Measuring multi-body QCD

Peter Jacobs
Lawrence Berkeley National Laboratory
University of California, Berkeley

Lecture 3: Quantifying the QGP - Bayesian Inference for jet quenching

Slides: https://tinyurl.com/JacobsICTS

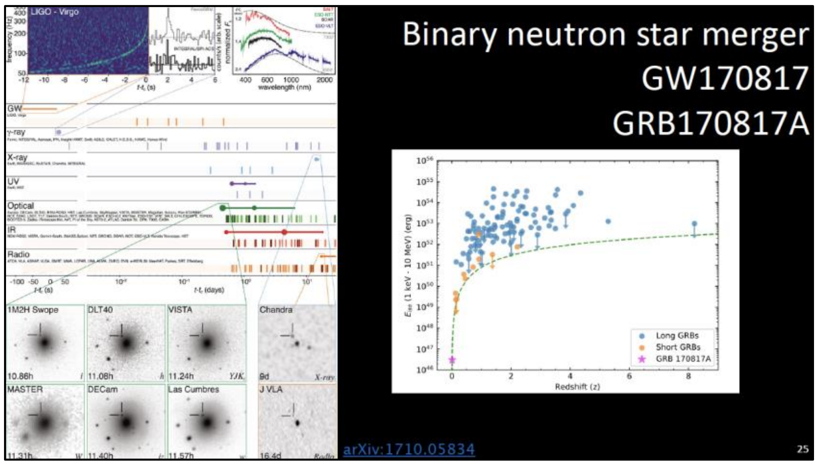
Hard probes in non-equilibrium QCD matter
March 16-27, 2026

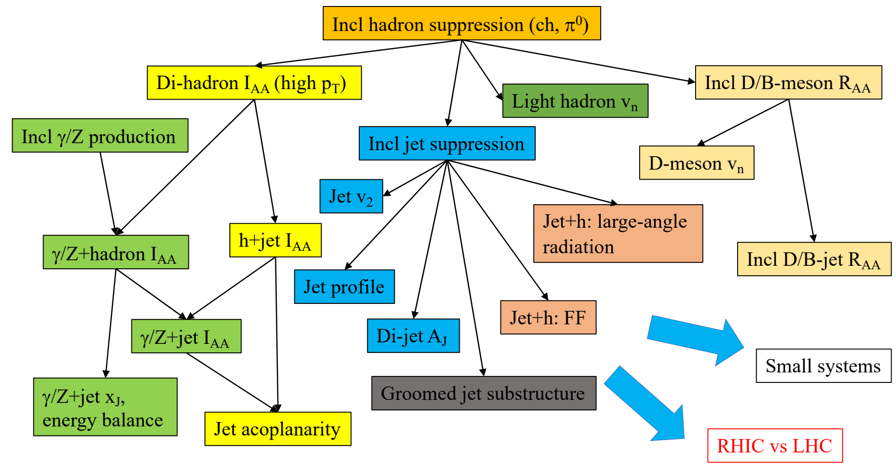
ICTS | INTERNATIONAL CENTRE *for* THEORETICAL SCIENCES
TATA INSTITUTE OF FUNDAMENTAL RESEARCH

Jet quenching: big picture

Jet quenching is multi-messenger physics:

Measure a system in multiple different ways and require a consistent picture





We need to connect this rich experimental phenomenology with theoretical modeling to learn about the structure and dynamics of the Quark-Gluon Plasma

Rigorous connection of data and models: Bayes's Theorem

For a given model: (i) how well does it represent multi-dimensional data, and (ii) what parameters are most compatible with the data?

Bayes's Theorem:

Likelihood

Prior knowledge of N model parameters

$$P(\vec{\theta}|\text{data}) = \frac{P(\text{data}|\vec{\theta})P(\vec{\theta})}{P(\text{data})}$$

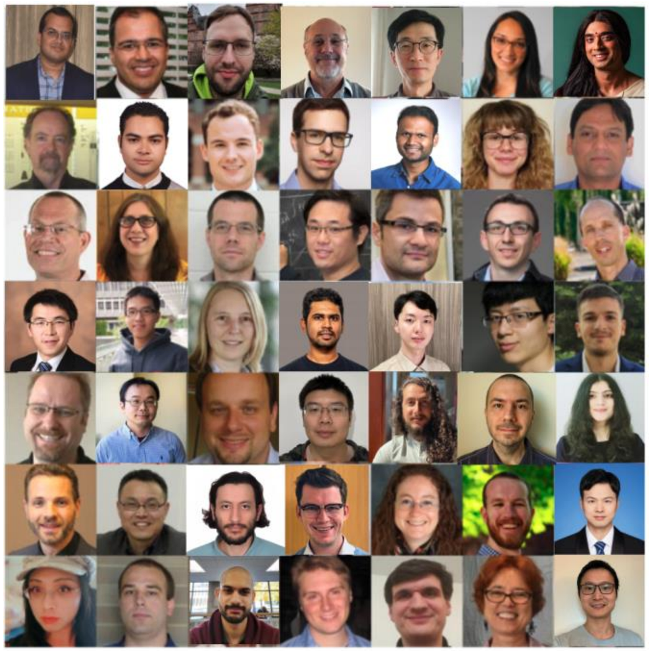
Posterior: probability density of parameters giving best description of the data

$\vec{\theta}$: Model parameters

Bayesian inference:

- sample likelihood over N-dim. parameter space with "sufficient" granularity
- posterior distribution = prior distribution constrained by likelihood

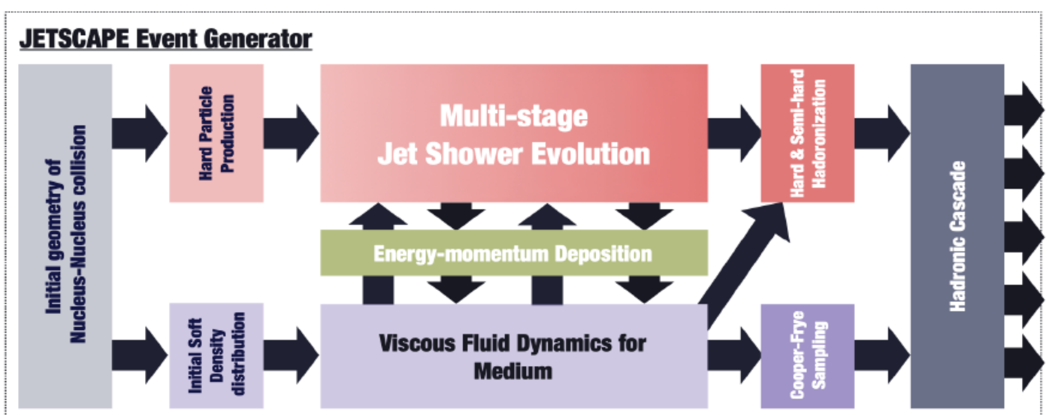
Bayesian inference using JETSCAPE

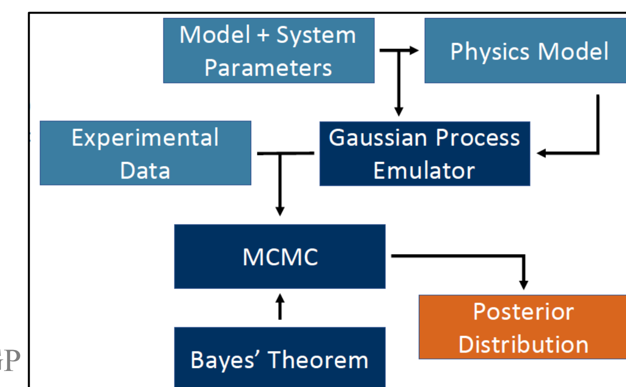


Collaboration of:

- NP experimentalists and theorists
- Data scientists
- Computer scientists

Framework for comprehensive modeling of heavy-ion collisions and Bayesian Inference with RHIC and LHC data





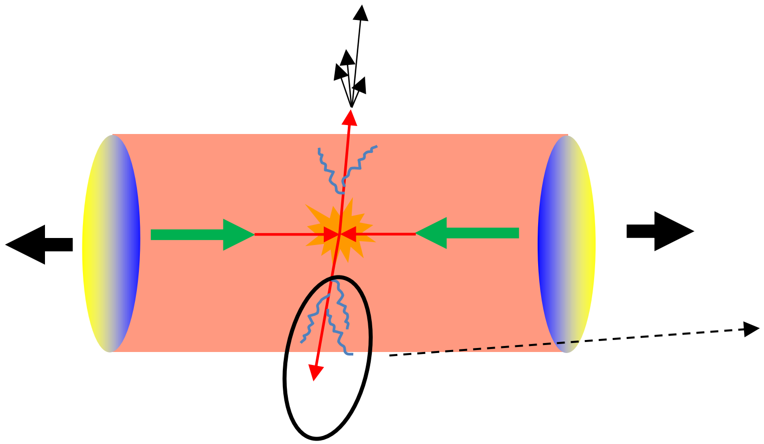
PHYSICAL REVIEW C **104**, 024905 (2021)

