Extracting physics parameters and examining observable sensitivity via Bayesian inference and machine learning

A perspective from jet physics in heavy ion collisions

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Probing the Frontiers of Nuclear Physics
with AI at the EIC, CFNS

Berkeley
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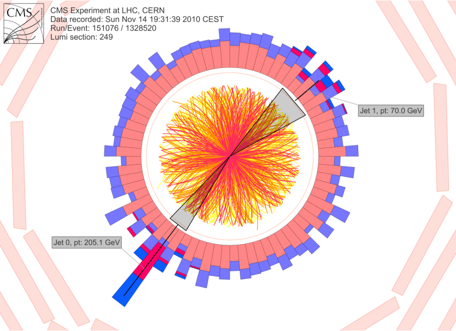
Heavy ion collisions & the Electron Ion Collider

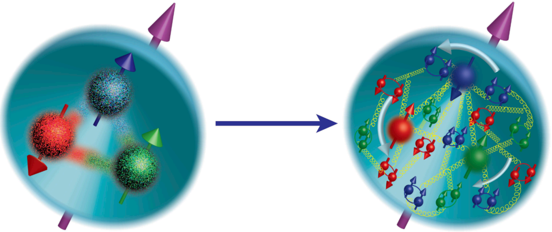
Heavy ion collisions

- Hot and dense QCD matter
- QGP properties $\rightarrow$ QCD: Length scales resolved by QGP, critical point, etc...
- Messy exp. environment



Electron Ion Collider

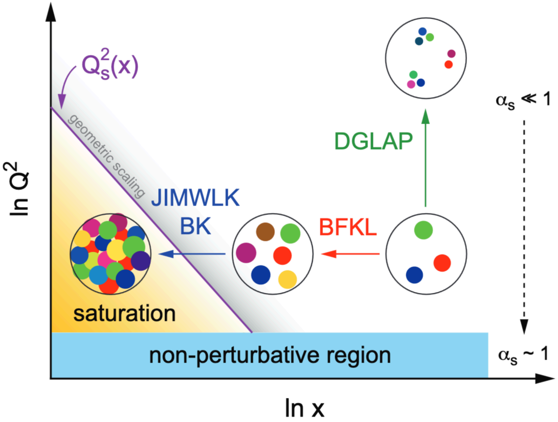
- Cold nuclear matter
- Gluon saturation, nucleon spin, nuclear imaging (TMDs, ...), etc...
- Cleaner exp. environment



Heavy ion collisions & the Electron Ion Collider

- Many ~~differences~~ similarities:
- Similar **analysis techniques and methods**
- **Cold nuclear matter effects (eA and pA)**, **hadronization**, **initial state**, etc
- eg. **Low *x*/gluon saturation**:
  - Forward pp/pA physics (eg. ALICE FOCAL) complementary to EIC
  - Sensitive to same scattering matrix elements, etc

- Today, share **tools and lessons from the heavy ion perspective** to apply at the EIC:



How to utilize Bayesian inference?

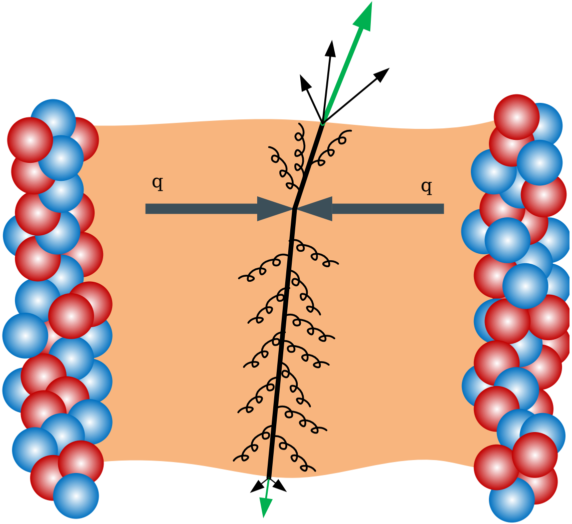
What information is contained in observables?

Thoughts on applying ML to experimental data

Heavy ion collisions and the quark-gluon plasma

- The quark-gluon plasma (QGP) is formed in ultra-relativistic heavy-ion collisions
- What can we learn about **QCD from this complex quantum matter**?
- How do **partons lose energy in the medium**?
- What are the **relevant length scales and what can the QGP resolve**?

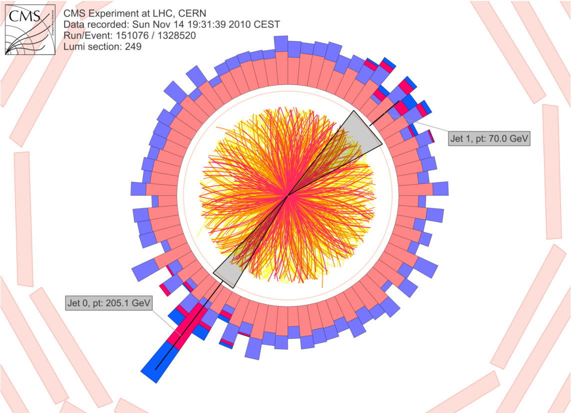
→ Today, mainly focus on using **jets and their substructure** to try to answer these questions



Quenching jets in the medium

- Partons propagate and interact with medium, **modifying the evolution** of the parton shower
- Jet-medium interactions modify the **internal jet structure**
  - e.g. quasi-particle scattering could deflect a (sub)jet
- Modifications collectively known as "**jet quenching**"
- These modifications encode properties of QGP, providing **opportunities to learn about QCD**

