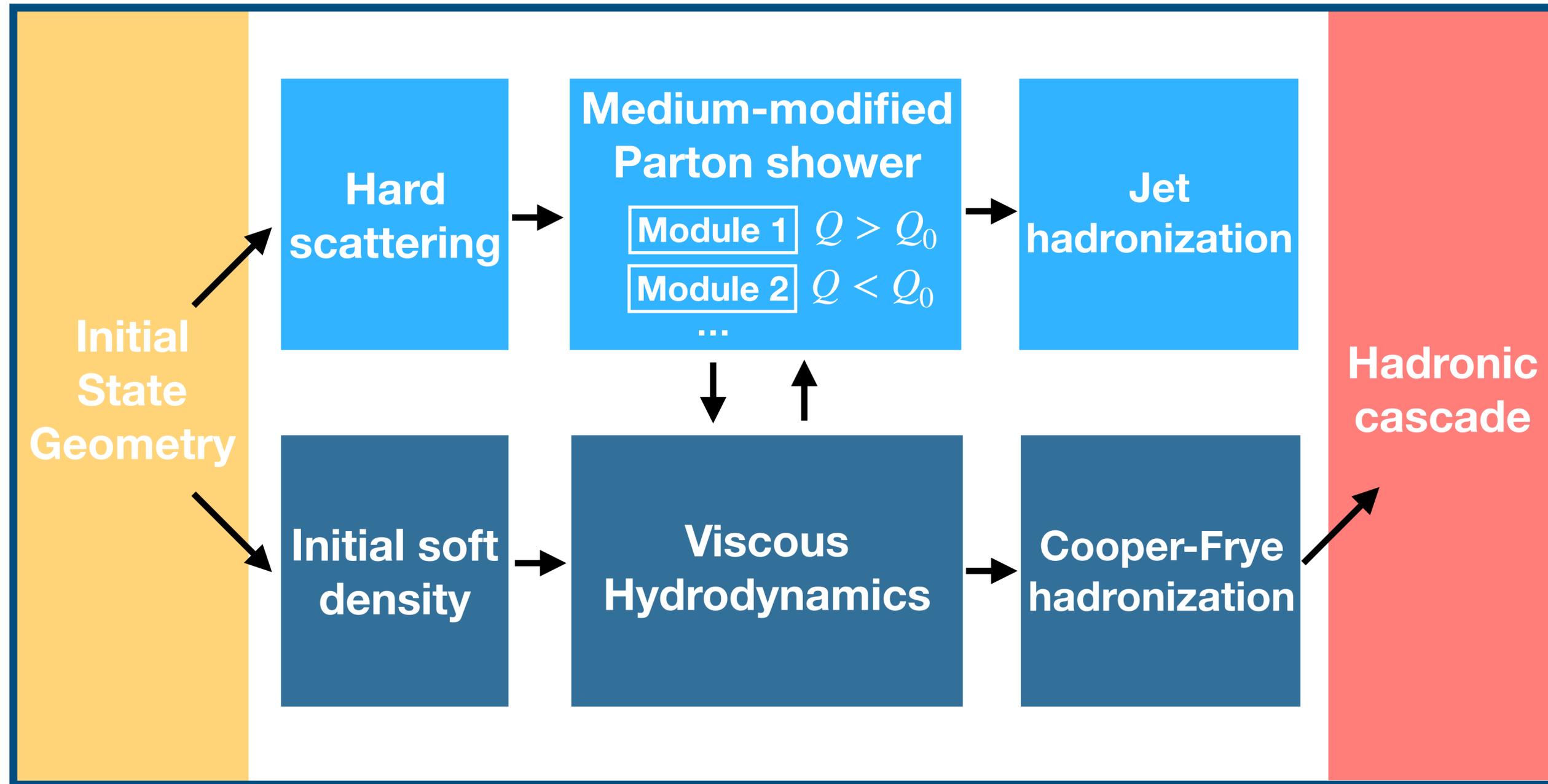
Cao, Luo, Qin, Wang PRC 94 (2016)
PLB 777 (2018)

Elastic and inelastic scatterings — linearized
Boltzmann transport of jet partons

Inelastic scatterings generate gluon
radiation — higher twist formalism

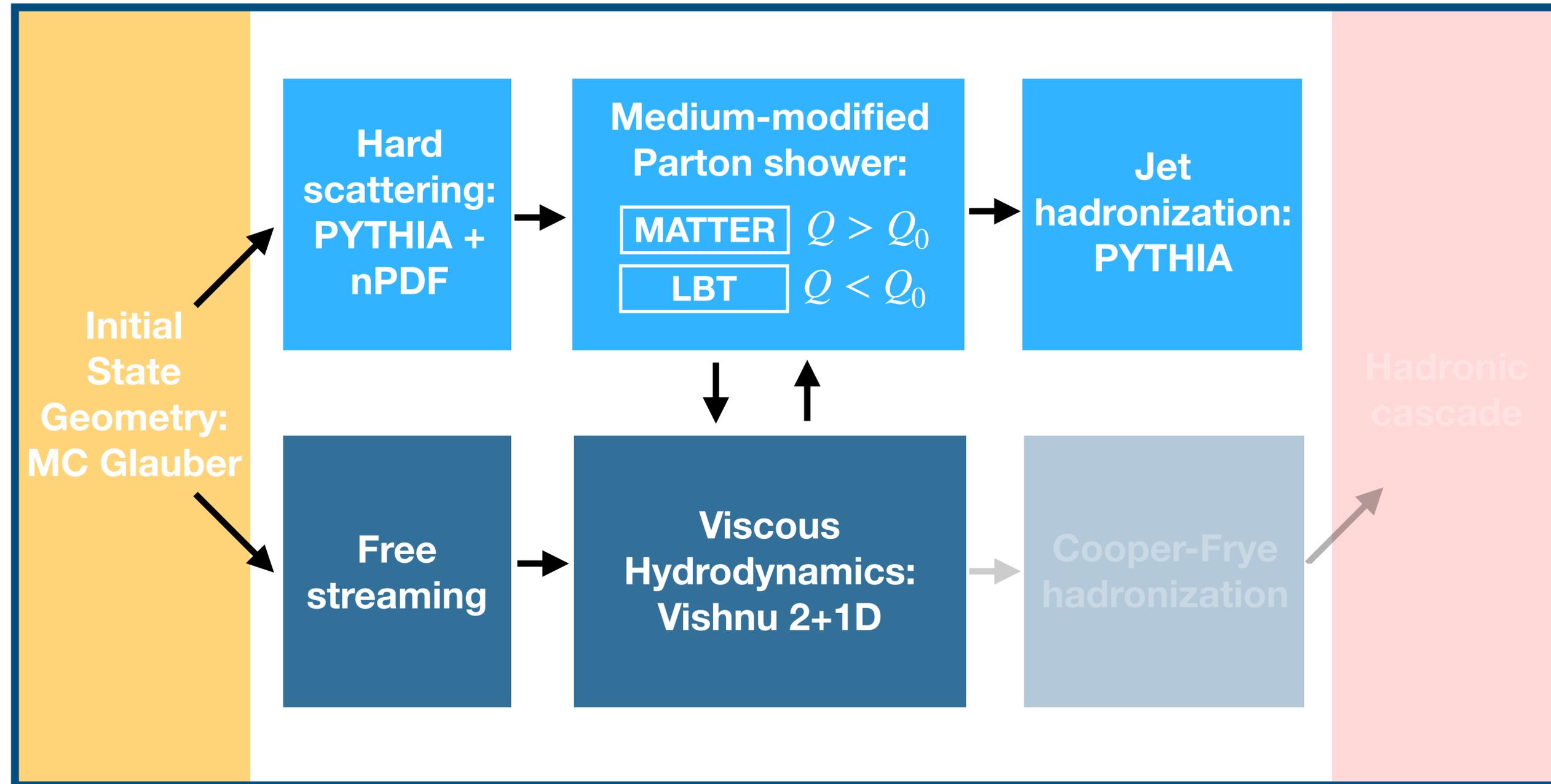
Low-virtuality, scattering-dominated regime
Broadening due to elastic scattering

