Multi-Observable Analysis of Jet Quenching Using Bayesian Inference

arXiv:2408.08247

Peter Jacobs

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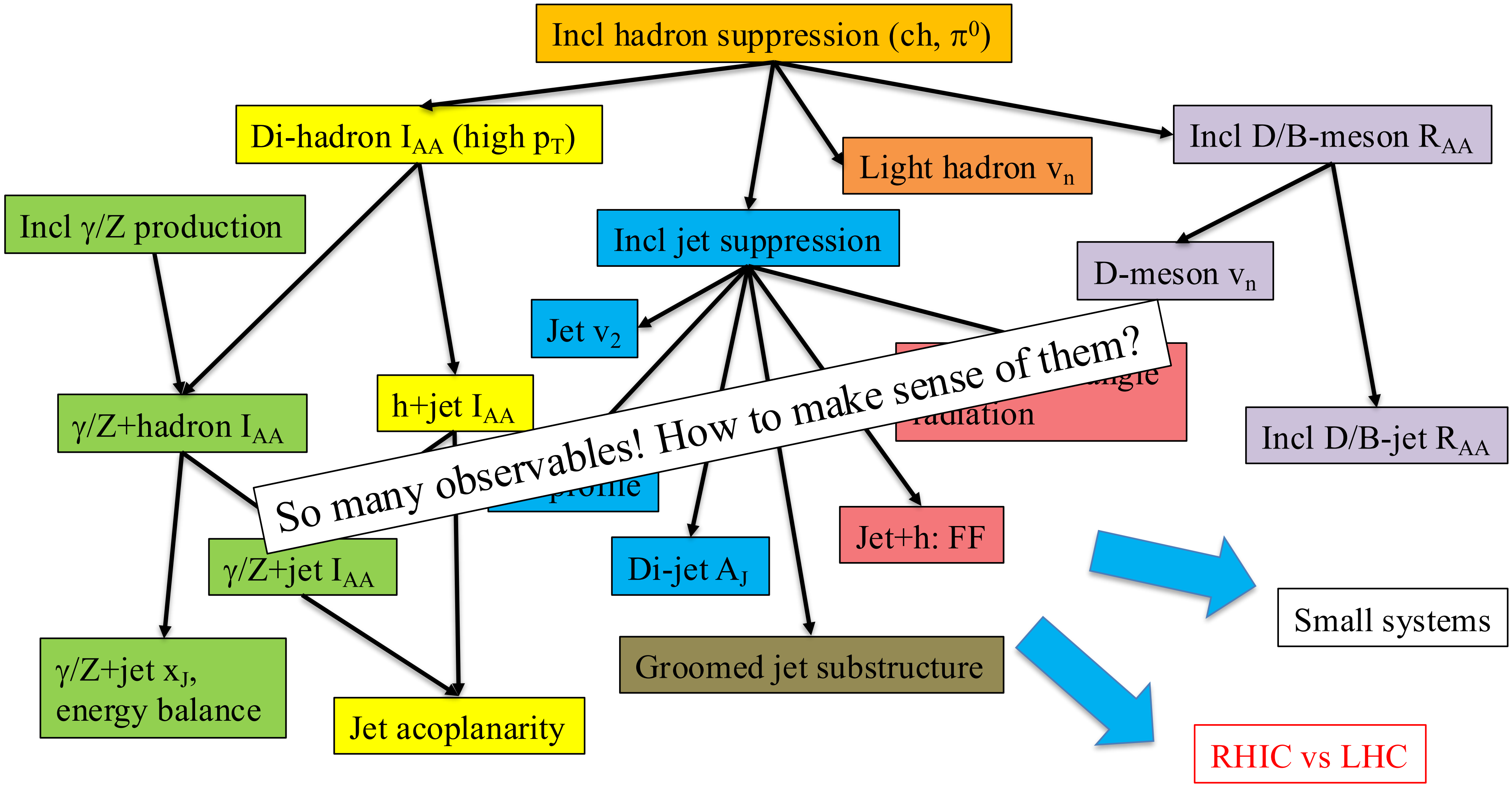
University of California, Berkeley

for the JETSCAPE Collaboration

Taxonomy of current jet quenching measurements

Driven by experimental considerations: arrows connect observables with just one thing changed



Rigorous connection of data and models: Bayes's Theorem

For a given theoretical model, which model parameters are most compatible with experimental data?

Bayesian Inference: combine knowledge of theory and experiment:

$$\vec{\theta}: \text{Model parameters}$$

Likelihood

Prior knowledge of 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

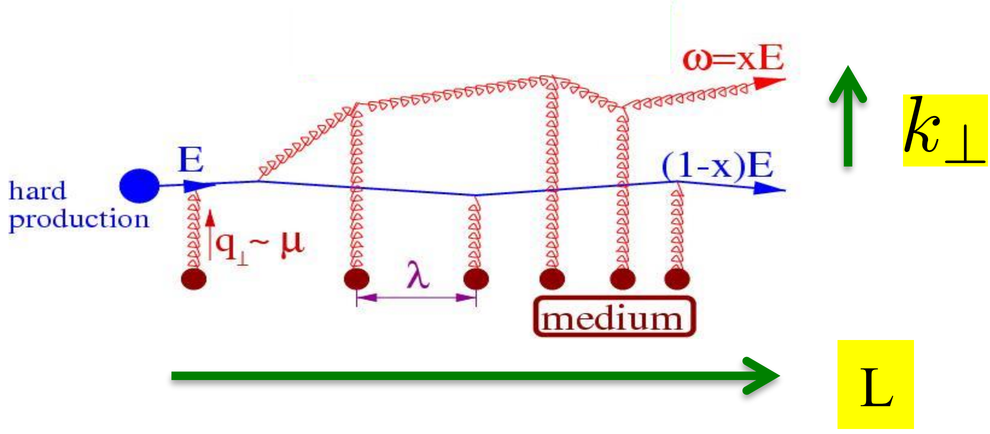
distribution of data ("Bayesian evidence")

Likelihood incorporates covariance of data uncertainties, theory uncertainties

1. Search for tension: do any model parameters consistently describe the data?
2. Constrain parameters: what do we learn quantitatively?

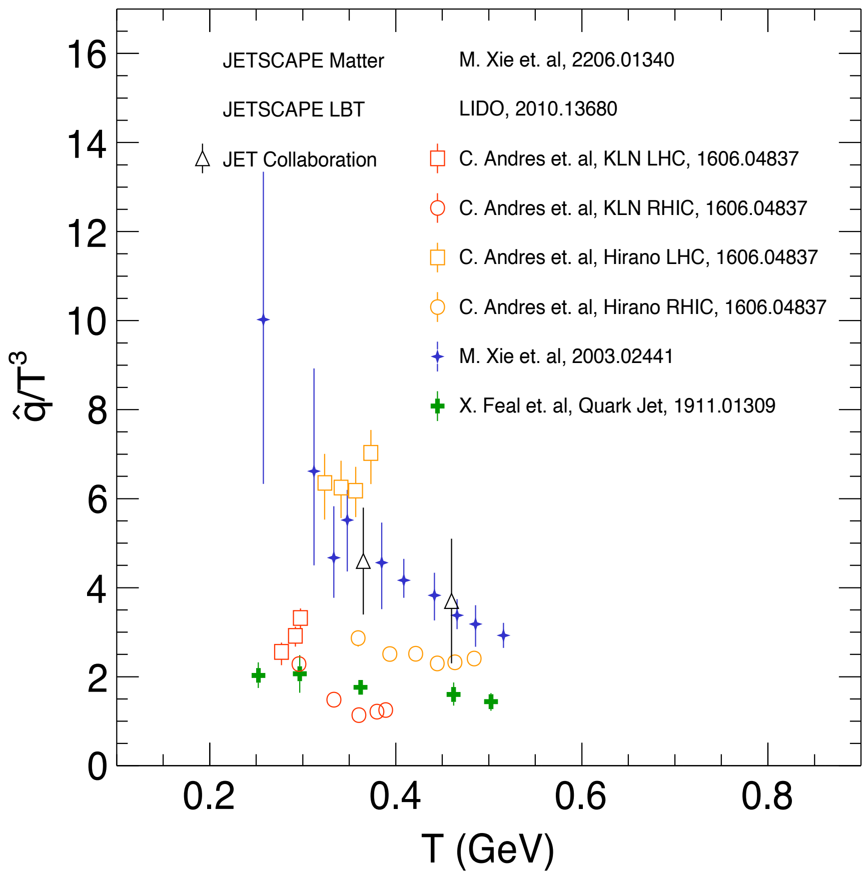
R. Ehlers, Plenary Thurs 12:05

Quantifying jet quenching



$$\hat{q} \equiv \frac{\langle k_\perp^2 \rangle_L}{L}$$

Apolinaro, Lee and Winn
Prog.Part.Nucl.Phys. 127 (2022) 103990



Based primarily on inclusive hadron R_{AA}

But datasets, theory formulations of $\hat{q}$, and QGP modeling differ
→ different $\hat{q}$ determinations are not strictly comparable

Different approach: study $\hat{q}$ differentially within a single, consistent framework

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]

(The JETSCAPE Collaboration)

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arXiv:2408.08247
submitted to Physical Review C

First multi-observable Bayesian analysis incorporating all available inclusive hadron and inclusive jet suppression data (R_{AA}) at RHIC and LHC

What do we learn by measuring R_{AA} of reconstructed jets?
Is $\hat{q}$ a universal property of the QGP?