→ Jets are in situ probes of **QCD dynamics**



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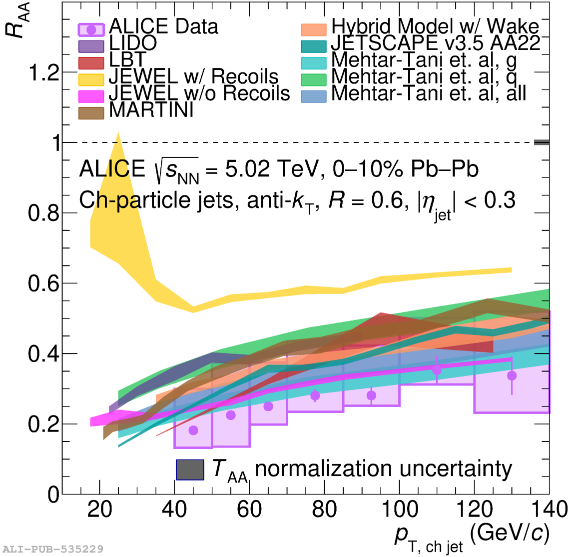
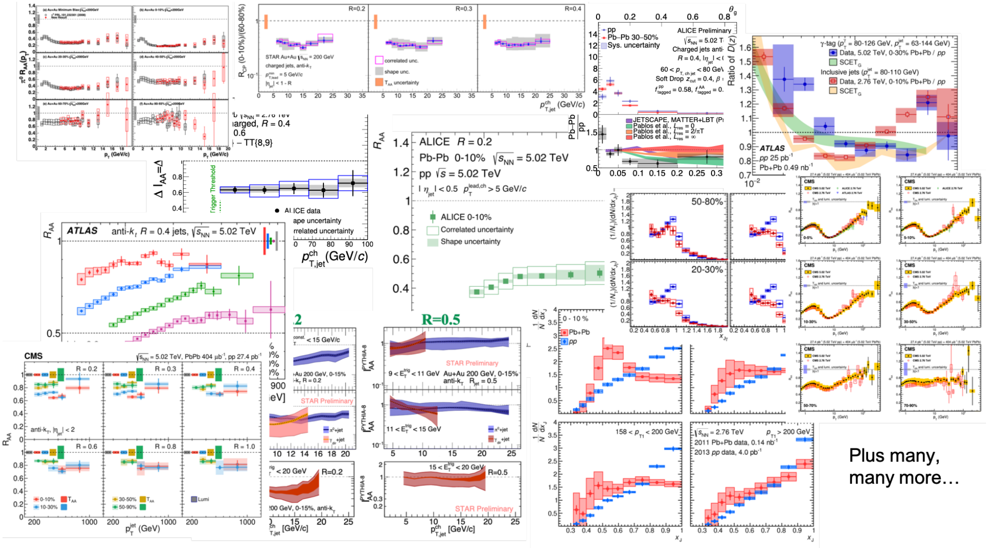


ALICE, arXiv:2303.00592

Wealth of jet quenching measurements



Plus many, many more…

Bayesian inference

Given data $\vec{x}$ and parameters $\vec{\theta}$, we can apply **Bayes' theorem**:

$$P(\theta|x) = \frac{P(x|\theta)P(\theta)}{P(x)}$$

- $P(\theta|x)$: **posterior dist.**:
  prob. of θ given x
  - Most prob. value
    $\rightarrow$ **best description** of data
- $P(x|\theta)$: **likelihood**
  x is described by θ
  - Depends on covariance,
    data + theory uncert.
- $P(\theta)$: **prior**
  distribution for θ
  - Choice makes
    assumptions explicit

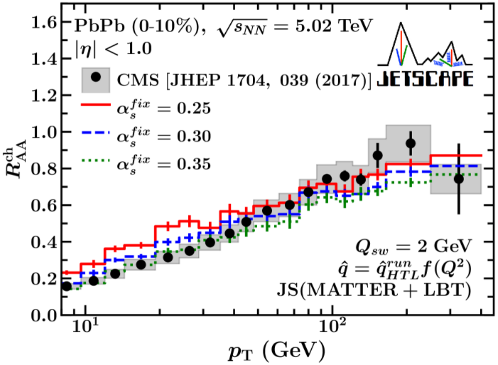
$\rightarrow$ **Posterior encodes everything we want to learn**

- Approach enables **computationally tractable approach** to extract parameters
  - Although still CPU intensive!

NOTE: Similarities to (n)PDF extraction

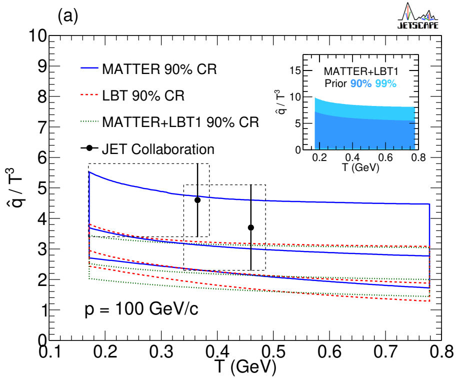
Bayesian inference: high level summary

Qualitative



Bayes →

Quantitative



JETSCAPE, Phys.Rev.C 107 (2023) 3, 034911
JETSCAPE, Phys.Rev.C 104 (2021) 2, 024905

Bayesian inference in the hard sector (2022-present)

- Use recent Bayesian inference results as case study

Data

- Hadron + **jet R_{AA}**
- **Additional jet observables**
- 3 $\sqrt{s_{NN}}$, **all eligible data**
- Treat experimental uncert. correlations **where possible**

Model

- Extract **reparametrized $\hat{q}(T, E, Q)$**
- Use **calibrated 2+1D hydro**
- Multistage: MATTER + LBT
- Goal: what do **jets bring to the analysis**?

Strategy

- **Significant computing effort** - O(10M) CPU hours
- Calculated many **more observables for differential studies**

One of many analyses. See also:
Nature Phys. 15 (2019) 11, PRL.126.202301, PRL.126.242301, ...

