Flavor hierarchy of parton energy loss in quark-gluon plasma from a Bayesian analysis

Guang-You Qin

Central China Normal University

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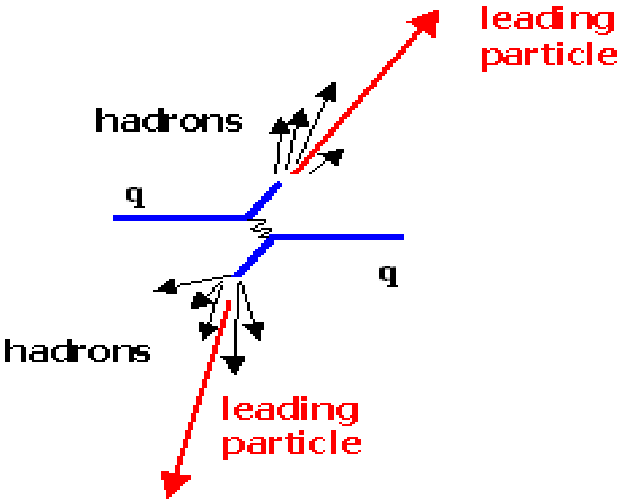
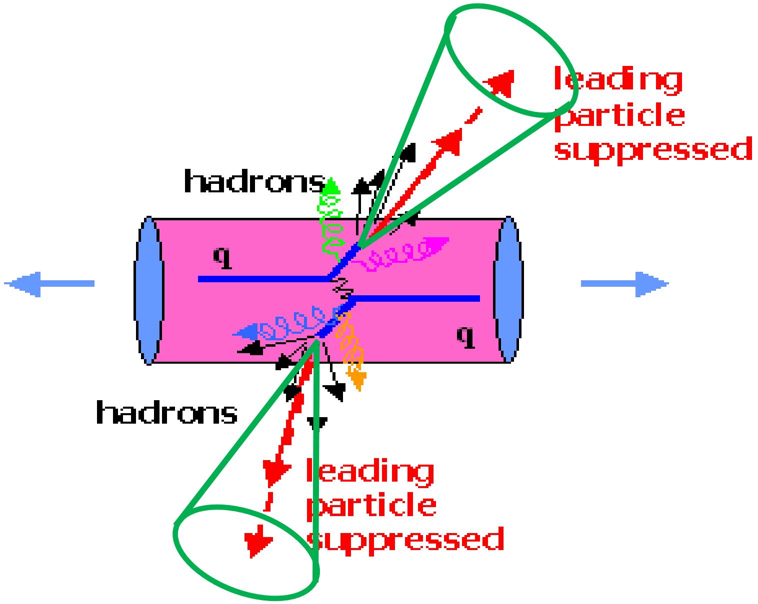
Jets are versatile probes of QGP