Theoretical Model

arXiv:2408.08247

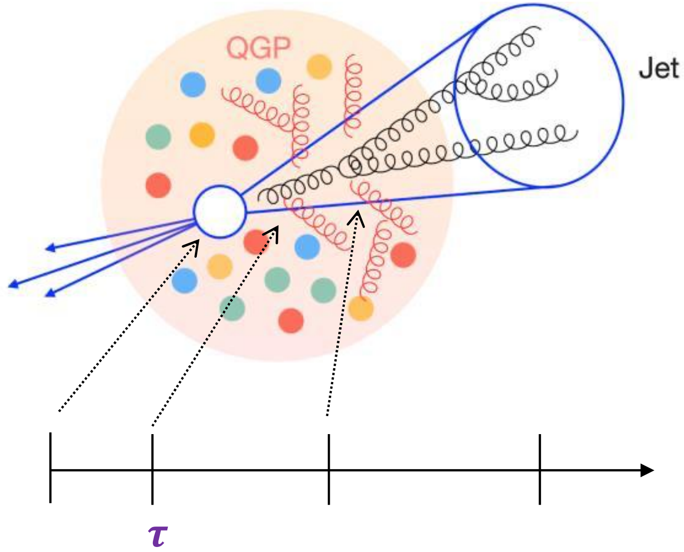
JETSCAPE Framework:

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



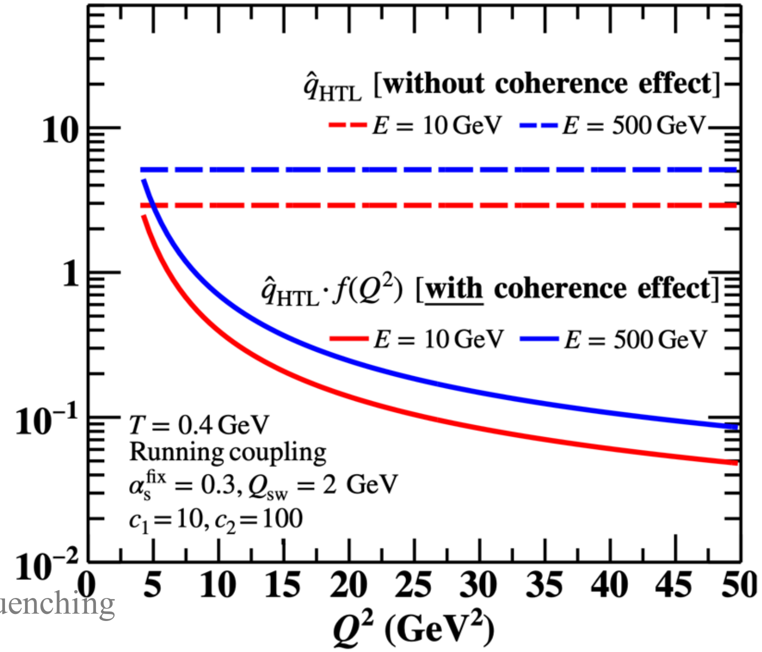
$$\hat{q}(E,\mu^2,T) = \hat{q}^{HTL} \times f(\mu^2)$$

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

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

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

$f(\mu^2)$ 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

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

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

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

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

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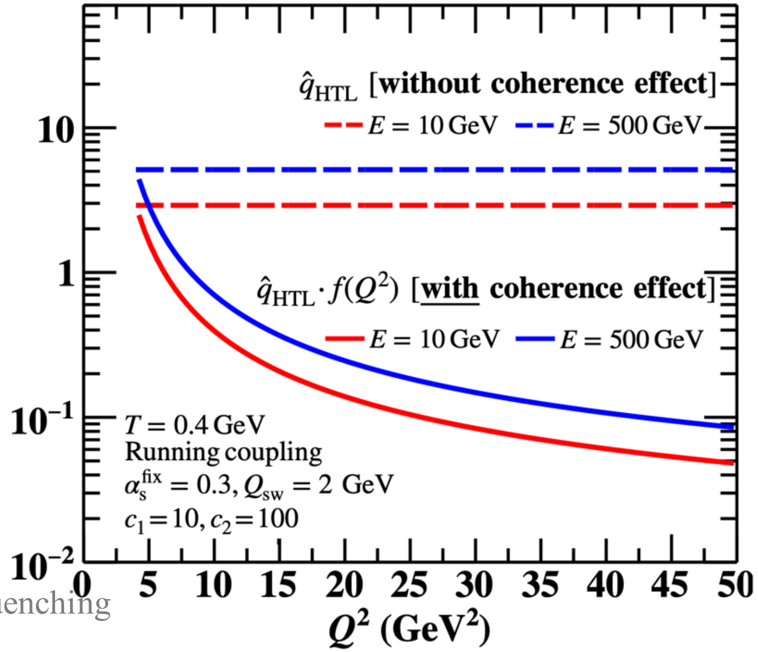


Data sets

JETSCAPE

arXiv:2408.08247

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

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

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

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

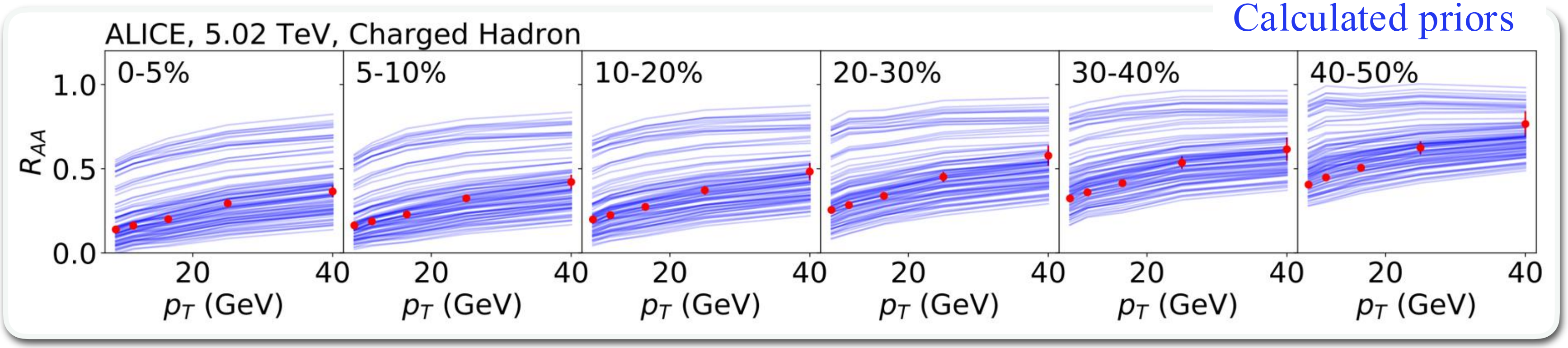
Broad-based results: many physics observables calculated for differential studies