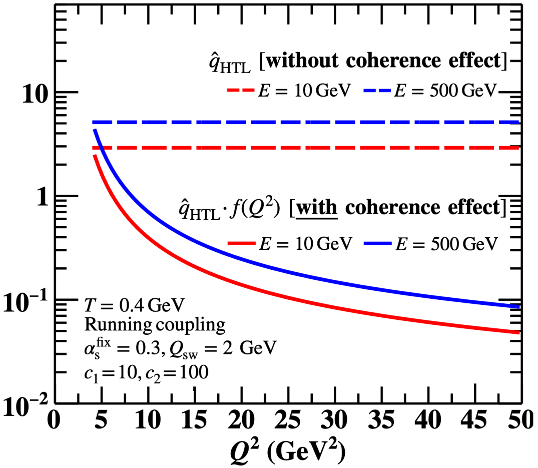
$\hat{q}$ parametrization

$$\hat{q}(E,T,Q) = \hat{q}^{\text{run}}_{\text{HTL}} \times f(Q^2)$$

$$\hat{q}^{\text{run}}_{\text{HTL}} = \alpha_{s,\text{fix}} \times \alpha_s(\mu^2) C_a \frac{42\zeta(3)}{\pi} T^3 \log\left(\frac{\mu^2}{6\pi T^2 \alpha_{s,\text{fix}}}\right)$$

$$f(Q^2) = \left. \frac{N\left(\exp\left(c_3 (1-x_B)\right)\right)}{1 + c_1 \ln\left(Q^2/\Lambda^2_{\text{QCD}}\right) + c_2 \ln^2\left(Q^2/\Lambda^2_{\text{QCD}}\right)} \right|_{Q \geq Q_0}$$

- 6 total parameters:
  - α_s
  - c_1, c_2, c_3
  - Q_0 (switching virtuality)
  - τ_0 (start time)

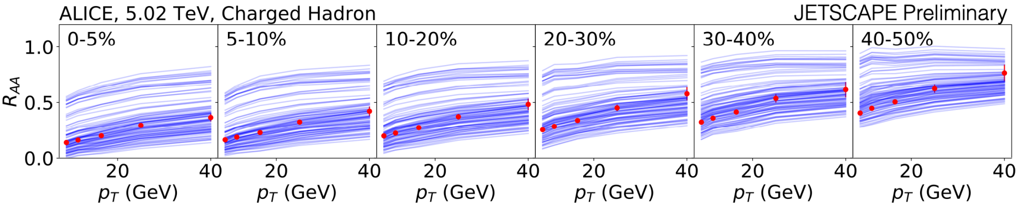


- Taken as **one possible candidate** model

JETSCAPE, Phys.Rev.C 107 (2023) 3, 034911
JETSCAPE, arXiv:2301.02485

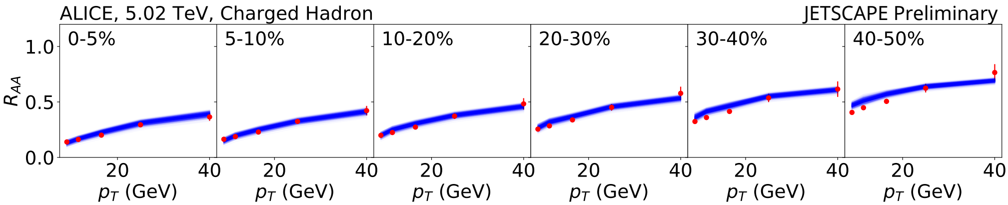
From prior to posterior

Prior:
Data
Calculations



analysis

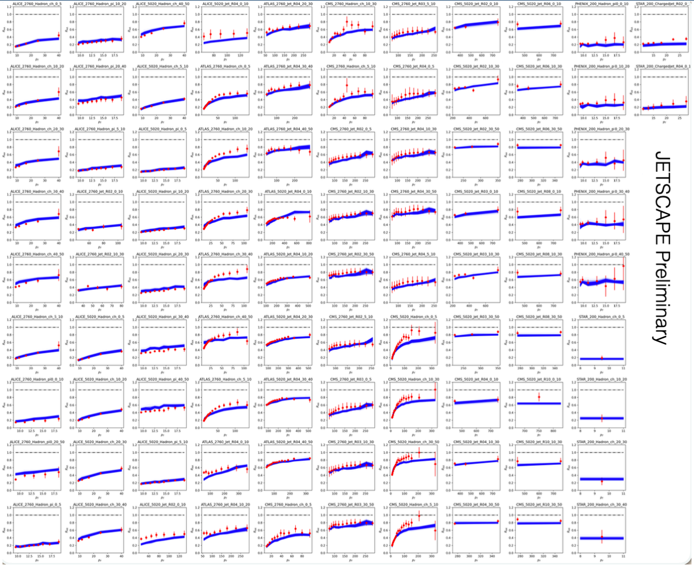
Posterior:
Data
Best fit



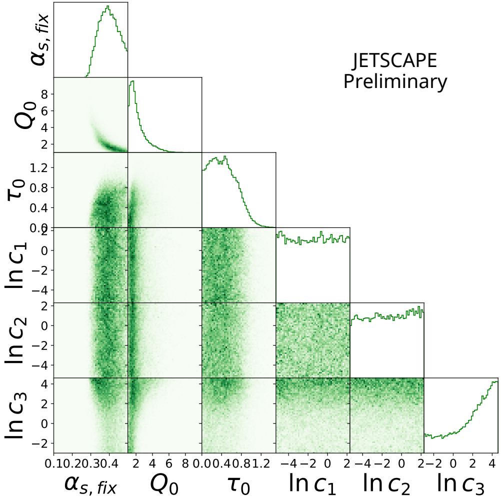
Observables posterior

- **Reasonable overall agreement**
- **Some tension** for particular measurements