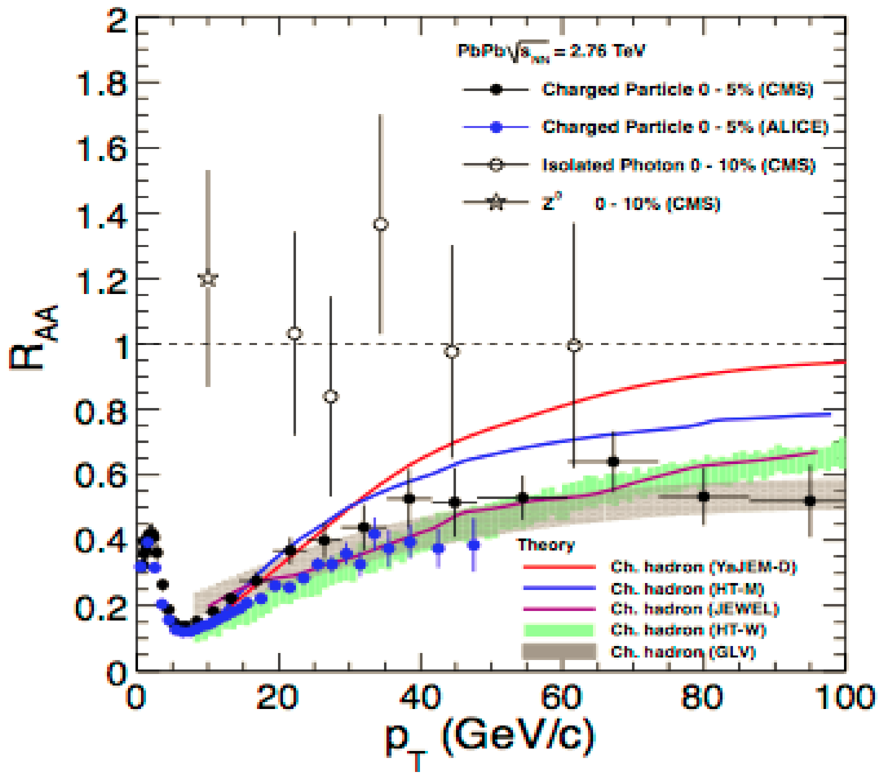
N+N

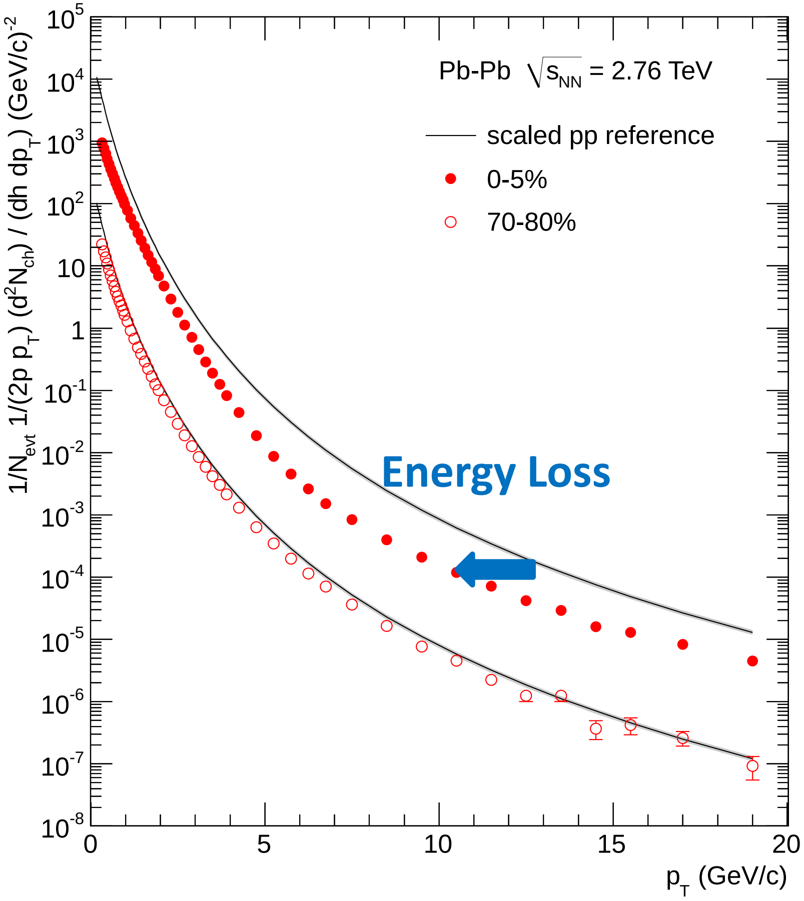


A+A: jet quenching

Jet quenching: energy loss, broadening, substructure, medium response

Evidences for jet quenching



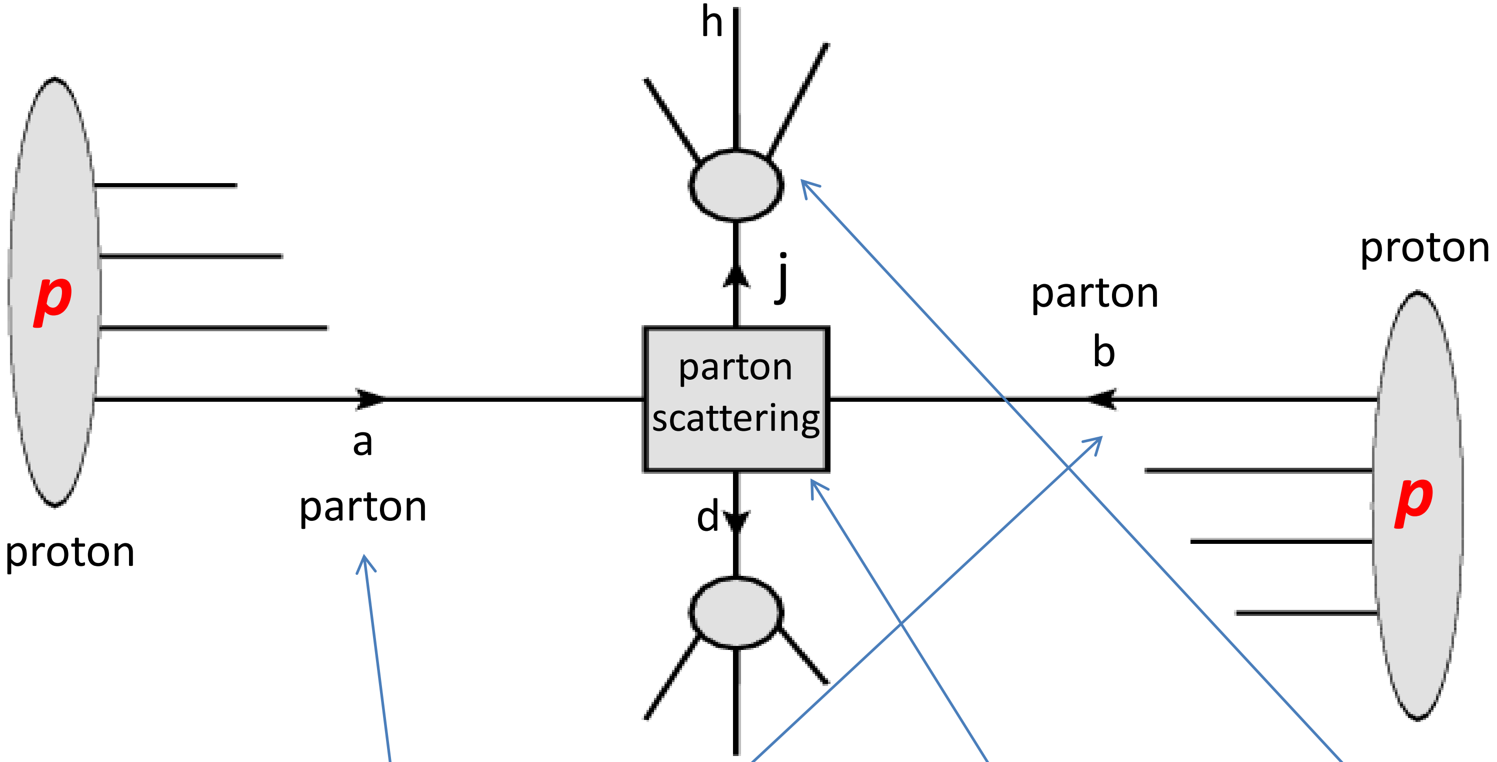


Energy Loss

Nuclear modification factor:

$$R_{AA}(p_T) = \frac{dN_{AA}/dp_T}{N_{coll}dN_{pp}/dp_T} = \frac{dN_{pp}(p_T+\Delta p_T)/dp_T}{dN_{pp}(p_T)/dp_T}$$

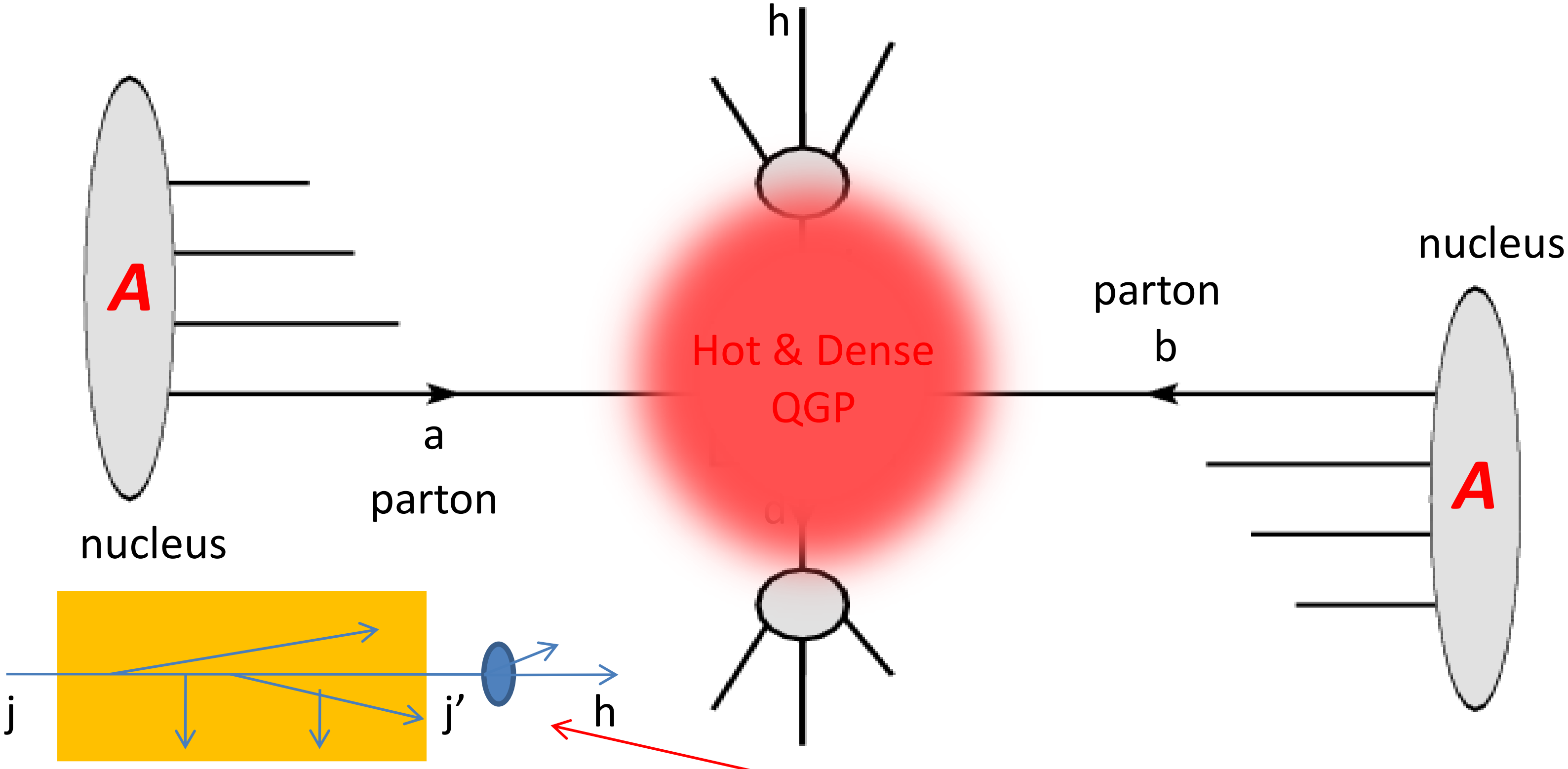
General framework for jet quenching study



