Data-driven analysis of the heavy-quark transport coefficient temperature dependence

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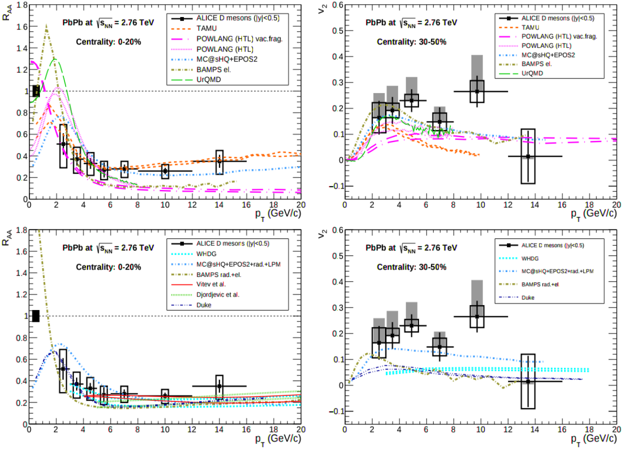
HQ in-medium evolution

Simultaneously describing *D*-meson R_{AA} and v_2??

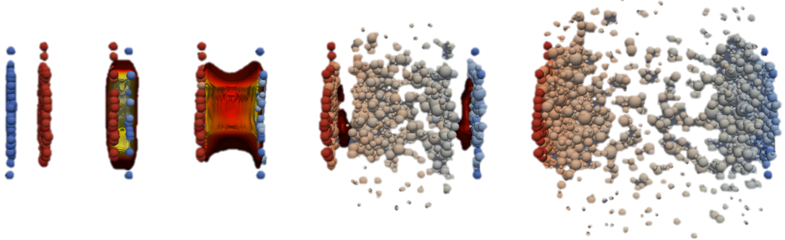
arxiv: 1506.03981



Pb+Pb @ 2.76 TeV: comparison between models and experimental observables

HQ in-medium evolution

figure credit: Hannah Petersen(Au-Au collisions)



Initial condition

Spatial IC: T$_R$ENTo
Momentum IC: pQCD

HQ in-medium

HQ transport: Langevin (col + rad)
Medium: hydrodynamic

Hadronization

Hybrid model: fragmentation + recombination

Initial condition

Position space: T_RENTo (A parametric IC model)

- Entropy deposition proportional to eikonal parameterization

$$\left.\frac{ds}{dy}\right|_{\tau=\tau_0} \propto \left(\frac{T_A^p + T_B^p}{2}\right)^{1/p}$$

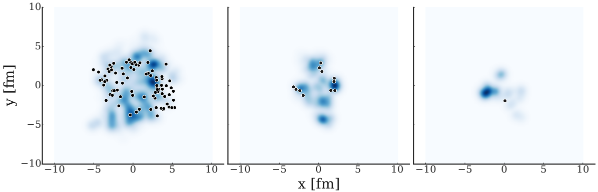
J.S.Moreland,J.Bernhard, and S.A.Bass, Phys.Rev.C 92, 011901(2015)

- $p = 0 \Rightarrow ds/dy \propto \sqrt{T_A T_B}$ (mimic the behavior of IP-Glasma)
- Heavy quark initial production probability: $\left.\frac{dN}{dy}\right|_{\tau=\tau_0} \propto T_A T_B$

Momentum space: Leading order pQCD

- Parton distribution function: CTEQ5
- Nuclear shadowing effect: EPS09

S.Cao, G.Qin, and S.A.Bass, Phys.Rev.C 92, 024907(2015)



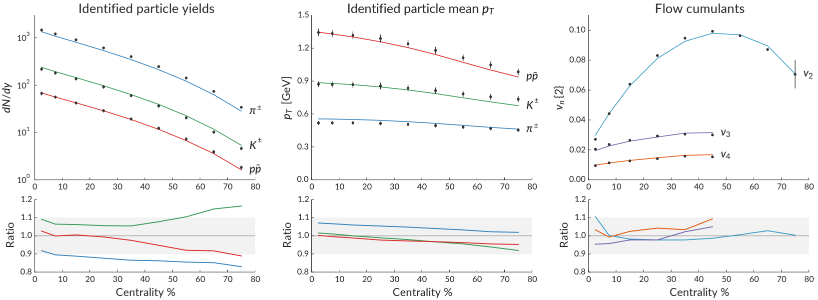
Calibration of the medium

Medium evolution: hydrodynamics

H.Song and U.W.Heinz, Phys.Rev.C 77, 064901(2008)

