Bayesian Inference for QGP Properties: Integrating high-$p_\perp$ and low-$p_\perp$ data with Bayes-DREENA

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in collaboration with: Magdalena Djordjevic, Bithika Karmakar, Jussi Auvinen, Igor Salom, Pasi Huovinen and Marko Djordjevic

МИНИСТАРСТВО ПРОСВЕТЕ,
НАУКЕ И ТЕХНОЛОШКОГ РАЗВОЈА

DREENA framework

- **D**ynamical **R**adiative and **E**lastic **EN**ergy loss **A**pproach

- fully optimized numerical procedure capable of generating high $p_{\perp}$ predictions
- includes:
  - parton production
  - multi gluon-fluctuations
  - path-length fluctutations
  - fragmentation functions
- keeping all elements of the state-of-the art energy loss formalism, while introducing more complex medium evolutions:
  - DREENA-C: constant temperature medium
    D. Z., I. Salom, J. Auvinen, M. Djordjevic and M. Djordjevic, J. Phys. G **46**, no. 8, 085101 (2019).
  - DREENA-B: Bjorken expansion
    D. Z., I. Salom, J. Auvinen, M. Djordjevic and M. Djordjevic, Phys. Lett. B **791**, 236 (2019).
  - DREENA-A: smooth (2+1)D temperature evolution
    D. Z, I. Salom, J. Auvinen, P. Huovinen and M. Djordjevic, Front. in Phys. **10**, 957019 (2022).
  - ebe-DREENA: event-by-event fluctuating hydro background
    D. Z, J. Auvinen, I. Salom, P. Huovinen and M. Djordjevic, Phys. Rev. C **106**, no.4, 044909 (2022)

QGP tomography

Bulk QGP properties are traditionally explored by low-$p_\perp$ observables that describe the collective motion of 99.9% of QCD matter

⬇

However, some important bulk QGP properties are known to be difficult to constrain by low-$p_\perp$ observables and the corresponding theory / simulations

⬊

Rare high energy probes are, on the other hand, almost exclusively used to understand high-$p_\perp$ parton - medium interactions

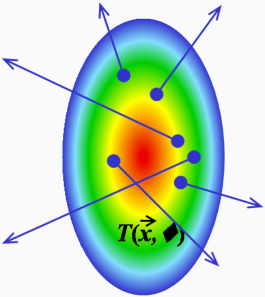
⬇

While high-$p_\perp$ physics played a decisive role in QGP discovery, it has rarely been used to understand bulk QGP properties

⬋

We advocate high-$p_\perp$ QGP tomography, where low- and high-$p_\perp$ physics jointly constrain bulk QGP parameters

QGP tomography



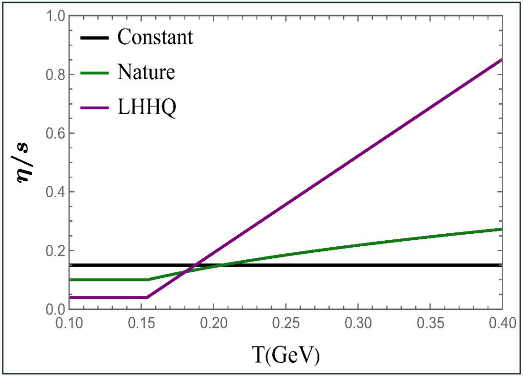
- high energy particles lose energy
- energy loss sensitive to QGP properties
- predict the energy loss of high $p_\perp$ probes
- use high $p_\perp$ probes to infer QGP properties:
  - QGP anisotropy
  - early evolution
  - η/s parametrization
  - initial stages

    talk by Bithika, Tuesday 11:45

- DREENA-A on github:
  https://github.com/DusanZigic/DREENA-A
  https://github.com/DusanZigic/ebeDREENA

eta/*s* parametrization

different parametrization of η/s



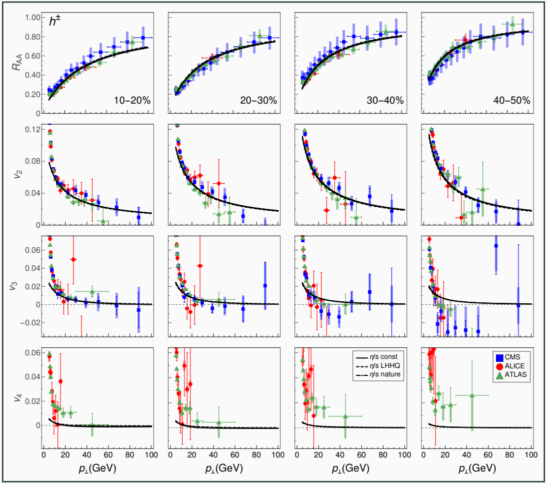
can high-$p_\perp$ further constrain η/s?