$$d\sigma_h = \sum_{abj} f_{a/A} \otimes f_{b/B} \otimes d\sigma_{ab\to jX} \otimes D_{h/j}$$

pQCD factorization: Large-p_T processes may be factorized into long-distance pieces in terms of PDF & FF, and short-distance parts describing hard interactions of partons.

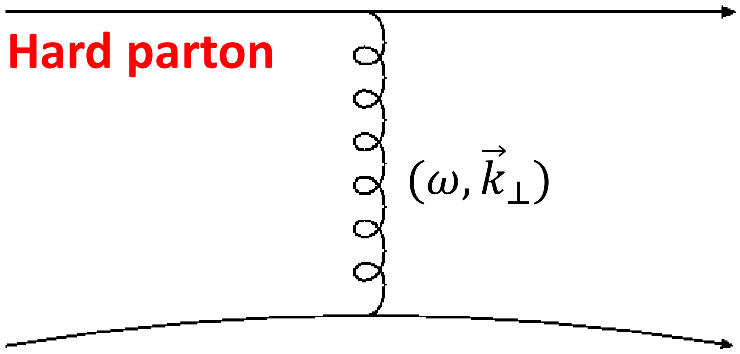
General framework for jet quenching study



$$d\tilde{\sigma}_h = \sum_{abjX} f_{a/A} \otimes f_{b/B} \otimes d\sigma_{ab\to jX} \otimes \tilde{D}_{h/j}$$

$$d\tilde{\sigma}_h = \sum_{abjj'} f_a \otimes f_b \otimes d\sigma_{ab\to jX} \otimes \boxed{P_{j\to j'} \otimes D_{h/j'}}$$

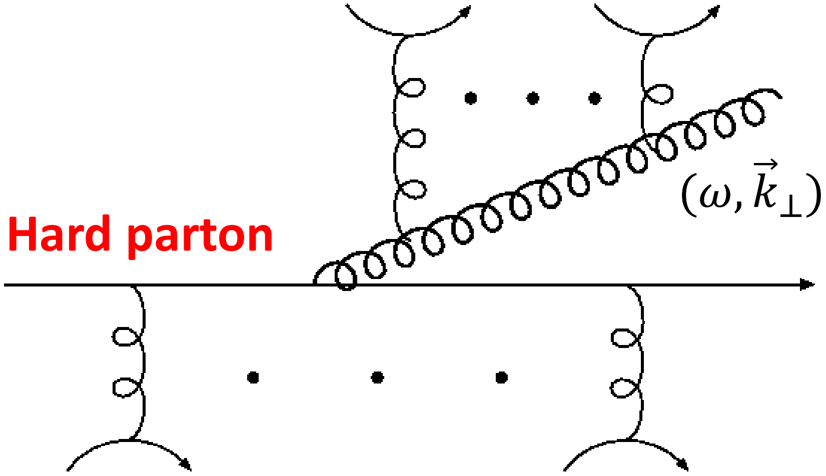
Jet-medium interaction



Elastic (collisional)

$$\frac{d\Gamma_{coll}}{d\omega dk_\perp^2 dt}(T, E, \ldots) = ?$$

Bjorken 1982; Bratten, Thoma 1991; Thoma, Gyulassy, 1991; Mustafa, Thoma 2005; Peigne, Peshier, 2006; Djordjevic, 2006; Wicks et al (DGLV), 2007; GYQ et al (AMY), 2008; …