- (2+1)D viscous hydro: iEbE-VISHNU
- Temperature-dependent shear + bulk vis correction
- $(\eta/s)(T) = (\eta/s)_{\min} + (\eta/s)_{\text{slope}}(T - T_c)$, for $T > T_c$
- All the initial/medium related parameters ($\text{norm}, p, \eta/s$ etc.) are calibrated by Bayesian analysis with experimental observables ($\kappa, \pi, \text{proton}$: yields, mean p_T, flow cumulants $v_n\{2\}, v_3, v_4$)

J.Bernhard,J.S.Moreland,S.A.Bass, J.Liu, and U.Heinz Phys.Rev.C 94, 024907(2015)



HQ in-medium evolution

Improved Langevin transport model

S.Cao, G.Qin, and S.A.Bass, Phys.Rev.C 92, 024907(2015)

$$\frac{d\vec{p}}{dt} = -\eta_D(p)\vec{p} + \vec{\xi} + \vec{f_g} \tag{1}$$

- Drag force: $\eta_D(p) = \kappa/(2TE)$
- Thermal random force: $\langle \xi^i(t)\xi^j(t') = \kappa\delta^{ij}\delta(t-t')\rangle$
- Recoil force from gluon radiation: $\vec{f_g} = -d\vec{p_g}/dt$
- Gluon emission probability:

$$\frac{dN_g}{dxdk_\perp^2 dt} = \frac{2\alpha_s P(x)\hat{q}_g}{\pi k_\perp^4}\sin^2(\frac{t-t_i}{2\tau_f})(\frac{k_\perp^2}{k_\perp^2 + x^2M^2})^4 \tag{2}$$

- $\hat{q}_g = \hat{q}C_A/C_F = 2\kappa C_A/C_F, D_s = 2T^2/\kappa$
- **Diffusion coefficient D_s=?**

Bayesian model-to-data analysis

model eg. HQ transport → **model parameters** α, β, γ eg. $D_s 2\pi T(\alpha, \beta)$ ↔ **experimental obs** eg. R_{AA}, v_2

Bayesian analysis:

- Physical properties of the system encapsulated in parameters of the model
- Bayesian analysis allows us to simultaneously calibrate all model parameters through model-to-data comparison
- Find the optimal parameters such that the model best describes the experimental observables
- Extract the probability distribution of all parameters

Model parameters

$D_s 2\pi T(\alpha, \beta)$

Latin hypercube

Physics model

- T$_\mathrm{R}$ENTo+ LO pQCD
- Langevin + iEbE-VISHNU
- Frag + recomb

Gaussian process emulator

- Non-parametric interpolation
- Fast surrogate to full Physics Model

Experimental data

-LHC + RHIC: R_{AA}, v_2

MCMC

- Random walk through parameter space weighted by posterior probablility

Bayes' Theorem:

$\text{posterior} \propto \text{likelihood} \times \text{prior}$

After equilibrium

Posterior distribution

- Diagonals: probability distribution of each parameter, integrating out all others
- Off-diagonals: pairwise distributions showing dependence between parameters

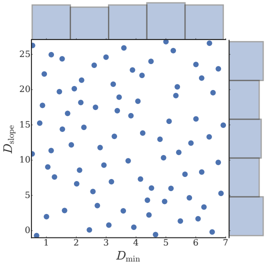
J.Bernhard, P.Marcy, C.Coleman-Smith, S.Huzurbazar, R.Wolpert and S.A.Bass, Phys.Rev.C 91, 054910(2015)

Prior calibration

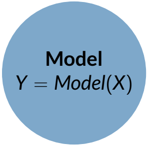
HQ diffusion coefficient parameterization:

$$D_s 2\pi T = D_{\rm min} + D_{\rm slope}(T - T_c) \qquad (3)$$

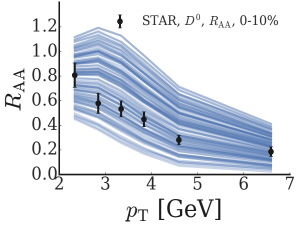
- Parameter space: $D_{\rm min} \in (0.5, 7), D_{\rm slope} \in (-1, 27)\ \mathrm{GeV}^{-1}$
- Uniformly sample 100 design points throughout parameter space: $\vec{x^*} = (D_{\rm min}, D_{\rm slope})$
- Full Langevin framework calculation at each design point $\Rightarrow$ 100 sets of prior results: $\vec{y^*} = \mathrm{Model}(\vec{x^*})\,, \vec{y^*} = (R_{\rm AA}, v_2)$



