BAYESIAN ANALYSIS OF QGP JET TRANSPORT USING MULTI-SCALE MODELING APPLIED TO INCLUSIVE HADRON AND RECONSTRUCTED JET DATA*

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The JETSCAPE Collaboration reports on a new determination of jet transport coefficients in the Quark–Gluon Plasma, using both reconstructed jet and hadron data measured at RHIC and the LHC. The JETSCAPE framework incorporates detailed modeling of the dynamical evolution of the QGP; a multi-stage theoretical approach to in-medium jet evolution and medium response; and Bayesian inference for quantitative comparison of model calculations and data. The multi-stage framework incorporates multiple models to cover a broad range in scale of the in-medium parton shower evolution, with a dynamical choice of model that depends on the current virtuality or energy of the parton. We will discuss the physics of the multi-stage modeling, and then present a new Bayesian analysis incorporating it. This analysis extends the recently published JETSCAPE determination of the jet transport parameter $\widehat{q}$ that was based solely on inclusive hadron suppression data, by incorporating reconstructed jet measurements of quenching. We explore the functional dependence of jet transport coefficients on QGP temperature and jet energy and virtuality, and report the consistency and tensions found for current jet quenching modeling with hadron and reconstructed jet data over a wide range in kinematics and $\sqrt{s_{NN}}$. This analysis represents the next step in the program of a comprehensive analysis of jet quenching phenomenology and its constraint of properties of the QGP.

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1. Introduction

The multitude of unfolded experimental jet quenching measurements from RHIC and the LHC contains a wealth of information. Given the ability of models to successfully describe individual measurements despite utilizing

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different formulations of the underlying physical phenomena, broader data-model comparisons are required to assess the ability of a model to describe the full set of measured data. Is it currently possible to make a consistent picture of all of these measurements? And if we can construct such a picture, what physics can we extract?

To address these questions, we reframe our perspective to ask: for a given model, what parameters are most compatible with experimental measurements? When reframed in this inherently Bayesian manner, Bayesian inference provides a clear approach to extract model parameters while incorporating knowledge about both theory and experiment, including their respective uncertainties.

Bayesian inference is performed by taking advantage of Bayes' theorem,

$$P(\theta|x) = \frac{P(x|\theta)P(\theta)}{P(x)}\,, \tag{1}$$

where x represents the data and θ the model parameters. This expression relates the prior distribution, $P(\theta)$, to the posterior distribution, $P(\theta|x)$, via the likelihood that the data is described by the model parameters, $P(x|\theta)$. In heavy-ion physics, Bayesian inference has been successfully used in the soft sector [1–4], but its application to the hard sector — as discussed here — is less well developed.

In these proceedings, we report on the status of Bayesian inference with jet quenching data using JETSCAPE. In order to explore our model using Bayesian inference, the jet transport coefficient $\widehat{q}$ is parametrized with a physics-inspired expression with externally tunable parameters, which form an N-dimensional parameter space. Simulations for any given set of parameters are computationally expensive since they should ideally have uncertainties much smaller than the experimental observables used for constraining the parameters. Consequently, full exploration of the parameter space with the available computational resources requires a careful strategy to maximize the combination of statistical precision and coverage of the phase space with precise calculations. To address this issue, simulations are performed for a representative set of "design points", and non-parametric interpolation is performed via Gaussian Process Emulation. The parameter space is then explored via Markov Chain Monte Carlo methods, utilizing Bayes' theorem to determine the most probable model parameters.

2. Bayesian inference with inclusive charged hadron R_{AA}

As a proof-of-principle of Bayesian inference in the hard sector, we extracted model parameters using inclusive charged hadron R_{AA} measurements at $\sqrt{s_{NN}} = 200$ GeV at RHIC and $\sqrt{s_{NN}} = 2.76$ and 5.02 TeV at the

LHC as a function of centrality [5]. This analysis utilizes the JETSCAPE framework. Jet propagation in the QGP was calculated using three different formulations: MATTER, LBT, and an early version of the multi-stage MATTER+LBT approach [6–11]. In this analysis, the $\widehat{q}$ parametrization used in each model has four or five parameters. The partons were propagated through pre-computed 2+1D hydrodynamics events. Full details of the analysis are described in [5].