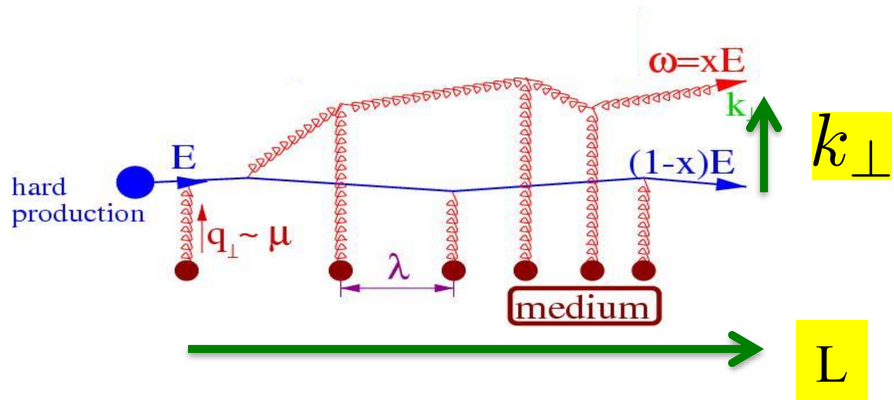
Determining the jet transport coefficient $\hat{q}$ from inclusive hadron suppression measurements using Bayesian parameter estimation

S. Cao,[1,2] Y. Chen,[3] J. Coleman,[4] J. Mulligan,[5,6] P. M. Jacobs,[5,6] R. A. Soltz,[1,7] A. Angerami,[7] R. Arora,[8] S. A. Bass,[9] L. Cunqueiro,[10,11] T. Dai,[9] L. Du,[12] R. Ehlers,[10,11] H. Elfner,[13,14,15] D. Everett,[12] W. Fan,[9] R. J. Fries,[16,17] C. Gale,[18] F. Garza,[16,17] Y. He,[19] M. Heffernan,[18] U. Heinz,[12] B. V. Jacak,[5,6] S. Jeon,[18] W. Ke,[5,6] B. Kim,[16,17] M. Kordell, II,[16] A. Kumar,[1] A. Majumder,[1] S. Mak,[4] M. McNelis,[12] C. Nattrass,[10] D. Oliinychenko,[6] C. Park,[18,1] J.-F. Paquet,[9] J. H. Putschke,[1] G. Roland,[20] A. Silva,[10] B. Schenke,[21] L. Schwiebert,[22] C. Shen,[1,23] C. Sirimanna,[1] Y. Tachibana,[1,24] G. Vujanovic,[1] X.-N. Wang,[19,5,6] R. L. Wolpert,[4] and Y. Xu[9]
(JETSCAPE Collaboration)
[1]*Department of Physics and Astronomy, Wayne State University, Detroit, Michigan 48201, USA*

We report a new determination of $\hat{q}$, the jet transport coefficient of the quark-gluon plasma. We use the JETSCAPE framework, which incorporates a novel multistage theoretical approach to in-medium jet evolution and Bayesian inference for parameter extraction. The calculations, based on the MATTER and LBT jet quenching models, are compared to experimental measurements of inclusive hadron suppression in Au + Au collisions at the BNL Relativistic Heavy Ion Collider (RHIC) and Pb + Pb collisions at the CERN Large Hadron Collider (LHC). The correlation of experimental systematic uncertainties is accounted for in the parameter extraction. The functional dependence of $\hat{q}$ on jet energy or virtuality and medium temperature is based on a perturbative picture of in-medium scattering, with components reflecting the different regimes of applicability of MATTER and LBT. In the multistage approach, the switch between MATTER and LBT is governed by a virtuality scale Q_0. Comparison of the posterior model predictions to the RHIC and LHC hadron suppression data shows reasonable agreement, with moderate tension in limited regions of phase space. The distribution of $\hat{q}/T^3$ extracted from the posterior distributions exhibits weak dependence on jet momentum and medium temperature T, with 90% credible region (CR) depending on the specific choice of model configuration. The choice of MATTER+LBT, with switching at virtuality Q_0, has 90% CR of $2 < \hat{q}/T^3 < 4$ for $p_{T,\text{jet}} > 40$ GeV/c. The value of Q_0, determined here for the first time, is in the range 2.0–2.7 GeV.

Modeling $\hat{q}$





Thermal field theory:

$$C(\mathbf{q}) = \frac{g_s^2 m_D^2 T}{\mathbf{q}^2 (\mathbf{q}^2 + m_D^2)}$$

$$m_D^2 = 3 g_s^2 T^2 / 2$$

$C(\mathbf{q})$ = Scattering kernel

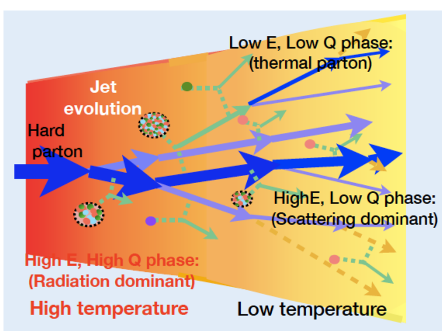
$\mathbf{q}$ = Momentum transfer

T = Temperature

m_D = Debye mass

$$\hat{q} \equiv \frac{\langle k_\perp^2 \rangle}{L} \sim \frac{1}{L} \int d\mathbf{q}^2 \mathbf{q}^2 C(\mathbf{q})$$

JETSCAPE parametrization



High jet virtuality Q>>T

Low jet virtuality Q~T (sensitive to thermal medium)

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

Bayesian inference:
$\hat{q}$ from inclusive hadron R_{AA}

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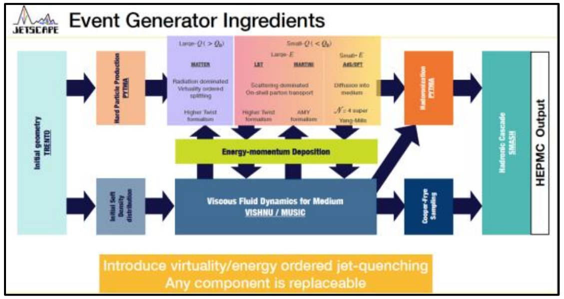
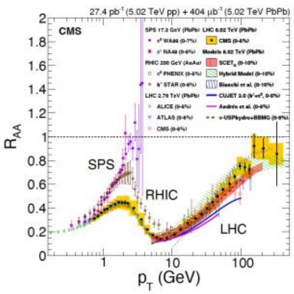


+

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

Prior distributions

+



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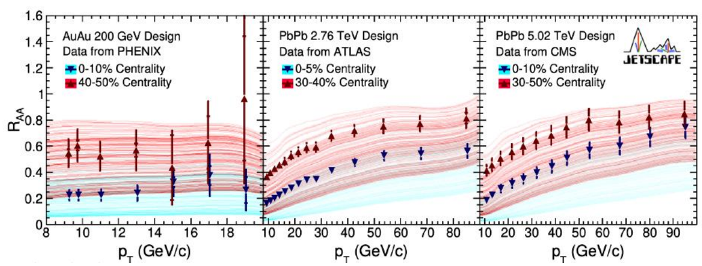
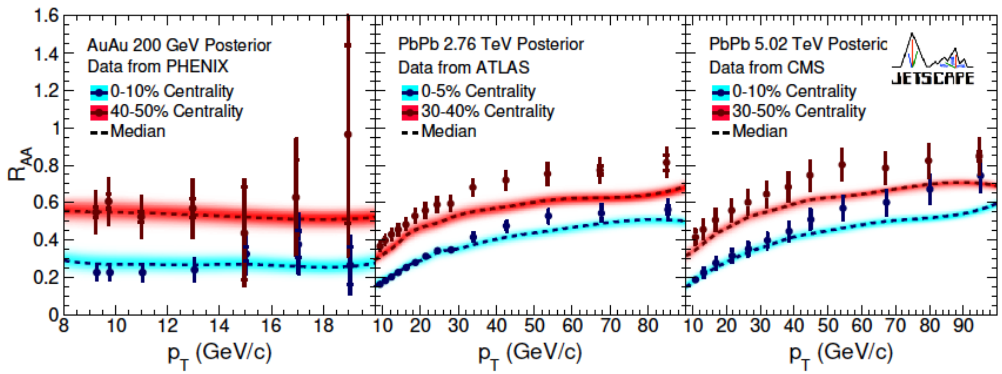


+

$$P(\vec{\theta}|\text{data}) = \frac{P(\text{data}|\vec{\theta})P(\vec{\theta})}{P(\text{data})}$$

Posterior distributions

=



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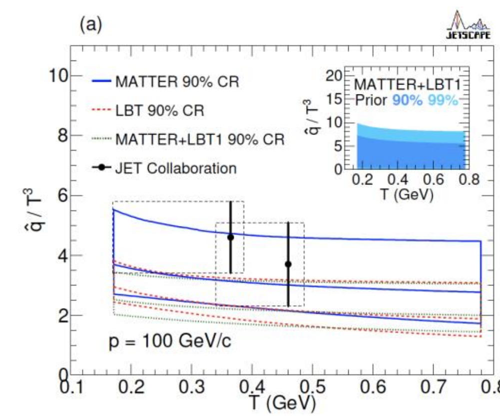

Posterior distributions: what can we learn?