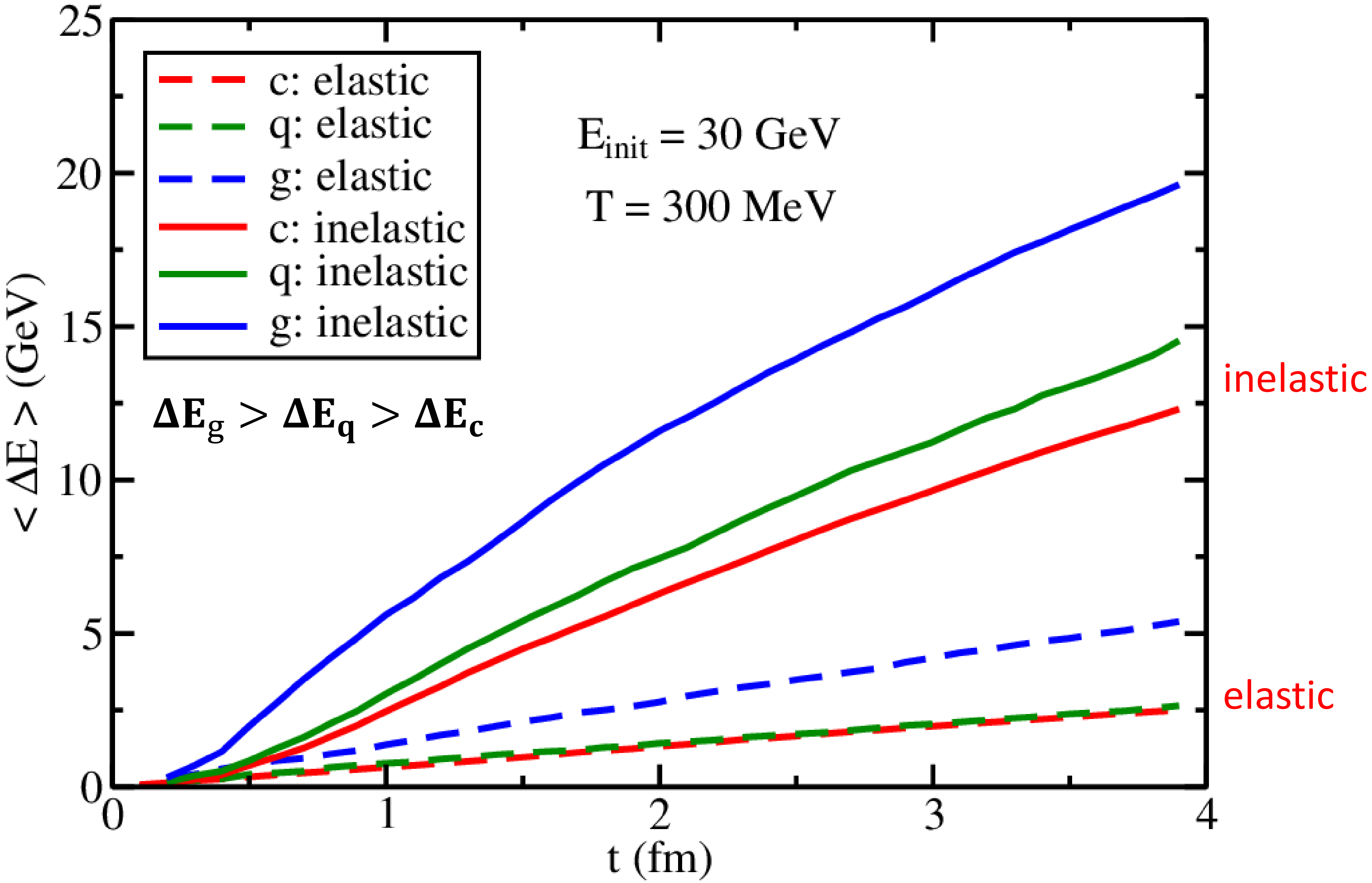


Inelastic (radiative)

$$\frac{d\Gamma_{rad}}{d\omega dk_\perp^2 dt}(T, E, \ldots) = ?$$

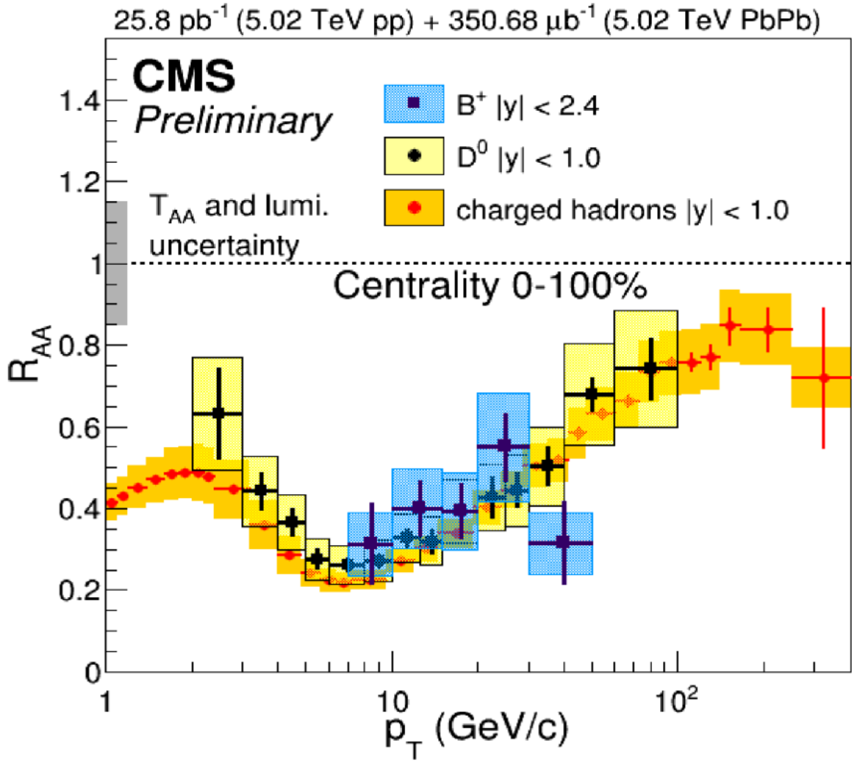
BDMPS-Z: Baier-Dokshitzer-Mueller-Peigne-Schiff-Zakharov
ASW: Amesto-Salgado-Wiedemann
AMY: Arnold-Moore-Yaffe (& Caron-Huot, Gale)
GLV: Gyulassy-Levai-Vitev (& Djordjevic, Heinz)
HT: Wang-Guo (& Zhang, Wang, Majumder & GYQ, Zhang, Hou)

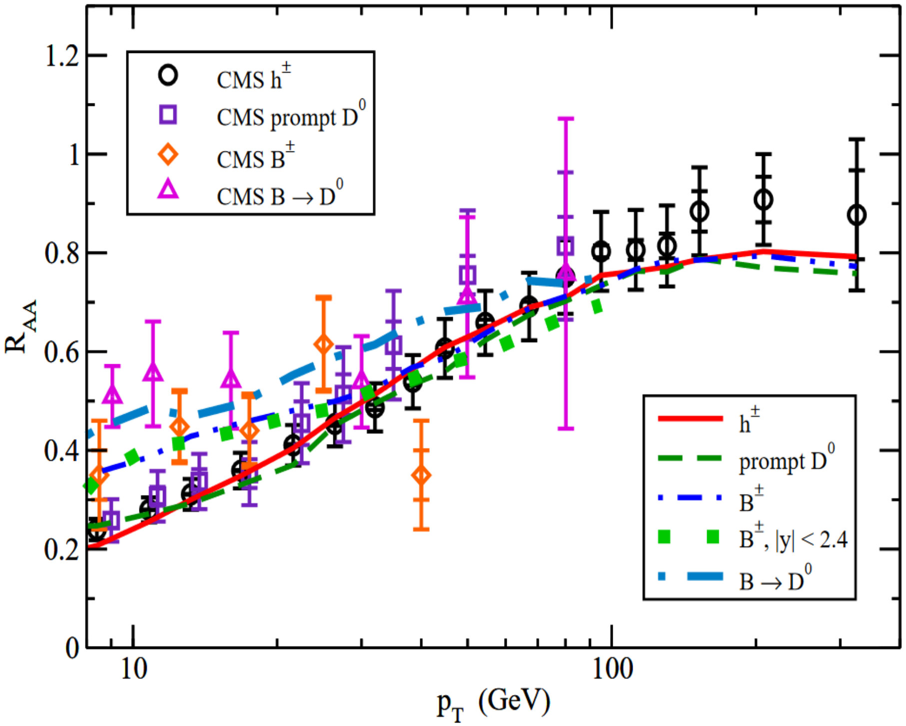
Flavor hierachy of parton energy loss



He, Luo, Wang, Zhu, PRC 2015; Cao, Luo, GYQ, Wang, PRC 2016 ; PLB 2018; etc.