B. Karmakar, D. Z, I. Salom, J. Auvinen, P. Huovinen, M. Djordjevic and M. Djordjevic, Phys. Rev. C **108**, no.4, 044907 (2023)

η/s parametrization

TRENTO+VISHNU+URQMD+DREENA

Pb+Pb, $\sqrt{s_{NN}}$=5.02TeV, $h^{\pm}$

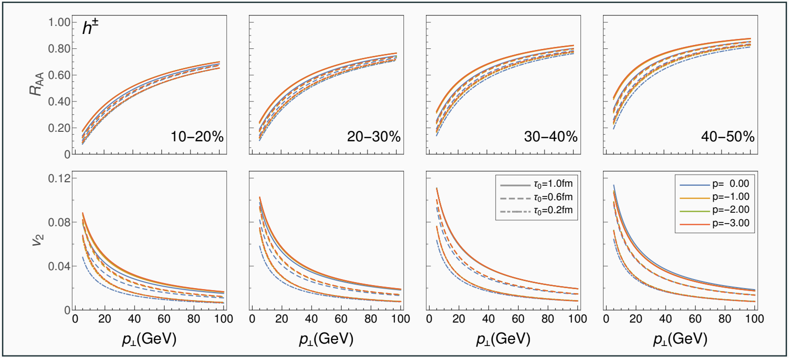


B. Karmakar, D. Z, I. Salom, J. Auvinen, P. Huovinen, M. Djordjevic and M. Djordjevic, Phys. Rev. C **108**, no.4, 044907 (2023)

Initial stages

TRENTO+VISHNU+URQMD+DREENA

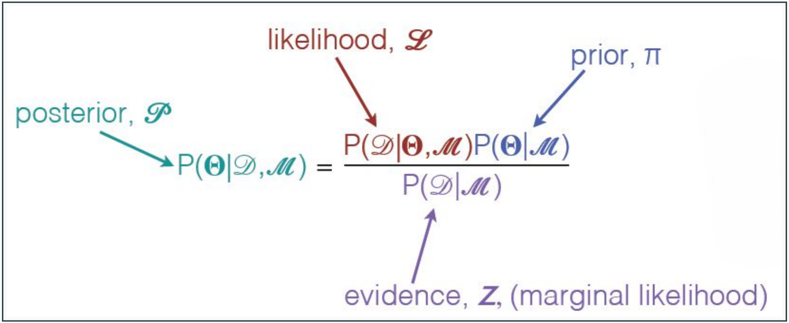
Pb+Pb, $\sqrt{s_{NN}}$=5.02TeV, $h^{\pm}$



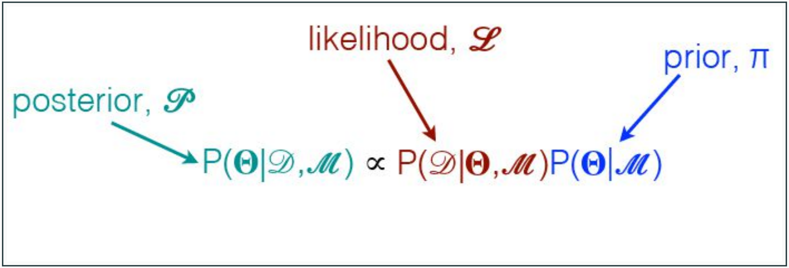
could not compensate earlier hydro onset with p

B. Karmakar, D. Z, M. Djordjevic, P. Huovinen, M. Djordjevic and J. Auvinen, Phys. Rev. C **110**, no.4, 044906 (2024)

Bayes theorem



Bayes theorem



Bayes inference

- generate model predictions on latin hypercube
- PCA on model outputs
- Gaussian processes
- MCMC