Jet quenching in JETSCAPE



This talk

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

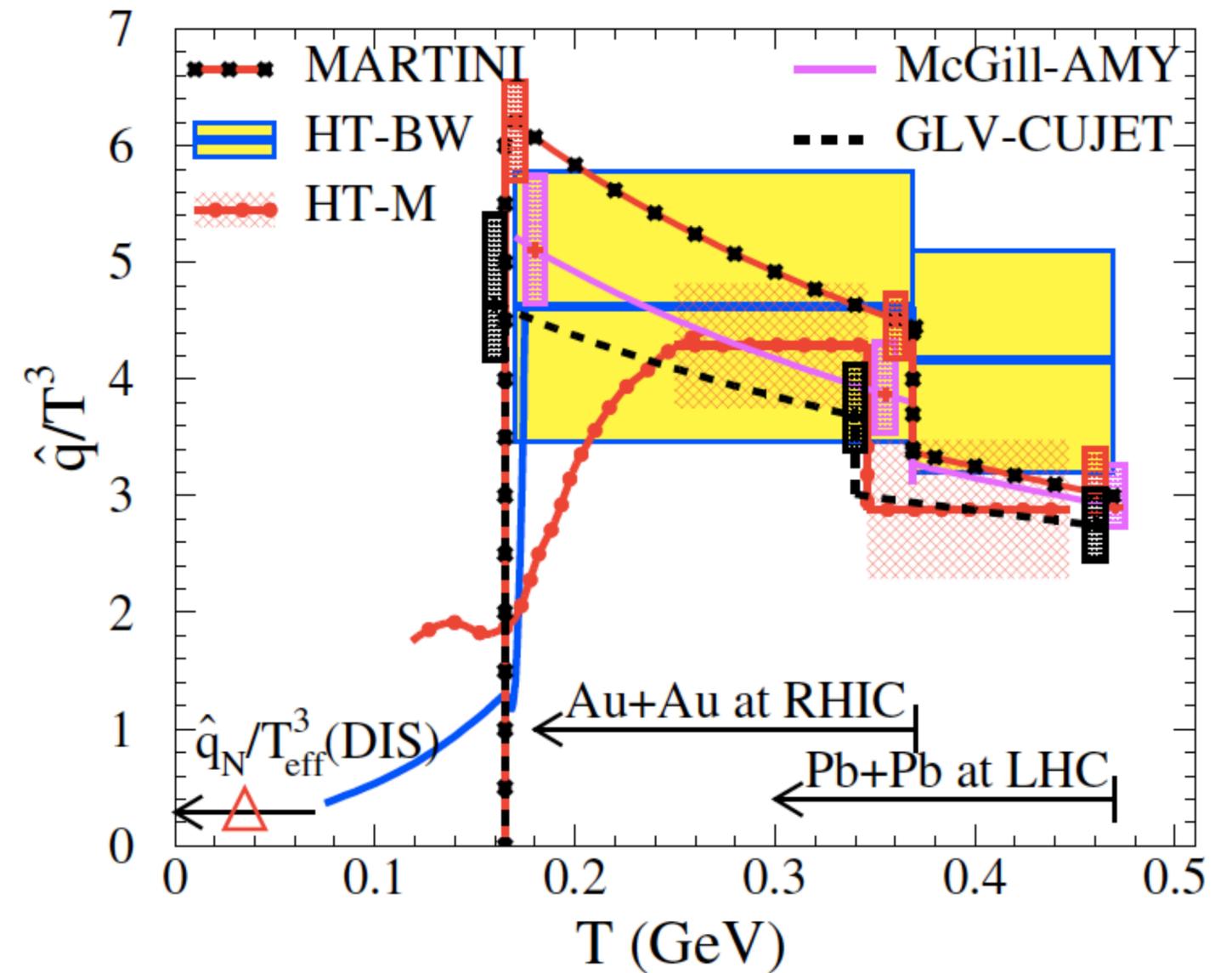


JET Collaboration

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



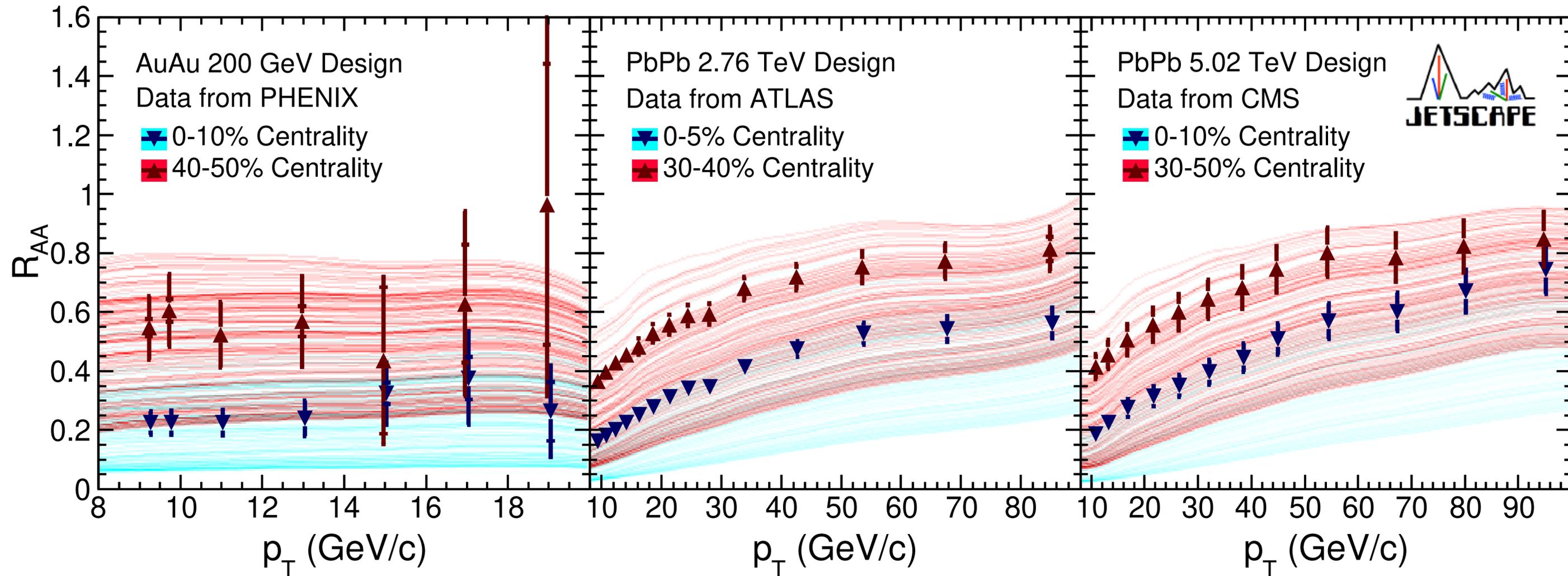
JET Collaboration, PRC 90 (2014)

Experimental data

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

Inclusive hadron R_{AA}

- Central + semi-central
- One dataset per $\sqrt{s_{NN}} = 0.2, 2.76, 5.02$ TeV) \longrightarrow Vary T
- Truncate at $p_T > 8$ GeV/c to avoid medium-modified hadronization effects



Experimental uncertainties

We decompose the experimental covariance matrix into several sources:

- Uncorrelated uncertainties — e.g. statistical
- Luminosity uncertainty — fully correlated across p_T , centrality bins
- T_{AA} uncertainty — fully correlated across p_T bins
- Other unspecified systematic uncertainties

$$\Sigma_k^E = \Sigma_k^{\text{uncorr}} + \Sigma_k^{\text{fcorr}} + \Sigma_k^{\text{lcorr}}$$

$$\Sigma_{k,ij}^{\text{uncorr}} = \sigma_{k,i}^{\text{uncorr}} \sigma_{k,j}^{\text{uncorr}} \delta_{ij}$$

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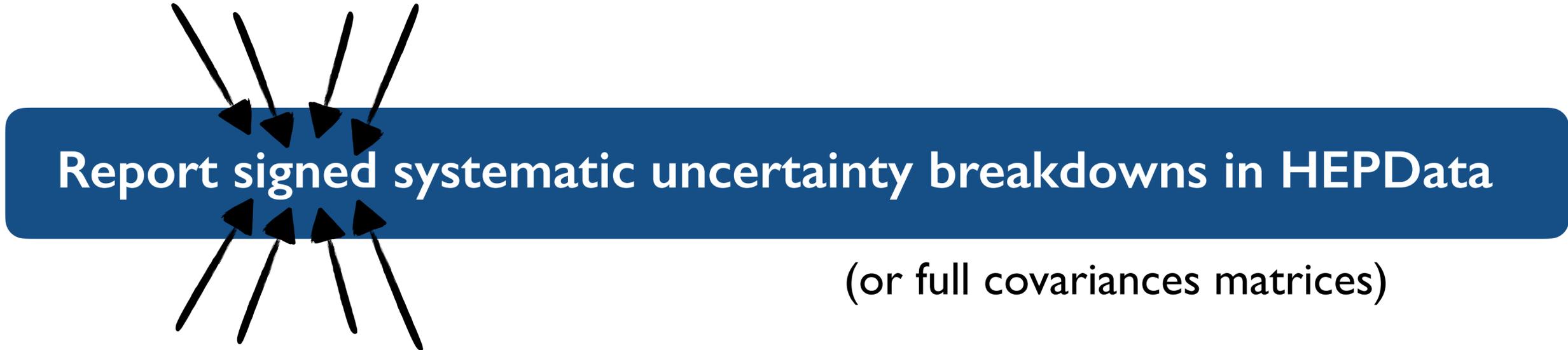
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There is a simple practice that we (experimentalists) need to start doing:



Report signed systematic uncertainty breakdowns in HEPData

(or full covariances matrices)

Bayesian parameter estimation

Goal: Use experimental data to constrain the value of $\hat{q}(E, T)$

1. Parameterize $\hat{q}(E, T) \Big|_{\theta=\{A,B,C,D\}}$ in a jet quenching model
2. Explore the parameter space θ to find the most likely values of θ for that model to explain the experimental data

We specifically want to constrain the **probability distribution** of \hat{q}

→ **Bayesian analysis**

Bayesian parameter estimation

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

Posterior Likelihood Prior

The diagram shows the equation $P(\theta | D) \sim P(D | \theta)P(\theta)$. Below the equation, three labels are positioned: 'Posterior' under $P(\theta | D)$, 'Likelihood' under $P(D | \theta)$, and 'Prior' under $P(\theta)$. Blue arrows point from each label to its corresponding term in the equation.