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

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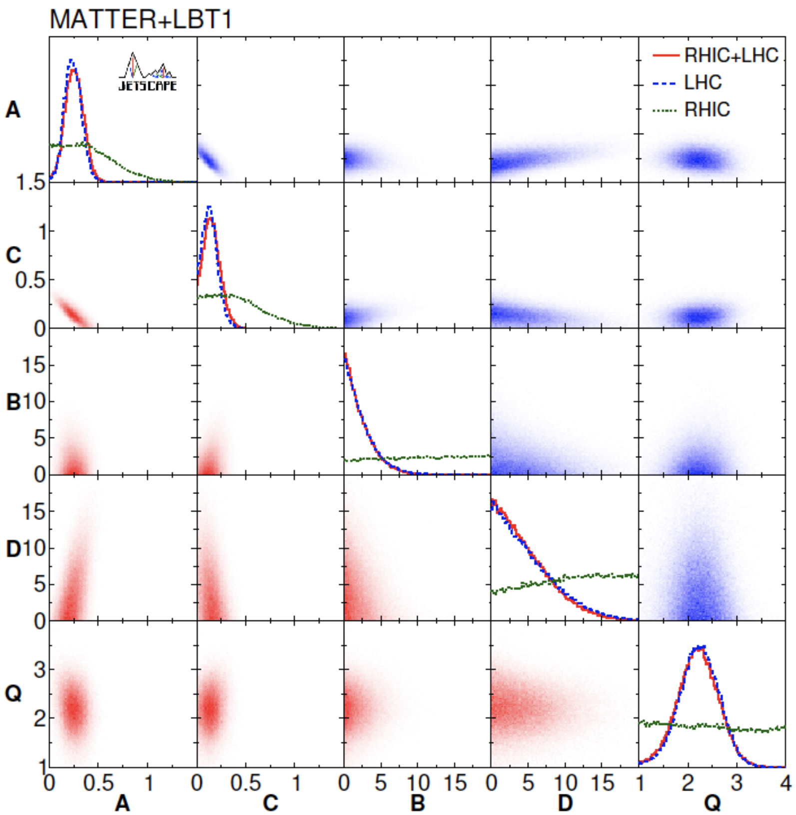
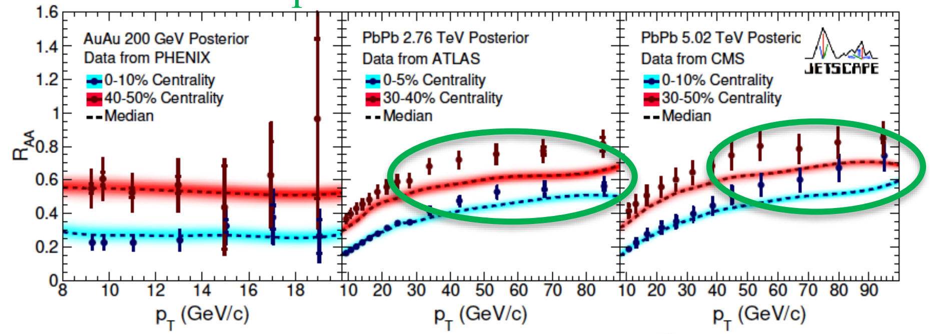
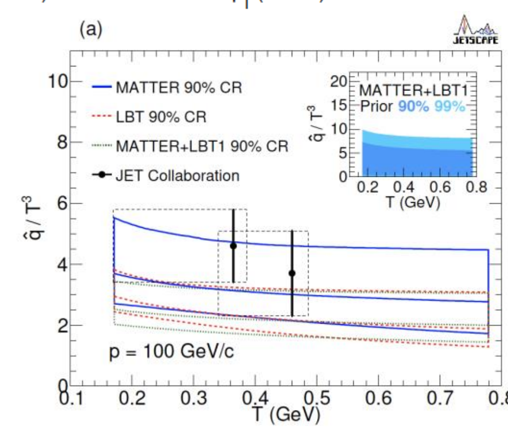
[slightly different formula: Q is switching scale between
Matter (virtuality-ordered) + LBT(thermal) e-loss]

- (anti-)correlation of parameters
- impact of RHIC vs LHC data
- etc.



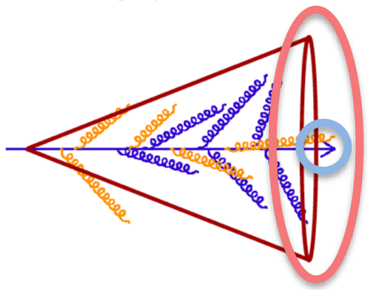
Tension with data: model is incorrect or incomplete





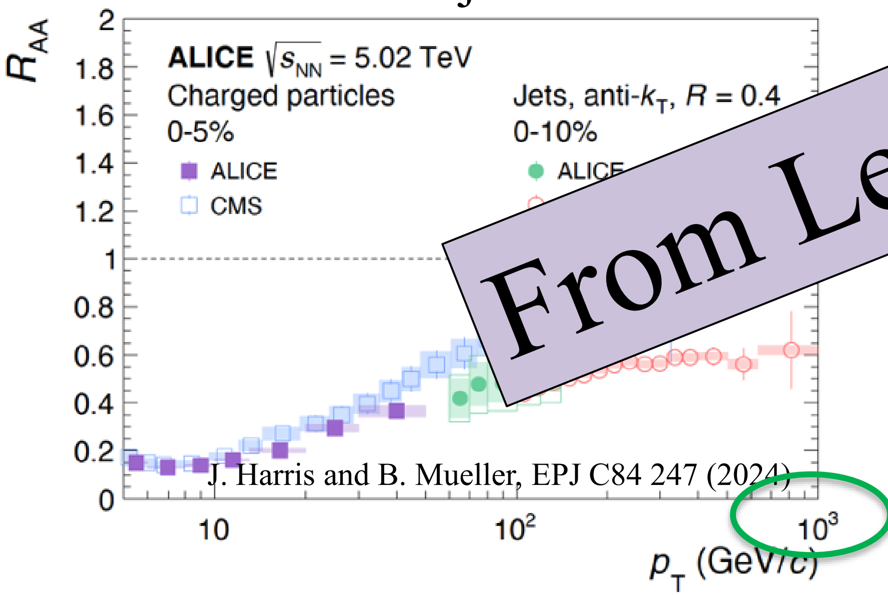
Successful proof-of-principle of the Bayesian approach

Energy loss: hadrons vs jets (inclusive)

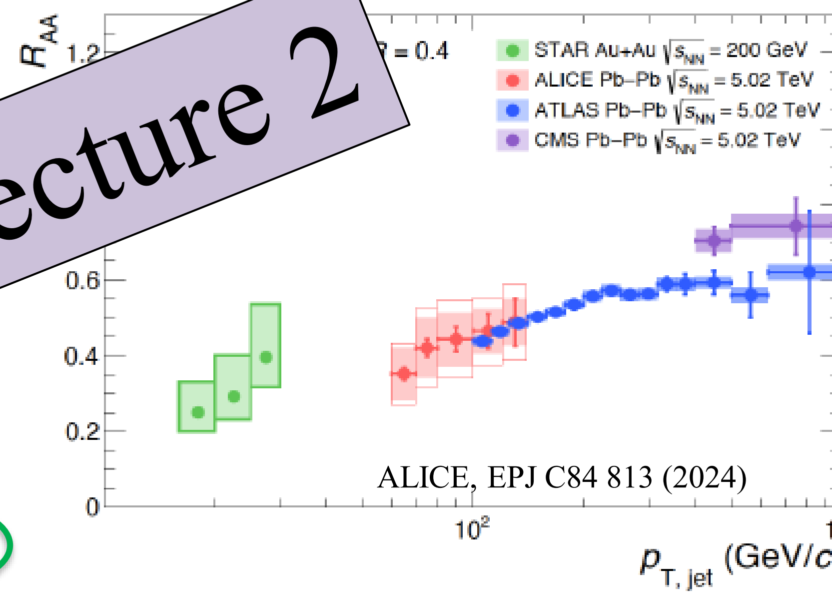


$$R_{AA} = \frac{dN_{AA}^{hard}/dp_T}{\langle T_{AA}\rangle d\sigma_{pp}^{hard}/dp_T}$$

Hadrons vs jets at LHC



Jets at RHIC and LHC



From Lecture 2

Jets probe much higher p_T

Phenomenology: broadly similar at RHIC vs LHC, hadrons vs jets

But quantitative differences: what do they teach us?