Flavor hierarchy of high p_T hadron suppression





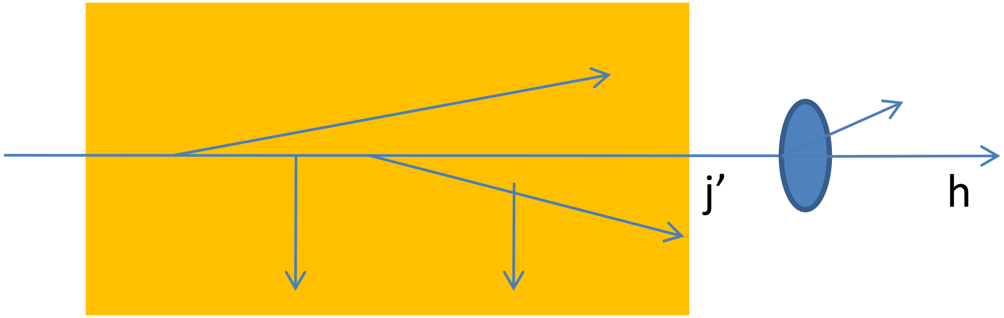
Combination of NLO-pQCD + LBT + Hydro can explain the flavor hierarchy of R_{AA}.

W. J. Xing, GYQ, S. Cao, H. Xing, PLB 2022

Constrain E-Loss using data-driven method

The theoretical framework:

$$\frac{d\sigma_{\mathrm{pp}\to hX}}{dp_{\mathrm{T}}^{h}} = \sum_{j}\int dp_{\mathrm{T}}^{j}dz\frac{d\hat{\sigma}_{\mathrm{pp}\to jX}}{dp_{\mathrm{T}}^{j}}(p_{\mathrm{T}}^{j})D_{j\to h}(z)\delta\left(p_{\mathrm{T}}^{h}-zp_{\mathrm{T}}^{j}\right)$$

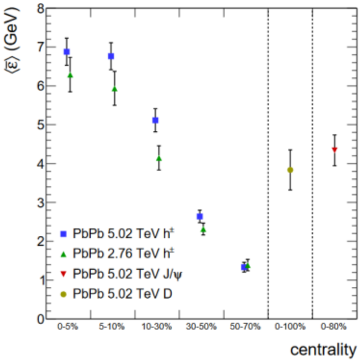


$$\frac{1}{\langle N_{\mathrm{coll}}\rangle}\frac{d\sigma_{\mathrm{AA}\to hX}}{dp_{\mathrm{T}}^{h}} = \sum_{j}\int dp_{\mathrm{T}}^{j}dxdz\frac{d\hat{\sigma}_{\mathrm{p'p'}\to jX}}{dp_{\mathrm{T}}^{j}}(p_{\mathrm{T}}^{j})W_{\mathrm{AA}}(x)D_{j\to h}(z)\delta\left(p_{\mathrm{T}}^{h}-z(p_{\mathrm{T}}^{j}-x\langle\Delta p_{\mathrm{T}}^{j}\rangle)\right)$$

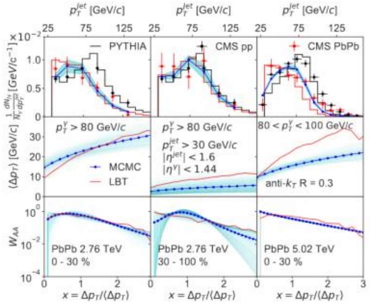
$\langle\Delta p_T^j\rangle$is the average energy loss for parton j, $W_{AA}(x)$ is the energy loss distribution with $x = \Delta p_T^j/\langle\Delta p_T^j\rangle$.

Some works on extracting $\langle \Delta p_T \rangle$ and $W_{AA}(x)$

- **F. Arleo, PRL 2017**
  - Take $W_{AA}(x)$ from BDMPS medium-induced gluon spectrum, & extract parton $\langle \Delta p_T \rangle$ from R_{AA} data on $h^{\pm}, D, J/\psi$.

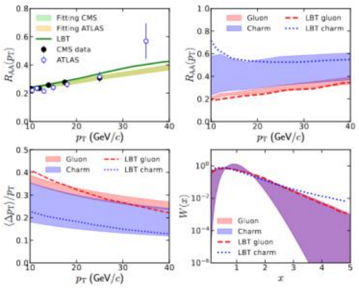


- **He, Pang, Wang, PRL 2019**
  - Use a general ansatz of jet $W_{AA}(x)$, and extract the flavor-averaged jet $\langle \Delta p_T \rangle$ and $W_{AA}(x)$ from single inclusive jet & γ-jet data.



- **Zhang, Liao, GYQ, Wang, Xing, Sci. Bull. 2023**
  - Extract gluon & charm quark $\langle \Delta p_T \rangle$ and $W_{AA}(x)$ for from J/ψ R_{AA} data.

- **This work (Xing, Cao, GYQ, PLB 2024) :**
  - Perform a simultaneous analysis on **parton $\langle \Delta p_T \rangle$** for all parton species (g, q, c, and b) from light & heavy flavor hadron R_{AA} data.



Details about the analysis

- **The formula for hadron production in AA collisions:**

$$\frac{1}{\langle N_{\mathrm{coll}}\rangle}\frac{d\sigma_{\mathrm{AA}\to hX}}{dp_{\mathrm{T}}^{h}}=\sum_{j}\int dp_{\mathrm{T}}^{j}dxdz\frac{d\hat{\sigma}_{\mathrm{p'p'}\to jX}}{dp_{\mathrm{T}}^{j}}(p_{\mathrm{T}}^{j})W_{\mathrm{AA}}(x)D_{j\to h}(z)\delta\left(p_{\mathrm{T}}^{h}-z(p_{\mathrm{T}}^{j}-x\langle\Delta p_{\mathrm{T}}^{j}\rangle)\right)$$

- **Parameterize p_T-dependence of $\langle\Delta p_T\rangle$ for gluons (g), light quarks (q), charm quarks (c) and bottom quarks (b) as:**