→ Explored in detail in backup



Parameter posterior distributions



Start time

Q-dep. terms

$$\hat{q}(E,T,Q) = \hat{q}^{\mathrm{run}}_{\mathrm{HTL}} \times f(Q^2)$$

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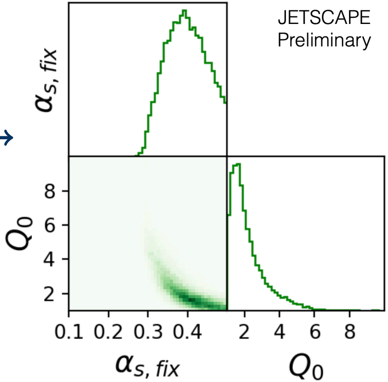
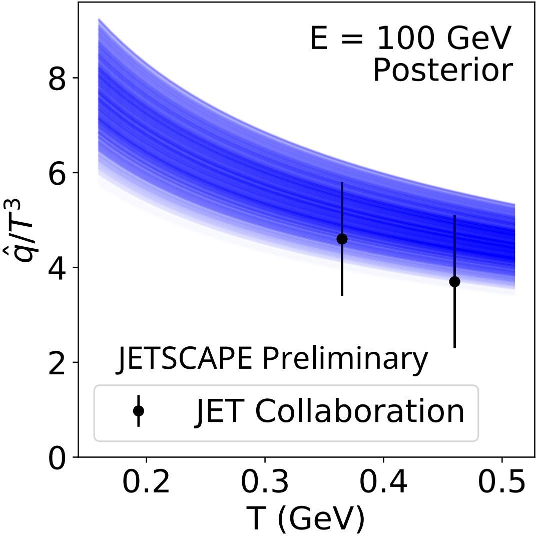
selection →



Extracting $\widehat{q}$

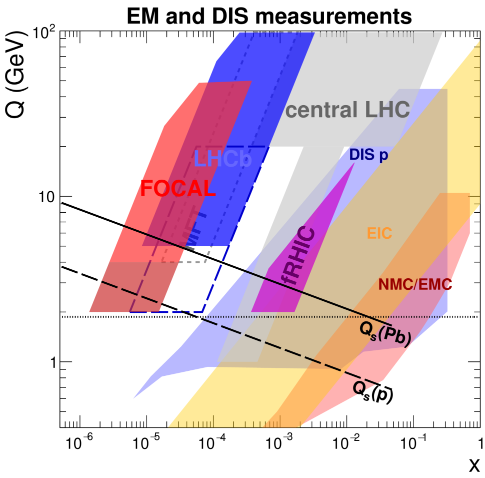
- **Sample parameter posterior** to extract $\widehat{q}$
- Integrate over Q dependence when reporting:
- i.e., $\widehat{q} = \widehat{q}^{\text{run}}_{\text{HTL}} \times f(Q^2)$

- **Consistent description** using hadron + jet R_{AA}
- **Compatible with previous extractions**



Application to EIC: gluon saturation

- Extract **saturation scale Q_s** using measurements at EIC
- If observables are **less precise or more ambiguous** than expected → **Bayesian inference can help**:
- **Improved precision** for cleaner extraction
- Test additional observables for **increased sensitivity to saturation scale** (see next)
    - See also: RJE, JETSCAPE @ RHIC/sPHENIX predictions, arXiv:2305.15491
- Can also include observables from **both EIC and forward LHC**



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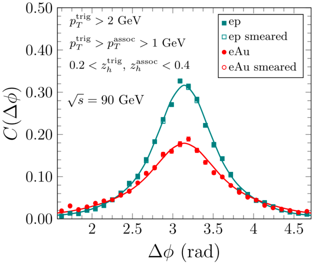
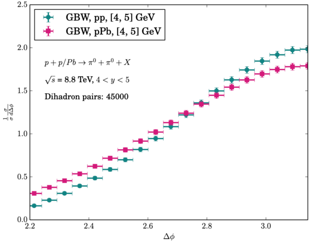
	Inclusive DIS	SIDIS	DIS dijet	Inclusive in p+A	γ+jet in p+A	dijet in p+A
xG_{WW}	−	−	+	−	−	+
xG_{DP}	+	+	−	+	+	+

EIC



Forward LHC



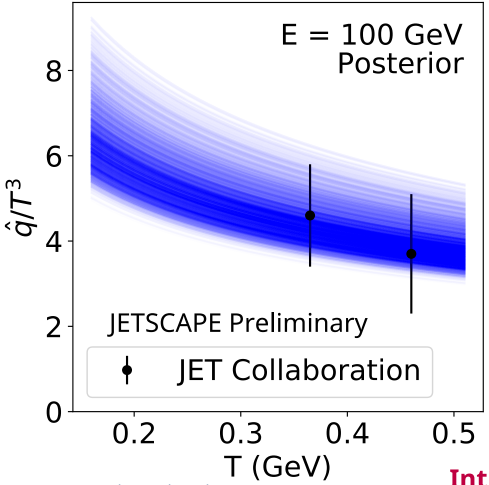
EIC Yellow Report, FOCAL LOI, PLB 2018.08.011

Enables many further investigations!

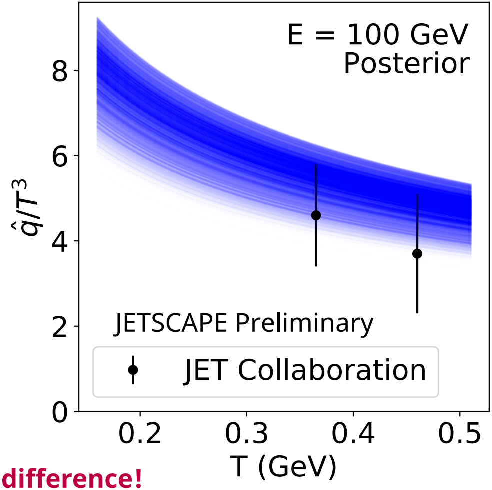
1. **Importance of theory uncertainties**
2. **Information content of observables**

Selecting only hadron or jet R_{AA}

Jet R_{AA} only



Hadron R_{AA} only



Intriguing difference!