Let's table the question until the lecture on Bayesian Inference, when we will study it in detail

PHYSICAL REVIEW C **111**, 054913 (2025)

Bayesian inference analysis of jet quenching using inclusive jet and hadron suppression measurements

R. Ehlers,[1,2] Y. Chen,[3,4,5] J. Mulligan,[1,2] Y. Ji,[6] A. Kumar,[7,8,9] S. Mak,[6] P. M. Jacobs,[1,2] A. Majumder,[9] A. Angerami,[10] R. Arora,[11] S. A. Bass,[12] R. Datta,[9] L. Du,[8,1,2] H. Elfner,[13,14,15] R. J. Fries,[16,17] C. Gale,[8] Y. He,[18,19] B. V. Jacak,[1,2] S. Jeon,[8] F. Jonas,[1,2] L. Kasper,[5] M. Kordell, II,[16,17] R. Kunnawalkam-Elayavalli,[5] J. Latessa,[11] Y.-J. Lee,[3,4] R. Lemmon,[20] M. Luzum,[21] A. Mankolli,[5] C. Martin,[22] H. Mehryar,[11] T. Mengel,[22] C. Nattrass,[22] J. Norman,[23] C. Parker,[16,17] J.-F. Paquet,[5] J. H. Putschke,[9] H. Roch,[9] G. Roland,[3,4] B. Schenke,[24] L. Schwiebert,[11] A. Sengupta,[16,17] C. Shen,[9,25] M. Singh,[5] C. Sirimanna,[9,12] D. Soeder,[26] R. A. Soltz,[9,10] I. Soudi,[9,27,28] Y. Tachibana,[29] J. Velkovska,[5] G. Vujanovic,[7] X.-N. Wang,[30,1,2] X. Wu,[8,9] and W. Zhao[9,1,2]
(JETSCAPE Collaboration)
[1]Department of Physics, University of California, Berkeley, California 94270, USA

The JETSCAPE Collaboration reports a new determination of the jet transport parameter $\hat{q}$ in the quark-gluon plasma (QGP) using Bayesian inference, incorporating all available inclusive hadron and jet yield suppression data measured in heavy-ion collisions at the BNL Relativistic Heavy Ion Collider (RHIC) and the CERN Large Hadron Collider (LHC). This multi-observable analysis extends the previously published JETSCAPE Bayesian inference determination of $\hat{q}$, which was based solely on a selection of inclusive hadron suppression data. JETSCAPE is a modular framework incorporating detailed dynamical models of QGP formation and evolution, and jet propagation and interaction in the QGP. Virtuality-dependent partonic energy loss in the QGP is modeled as a thermalized weakly coupled plasma, with parameters determined from Bayesian calibration using soft-sector observables. This Bayesian calibration of $\hat{q}$ utilizes active learning, a machine-learning approach, for efficient exploitation of computing resources. The experimental data included in this analysis span a broad range in collision energy and centrality, and in transverse momentum. In order to explore the systematic dependence of the extracted parameter posterior distributions, several different calibrations are reported, based on combined jet and hadron data; on jet or hadron data separately; and on restricted kinematic or centrality ranges of the jet and hadron data. Tension is observed in comparison of these variations, providing new insights into the physics of jet transport in the QGP and its theoretical formulation.

Theoretical Model

Phys.Rev.C 111 (2025) 054913

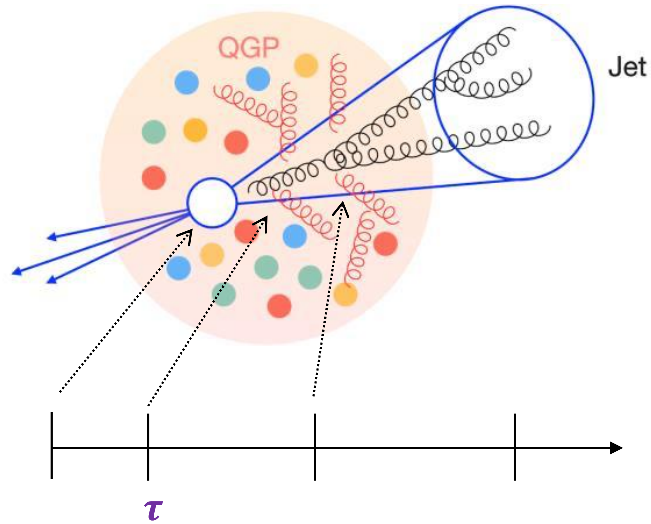
JETSCAPE Framework:

Hydro: calibrated 2+1D hydro

Bernhard, Moreland, and Bass,
Nat. Phys. 15, 1113–1117 (2019)

Jet quenching:
multistage, virtuality-dependent
MATTER + LBT

JETSCAPE, Phys.Rev.C 107 (2023) 3, 0349
JETSCAPE, arXiv:2301.02485



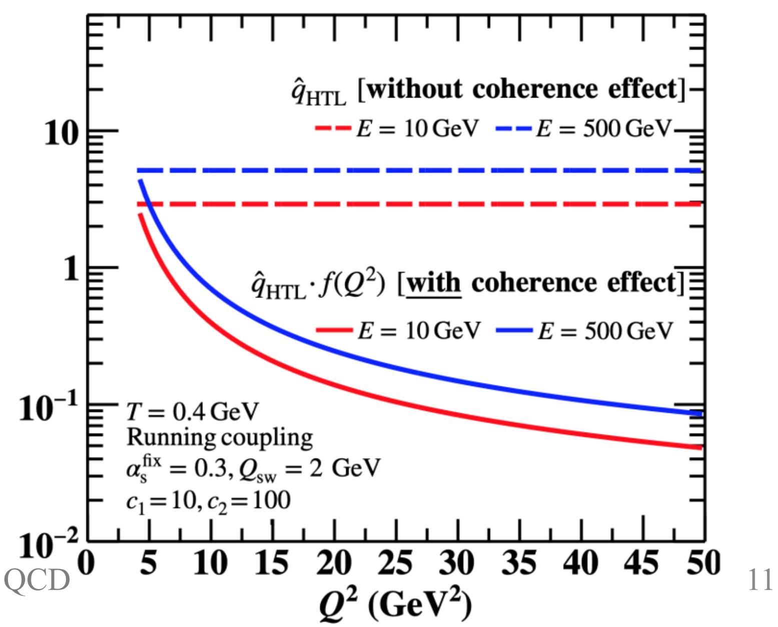
$$\hat{q}(E,\mu^2,T) = \hat{q}^{HTL} \times f(\mu^2)$$

$$\frac{\hat{q}^{HTL}}{T^3} = C_a \frac{50.48}{\pi} \alpha_{s,\mathrm{run}}(\mu^2)\alpha_{s,\mathrm{fix}} \log\left(\frac{2ET}{6\pi T^2 \alpha_{s,fix}}\right)$$

$$f(\mu^2) = N \frac{e^{c_3\left(1-\frac{\mu^2}{2ME}\right)} - 1}{1 + c_1 \log\left(\frac{\mu^2}{\Lambda^2_{QCD}}\right) + c_2 \log^2\left(\frac{\mu^2}{\Lambda^2_{QCD}}\right)}\Bigg|_{\mu \geq Q_0}$$

$N = 1/f(Q_0^2)$

$f(\mu^2)$ incorporates coherence effects which reduce $\hat{q}$ for $\mu \geq Q_0$



6 parameters

- $\alpha_{s,fix}$
- c_1, c_2, c_3
- Q_0 (switching virtuality)
- τ (start time)

Theoretical Model

Phys.Rev.C 111 (2025) 054913

JETSCAPE Framework:

Hydro: calibrated 2+1D hydro
Bernhard, Moreland, and Bass, Nat. Phys. 15, 1113–1117 (2019)

Jet quenching:
multistage, virtuality-dependent
MATTER + LBT
JETSCAPE, Phys.Rev.C 107 (2023) 3, 034911
JETSCAPE, arXiv:2301.02485

Physically-motivated model which provides a valuable test-bench for development

JETSCAPE framework is modular
- other models can be implemented
- crucial future direction

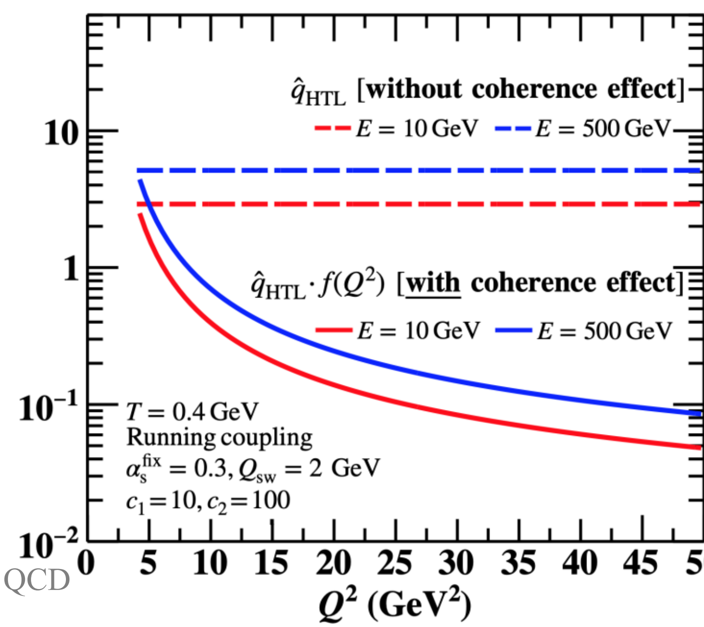
$$\hat{q}(E,\mu^2,T) = \hat{q}^{HTL} \times f(\mu^2)$$

$$\frac{\hat{q}^{HTL}}{T^3} = C_a \frac{50.48}{\pi} \alpha_{s,\mathrm{run}}(\mu^2)\boldsymbol{\alpha_{s,\mathrm{fix}}} \log\left(\frac{2ET}{6\pi T^2 \boldsymbol{\alpha_{s,fix}}}\right)$$

$$f(\mu^2) = N \left.\frac{e^{c_3\left(1-\frac{\mu^2}{2ME}\right)} - 1}{1 + c_1 \log\left(\frac{\mu^2}{\Lambda^2_{QCD}}\right) + c_2 \log^2\left(\frac{\mu^2}{\Lambda^2_{QCD}}\right)}\right|_{\mu \geq Q_0}$$