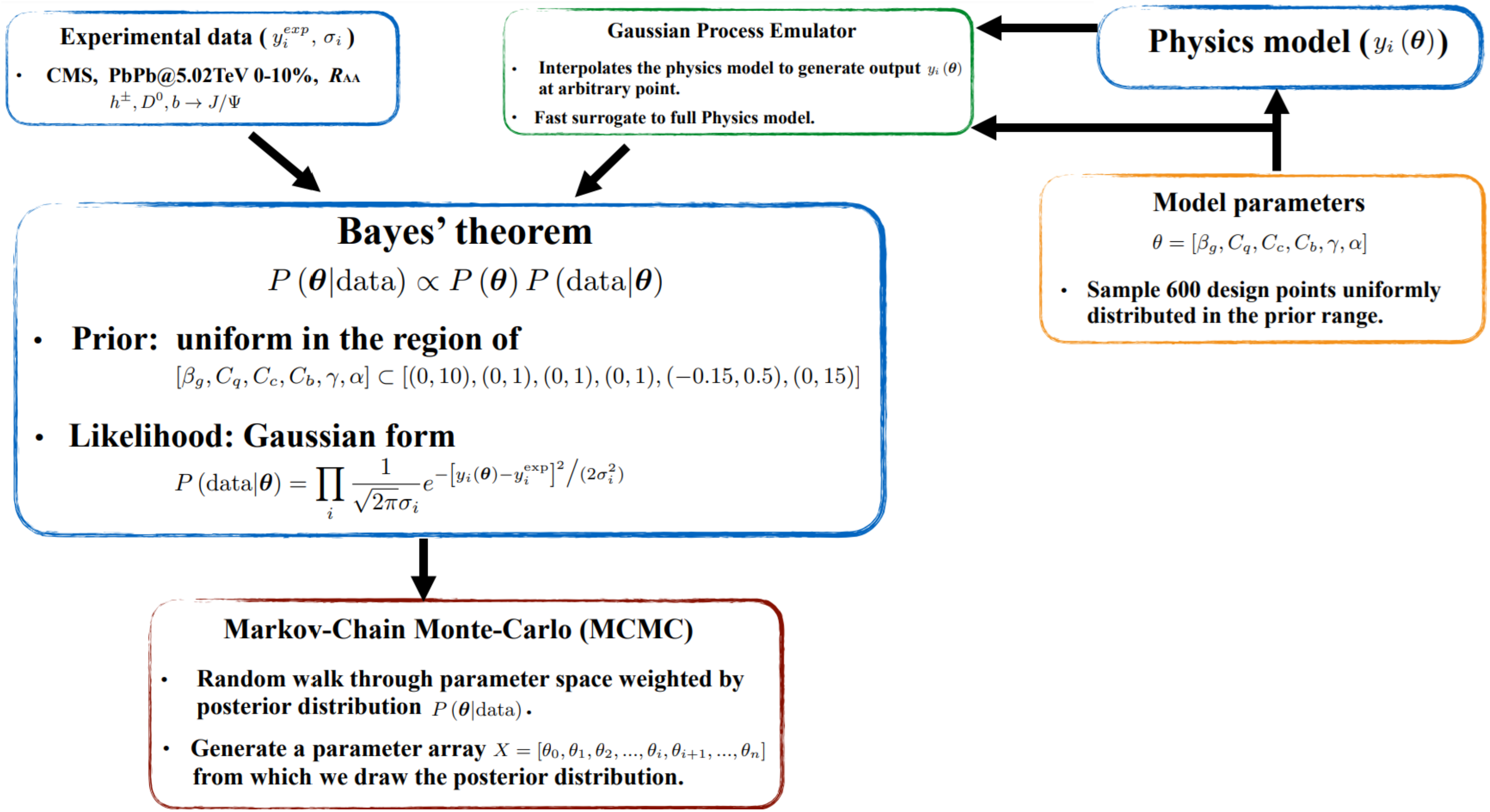
$$\left\langle\Delta p_{\mathrm{T}}^{j}\right\rangle=C_j\beta_g p_{\mathrm{T}}^{\gamma}\log(p_{\mathrm{T}})$$

  - **$C_g=1$ and C_q, C_c, C_b represents the $\langle\Delta p_T\rangle$ ratio relative to gluon's.**
- **The parton energy loss distribution $W_{AA}(x)$ is taken as:**

$$W_{\mathrm{AA}}(x)=\frac{\alpha^{\alpha}x^{\alpha-1}e^{-\alpha x}}{\Gamma(\alpha)}$$

- **The parameter set $\theta=(\beta_g,C_q,C_c,C_b,\gamma,\alpha)$ is to be calibrated.**

Bayesian analysis



Experimental data (y_i^{exp}, σ_i)

- CMS, PbPb@5.02TeV 0-10%, R_{AA}
  $h^{\pm}, D^0, b \to J/\Psi$

Gaussian Process Emulator

- Interpolates the physics model to generate output $y_i(\theta)$ at arbitrary point.
- Fast surrogate to full Physics model.

Physics model ($y_i(\boldsymbol{\theta})$)

Model parameters

$$\theta = [\beta_g, C_q, C_c, C_b, \gamma, \alpha]$$

- Sample 600 design points uniformly distributed in the prior range.

Bayes' theorem

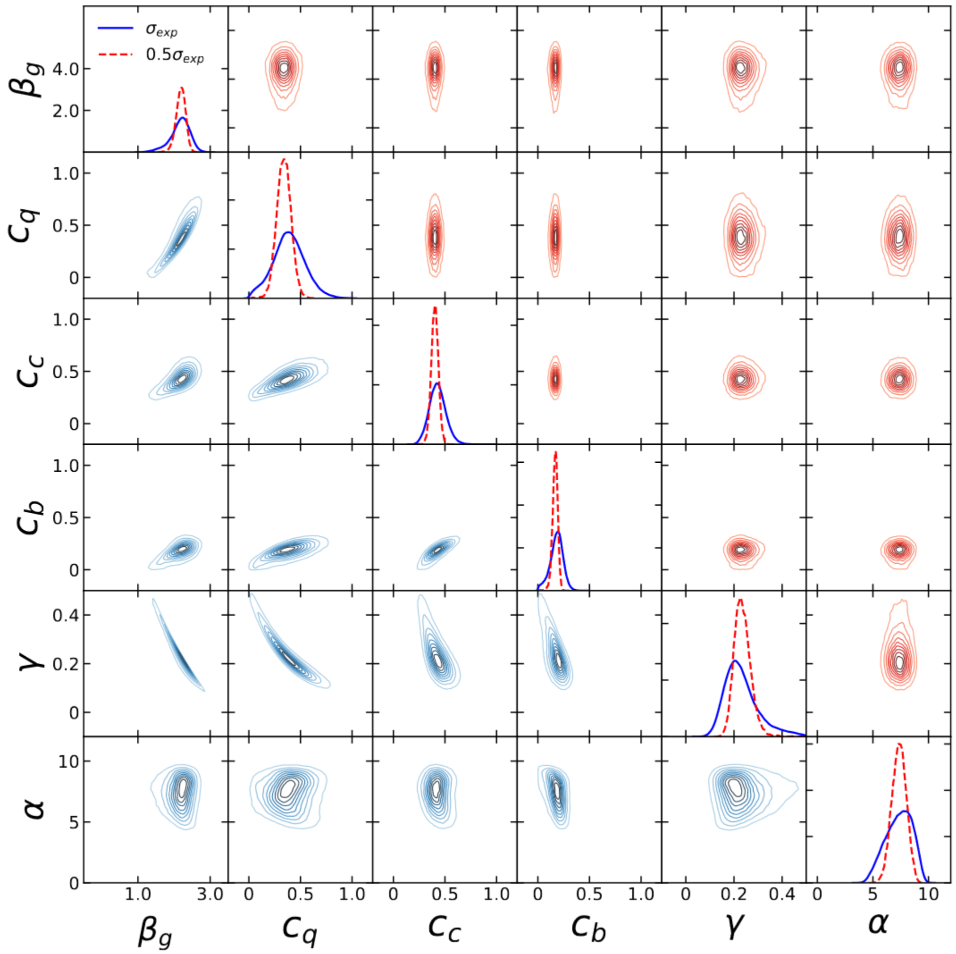
$$P(\boldsymbol{\theta}|\text{data}) \propto P(\boldsymbol{\theta})\, P(\text{data}|\boldsymbol{\theta})$$