From prior to posterior

arXiv:2408.08247

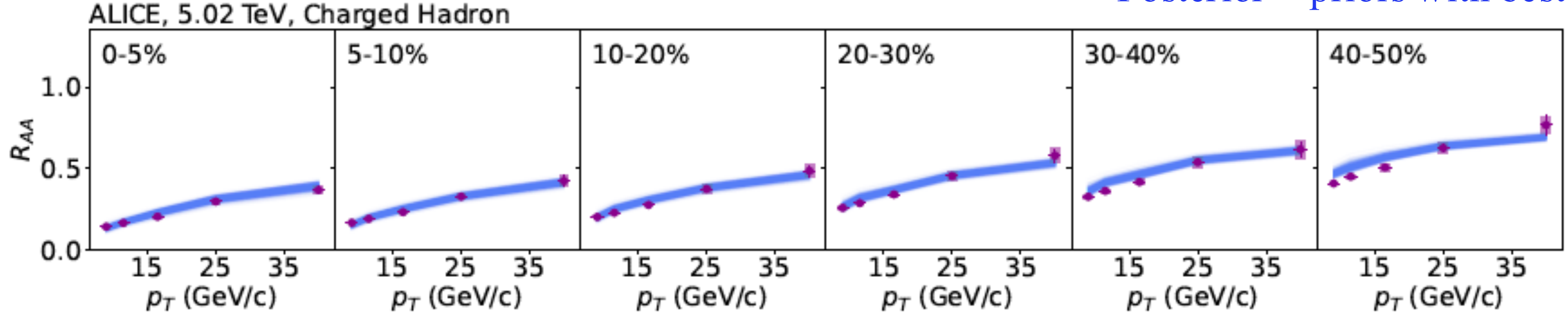
$$P(\vec{\theta}|\text{data}) = \frac{P(\text{data}|\vec{\theta})P(\vec{\theta})}{P(\text{data})}$$

Data
Calculated priors



analysis

Data
Posterior = priors with best fit



Data-posterior comparison: all data

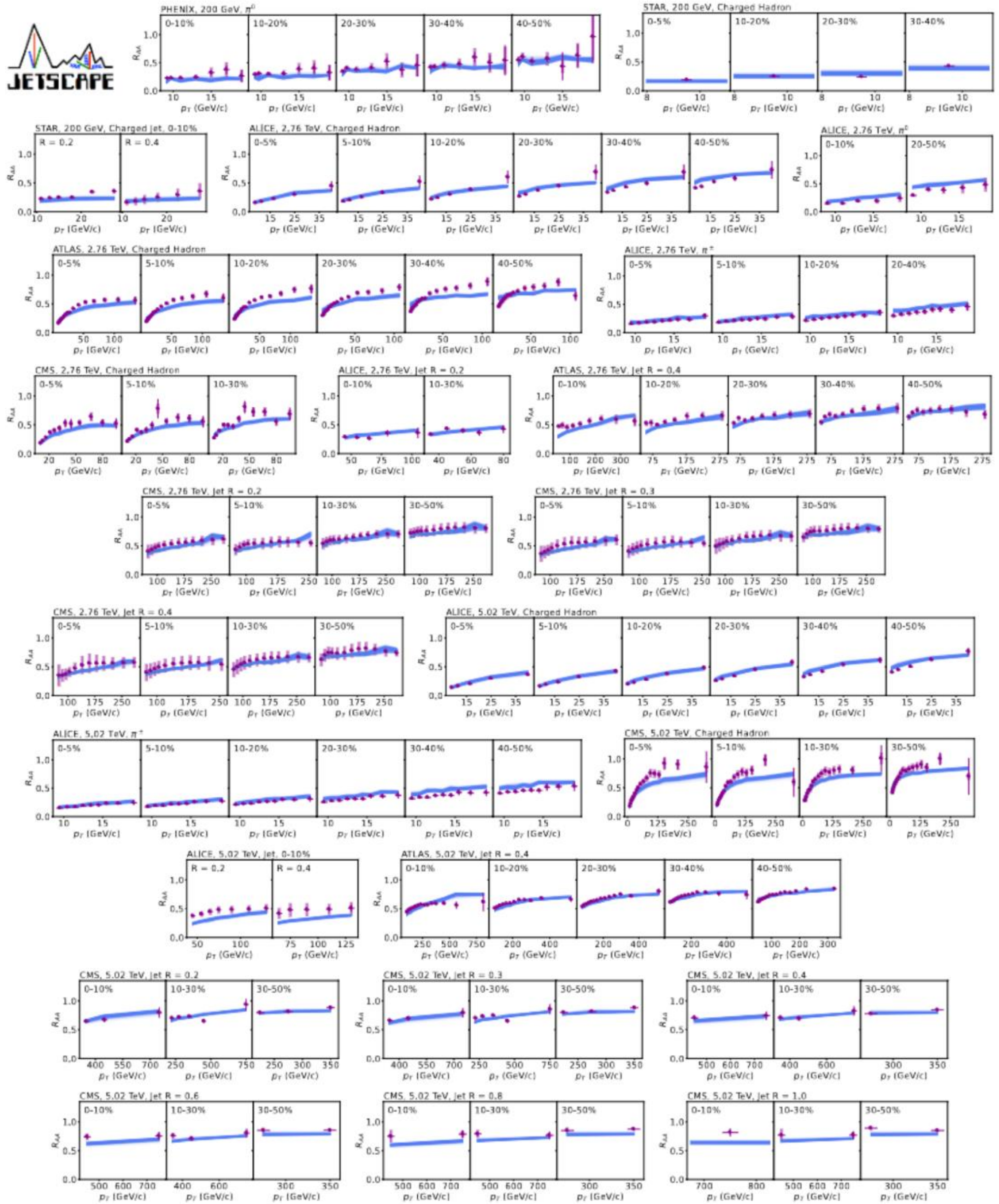
(details in subsequent slides)

arXiv:2408.08247

Overall reasonable agreement

Significant tension in limited regions

→ explore more differentially



Parameter posterior distributions

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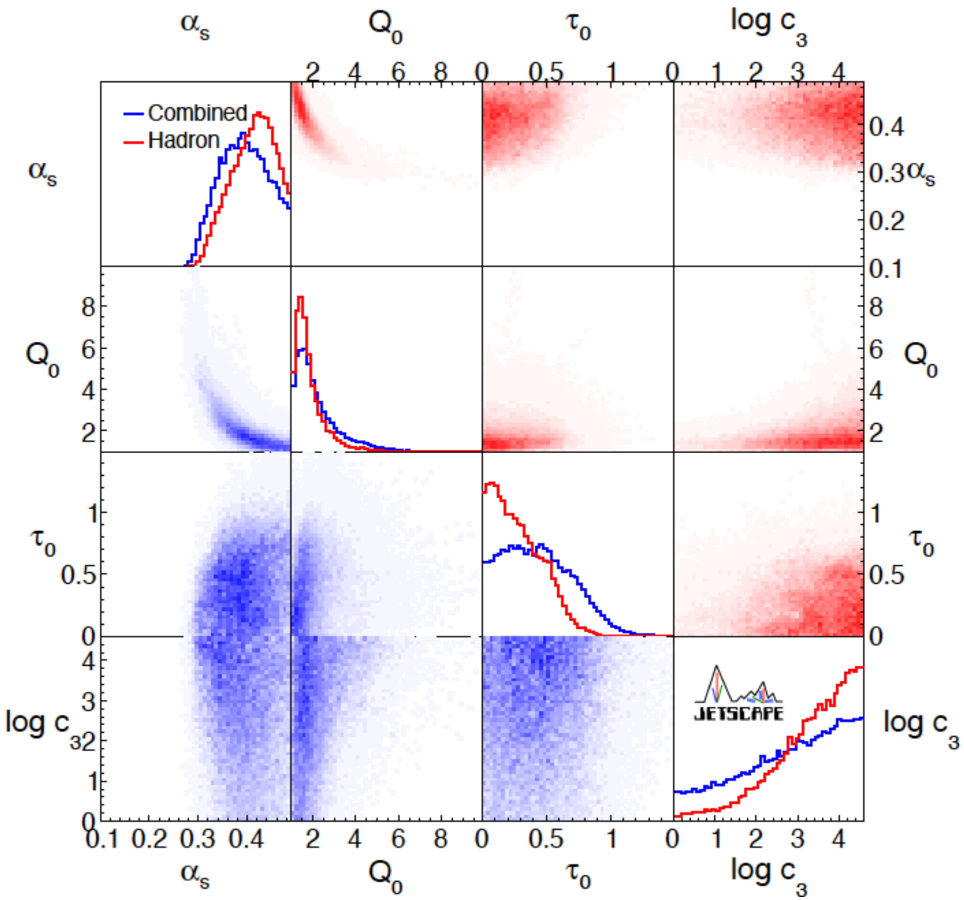
Combined: inclusive hadron and jet
Hadron: inclusive hadron