$N = 1/f(Q_0^2)$

$f(\mu^2)$ includes coherence effects; reduces $\hat{q}$ for $\mu \geq Q_0$



6 parameters
- $\alpha_{s,fix}$
- c_1, c_2, c_3
- Q_0 (switching virtuality)
- τ (start time)

Data sets

Phys.Rev.C 111 (2025) 054913

All hadron and jet R_{AA} data from RHIC and LHC published prior to Febuary 2022

729 data points

- previous JETSCAPE $\hat{q}$ calibration: 66 datapoints
  Phys.Rev.C 104 (2021) 024905

Uncertainty covariance taken from publication or estimated

Inclusive hadron R_{AA}					
Collab./ref.	System; $\sqrt{s_{NN}}$ [TeV]	Species	Accept.	centr. %	p_T range [GeV/c]
STAR [101]	Au–Au; 0.2	charged	$\|\eta\| < 0.5$	[0,40]	[9,12]
ALICE [102]	Pb–Pb; 2.76, 5.02	charged	$\|\eta\| < 0.8$	[0,50]	[9,50]
ATLAS [99]	Pb–Pb; 2.76	charged	$\|\eta\| < 2$	[0,40]	[9,150]
CMS [103]	Pb–Pb; 2.76	charged	$\|\eta\| < 1.0$	[0,50]	[9,100]
CMS [100]	Pb–Pb; 5.02	charged	$\|\eta\| < 1.0$	[0,50]	[9,400]
PHENIX [104]	Au–Au; 0.2	π^0	$\|\eta\| < 0.35$	[0,50]	[9,20]
ALICE [105, 106]	Pb–Pb; 2.76	π^0	$\|\eta\| < 0.7$	[0,50]	[9,20]
ALICE [107, 108]	Pb–Pb; 2.76	$\pi^\pm$	$\|\eta\| < 0.8$	[0,40]	[9,20]
ALICE [109]	Pb–Pb; 5.02	$\pi^\pm$	$\|\eta\| < 0.8$	[0,50]	[9,20]

Inclusive jet R_{AA}						
Collab./ref.	System; $\sqrt{s_{NN}}$ [TeV]	type	R	Accept.	centr. %	p_T range [GeV/c]
STAR [110]	Au–Au; 0.2	charged	[0.2,0.4]	$\|\eta\| < 1 - R$	[0,10]	[15,30]
ALICE [111]	Pb–Pb; 2.76	full	0.2	$\|\eta\| < 0.5$	[0,30]	[30,100]
ALICE [22]	Pb–Pb; 5.02	full	0.2,0.4	$\|\eta\| < 0.5$	[0,10]	[40,140]
ATLAS [112]	Pb–Pb; 2.76	full	0.4	$\|\eta\| < 2.1$	[0,50]	[32,500]
ATLAS [113]	Pb–Pb; 5.02	full	0.4	$\|\eta\| < 2.8$	[0,50]	[50,1000]
CMS [114]	Pb–Pb; 2.76	full	[0.2,0.4]	$\|\eta\| < 2.0$	[0,50]	[70,300]
CMS [115]	Pb–Pb; 5.02	full	[0.2,1.0]	$\|\eta\| < 2.0$	[0,50]	[200,1000]

Bayesian Inference in practice

JETSCAPE

Phys.Rev.C 111 (2025) 054913

$$\frac{\hat{q}^{HTL}}{T^3} = C_a \frac{50.48}{\pi} \alpha_{s,\mathrm{run}}(\mu^2)\boldsymbol{\alpha_{s,\mathrm{fix}}} \log\left(\frac{2ET}{6\pi T^2 \boldsymbol{\alpha_{s,fix}}}\right)$$

$$f(\mu^2) = N \left.\frac{e^{c_3\left(1-\frac{\mu^2}{2ME}\right)} - 1}{1 + \boldsymbol{c_1}\log\left(\frac{\mu^2}{\Lambda_{QCD}^2}\right) + \boldsymbol{c_2}\log^2\left(\frac{\mu^2}{\Lambda_{QCD}^2}\right)}\right|_{\mu \geq \boldsymbol{Q_0}}$$

Model calculation only at limited number of parameter "design points"
→ interpolation

6 parameters

- $\alpha_{s,fix}$
- c_1, c_2, c_3
- Q_0 (switching virtuality)
- τ (start time)

Optimize interpolation error: choice of design points

- AI/ML methods: active learning

Large computing effort: O(10M) CPU-hours on NSF HPC facilities

Broad-based results: many physics observables calculated for differential studies

From prior to posterior

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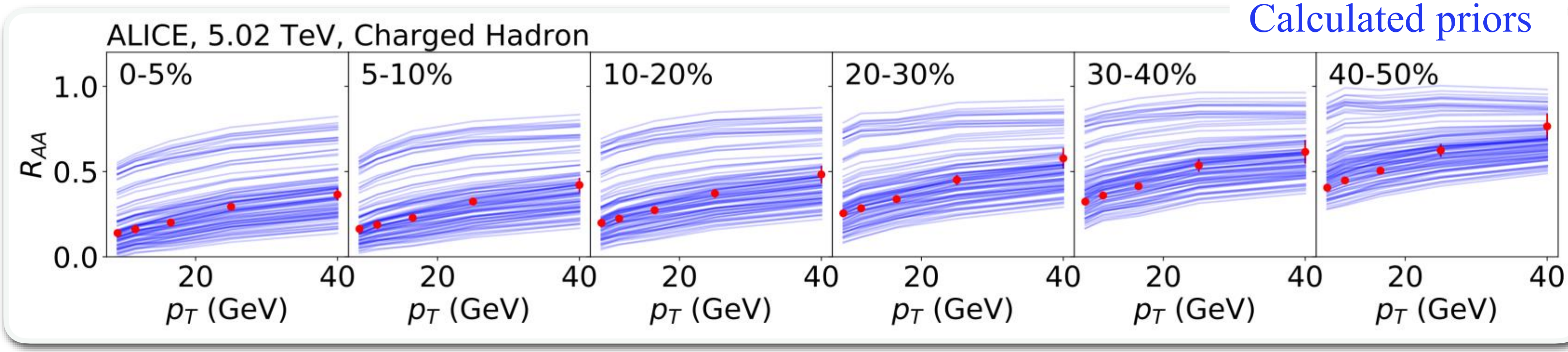
$$P(\vec{\theta}|\mathrm{data}) = \frac{P(\mathrm{data}|\vec{\theta})P(\vec{\theta})}{P(\mathrm{data})}$$

Data

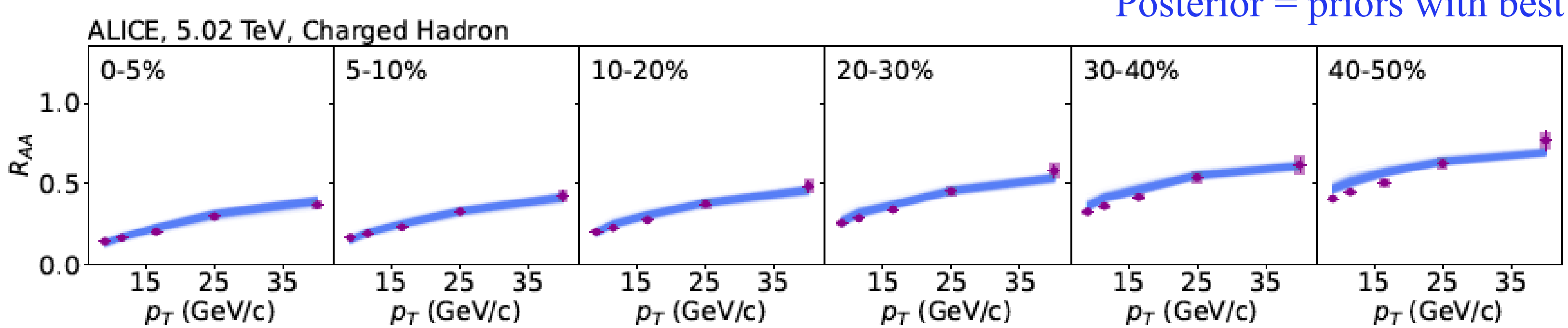
Calculated priors



analysis

Data

Posterior = priors with best fit



Posterior distribution compared to all jet and hadron R_{AA} data (prior to Feb '22)

JETSCAPE

Phys.Rev.C 111 (2025) 054913

What does this tell us?