Figure 1 shows the posterior distribution for the temperature dependence of $\widehat{q}$ from this analysis. The extracted posterior is significantly constrained compared to the prior distribution shown in the inset panel. Further, the values from the three different models are consistent with each other, as well as with the previous determination of $\widehat{q}$ by the JET Collaboration [12]. This result demonstrates the viability of Bayesian inference in the hard sector, setting the stage for more complex analyses.

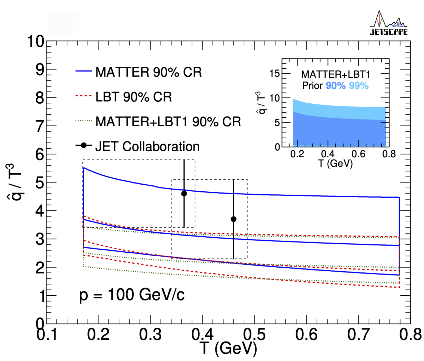

Fig. 1. Posterior distribution of the temperature dependence of the jet transport coefficient $\widehat{q}$ extracted from inclusive charged hadron R_{AA} measured at $\sqrt{s_{NN}}$ = 200 GeV, 2.76 TeV, and 5.02 TeV. The posterior is significantly constrained compared to the prior distribution.

3. Inclusive jet and hadron R_{AA}

As the next step after this proof-of-principle analysis, there are many possible directions. We elect to build on the previous analysis and adiabatically add observables alongside the inclusive charged hadron R_{AA}. For this next analysis, we only add inclusive jet R_{AA}. We do not select data but take an agnostic approach, including all relevant experimental measurements. This leaves it to the Bayesian inference analysis to determine the model compatibility, as well as to highlight possible experimental tensions.

For this analysis, we utilize a new multi-stage approach with MATTER+LBT in the JETSCAPE framework [13]. This multi-stage model includes the standard hard thermal-loop $\widehat{q}_{\mathrm{HTL}}$, modulated by additional coherence effects at high virtuality, which are manifest via fewer interactions at high Q^2. The overall jet transport coefficient is defined as $\widehat{q} = \widehat{q}_{\mathrm{HTL}} \cdot f(Q^2)$, where

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

and c_1, c_2, and c_3 are parameters to be extracted via Bayesian inference, and N normalizes the expression to ensure that $\widehat{q} = \widehat{q}_{\mathrm{HTL}}$ once the model transitions to LBT. In addition to the c parameters, $\widehat{q}$ also depends on α_{s}, τ_0, and model switching parameter Q_{switch}, for a total of six parameters. Due to the modular nature of the JETSCAPE framework, alternative models can be included in future Bayesian analyses.

Since there are multiple measurements from individual experiments, as well as additional systematic uncertainties related to jet analyses (such as shape uncertainties, which tend to be anti-correlated), the correlation of uncertainties requires particular care. The uncertainty treatment generally follows the procedure from our previous analysis [5]. Correlated uncertainties that are not specified in detail in the experimental publication are treated with a 10% correlation length.

The work-in-progress results of this analysis are presented here, with samples drawn from the posterior distribution shown in Fig. 2. The experimental data are shown in black, with the bars for the statistical errors and the boxes for the systematic uncertainties. The analysis shown here corresponds to only a small subset of calculations currently in progress, which require millions of CPU core hours. High-performance computing resources are required in order to complete such calculations. We utilize XSEDE computing resources [14] for this result. For these proceedings, we focus on the 0–10% most central Au–Au and Pb–Pb collisions, calibrating the model against the data enumerated in Table 1. This is likewise only a subset of the experiment data which will be used for the full analysis.

Table 1. Experimental data from RHIC and the LHC included in the work-in-progress analysis. Although the full analysis will include all available data, we first focused on a subset of the measurements in 0–10%.