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6 parameters

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

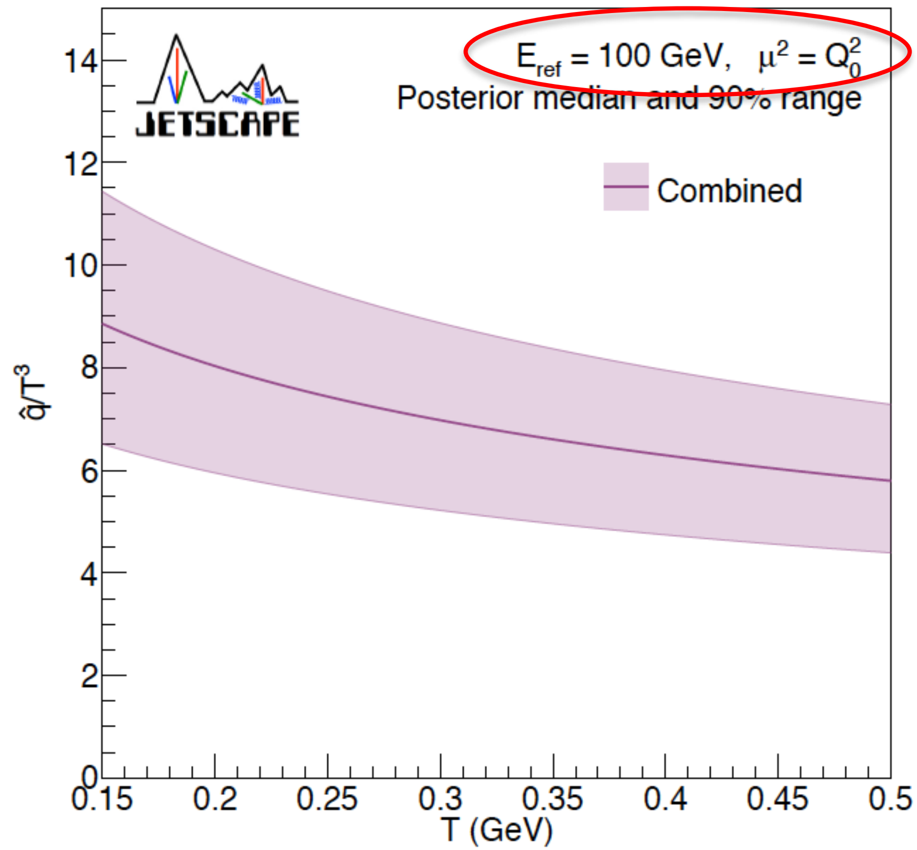
$\alpha_{\mathrm{s,fix}}$: 0.3 – 0.4
Q_0: ~1-2 GeV
τ_O: < 1 fm/c
c_3: larger values preferred
c_1,c_2: little sensitivity (not shown)

Extracting $\hat{q}$

arXiv:2408.08247

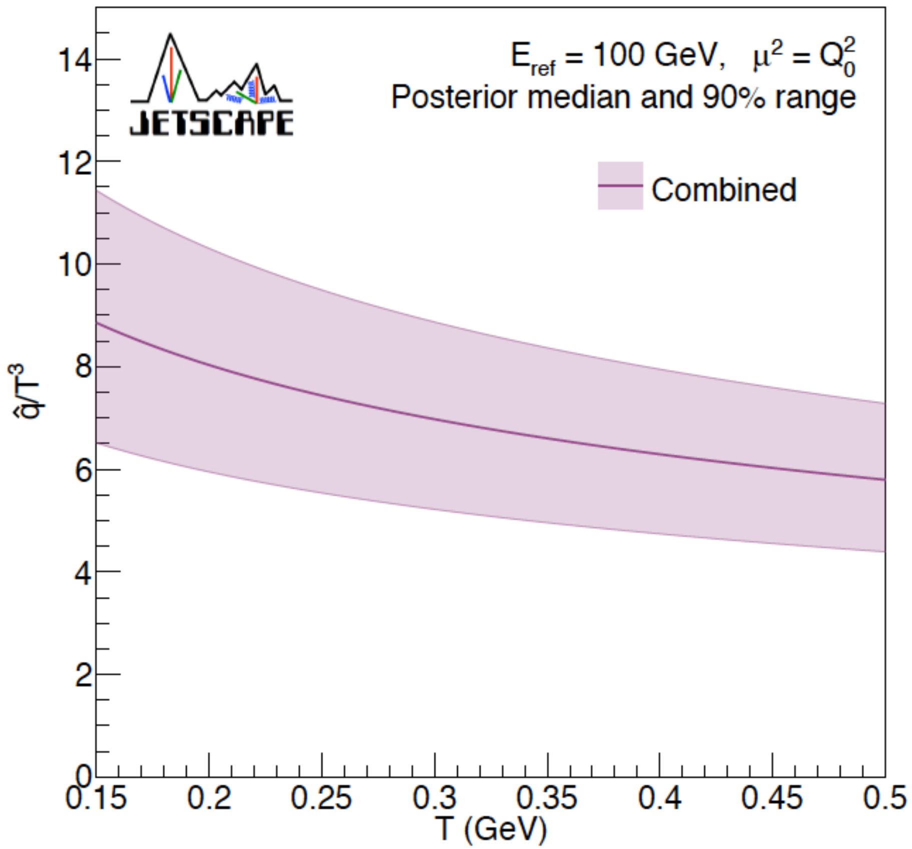
Put everything together: extract $\hat{q}$

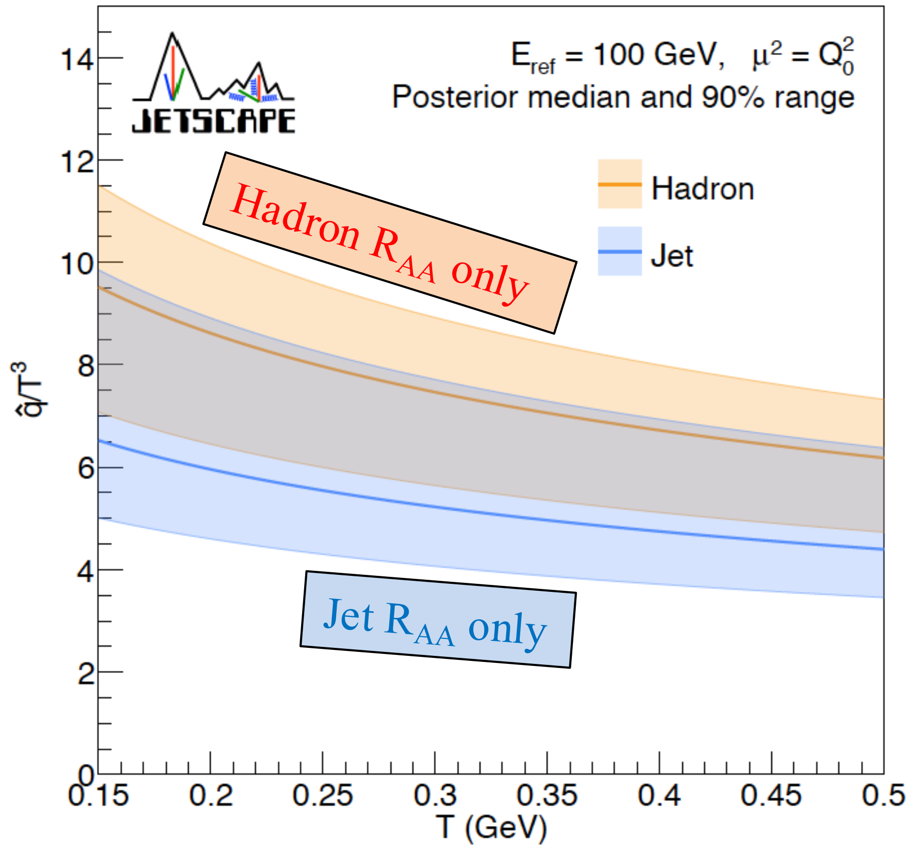
Plot $\hat{q}$ at low virtuality: $\hat{q} = \hat{q}_{HTL}^{run} \times f(Q^2)$