$\Rightarrow$

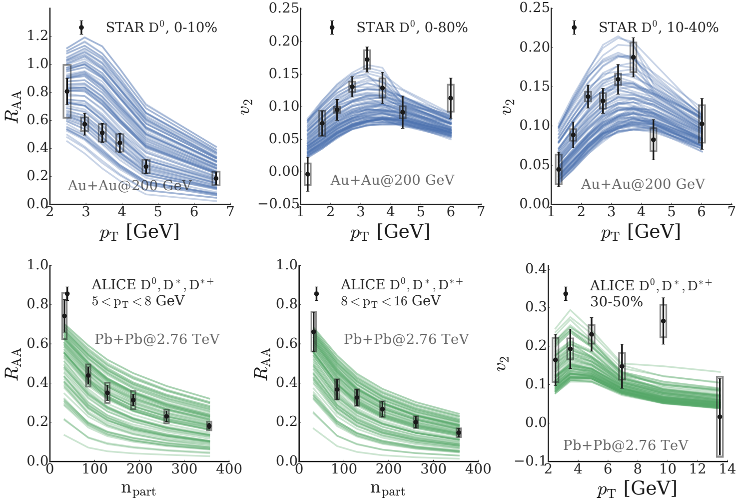


$\Rightarrow$



Prior calibration: training data

Model calculation of (R_{AA}, v_2) at 100 design points



[STAR Collaboration] arxiv:1601.00695; arXiv:1701.06060
[ALICE Collaboration] JHEP **1511**, 205 (2015); Phys.Rev.C **90**, no. 3, 034904 (2014)

Training GP emulator

$$\vec{x} = (D_{\mathrm{min}}, D_{\mathrm{slope}}) \longrightarrow \textbf{Model} \longrightarrow \vec{y} = (R_{\mathrm{AA}}, v_2)$$

Difficulties

Full Langevin framework run $\propto$ 8hrs for 100 events produced

$\Downarrow$

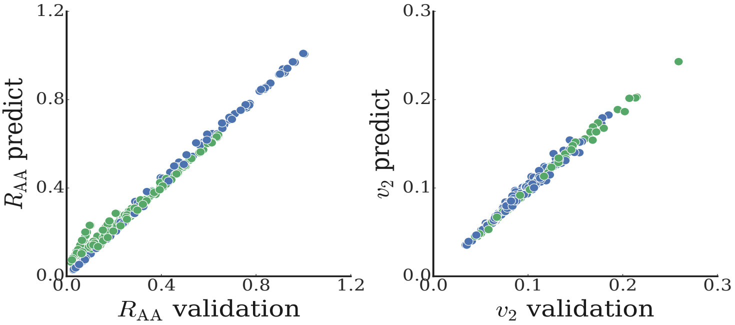
10000 events needed for an event-by-event study

$\Downarrow$

$O(10^3)$ CPU hours to evaluate one design point $\vec{x}$

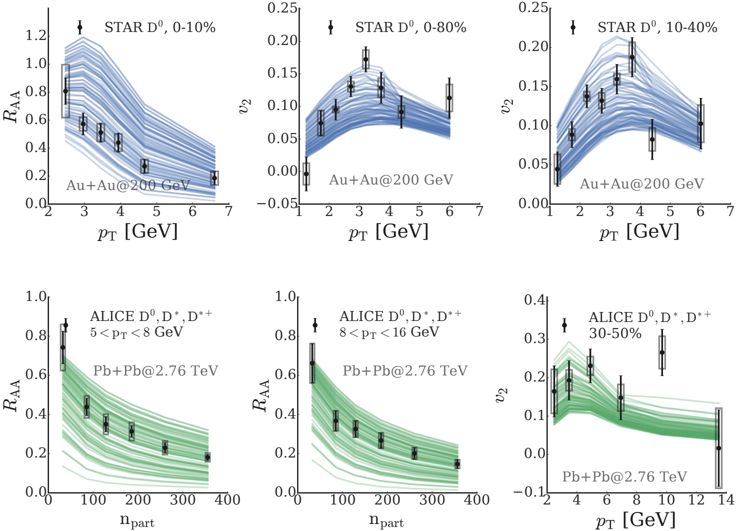
Training GP emulator

$\vec{x} = (D_{\text{min}}, D_{\text{slope}})$ $\longrightarrow$ **GP Emulator** $\longrightarrow$ $\vec{y} = (R_{\text{AA}}, v_2)$