Broadly: fairly good agreement of model + data

But detailed examination reveals significant tension

→ model (MATTER+LBT+ $\hat{q}$) is missing key elements

Parameter posterior distributions

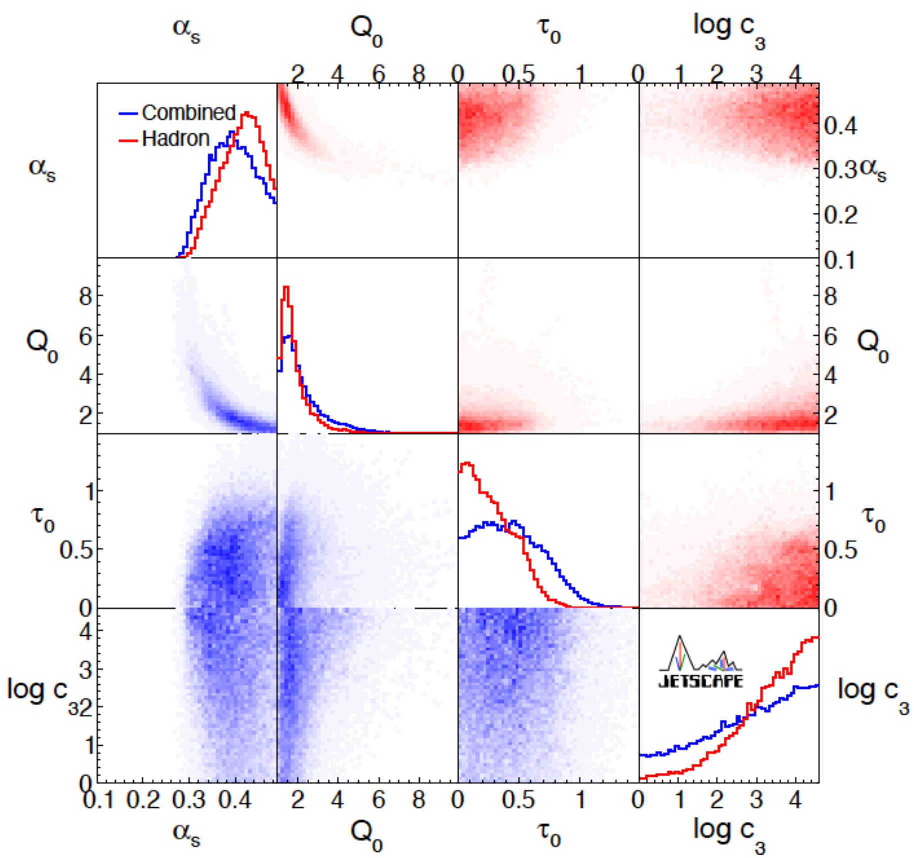
Phys.Rev.C 111 (2025) 054913

$$\hat{q}(E,\mu^2,T) = \hat{q}^{HTL} \times f(\mu^2)$$

$$\frac{\hat{q}^{HTL}}{T^3} = C_a \frac{50.48}{\pi} \alpha_{s,\mathrm{run}}(\mu^2) \boldsymbol{\alpha_{s,\mathrm{fix}}} \log\left(\frac{2ET}{6\pi T^2 \boldsymbol{\alpha_{s,fix}}}\right)$$

$$f(\mu^2) = N \left. \frac{e^{\boldsymbol{c_3}\left(1-\frac{\mu^2}{2ME}\right)} - 1}{1 + \boldsymbol{c_1} \log\left(\frac{\mu^2}{\Lambda^2_{QCD}}\right) + \boldsymbol{c_2} \log^2\left(\frac{\mu^2}{\Lambda^2_{QCD}}\right)} \right|_{\mu \geq \boldsymbol{Q_0}}$$

Combined: inclusive hadron and jet
Hadron: inclusive hadron



6 parameters

- $\alpha_{s,fix}$
- c_1, c_2, c_3
- Q_0 (switching virtuality)
- τ (start time)

$\alpha_{s,\mathrm{fix}}$: 0.3 – 0.4
Q_0: ~1-2 GeV
τ_o: < 1 fm/c
c_3: larger values preferred
c_1,c_2: little sensitivity (not shown)

Extracting $\hat{q}$

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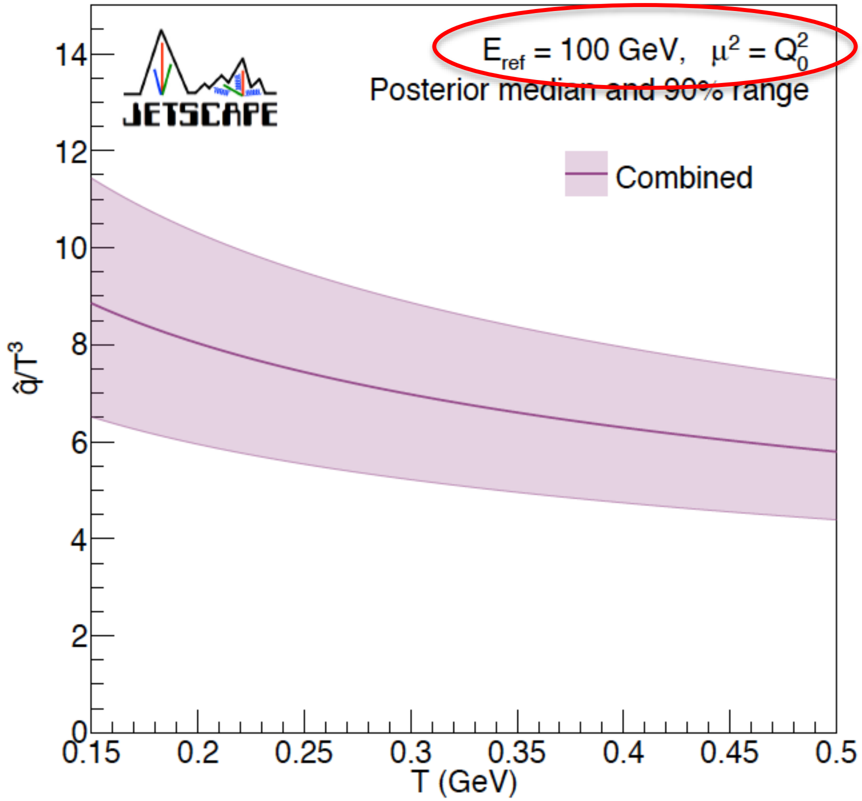
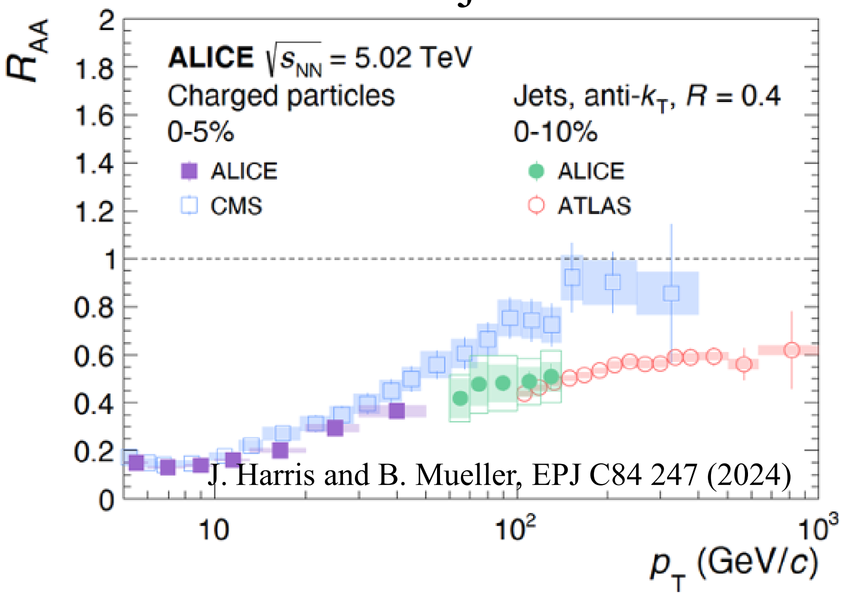