Experiment	$\sqrt{s_{NN}}$	Inclusive R_{AA} observables
STAR	200	jets $R = 0.2$, 0.4
PHENIX	200	π_0 R_{AA}
ALICE	2.76, 5.02	jets $R = 0.2$, 0.4
ATLAS	2.76, 5.02	hadron, jets $R = 0.4$
CMS	2.76, 5.02	hadron, jets $R = 0.2$–0.4

At a high level, the model is broadly consistent with the data. By exploring the details of the posterior distribution shown in Fig. 2, a wealth of information can be extracted. The model is consistent with the $\sqrt{s_{NN}} =$ 200 GeV data from PHENIX and STAR shown in the top row, although

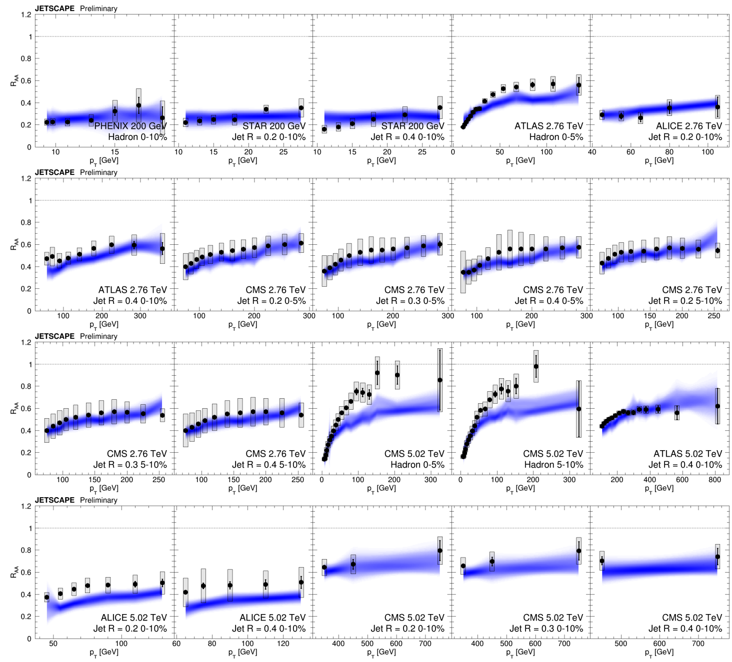

Fig. 2. (Color online) Posterior distribution of calibrated model parameters compared to inclusive jet and charged hadron R_{AA} data from RHIC and the LHC. The data are shown in black, while the sampled posterior is shown in blue/gray. The model is able to describe the data fairly well overall, although there are some regions of tension.

the constraining power is somewhat limited due to the large uncertainties at higher p_{T}. At $\sqrt{s_{NN}} = 2.76$ and 5.02 TeV, the model is able to describe the data over part of the p_{T} range, but there is an apparent tension between the model and the data at high p_{T}. Further tension is visible by focusing on the comparison of a single hadron and jet R_{AA} measurement at fixed $\sqrt{s_{NN}}$, with small uncertainties in both measurements driving the posterior distribution in different directions. This tension is most apparent at $\sqrt{s_{NN}} = 5.02$ TeV, where the posterior tends to describe the hadron R_{AA} and underpredict the jet R_{AA} at lower p_{T}, transitioning to underpredict the hadron R_{AA} and describe the ATLAS jet R_{AA} at higher p_{T}. Comparing $R = 0.4$ jet R_{AA} at $\sqrt{s_{NN}} = 5.02$ TeV across ALICE, ATLAS, and CMS illustrate some potential tensions between the measurements at high p_{T}, although the posterior tends towards ATLAS jets, correlating with the small uncertainties.

4. Outlook

We presented two Bayesian inference analyses using jet quenching measurements, utilizing the JETSCAPE framework. The analysis of inclusive charged hadron R_{AA} provides new constraints on the temperature and momentum dependence of $\widehat{q}$. We further presented the first multi-messenger Bayesian analysis for jet quenching, considering inclusive jet R_{AA} measurements with the hadron R_{AA} data. The posterior distribution of this work-in-progress analysis already demonstrates the wealth of information encoded in this multi-messenger approach. The model broadly describes the data, with some tension with the hadron and jet R_{AA}.

The treatment of uncertainties is critical to constrain model parameters, and we strongly encourage experimental collaborations to report full covariance matrices for their uncertainties, or at minimum to report the signs of individual uncertainties relative to the central values. Once the current simulations are completed, we will fully explore the parameter space and perform a Bayesian inference analysis to determine the distribution of model parameters which best describe the data. We will also explore the consistency, corroboration, and discriminating power of observables and kinematic selections, as well as expand to additional observables.

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