Prior calibration: training data

Prior results: 100 sets of (R_{AA}, v_2) from model calculation



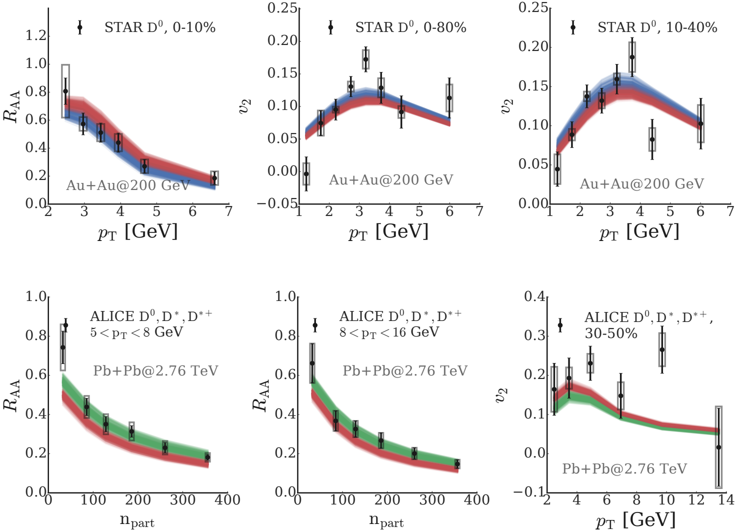
Model calculation
$\Downarrow$
training data $Y = f(X)$

GP emulator
$\Downarrow$
any $\vec{x}$ predict $\vec{y}$

MCMC
$\Downarrow$
$\vec{x}$ posterior distribution

Posterior calibration

Posterior results: 200 random sets of (R_{AA}, v_2)



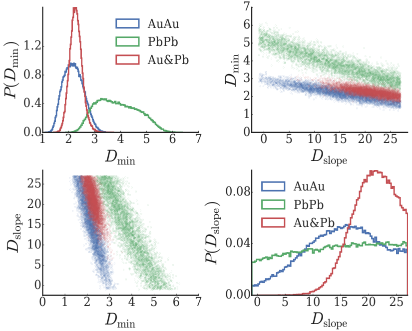
Model calculation
$\Downarrow$
training data $Y = f(X)$

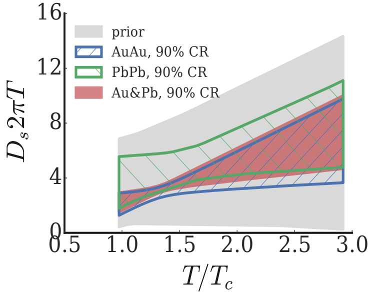
GP emulator
$\Downarrow$
any $\vec{x}$ predict $\vec{y}$

MCMC
$\Downarrow$
$\vec{x}$ posterior distribution

Posterior calibration

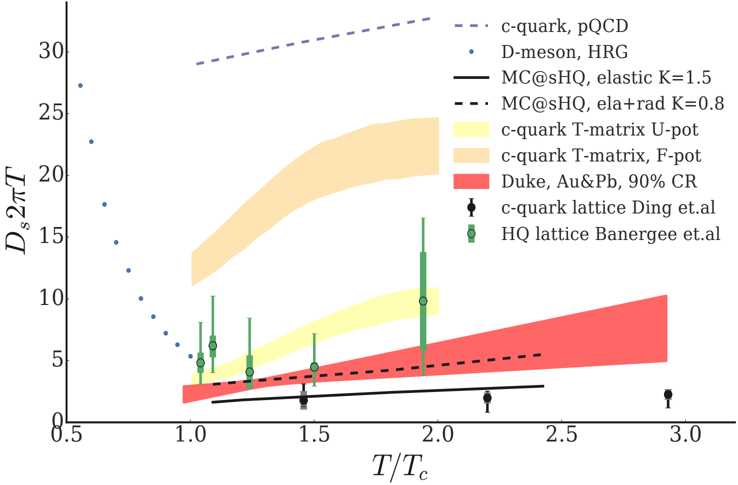
Posterior distributions of $(D_{\min}, D_{\mathrm{slope}})$