Hadron vs jet R_{AA}

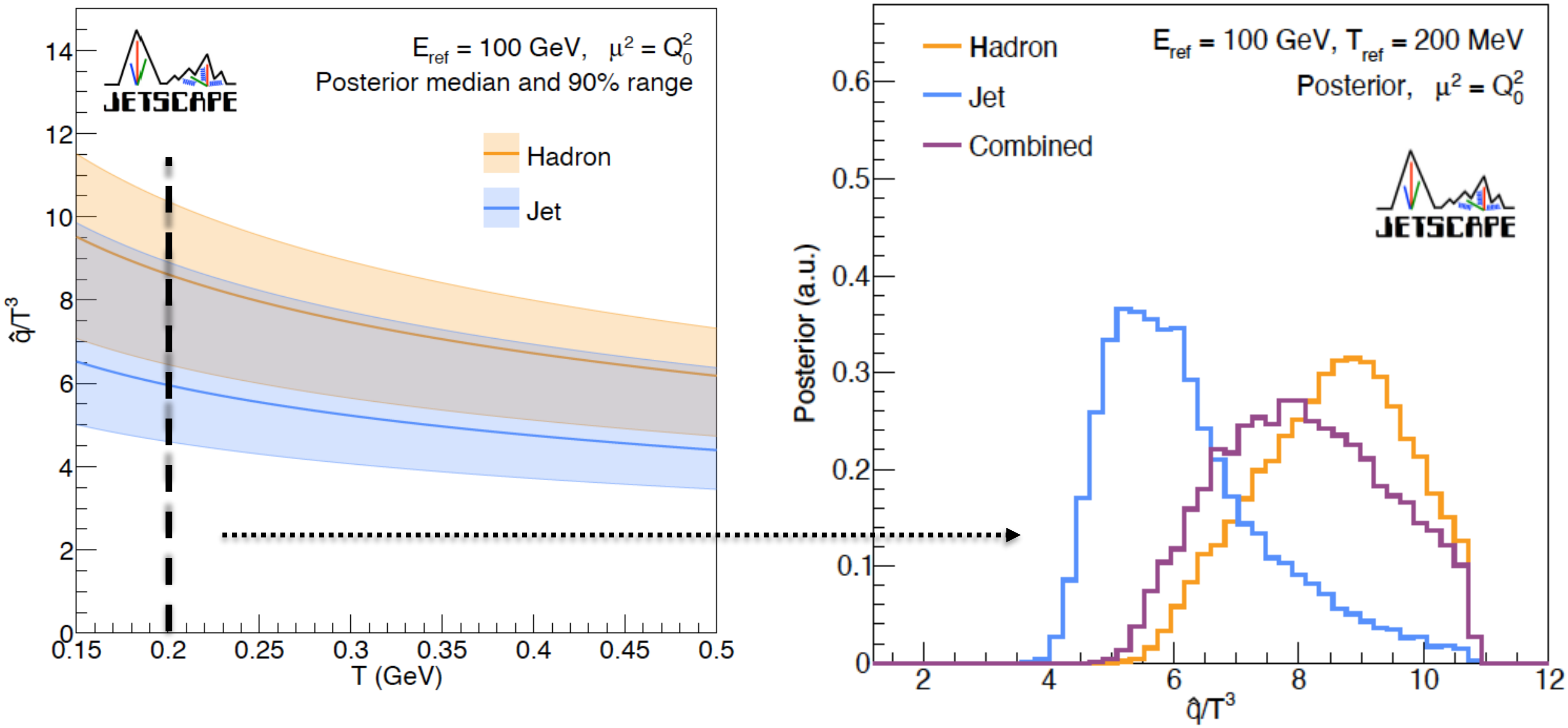
arXiv:2408.08247





Hadron vs jet R_{AA}

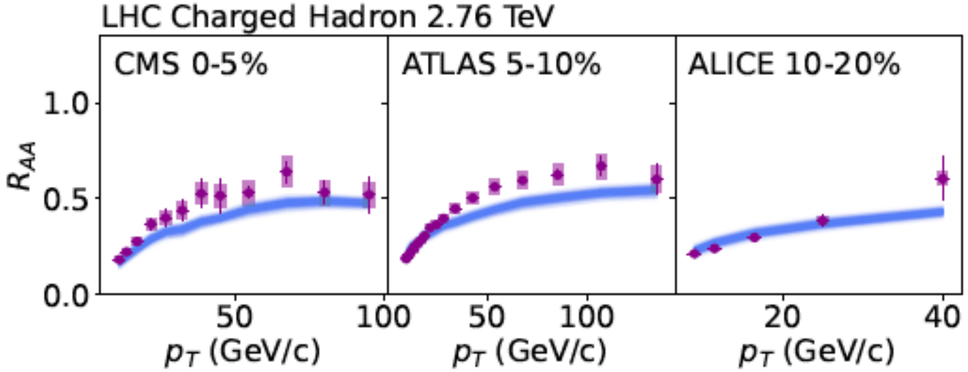
arXiv:2408.08247



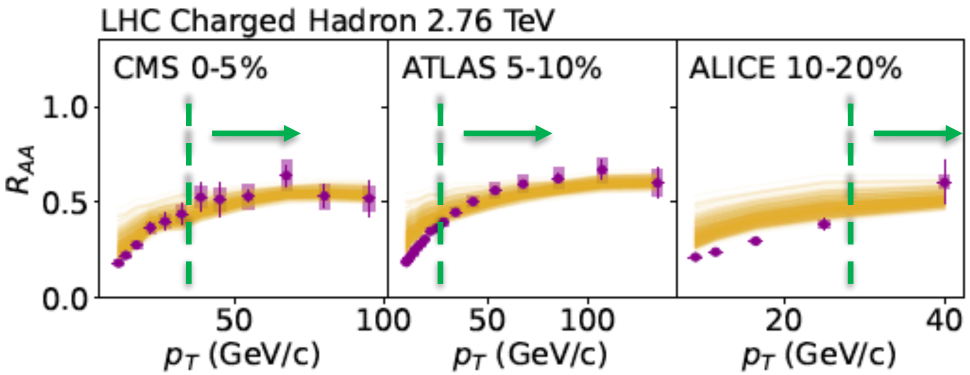
Hadron R_{AA}: low vs high p_T

arXiv:2408.08247

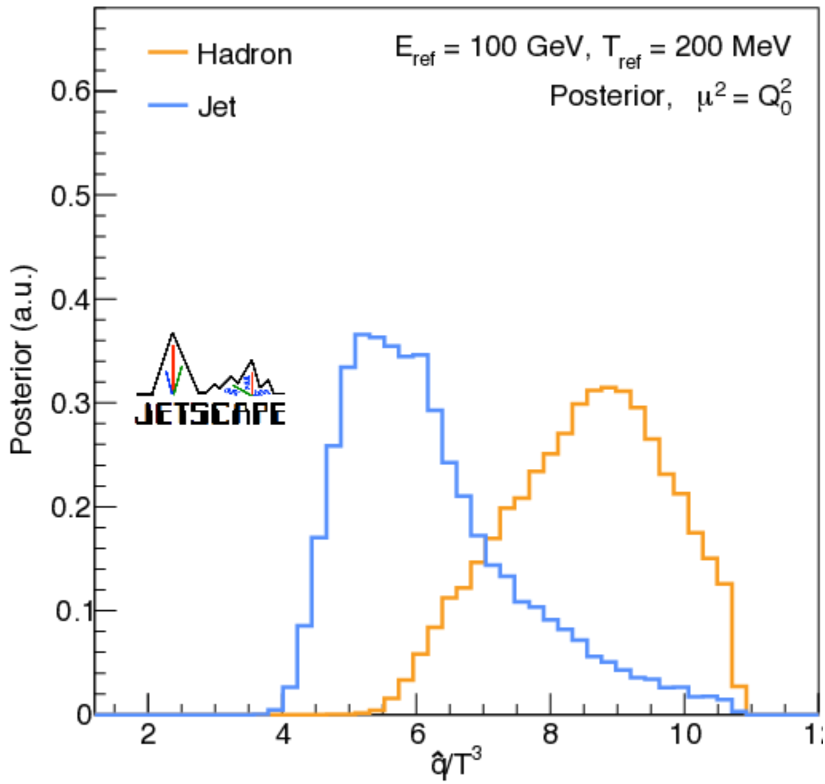
Combined calibration



Only hadron p_T>30 GeV/c



Vary hadron p_T threshold



Low p_T hadrons dominate

- due to small experimental uncertainties

High p_T hadrons consistent with jet data

Missing: theory uncertainty

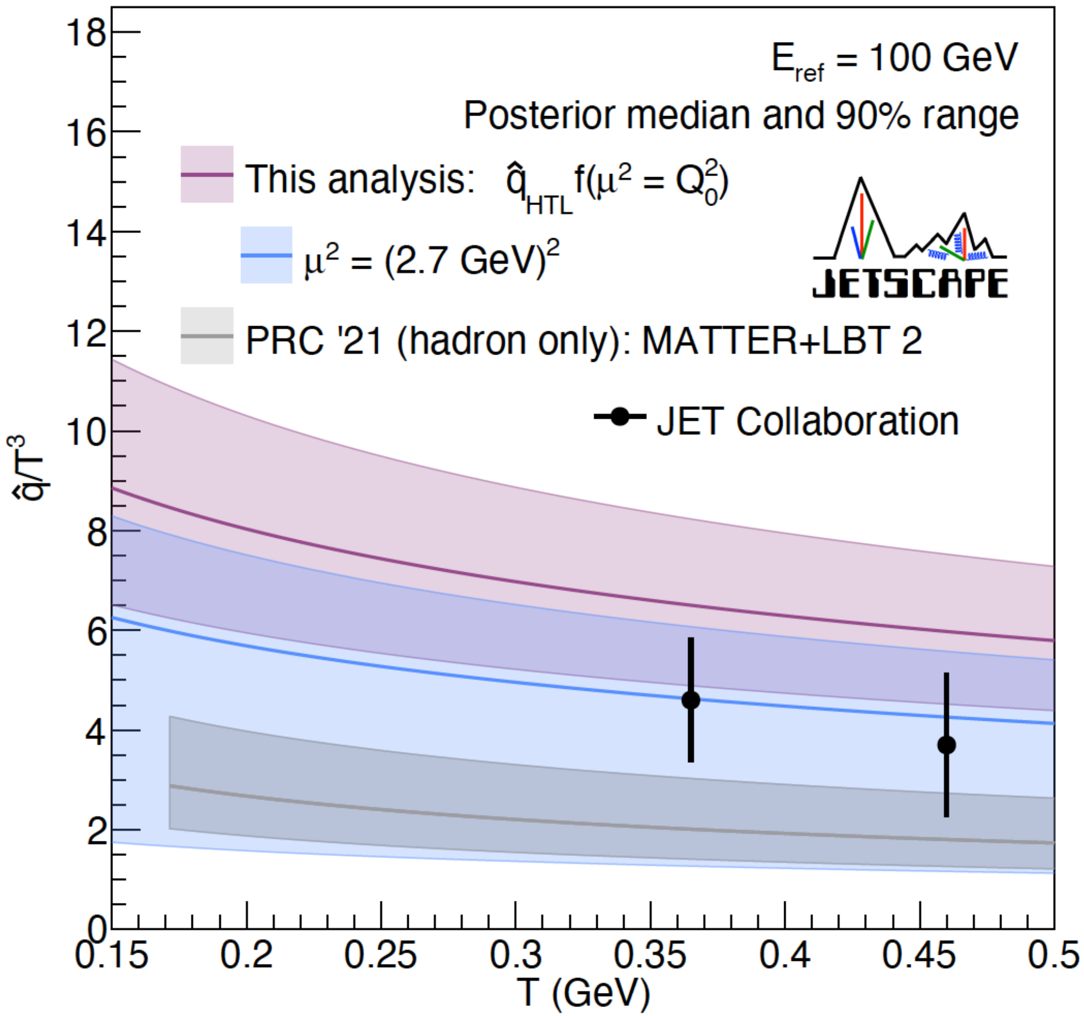
- large where exp uncert is small

p_T dependence of model does not decsribe data:

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