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

Bayesian parameter estimation

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Posterior Likelihood Prior

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The **prior** is our initial knowledge of the parameters — we will take a flat prior

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

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

Σ is the covariance matrix

Bayesian parameter estimation

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The **posterior** is what we want — probability distribution of \hat{q} , given the data

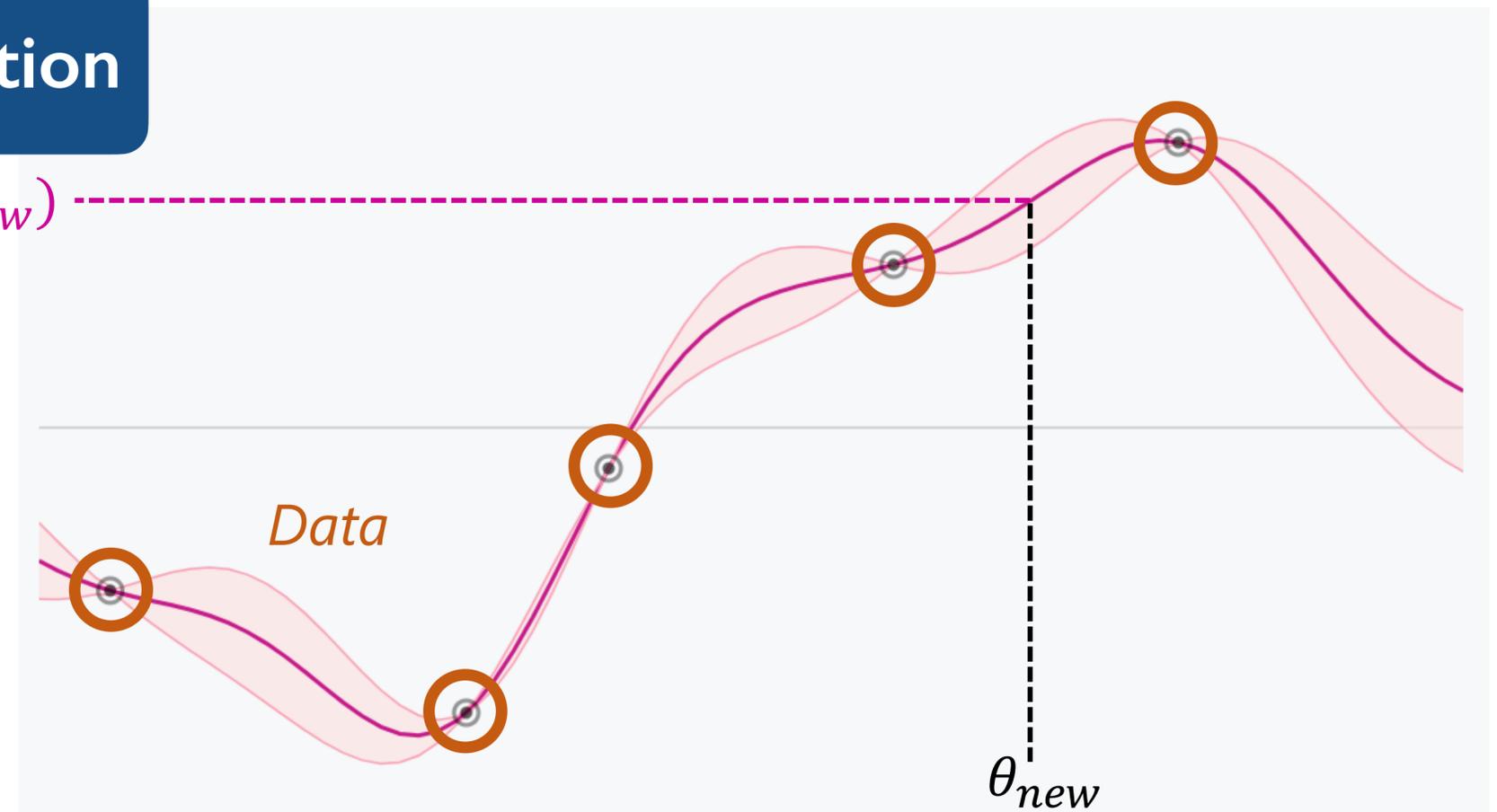
We will sample the posterior using Markov Chain Monte Carlo (MCMC)

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 $\mathcal{O}(10 \times \dim \theta)$ JETSCAPE model calculations with quantification of interpolation uncertainty



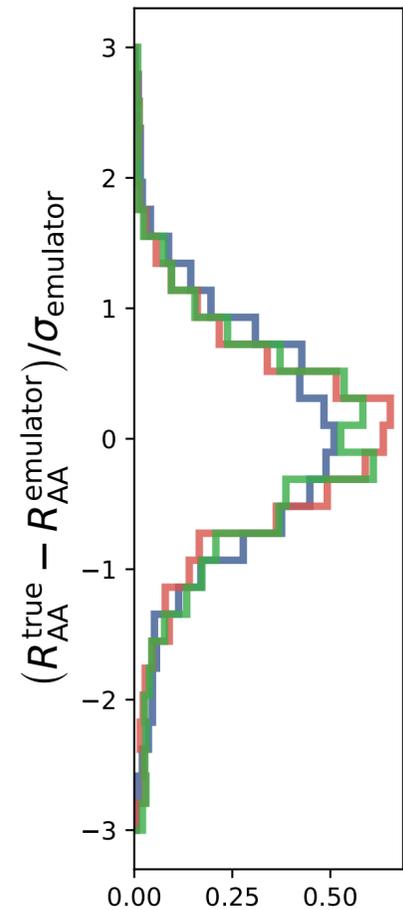
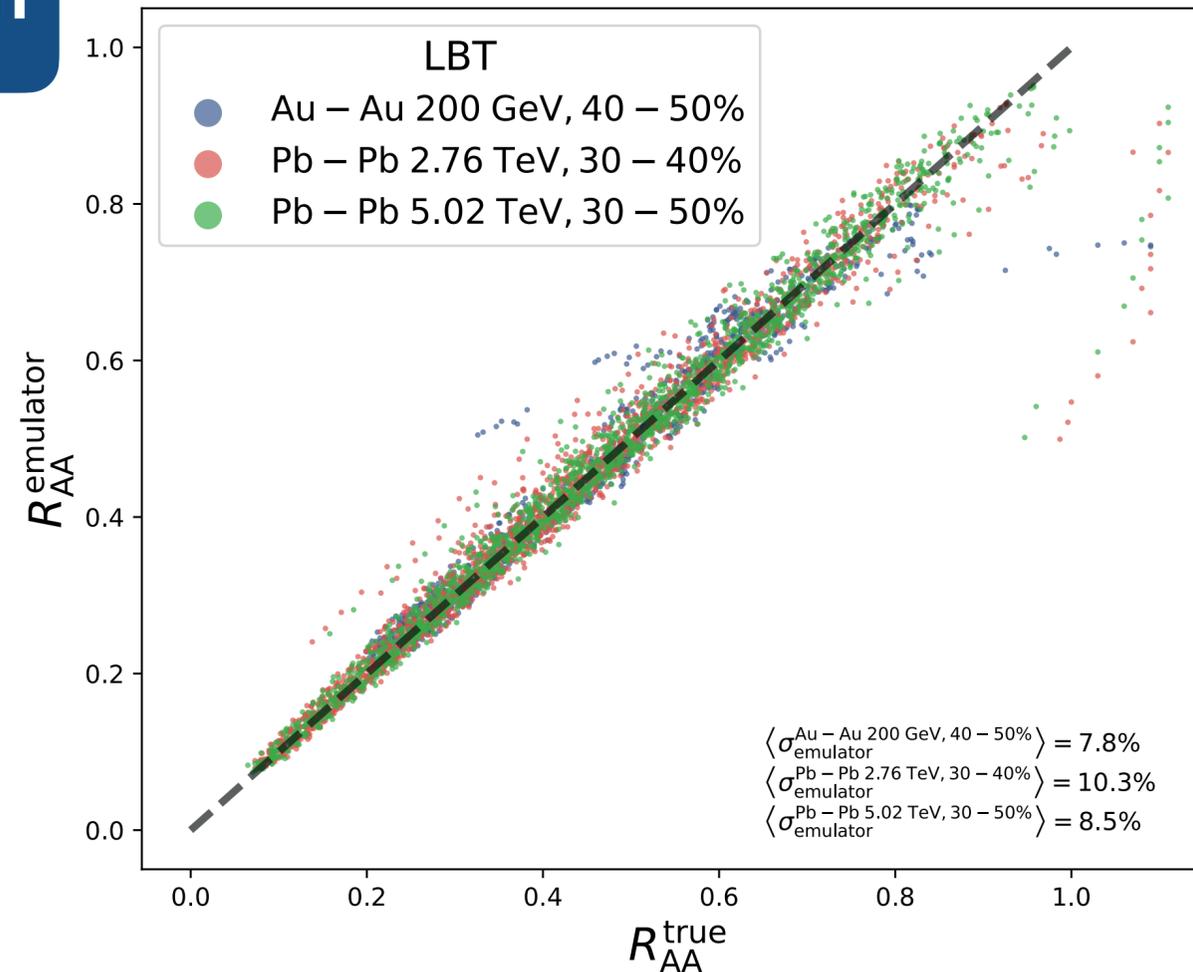
Simon Mak