- **Prior: uniform in the region of**
  $$[\beta_g, C_q, C_c, C_b, \gamma, \alpha] \subset [(0,10), (0,1), (0,1), (0,1), (-0.15, 0.5), (0,15)]$$
- **Likelihood: Gaussian form**
  $$P(\text{data}|\boldsymbol{\theta}) = \prod_i \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\left[y_i(\boldsymbol{\theta}) - y_i^{\text{exp}}\right]^2 / \left(2\sigma_i^2\right)}$$

Markov-Chain Monte-Carlo (MCMC)

- Random walk through parameter space weighted by posterior distribution $P(\boldsymbol{\theta}|\text{data})$.
- Generate a parameter array $X = [\theta_0, \theta_1, \theta_2, \ldots, \theta_i, \theta_{i+1}, \ldots, \theta_n]$ from which we draw the posterior distribution.

Posterior distributions of parameters

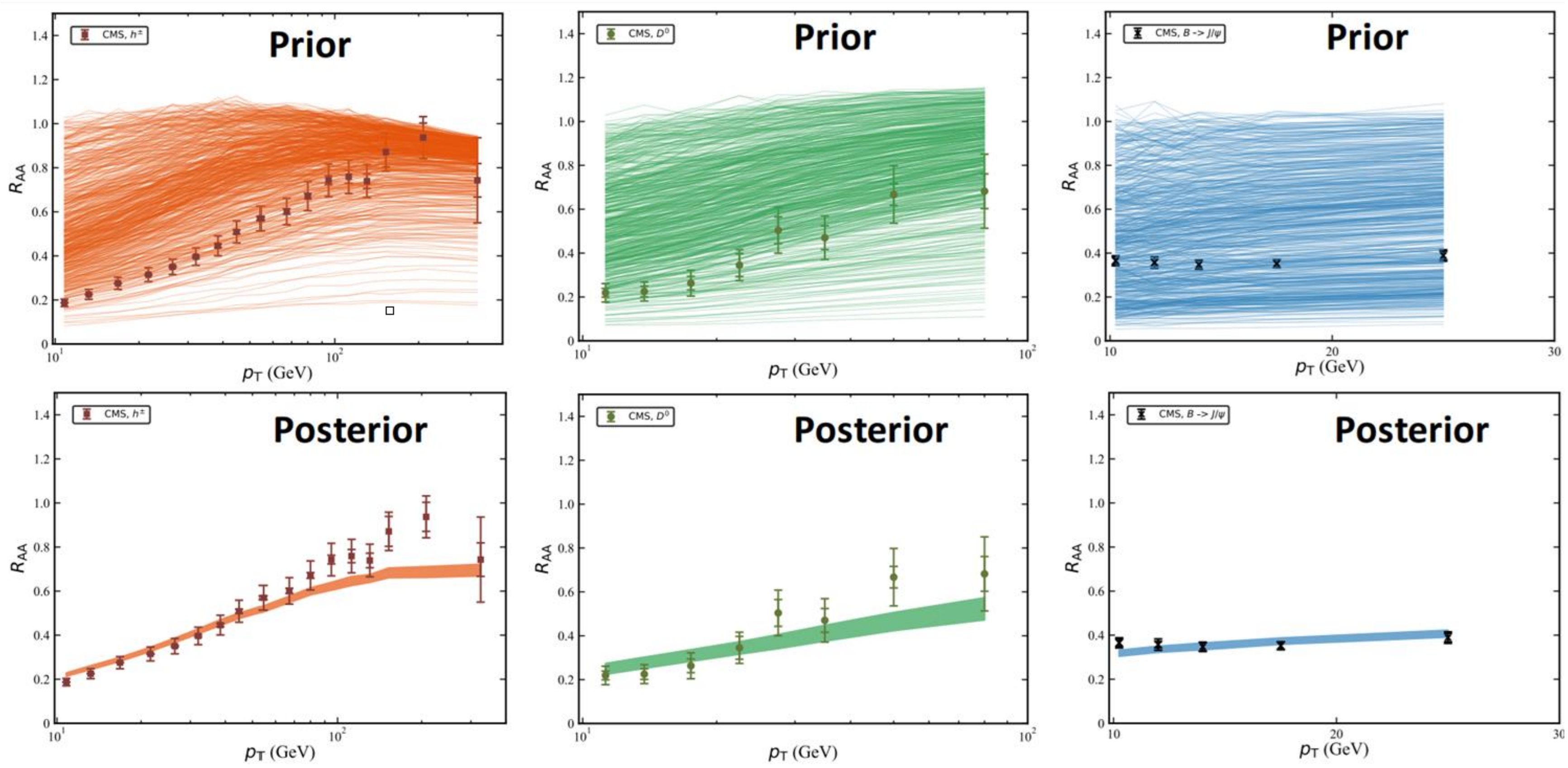


	with σ_{exp}	with $0.5\sigma_{\mathrm{exp}}$
β_g	(1.646, 2.56)	(1.96, 2.39)
C_q	(0.129, 0.65)	(0.226, 0.454)
C_c	(0.3, 0.567)	(0.344, 0.459)
C_b	(0.065, 0.277)	(0.124, 0.207)
γ	(0.137, 0.378)	(0.184, 0.295)
α	(5.287, 9.061)	(6.266, 8.401)

The energy loss parameters for jet-medium interaction can be well constrained by the Bayesian analysis.