Comparison to previous calibration

arXiv:2408.08247



First JETSCAPE $\hat{q}$ calibration

PRC 104 (2021) 024905

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

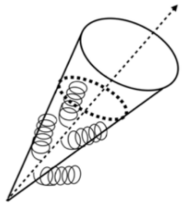
Evolve current analysis to compare at same scale

→ consistent

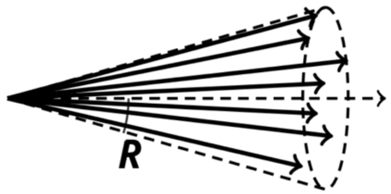
→ evolution captured correctly by Bayesian calibration

Next step: add jet substructure

Jet R_{AA}
- ALICE, ATLAS, CMS, STAR

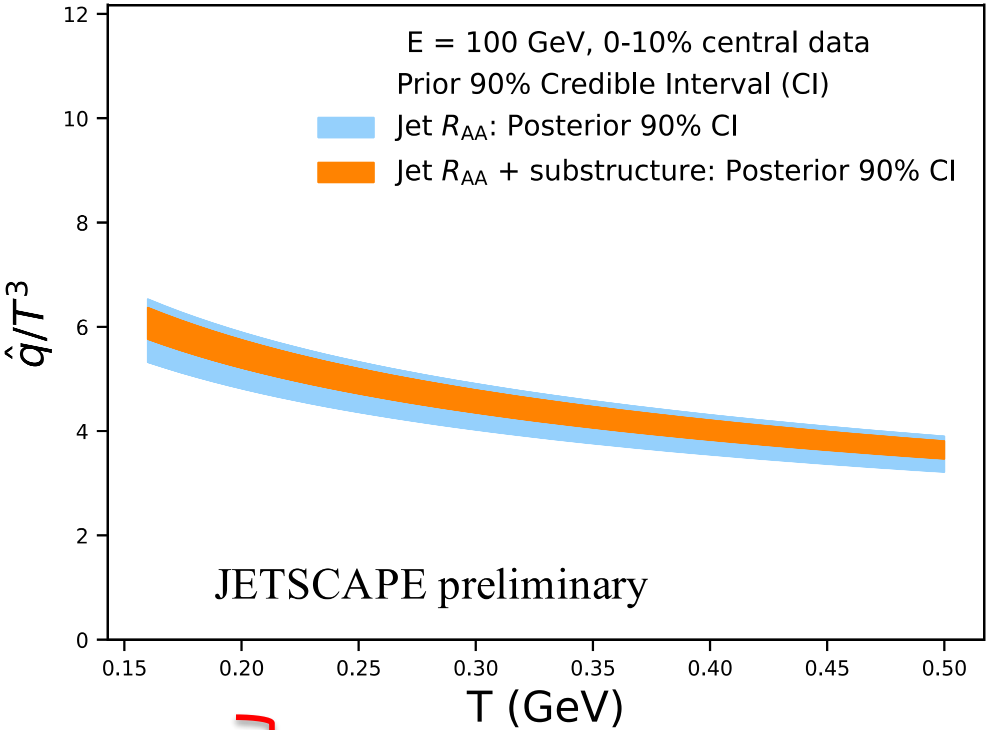


Fragmentation: $D(z)$
- ATLAS: $D(z)$
- CMS: $\xi(z)$



Groomed jet substructure
- ALICE: R_g, z_g

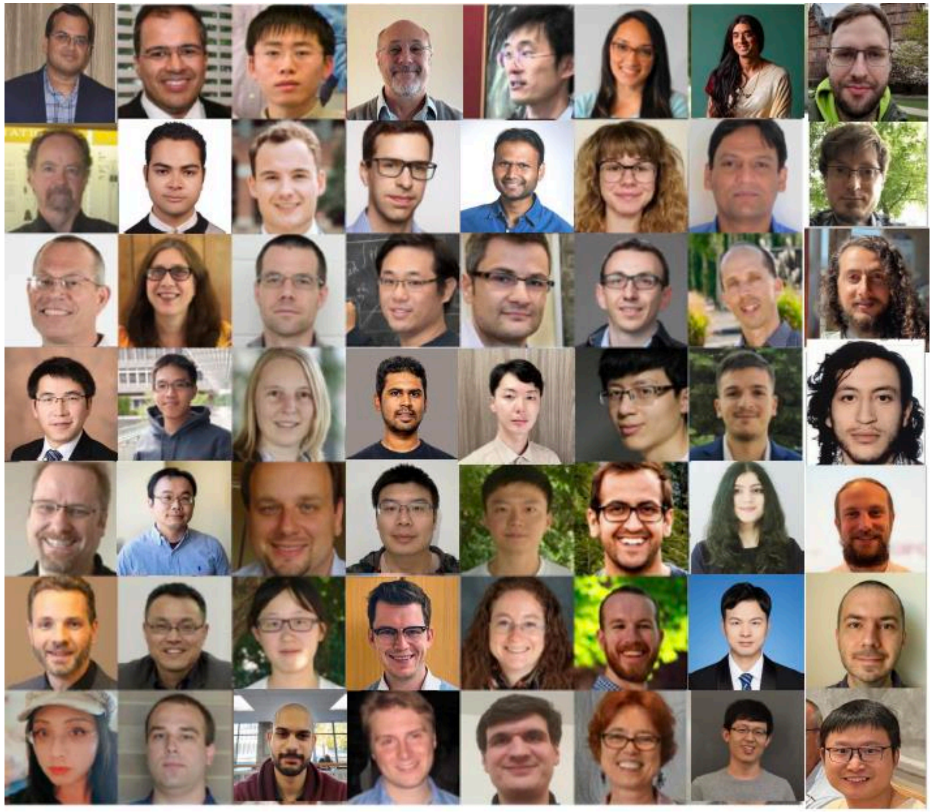
Substructure observables consistent with jet R_{AA}
- substructure: stronger relative constraint