Selecting only hadron or jet R_{AA}

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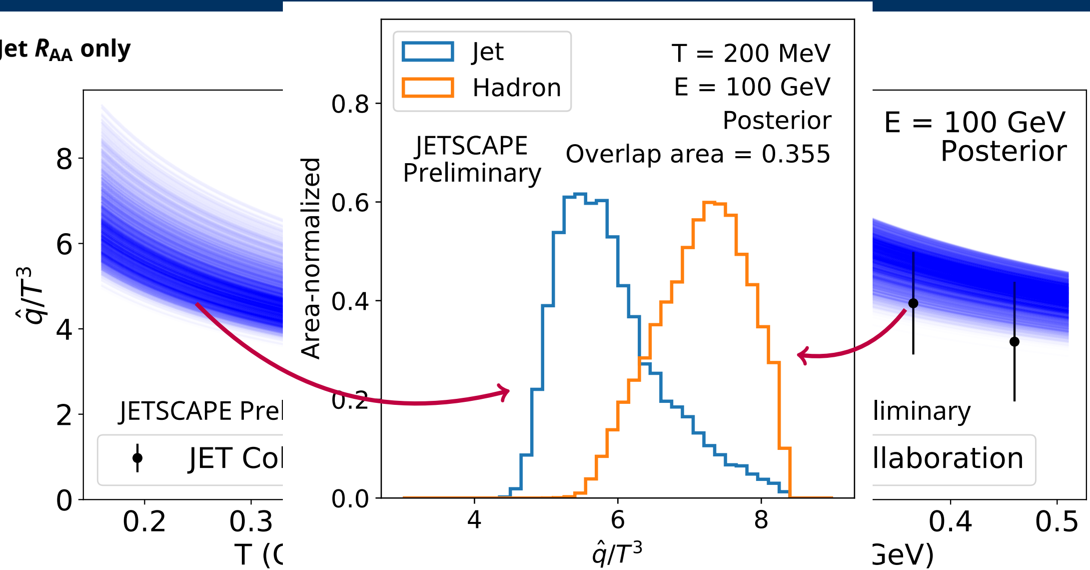
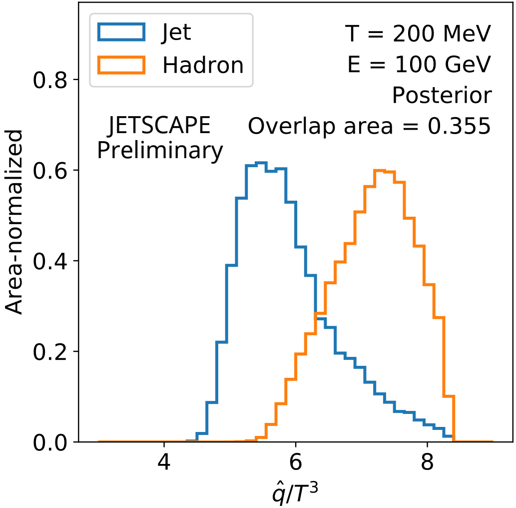
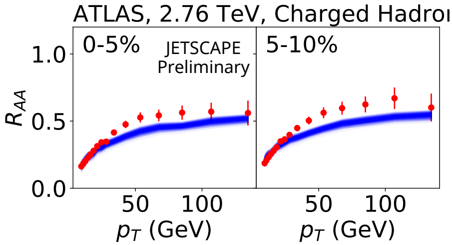


Intriguing difference!

Calibrating with low vs high p_T hadrons



Full p_T range



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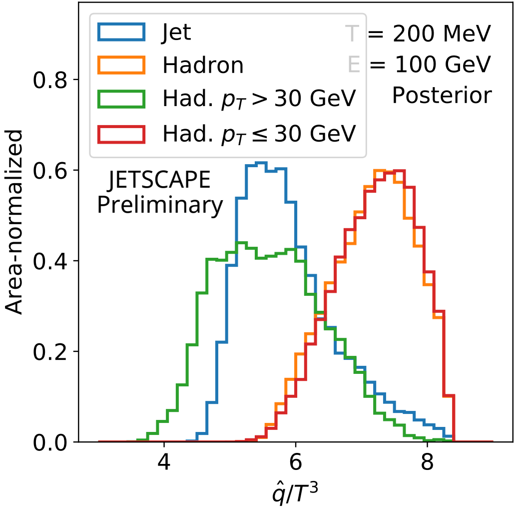
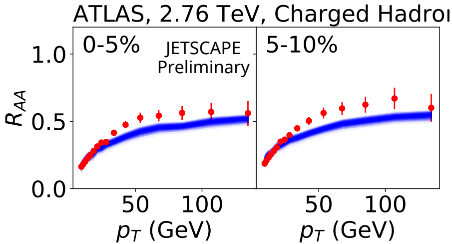
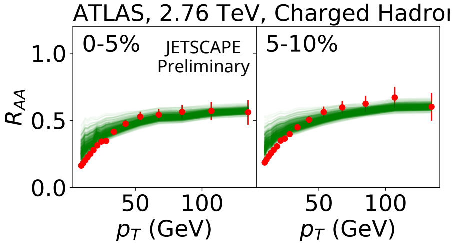


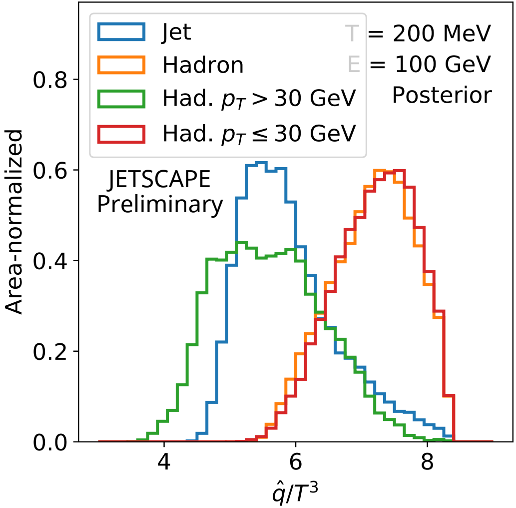
Full p_T range



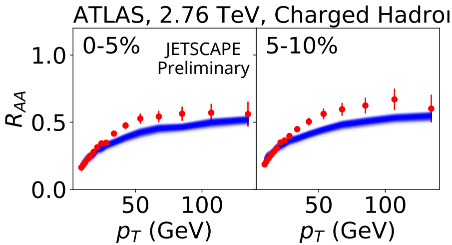
Only hadron $p_T > 30$ GeV/c



What's driving this behavior?