Gaussian Process Emulators

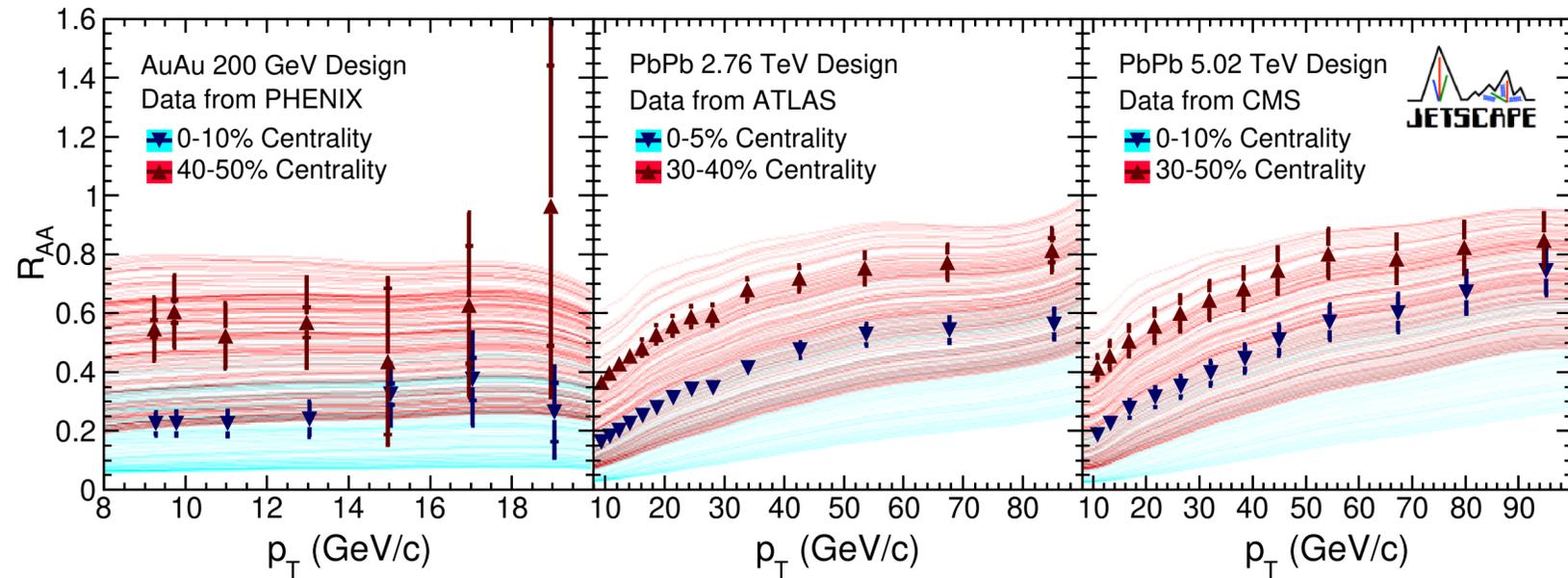
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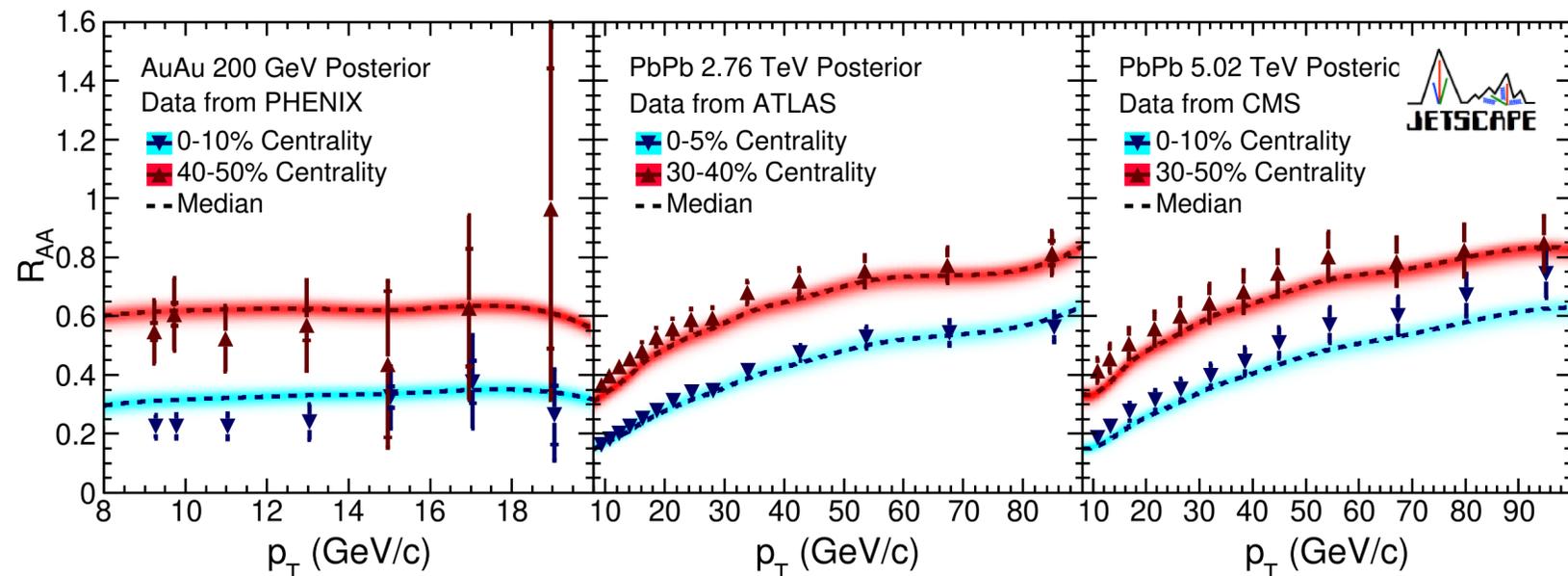
LBT model