Put everything together: extract $\hat{q}$

Plot $\hat{q}$ at low virtuality: $\hat{q} = \hat{q}_{HTL}^{run} \times f(Q^2)$

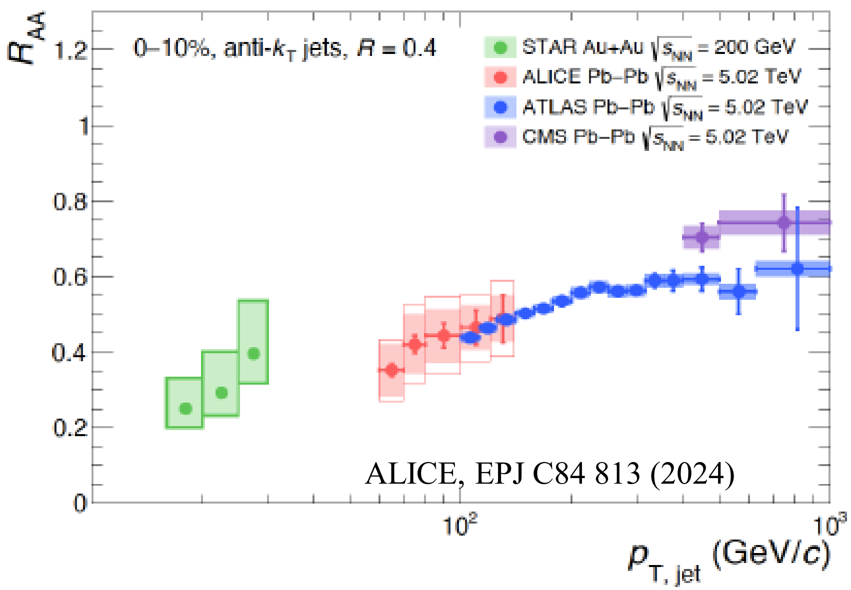
Data sets

Hadrons vs jets at LHC



J. Harris and B. Mueller, EPJ C84 247 (2024)

Jets at RHIC and LHC



ALICE, EPJ C84 813 (2024)

Hadron vs jet R_{AA}

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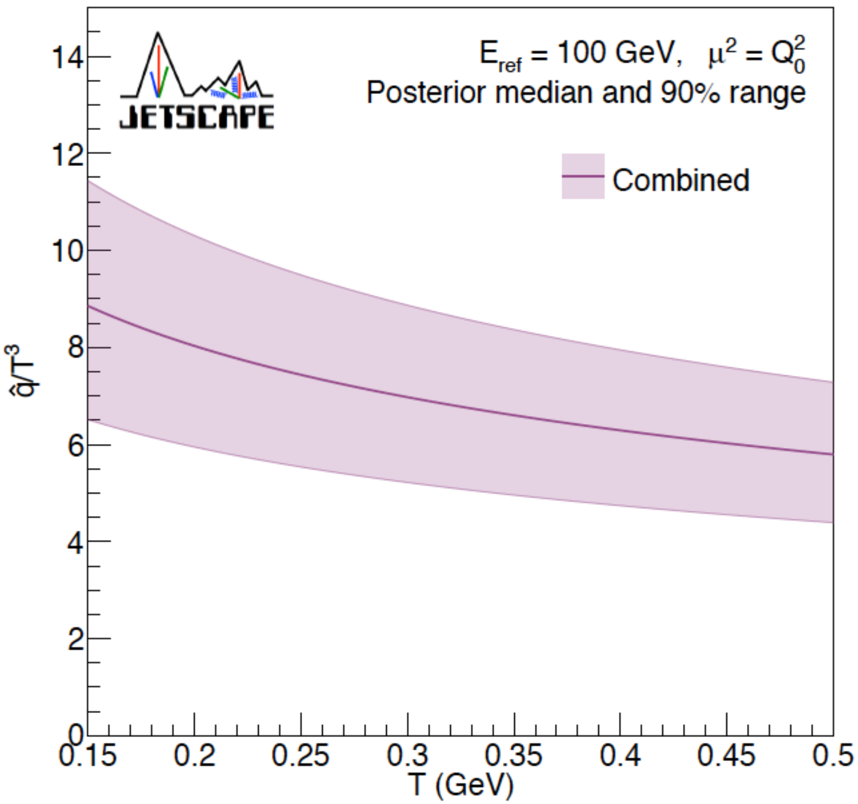

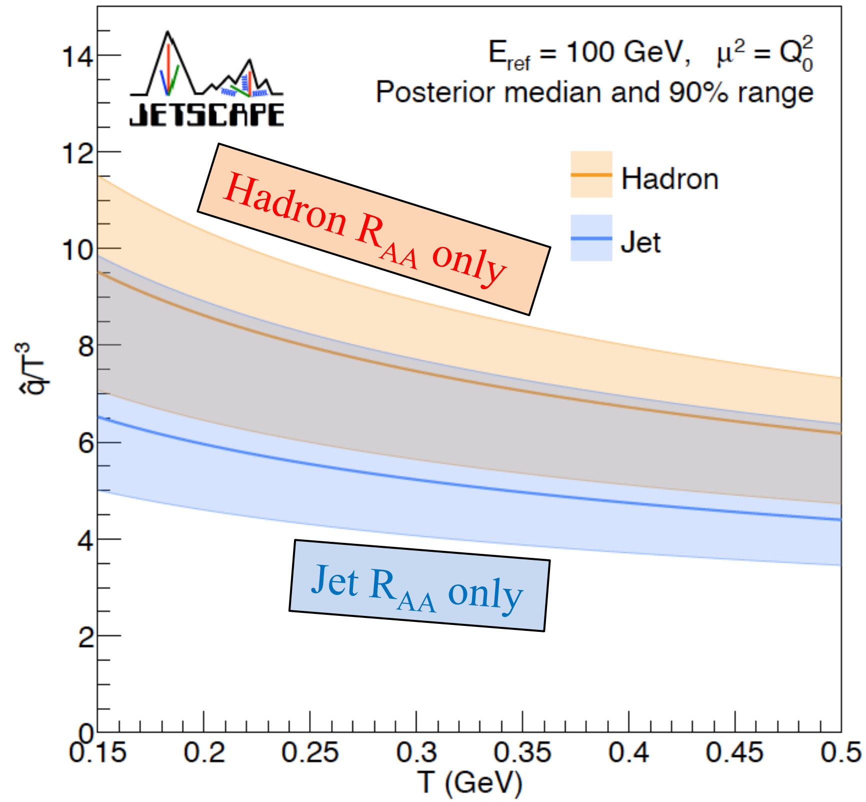

Hadron vs jet R_{AA}

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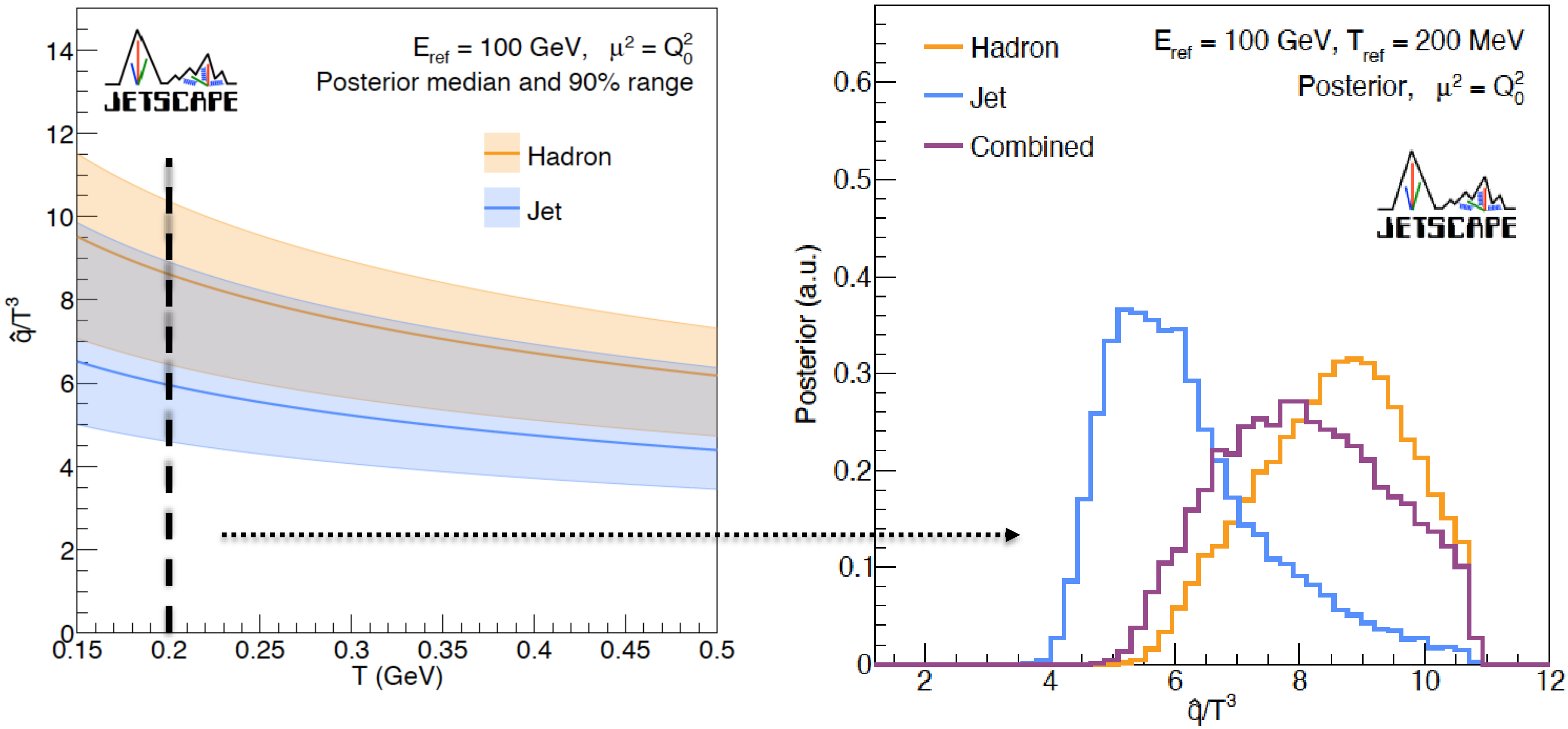