Full p_T range

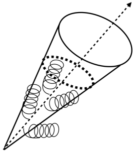


- **Low p_T dominates** due to small exp. uncert.
- **High p_T** in line with jet data
- Points to phase space for model improvement
- **Theory uncertainty is critical**!
  - eg. No shadowing included
- **Small exp. uncertainty where theory has largest uncertainty**

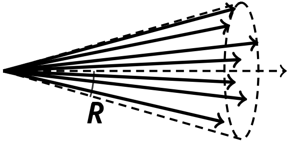
Jets and jet substructure

- **What (additional) information do jet substructure observables contain**?
- Further **insight into differences** in $\hat{q}$ from hadron- and jet-only extractions?
- Exploratory investigation with **simplified but consistent** error treatment
  - Focus on 0–10% central data
- **Baseline: Jet R_{AA} only**

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



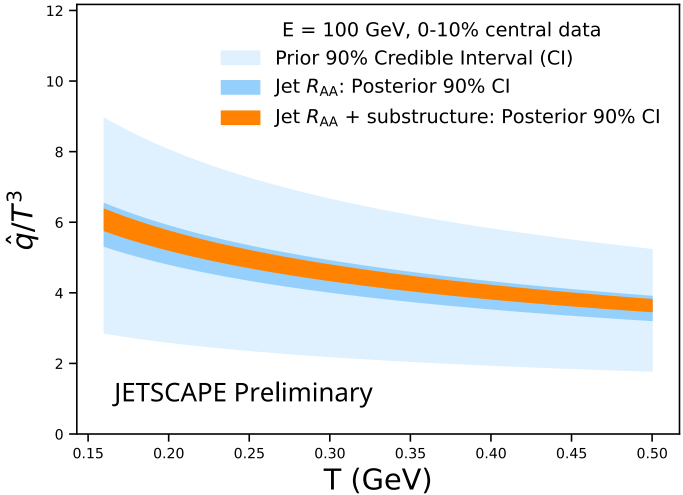
Fragmentation: $D(z)$
- ATLAS: $D(z)$
- CMS: $\xi(z)$



Groomed jet substructure
- ALICE: R_g, z_g

Constraints on $\hat{q}$

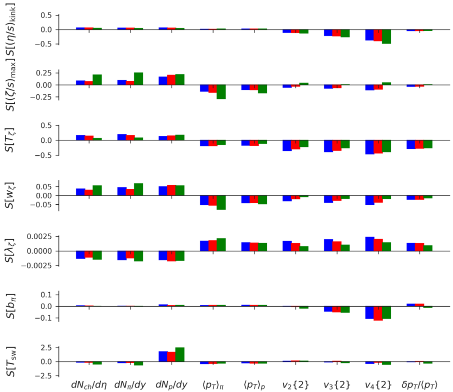
- **Consistent description of jet R_{AA} with substructure observables**
- Substructure yield **stronger relative constraint**
- Low p_T inclusive hadrons show tension, low z jet fragmentation consistent…?



Additional approaches to information content

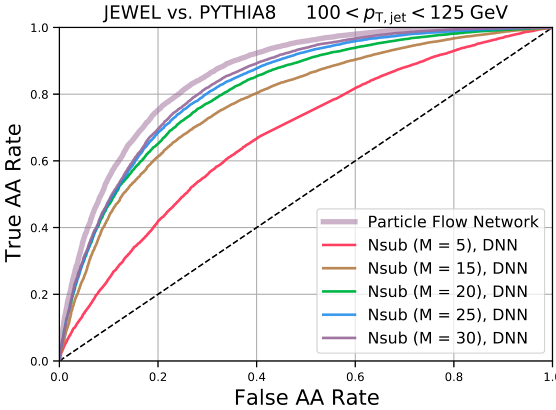
Observable sensitivity to posterior perturbation

JETSCAPE, PRC.103.054904



Information in *N*-subjettiness basis

Y.S. Lai et al, JHEP10(2022)011



Takeaways for Bayesian inference

1. Experiments should **report signed uncertainties**
    - **Covariance matrix matters**
    - Some are difficult, but many are straightforward
2. To generalize conclusions, need to include **theory uncertainties**
3. Inference can **extract and constrain parameters**, but can also use for **investigations**

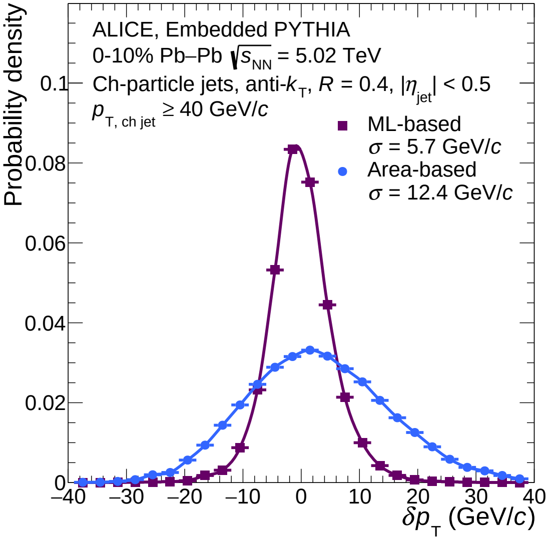
Applying ML to experimental data

Applying machine learning for background subtraction

- Jets are **experimentally challenging** due to **large uncorrelated background** from underlying event
  - Fluctuations can be $\sim p_{T,jet}$
- Usual approach is **subtract median background + unfold** for background fluctuations

→ Can ML be used to **reduce residual background fluctuations**?