Prior

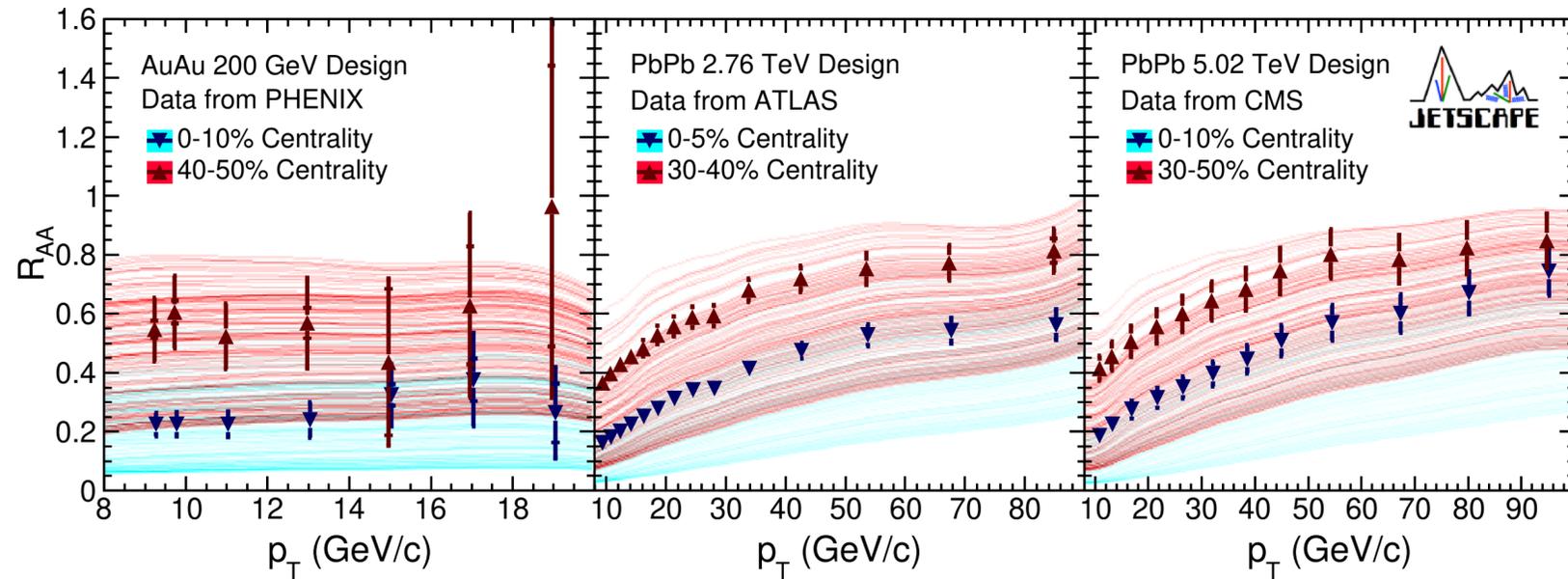


Posterior



LBT describes the data reasonably well
Some small systematic deviations

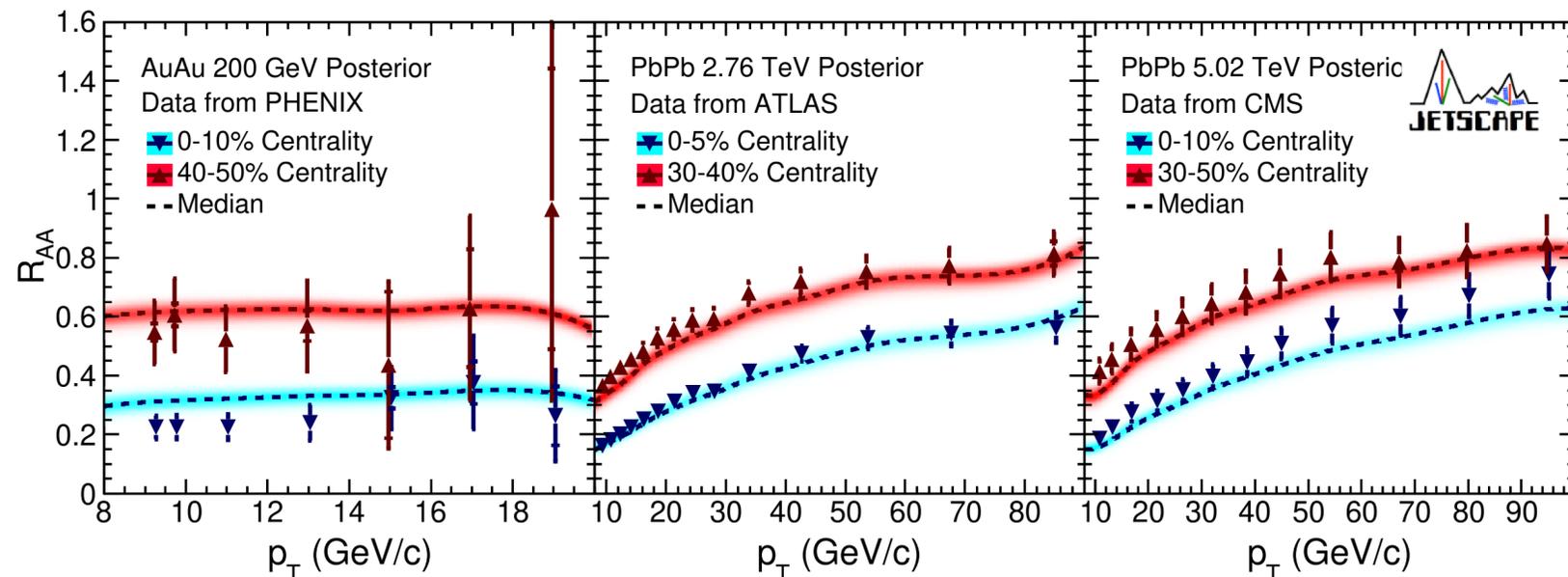
LBT model



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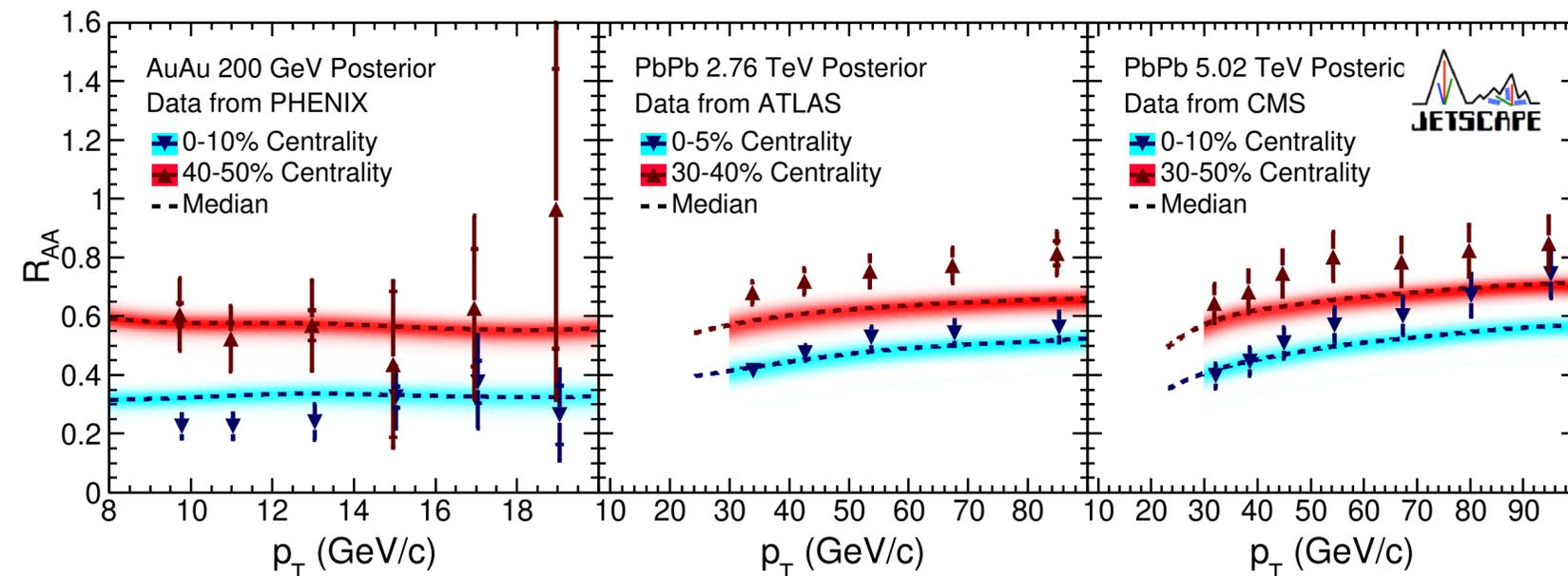
Posterior



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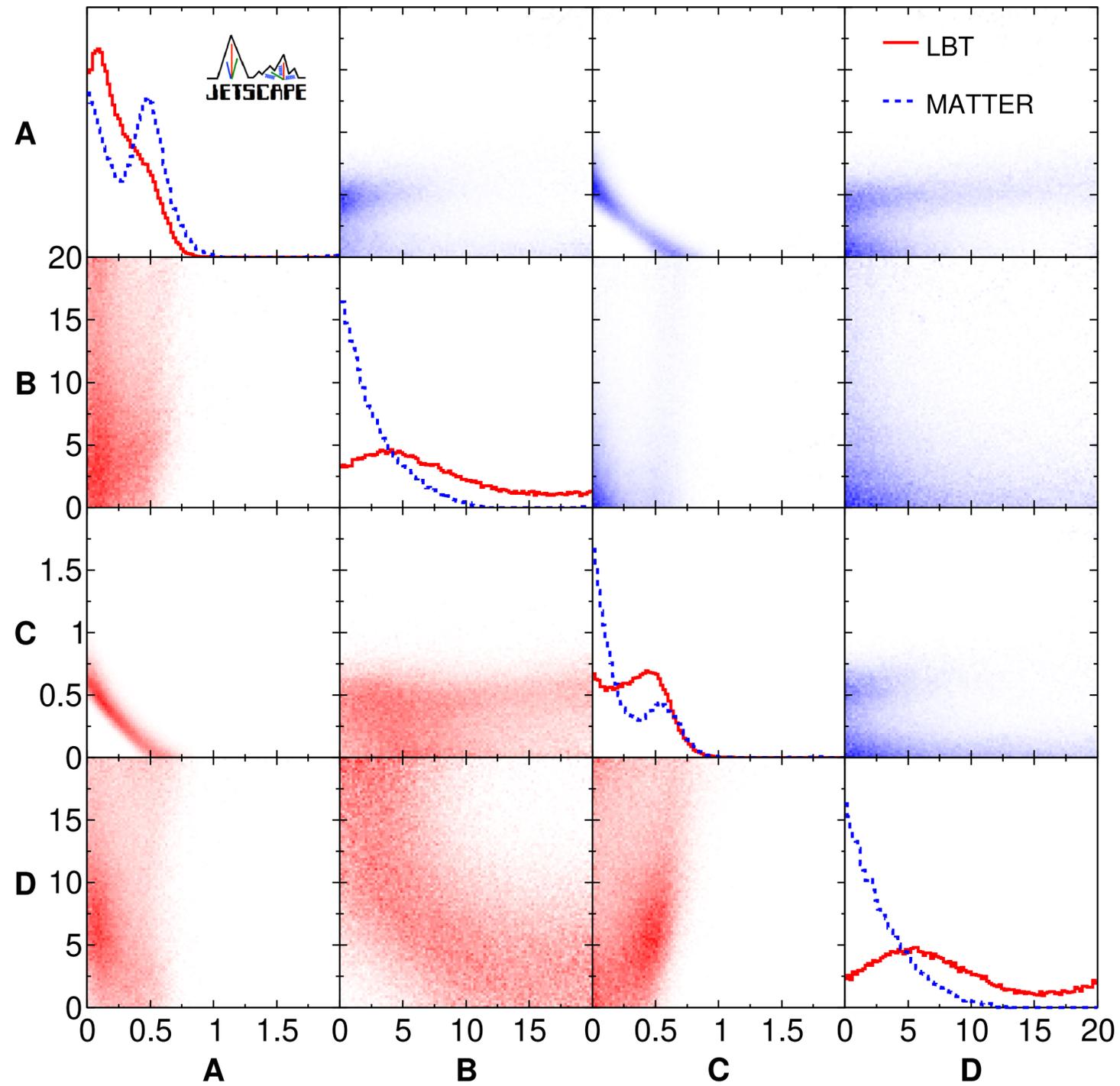
MATTER describes the data slightly less well
MATTER expected to be valid only at sufficiently high p_T ; fit restricted