Hadron R_{AA}: low vs high p_T

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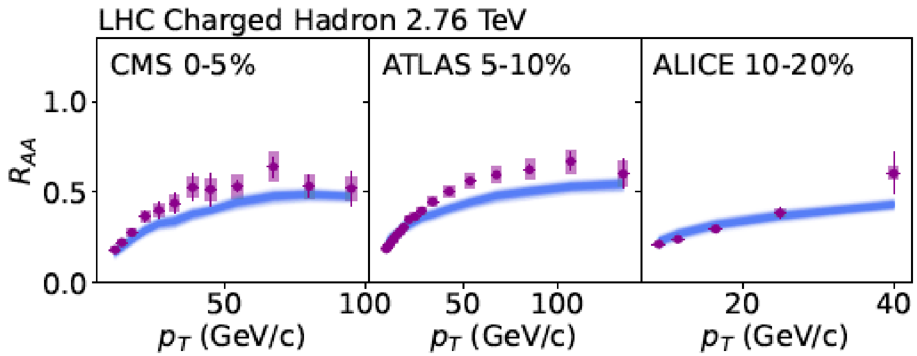
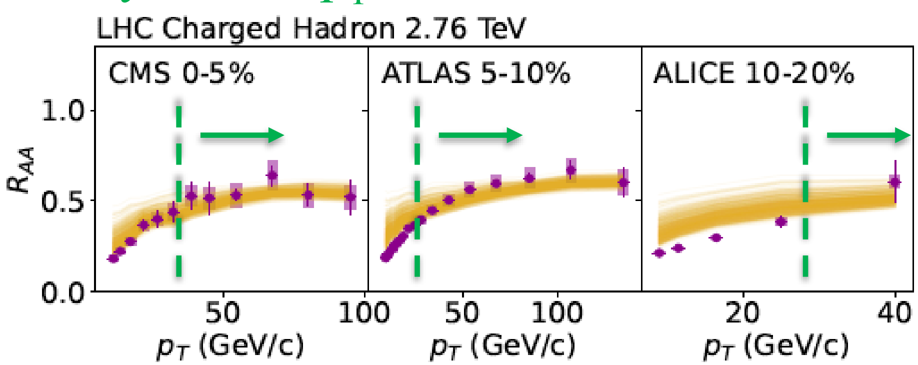
Combined calibration



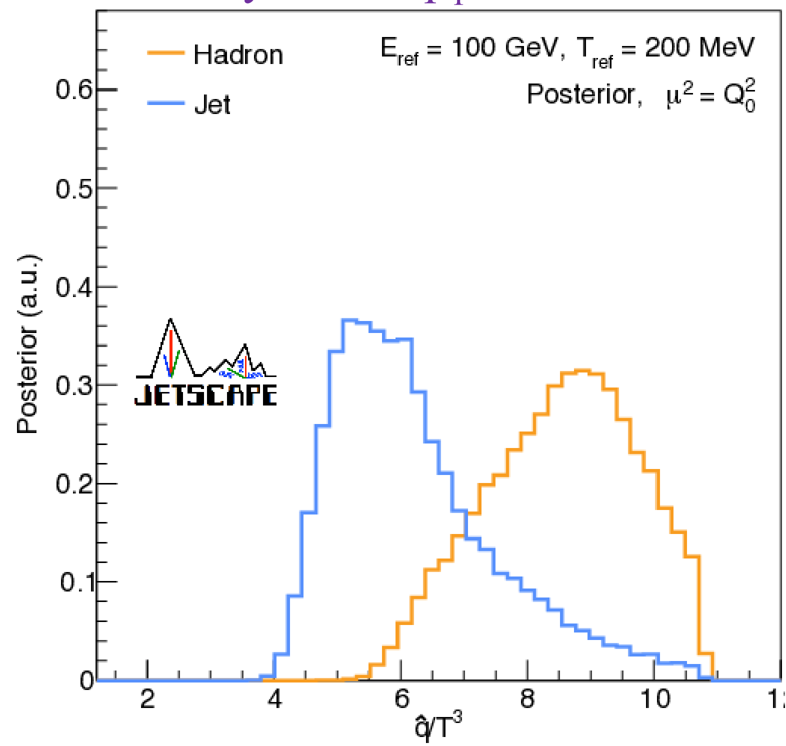
Only hadron p_T>30 GeV/c



Low p_T hadrons dominate

- due to small experimental uncertainties

Vary hadron p_T threshold



High p_T hadrons consistent with jet data

Missing: theory uncertainty

- large where exp uncert is small

p_T dependence of model does not describe data:

- NLO or non-pert. correction to HTL expression of $\hat{q}$?
- HTL not the correct framework? Nuclear shadowing? ...?

Comparison to previous calibration

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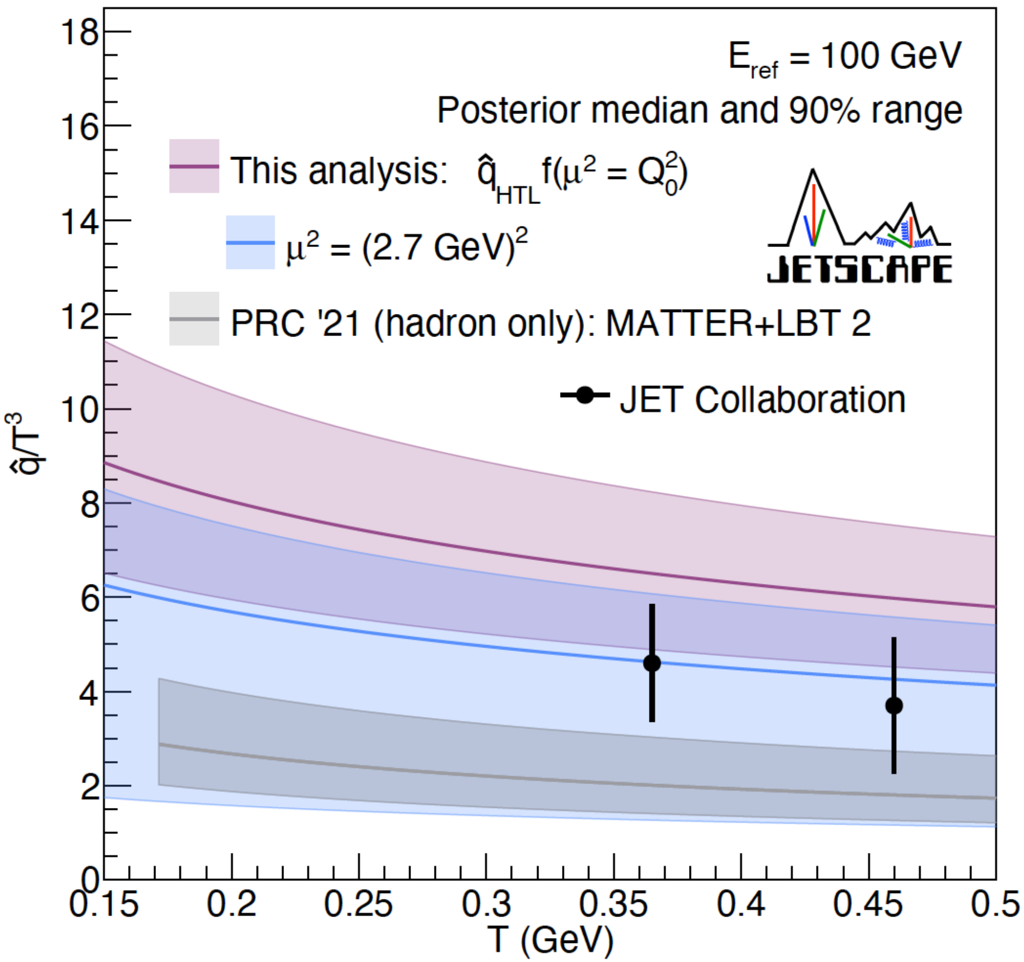

First JETSCAPE $\hat{q}$ calibration

PRC 104 (2021) 024905

- hadron R_{AA} only
- reported at μ^2=2.7 GeV^2

Evolve current analysis to compare at same scale

→ consistent

→ evolution captured correctly by Bayesian calibration

Bayesian inference of jet quenching: next steps

Add new observables
- Jet substructure
- Coincidence channels: γ/Z+jet, h+jet, di+jet
- Heavy flavor

  → adding new observables must be done slowly and cautiously; dialing too many knobs at once is just confusing

Add new models:
- integration of Hybrid Model (JHEP 1410, 19 (2014)) in progress
- Radically different approach vis a vis JETSCAPE: energy loss in QGP based on AdS/CFT approach

  → Compare and contrast