- TRENTO+VISHNU+URQMD+DREENA
  - τ_0: 0.2-1.3fm
  - constant η/s: 0.02-0.2
  - norm: 60-360

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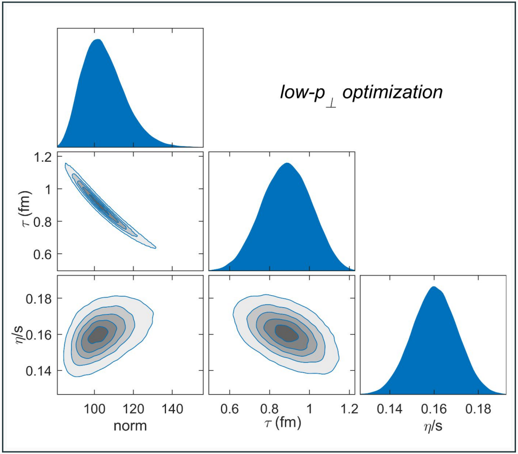
marginal distributions of parameters obtained with Bayesian inference on low-$p_\perp$ data



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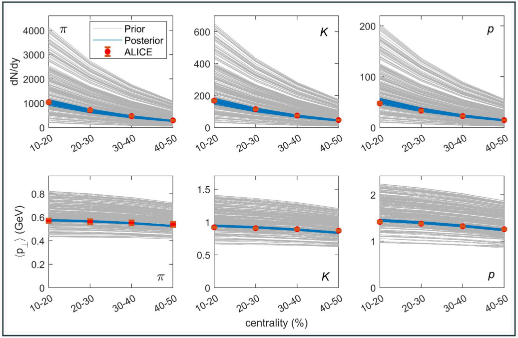
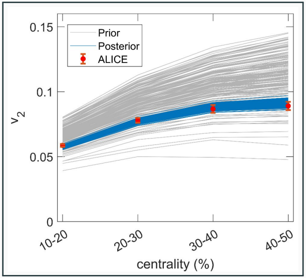
Bayes inference

prior vs. posterior: low-$p_\perp$ data





very good agreement with low-$p_\perp$ data

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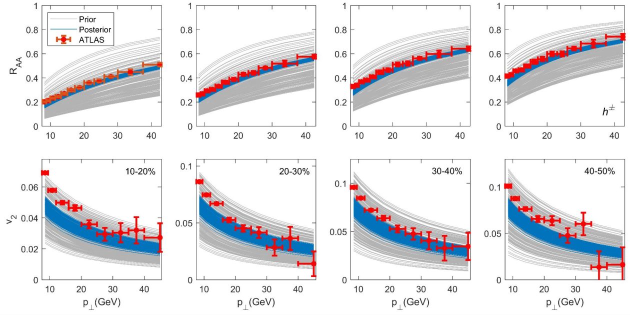
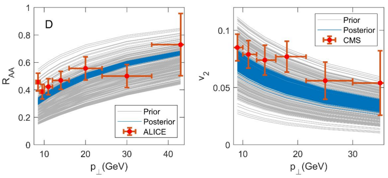
prior vs. posterior: high-$p_\perp$ data





suboptimal agreement with high-$p_\perp$ data

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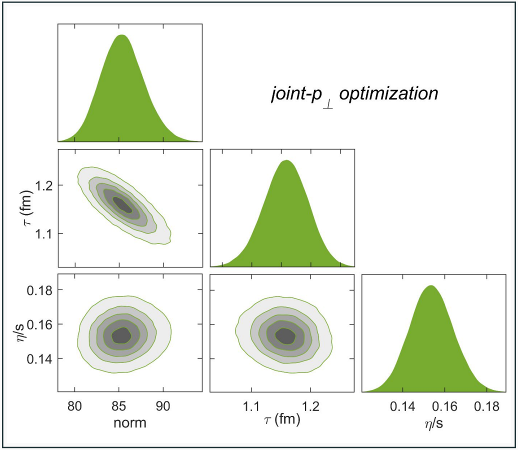
Bayes inference

marginal distributions of parameters obtained with Bayesian inference on both low- and high-$p_\perp$ data