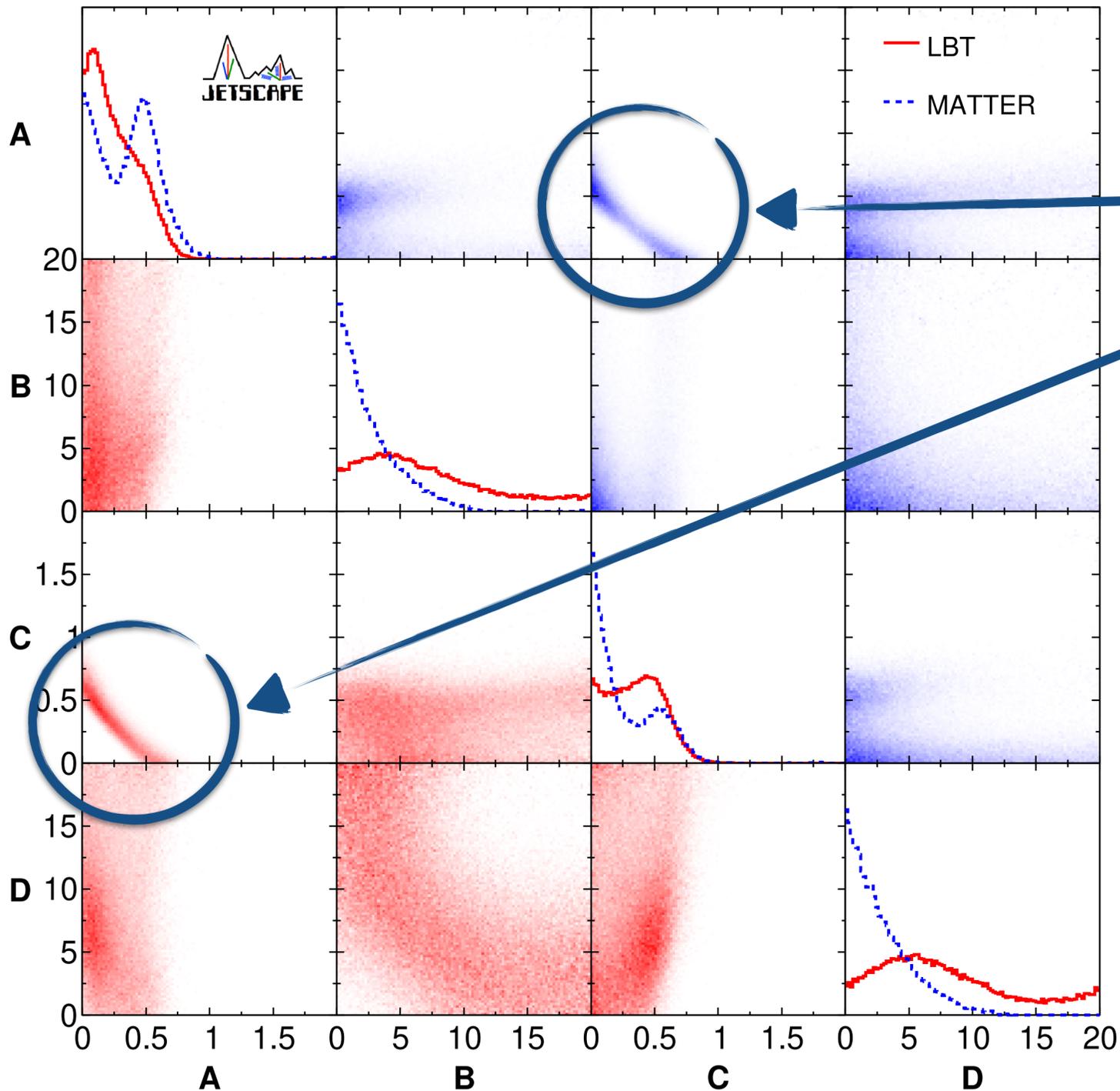
MATTER model



Results

2102.11337





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:

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

High-virtuality inspired
 T -independent

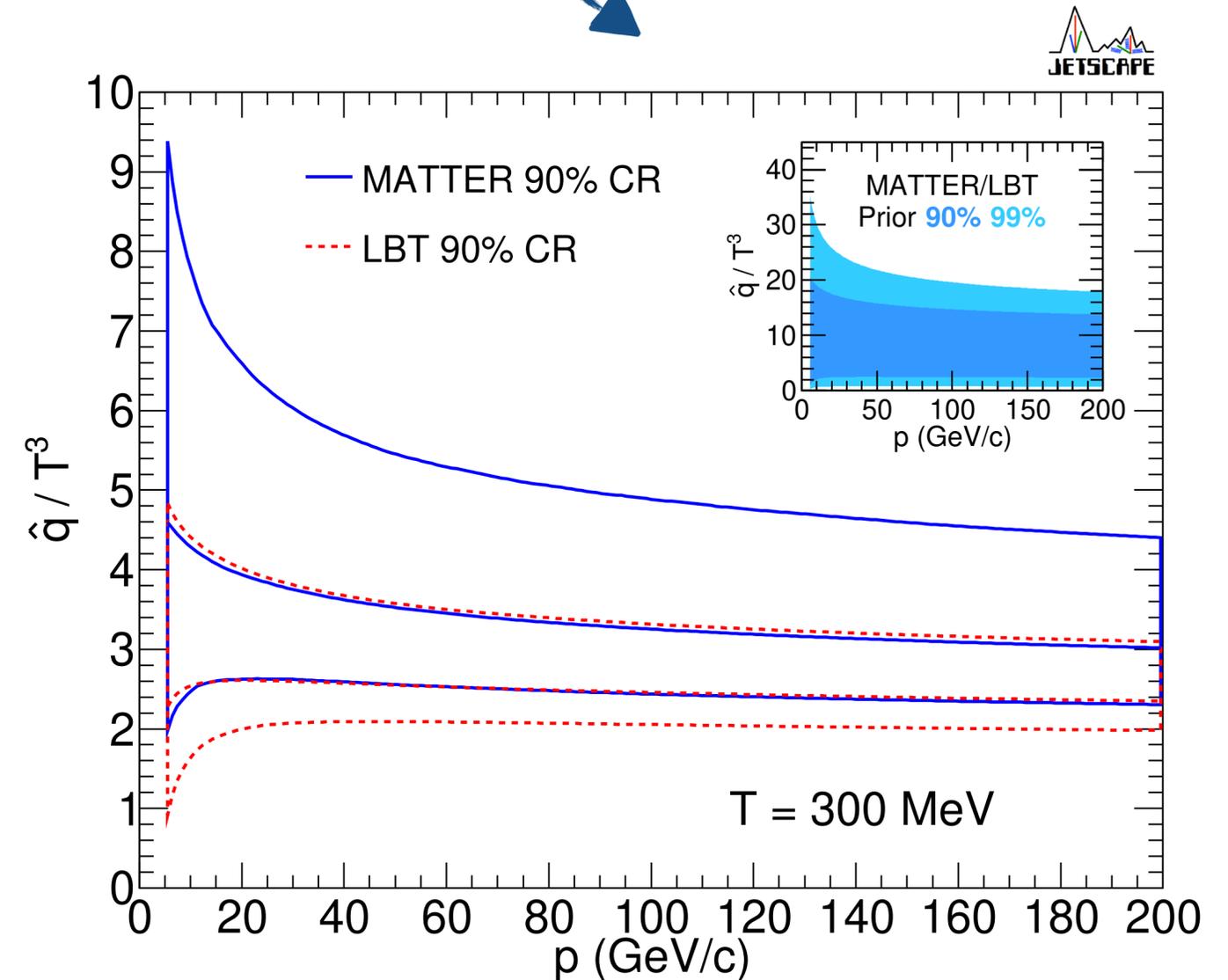
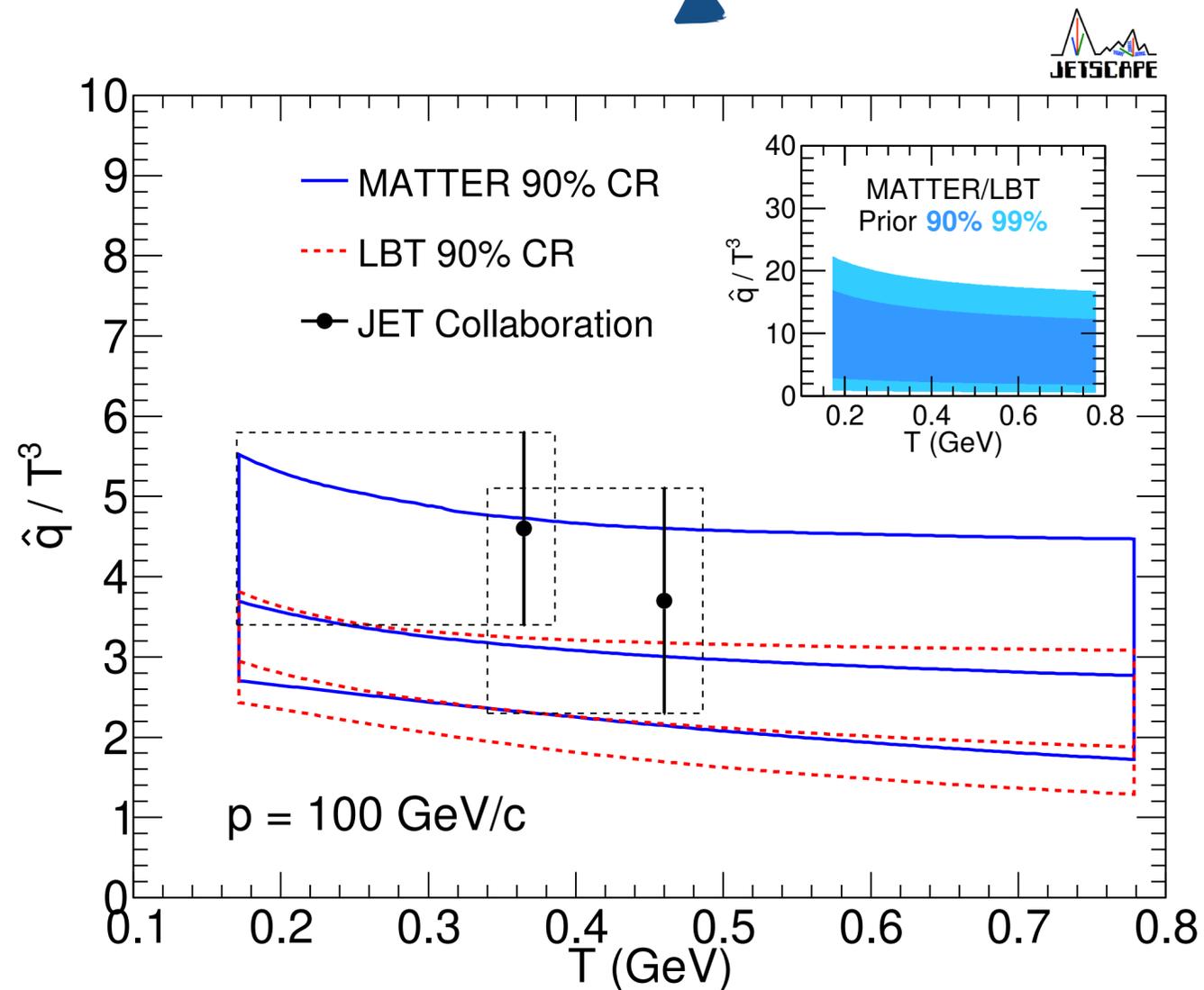
HTL-inspired
 elastic scattering off temperature T