Inclusive jet R_{AA} vs low p_T hadron R_{AA}: tension
Inclusive jet R_{AA} vs low p_T jet fragmentation: consistent

???

JETSCAPE Collaboration



Parallel talks:

Multi-observable analysis of jet quenching using Bayesian inference
Peter Jacobs, Monday 15:40

Extraction of jet-medium interaction details through jet substructure for inclusive and gamma-tagged jets
Yasuki Tachibana, Monday 17:50

Effects of hadronic reinteraction on jet fragmentation from small to large systems
Hendrik Roch, Monday 18:10

Energy-energy correlators of inclusive jets in heavy-ion collisions
Yayun He, Tuesday 9:40

Correlations between hard probes and bulk dynamics in small systems
Abhijit Majumder, Tuesday 16:15

Interplay of prompt and non-prompt photons in photon-triggered jet observables
Chathuranga Sirimanna, Wednesday 9:40

Poster:

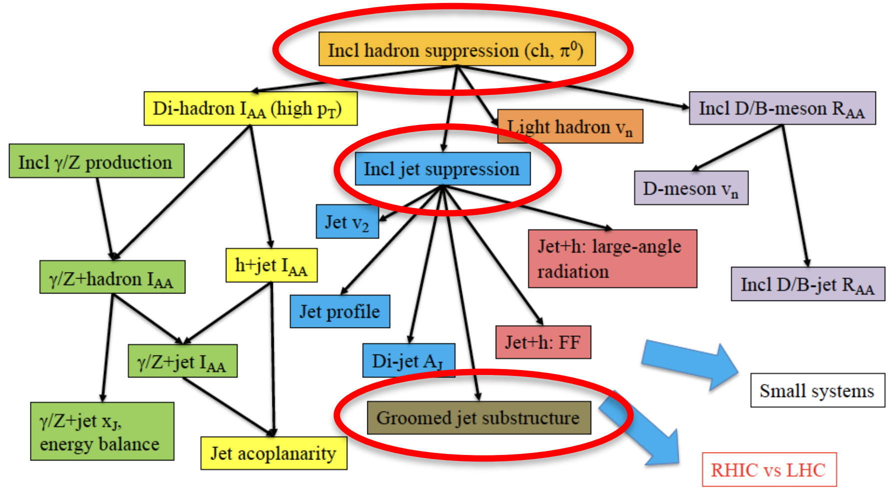
X-SCAPE as a universal event generator for e+p, e+e- and pp collisions
Cameron Parker, Poster Session

See also: R. Ehlers, Plenary talk, Thursday 12:05

Summary

First comprehensive multi-observable Bayesian analysis of jet quenching

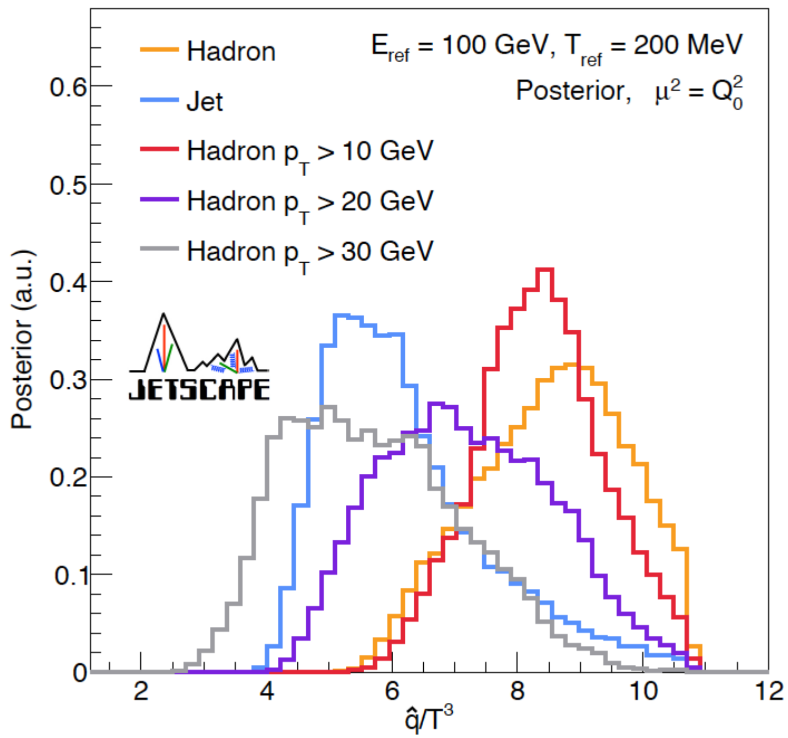
- enables much larger program



Overall reasonable agreement of model with data

But significant tension observed:

- low p_T hadron R_{AA} not consistent with jet and higher p_T hadron data



Incisive probe of our understanding of jet quenching:

- modeling improvements needed?
- different theory approaches?