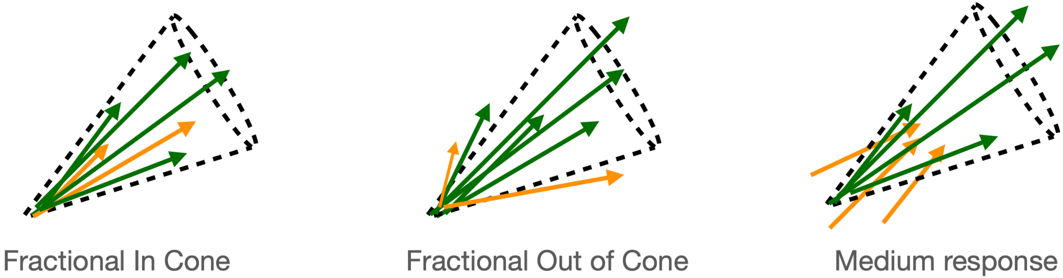
- Utilize **jet properties** to train NN to subtract jet-by-jet background
- **Issue: lack of ground truth model** to use for reliable training
- Training introduces model dependent **fragmentation bias**



RJE, ALICE, arXiv:2303.00592

Varying fragmentation to assess the systematic uncertainty

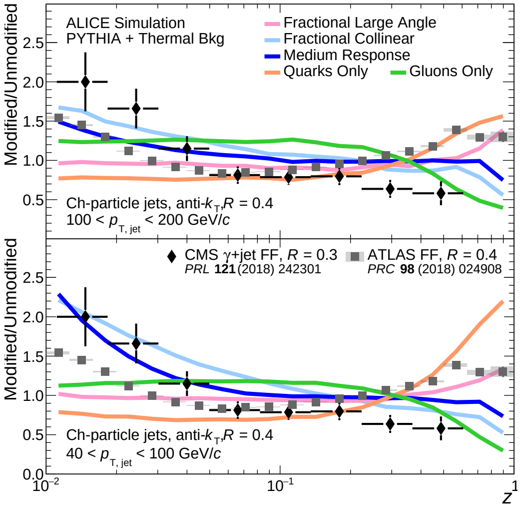
- Estimate systematic uncertainty with **physics inspired** fragmentation toy model



RJE, ALICE, arXiv:2303.00592

Fragmentation toy

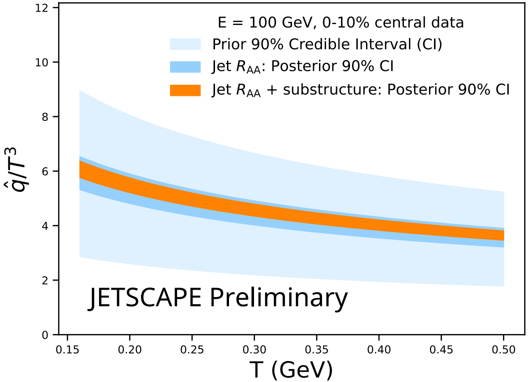
- **Calibrate to available measurements** in different parts of phase space
- **Train new model on modified fragmentation**, with difference taken as systematic uncertainty
- This is the dominant systematic, but such toys can be **useful if nothing else suitable is available**



RJE, ALICE, arXiv:2303.00592

Summary (for the EIC)

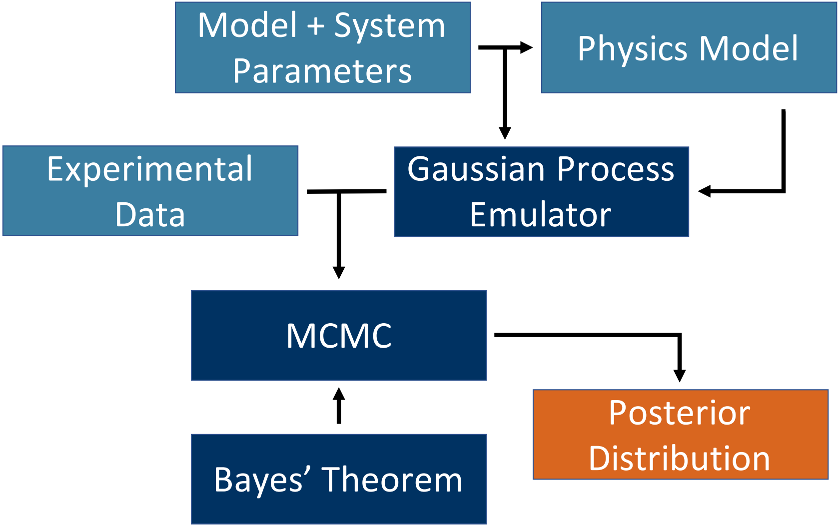
1. Bayesian inference is a **powerful tool** for understanding data and theory
2. Experiments should **report signed uncertainties**
3. Need to include **theory uncertainties** to generalize conclusions
4. Applying ML to experimental data **often requires novel solutions**
   - Physics inspired (toy) models can help



Backup

Practical Bayesian workflow

- Need to **populate N-dim parameter space** ($N \sim 5$)
- **High computational cost** for simulations
- **Millions** of cores hours provided by XSEDE (NSF)
- Interpolate between simulations using **Gaussian Process Emulator**



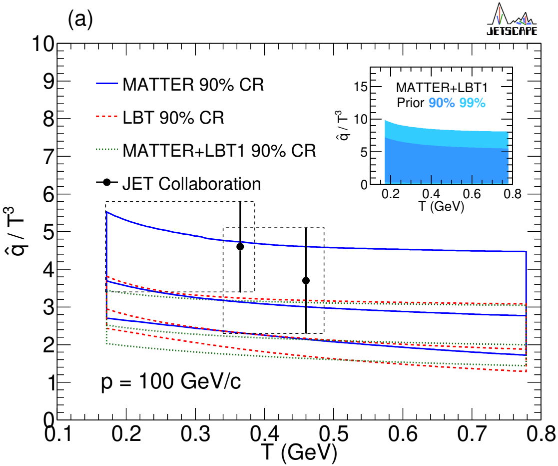
First JETSCAPE analysis of hard sector (2021)

Data

- **Hadron R_{AA}**
- 3 $\sqrt{s_{NN}}$, 2 centralities per energy
- Treat experimental uncert. correlations where possible