Results

2102.11337

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

(Plotted \hat{q} is for quarks)

Multi-stage model

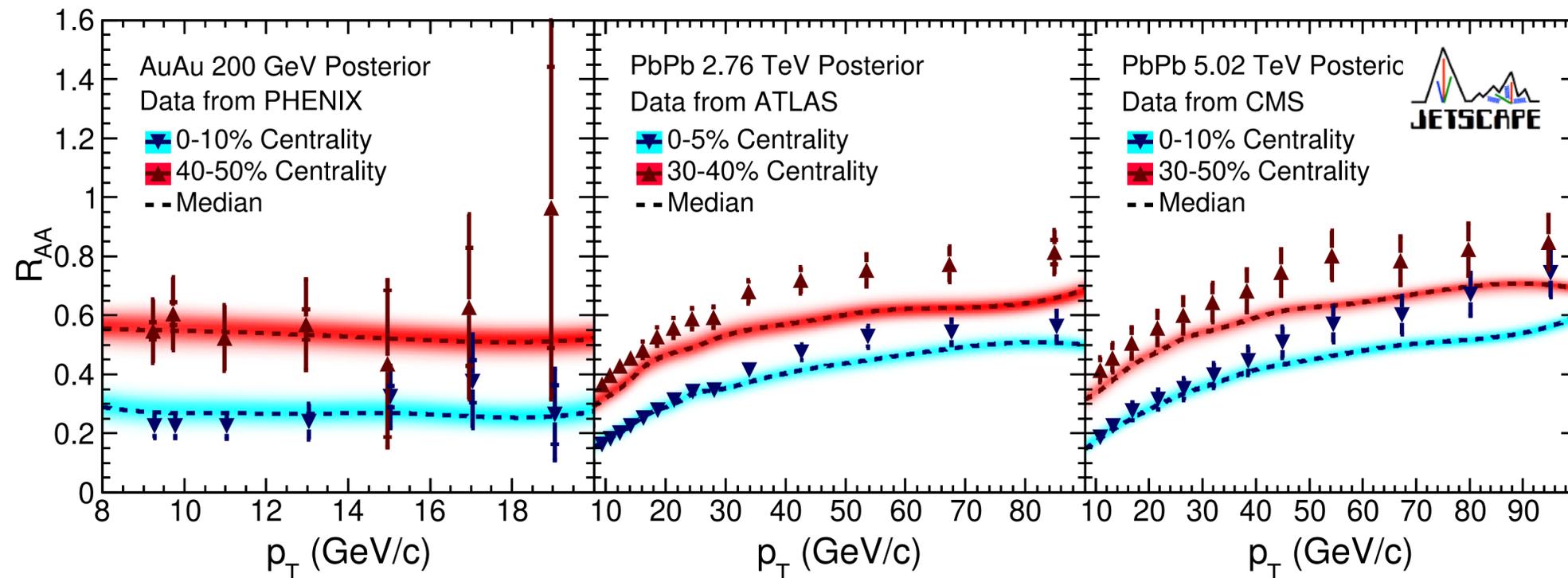
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Theoretical arguments suggest that a multi-stage model is more well-founded:

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

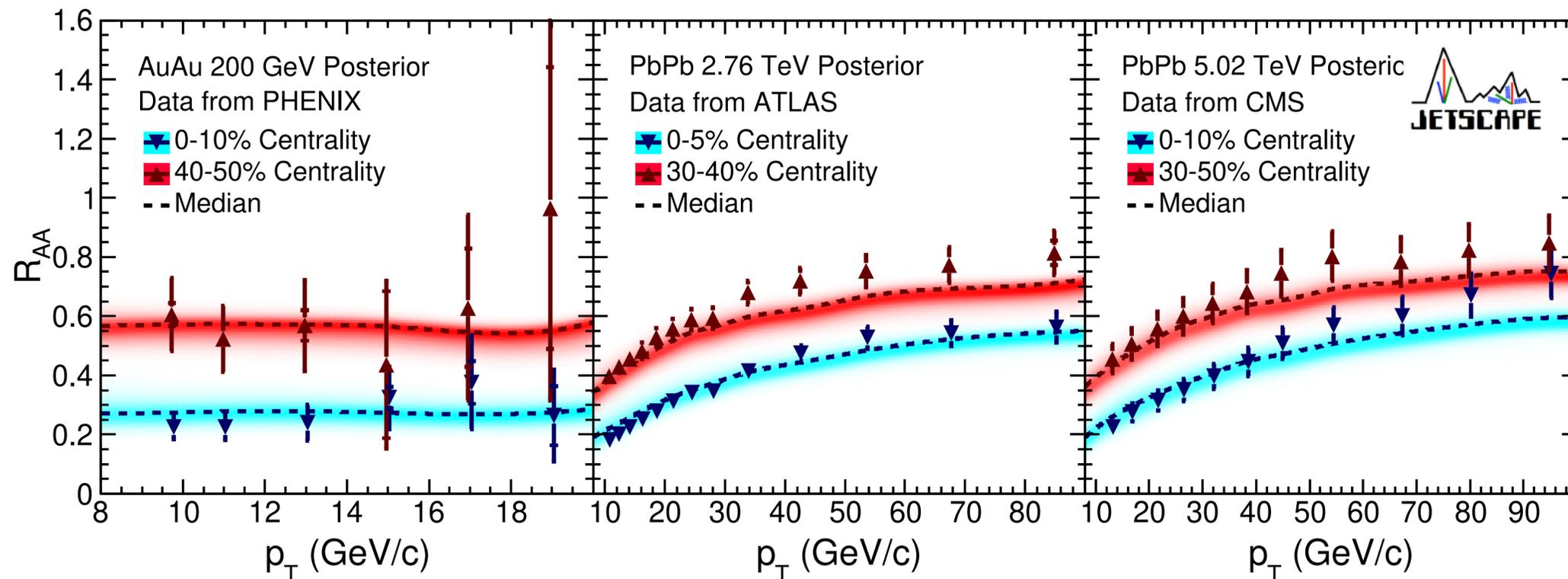
- Caveat: p_T range not restricted as in MATTER only case

Multi-stage model

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

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



Improved fit

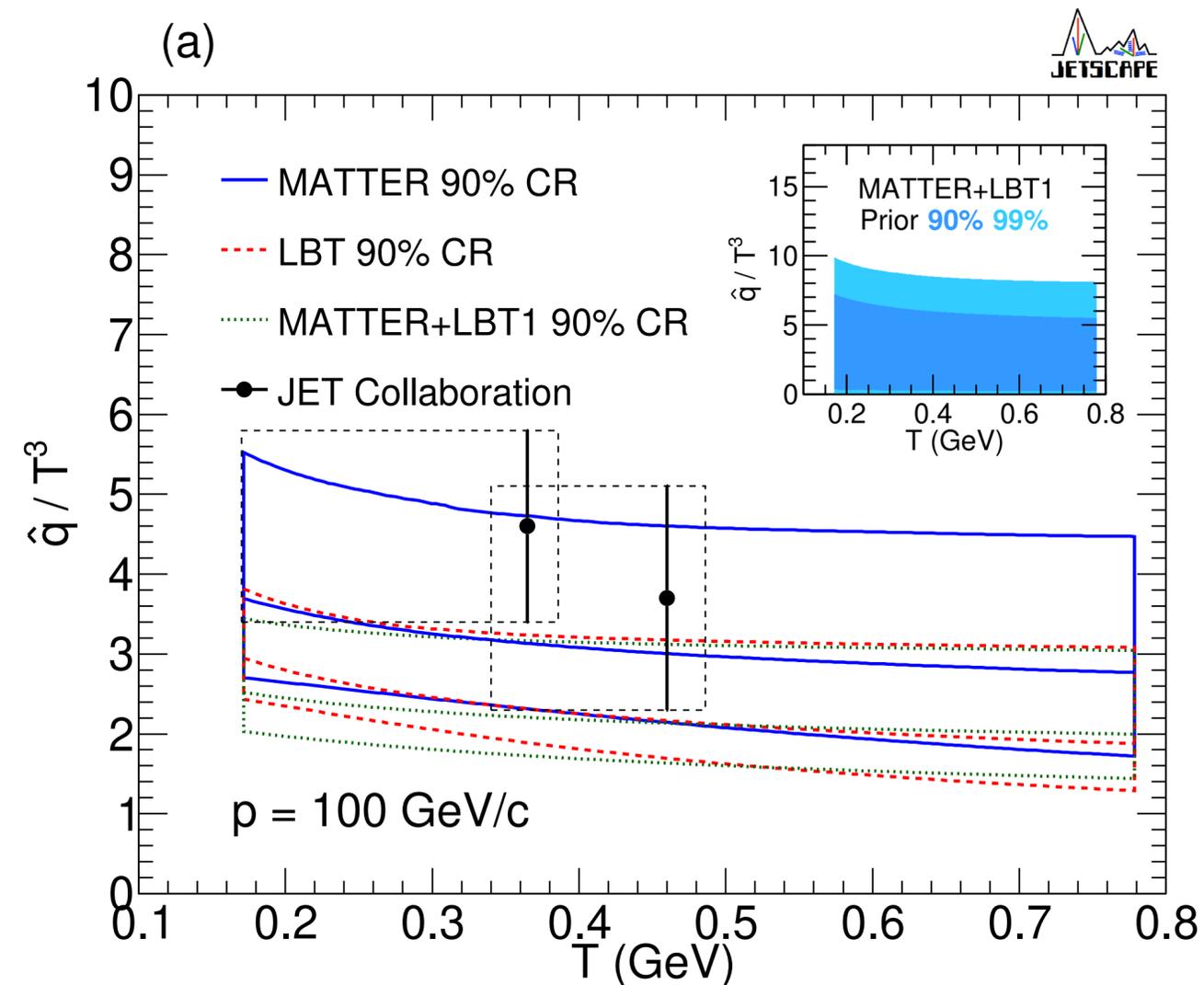
Will require additional observables to make more definitive statement about multi-stage model