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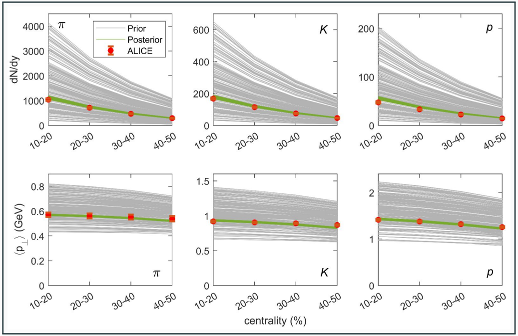
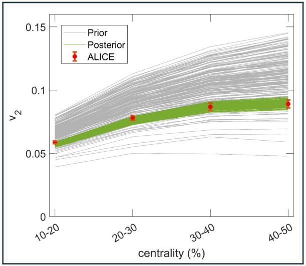
prior vs. posterior: low-$p_\perp$ data





very good agreement with low-$p_\perp$ data

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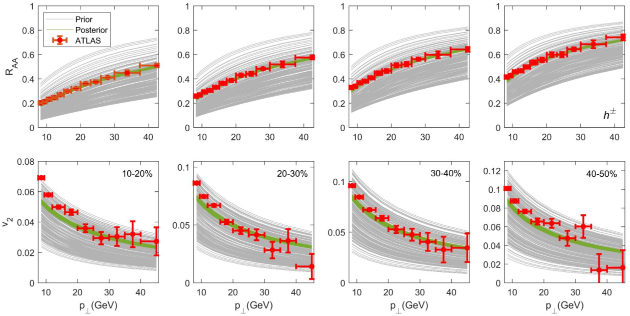
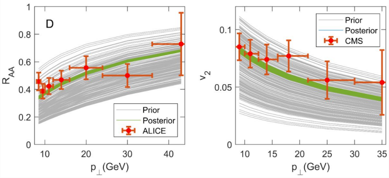
prior vs. posterior: high-$p_\perp$ data





very good agreement with high-$p_\perp$ data as well

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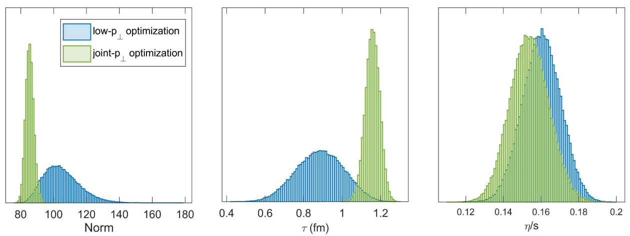
Bayesian inference

comparison of parameter distributions from low- and joint-$p_\perp$ Bayesian inference



- distributions are not inconsistent with each other
- inclusion of high-$p_\perp$ data significantly narrows the distributions of parameters
- high-$p_\perp$ data is necessary for precision extraction of QGP parameters
- overall, jet tomography is crucial for constraining QPG properties

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Summary

- manually:
  - η/s parametrization
  - initial stages
- Bayes rule and MCMC
  - distributions consistent with each other
  - high-$p_\perp$ narrows distributions
- there are link for all papers, codes, youtube lectures,...

Acknowledgements

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Thank you for your attention!

Backup slides

priors

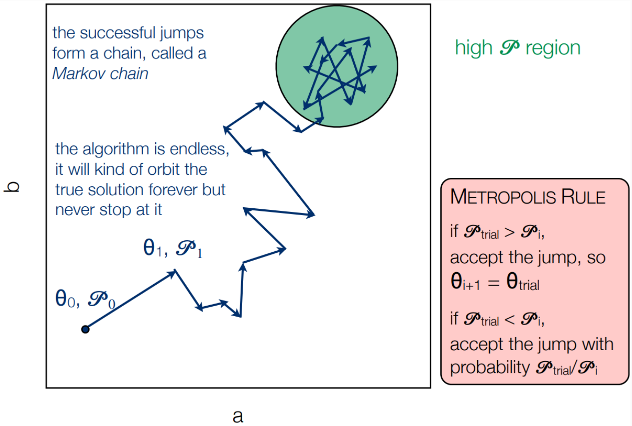
$$P\left(\boldsymbol{\theta}|\mathscr{M}\right) \propto \begin{cases} 1 & \text{if } min\left(\theta_i\right) \leq \theta_i \leq max\left(\theta_i\right) \text{ for all } i \\ 0 & \text{else} \end{cases}$$

likelihood

$$P\left(\mathscr{D}|\boldsymbol{\theta},\mathscr{M}\right) = \prod_{i=i}^{N} \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{1}{2}\frac{\left(y_{m_i}-y_{e_i}\right)^2}{\sigma_i^2}}$$