Model

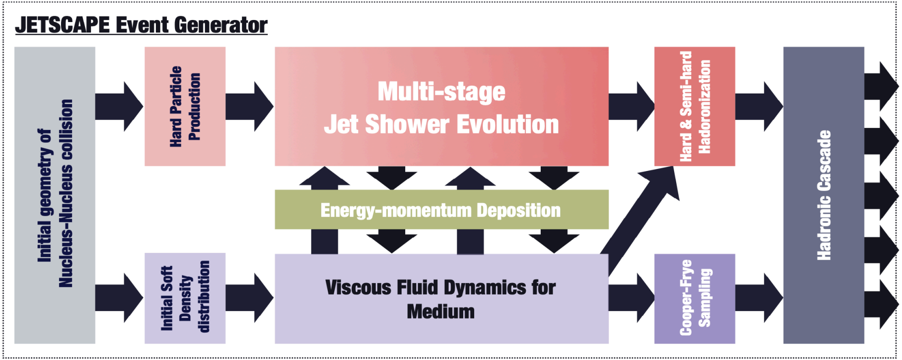
- Extract parametrized $\hat{q}(T, E, Q)$
- Multistage: MATTER + LBT
- Goal: One step forward from JET results, **proof of concept for one unified $\hat{q}$ across $\sqrt{s_{NN}}$**



JETSCAPE, Phys.Rev.C 104 (2021) 2, 024905

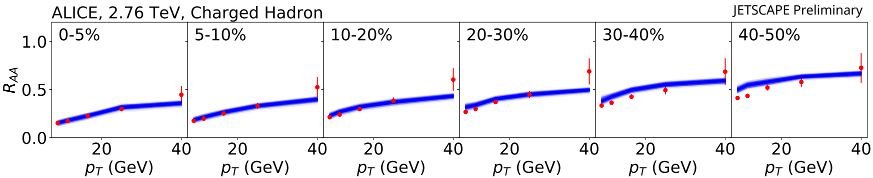
JETSCAPE Framework

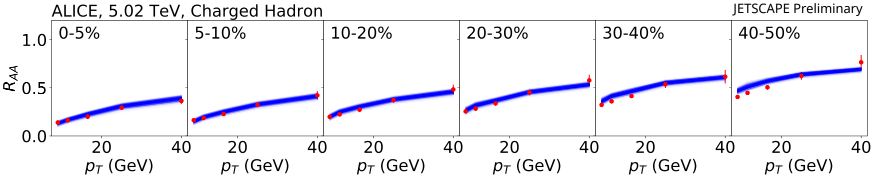
- **MC event generator package for heavy ion collisions**
  - General, modular and extensible
  - Communication between modules
  - Available on GitHub github.com/JETSCAPE

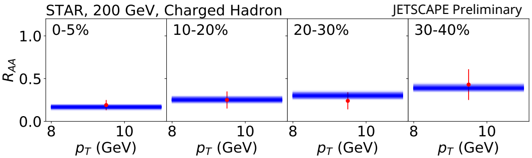


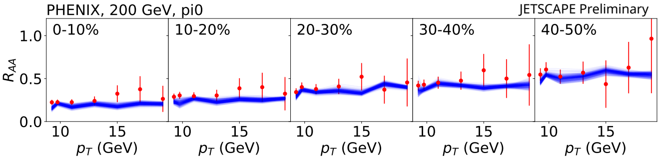
Posterior: hadron R_{AA} at low p_T

- **Good agreement at lower p_T**
- Fairly **consistent across experiments**



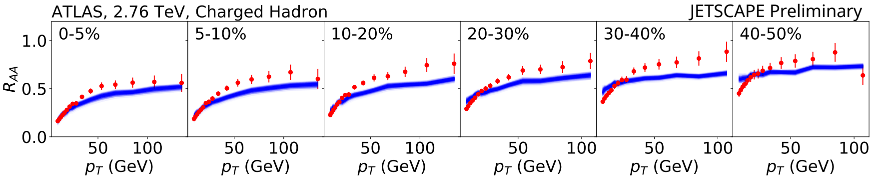


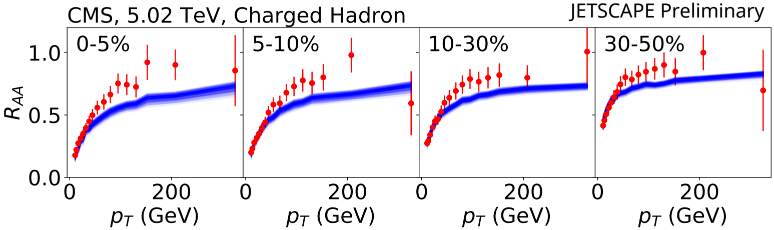


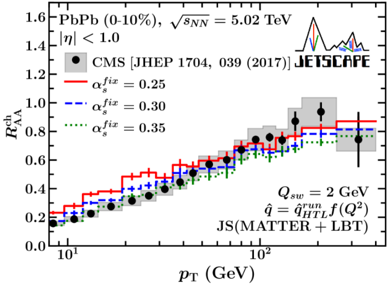


Posterior: hadron R_{AA} at high p_T

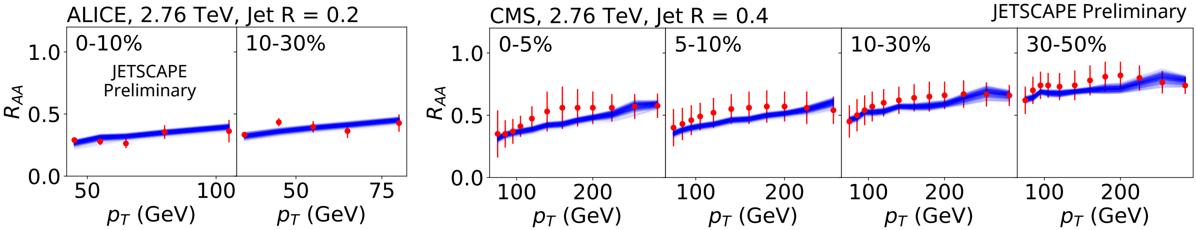
- Some **tension at high p_T**
- **Uncertainty smallest at low p_T**
  $\rightarrow$ drives result







Posterior: jets



- Generally **reasonable agreement**
- **Systematically slightly lower** R_{AA}