Multi-stage model

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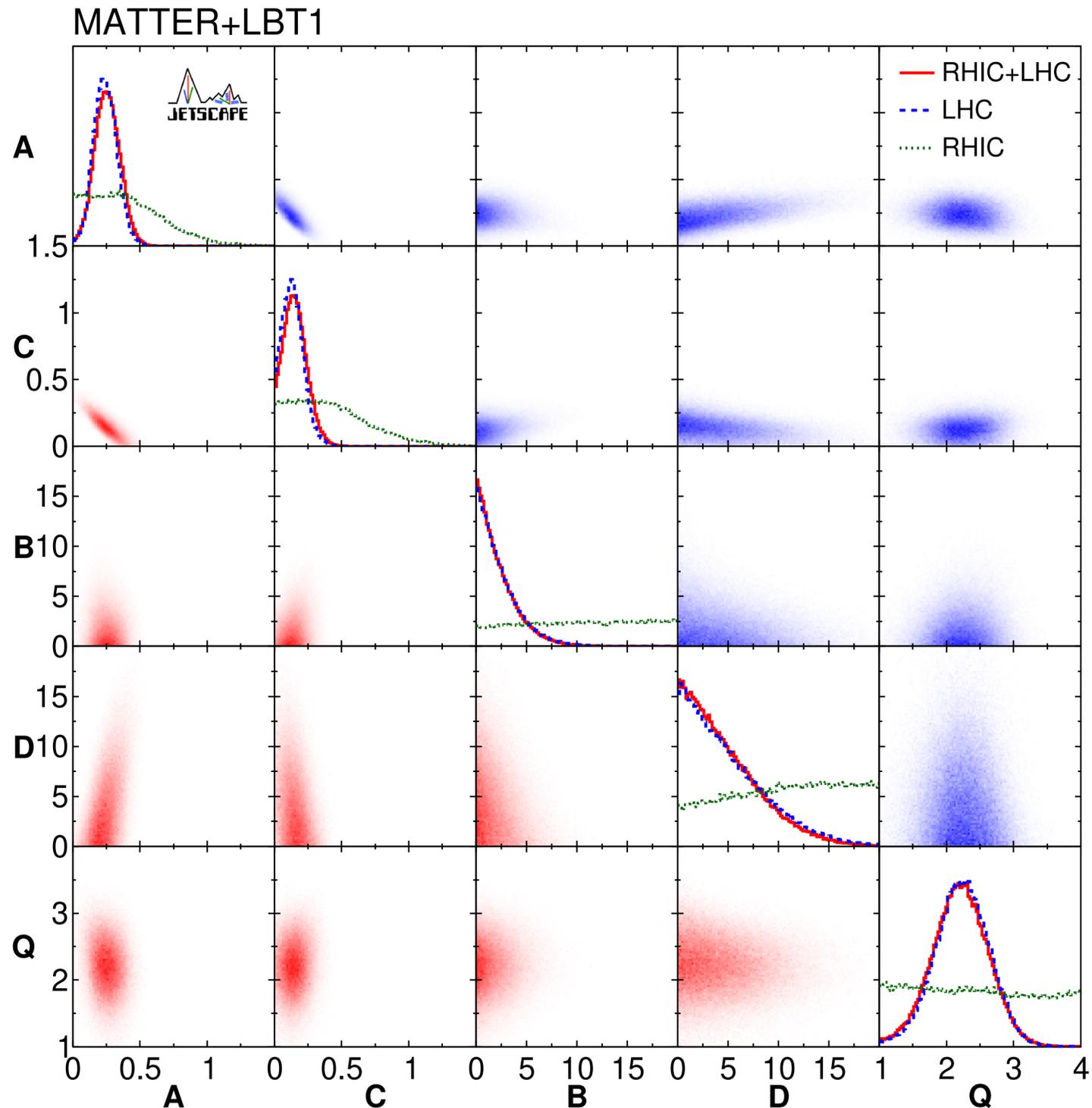
Extracted \hat{q} of MATTER+LBT is smaller than MATTER,LBT alone

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



Multi-stage model

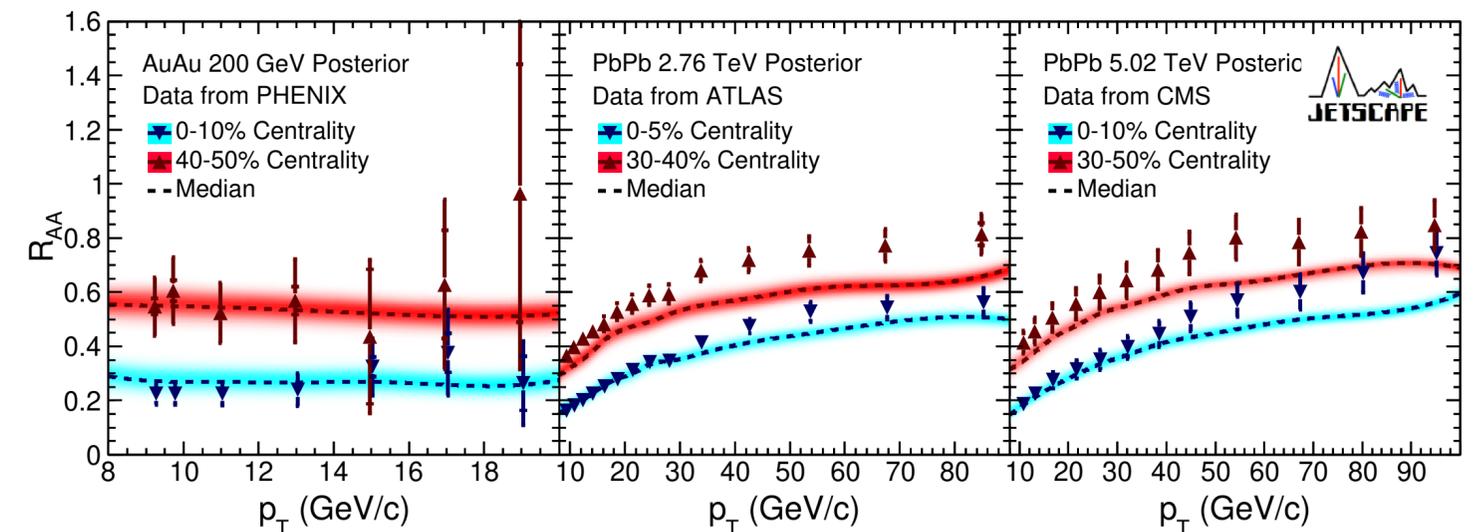
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We also test the impact of RHIC vs. LHC data

Fit dominated by LHC data

Due to choice of cutoff: $p_T < 8 \text{ GeV}/c$



First extraction of virtuality-switching parameter: $Q_0 \sim 2 - 3 \text{ GeV}/c$

Summary

We extracted $\hat{q}(E, T)$ as a continuous function of E, T using Bayesian parameter estimation with inclusive hadron R_{AA} data

- Several JETSCAPE models considered: MATTER, LBT, MATTER+LBT
- Data significantly constrains prior distributions
- No evidence for multi-stage model being preferred by data

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We extracted $\hat{q}(E, T)$ as a continuous function of E, T using Bayesian parameter estimation with inclusive hadron R_{AA} data

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Global analysis is key to the future of the jet quenching physics program

- Extension to additional observables — jet R_{AA} , substructure, correlations
 - **Need theory input:** model parameterizations, multi-stage paradigm, improved modeling of heavy-ion stages (hydro calibration, quenching in hadronic phase), ...
 - **Need experiment input:** reporting of uncertainty correlations on HEPData
- Provide experimental guidance — observables, systems, centrality to best constrain models