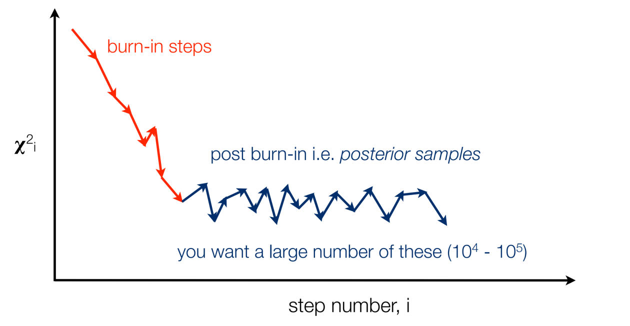
$$P\left(\mathscr{D}|\boldsymbol{\theta},\mathscr{M}\right) = \frac{1}{\sqrt{2\pi det\Sigma}} e^{-\frac{1}{2}[\boldsymbol{y}_m(\boldsymbol{x})-\boldsymbol{y}_e]^T\Sigma^{-1}[\boldsymbol{y}_m(\boldsymbol{x})-\boldsymbol{y}_e]}$$

MCMC



David Kipping, Sagan Workshop 2016

MCMC



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Backup slides

energy loss:

$$\frac{dE_{col}}{d\tau} = \frac{2C_R}{\pi v^2}\alpha_S(E\,T)\,\alpha_S(\mu_E^2(T)) \times$$

$$\int_0^\infty n_{eq}(|\vec{\mathbf{k}}|,T)d|\vec{\mathbf{k}}| \left(\int_0^{|\vec{\mathbf{k}}|/(1+v)} d|\vec{\mathbf{q}}| \int_{-v|\vec{\mathbf{q}}|}^{v|\vec{\mathbf{q}}|} \omega d\omega + \int_{|\vec{\mathbf{k}}|/(1+v)}^{|\vec{\mathbf{q}}|_{max}} d|\vec{\mathbf{q}}| \int_{|\vec{\mathbf{q}}|-2|\vec{\mathbf{k}}|}^{v|\vec{\mathbf{q}}|} \omega d\omega \right) \times$$

$$\left(|\Delta_L(q,T)|^2 \frac{(2|\vec{\mathbf{k}}|+\omega)^2 - |\vec{\mathbf{q}}|^2}{2} + |\Delta_T(q,T)|^2 \frac{(|\vec{\mathbf{q}}|^2-\omega^2)((2|\vec{\mathbf{k}}|+\omega)^2 + |\vec{\mathbf{q}}|^2)}{4|\vec{\mathbf{q}}|^4}(v^2|\vec{\mathbf{q}}|^2-\omega^2)\right)$$

$$\frac{d^2N_{\rm rad}}{dx d\tau} = \int \frac{d^2k}{\pi}\,\frac{d^2q}{\pi}\,\frac{2\,C_R C_2(G)\,T}{x}\,\frac{\mu_E(T)^2-\mu_M(T)^2}{(\boldsymbol{q}^2+\mu_M(T)^2)(\boldsymbol{q}^2+\mu_E(T)^2)}\,\frac{\alpha_S(E\,T)\,\alpha_S(\frac{\boldsymbol{k}^2+\chi(T)}{x})}{\pi}$$

$$\times\frac{(\boldsymbol{k}+\boldsymbol{q})}{(\boldsymbol{k}+\boldsymbol{q})^2+\chi(T)}\left(1-\cos\left(\frac{(\boldsymbol{k}+\boldsymbol{q})^2+\chi(T)}{xE^+}\,\tau\right)\right)\left(\frac{(\boldsymbol{k}+\boldsymbol{q})}{(\boldsymbol{k}+\boldsymbol{q})^2+\chi(T)} - \frac{\boldsymbol{k}}{\boldsymbol{k}^2+\chi(T)}\right)$$