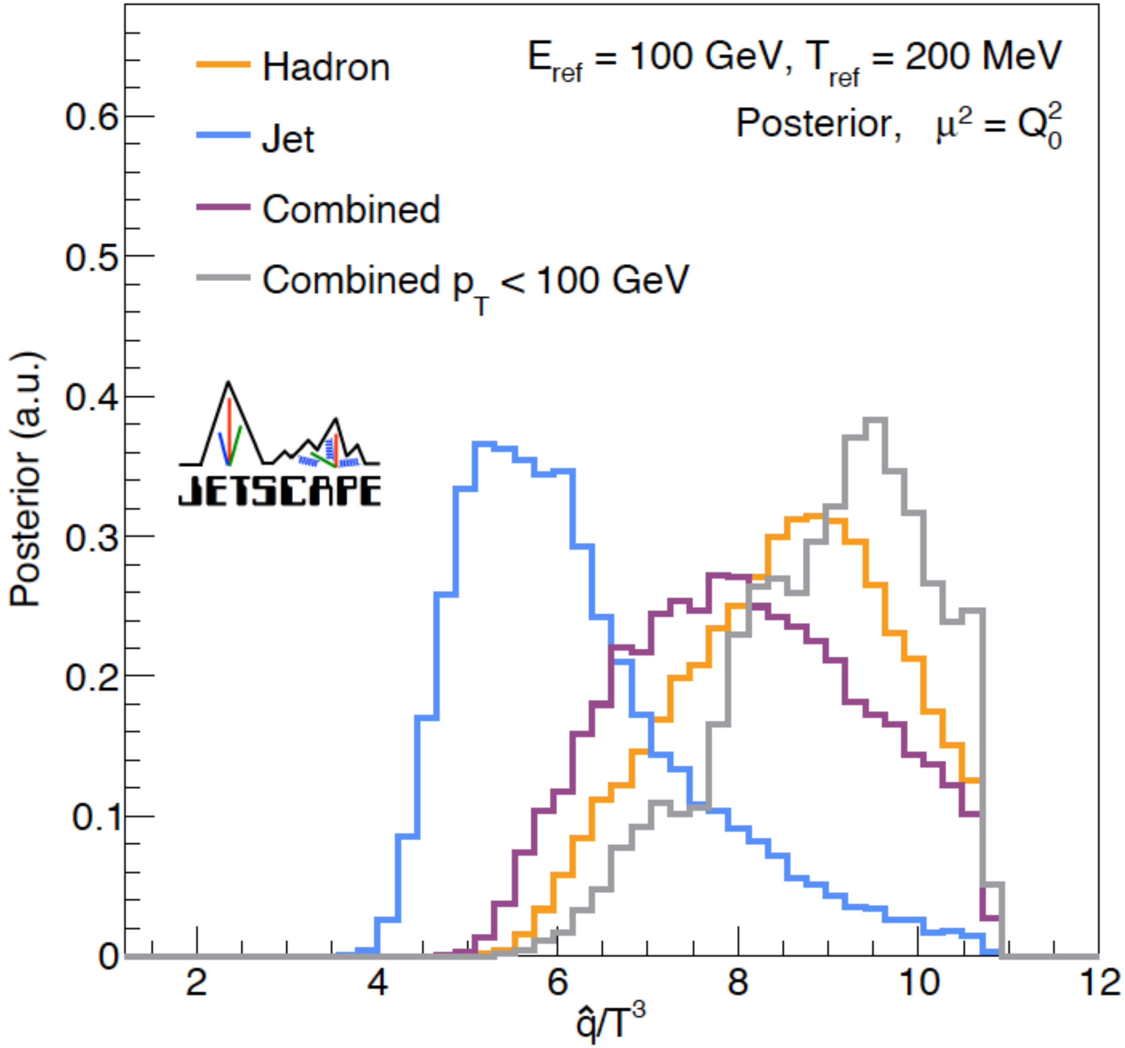
Next step(s): additional observables

Major issue for the field: theory uncertainty!

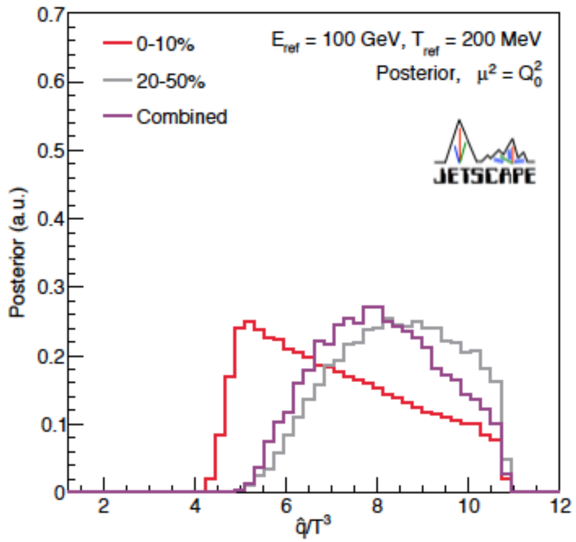
Extra slides

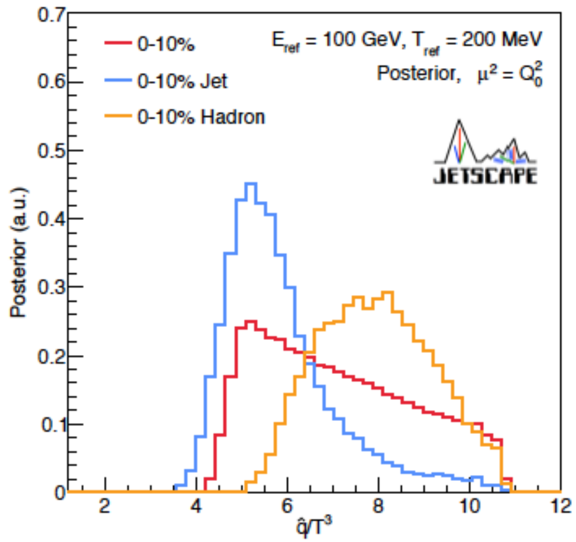
Effect of high p_T jet R_{AA}

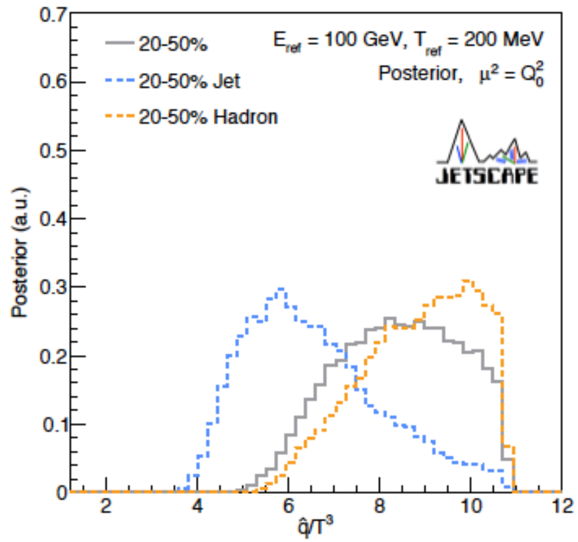
arXiv:2408.08247



Centrality dependence







Bayesian Inference with Active Learning

arXiv:2408.08247

6-dimensional parameter space

Can only calculate at limited number of "design points"

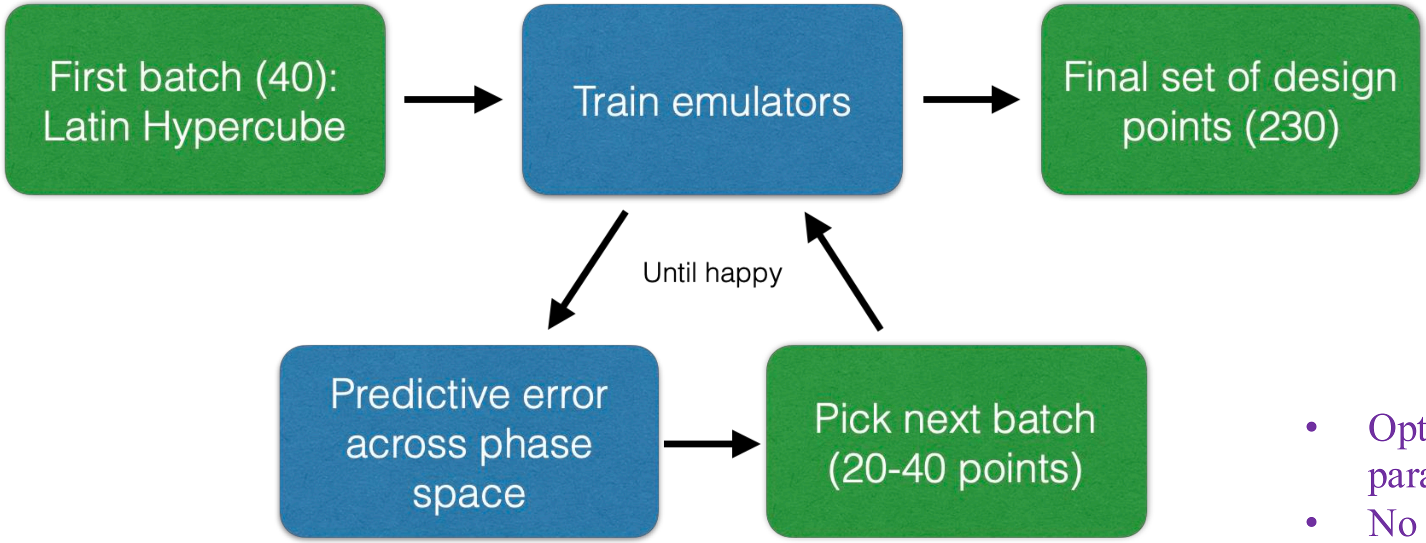
Interpolate between points using Gaussian Process Emulators

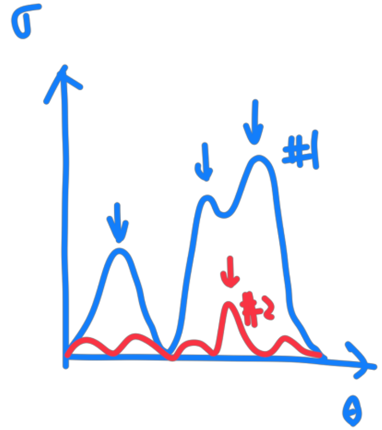
→ choose design points to optimize interpolation error

Active learning: ML-based optimization

Journal of Artificial Intelligence Research (1996) 129

arXiv:2306.07480





- Optimize predictive error across parameter space
- No consideration of experimental data