param	prior range	posterior(AuAu)	posterior(PbPb)	posterior(AuAu&PbPb)
$D_{\min}$	(0.5,7)	(1.60, 2.83)	(2.70, 5.19)	(1.90, 2.67)
D_{slope}	(-1, 27)	(3.47, 25.56)	(0.86, 25.74)	(14.16, 26.23)

Comparison between different models



F.Riek,and R.Rapp, Phys.Rev.C 82,035201(2010)

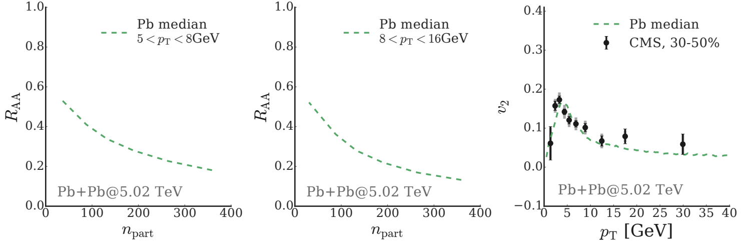
M.He,R.J.Fries,and R.Rapp, Phys.Rev.Lett 11,112301(2013)

H.Ding,A.Francis,O.Kaczmarek,et.al, Phys.Rev.D 86,014509(2012)

D.Banerjee,S.Datta,R.Gavai,P.Majumdar, Phys.Rev.D 85,014510(2012)

Pb+Pb @ 5.02 TeV

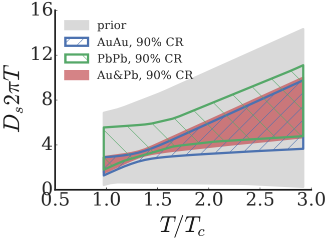
Langevin calculation taking the favorable value of $(D_{\min}, D_{\text{slope}})$ on another system.



Not a calibration!

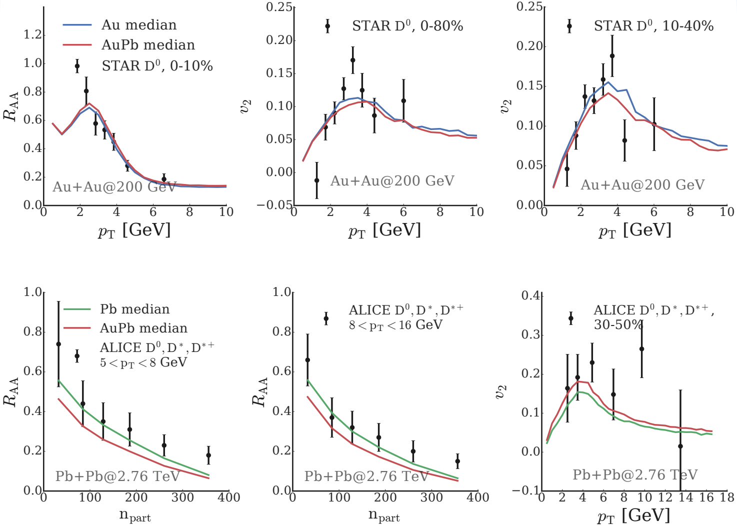
Summary

- Bayesian model-to-data analysis $\Rightarrow$ extract the temperature dependence of $D_s 2\pi T \propto (2-10)$



- Simultaneous agreement of R_{AA} and v_2 compared to data
- A higher precision of experimental data? $\Rightarrow$
  - Better constrain diffusion cofficient
  - Further discriminate between different HQ in-medium transport models
- Extension of calibrating on Pb+Pb @ 5.02 TeV, p+Pb @ 5.02 TeV; improve uncertainty analysis

Full Langevin run with favorable values



$(D_{\min}, D_{\text{slope}})$:

Au median (2.10, 16.44) ; Pb median (3.60, 14.01); AuPb median (2.26, 18.63)