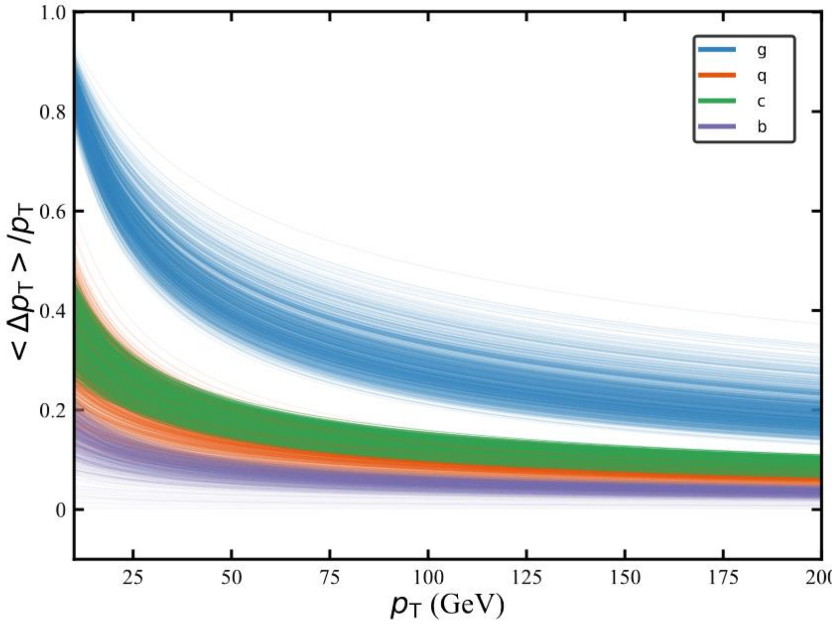
Reducing experimental data error bars can improve the precision of the extracted parameters.

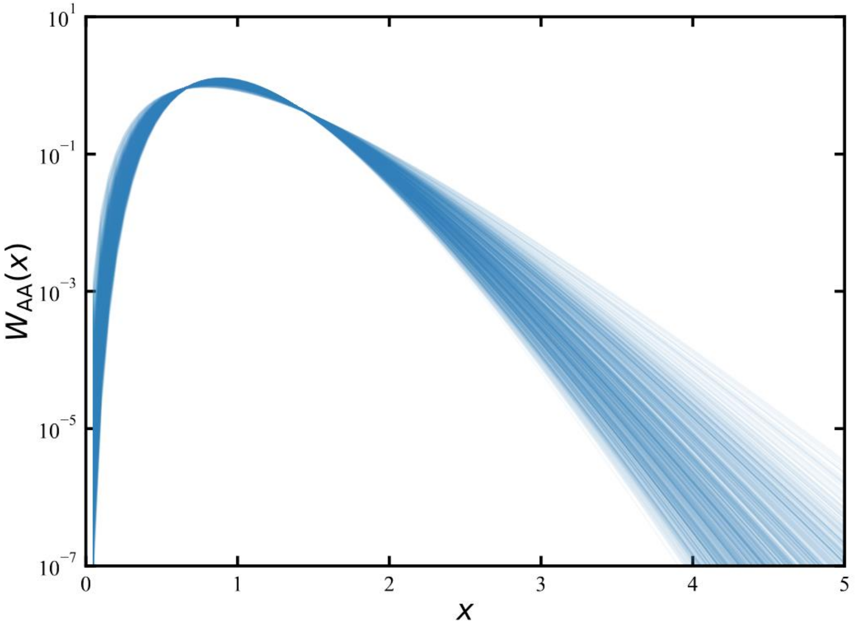
Prior and posterior R_{AA}



Our calibrated model calculation provides a simultaneous description on R_{AA} data of charged hadrons, D mesons and B-decayed J/ψ measured by CMS.

Flavor hierarchy of parton energy loss





$$\frac{1}{\langle N_{\rm coll}\rangle}\frac{d\sigma_{\rm AA\to hX}}{dp_{\rm T}^h}=\sum_j\int dp_{\rm T}^j dx dz\frac{d\hat{\sigma}_{\rm p'p'\to jX}}{dp_{\rm T}^j}(p_{\rm T}^j)\; W_{\rm AA}(x)D_{j\to h}(z)\delta\left(p_{\rm T}^h-z(p_{\rm T}^j-x\langle\Delta p_{\rm T}^j\rangle)\right)$$

$$\langle\Delta E_g\rangle>\langle\Delta E_q\rangle\sim\langle\Delta E_c\rangle>\langle\Delta E_b\rangle$$

Direct extraction of the flavor dependence of parton energy loss in QGP from data.

Provides a stringent test of pQCD calculation of parton-medium interaction.

W. J. Xing, S. Cao, GYQ, PLB 2024

Summary

- **Based on a NLO-pQCD calculation of parton production, a general ansatz for parton E-loss function & parton FF, we calculate R_{AA} for both heavy & light flavor hadrons over a wide p_T range.**

- **Using a Bayesian model-to-data analysis, we perform first simultaneous extraction of E-loss of gluons, light quarks, charm quarks & bottom quarks inside the QGP.**

- **The extracted parton E-loss inside the QGP exhibits a clear flavor hierarchy: $\langle \Delta E_g \rangle > \langle \Delta E_q \rangle \sim \langle \Delta E_c \rangle > \langle \Delta E_b \rangle$, consistent with the pQCD expectation.**

- **More data and more precise data can improve the precision for the extracted parton E-loss, providing better constraint on theoretical models.**

The 9th International Symposium on Heavy Flavor Production in Hadron and Nuclear Collisions

(HF-HNC 2024)

Guangzhou, China, December 6-11, 2024

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Linear Boltzmann Transport (LBT) Model

- **Boltzmann equation:** $p_1 \cdot \partial f_1(x_1, p_1) = E_1 C\left[f_1\right]$
- **Elastic collisions:**

$$\Gamma_{12\to34} = \frac{\gamma_2}{2E_1} \int \frac{d^3p_2}{(2\pi)^3 2E_2} \int \frac{d^3p_3}{(2\pi)^3 2E_3} \int \frac{d^3p_4}{(2\pi)^3 2E_4}$$
$$\times f_2(\vec{p}_2)\left[1 \pm f_3(\vec{p}_1 - \vec{k})\right]\left[1 \pm f_4(\vec{p}_2 + \vec{k})\right]$$
$$\times (2\pi)^4 \delta^{(4)}(p_1 + p_2 - p_3 - p_4)|\mathcal{M}_{12\to34}|^2$$

$$P_{el} = 1 - e^{-\Gamma_{el}\Delta t}$$

Matrix elements taken from LO pQCD

- **Inelastic collisions:** $\langle N_g \rangle = \Gamma_g \Delta t = \Delta t \int dx dk_\perp^2 \frac{dN_g}{dx dk_\perp^2 dt}$

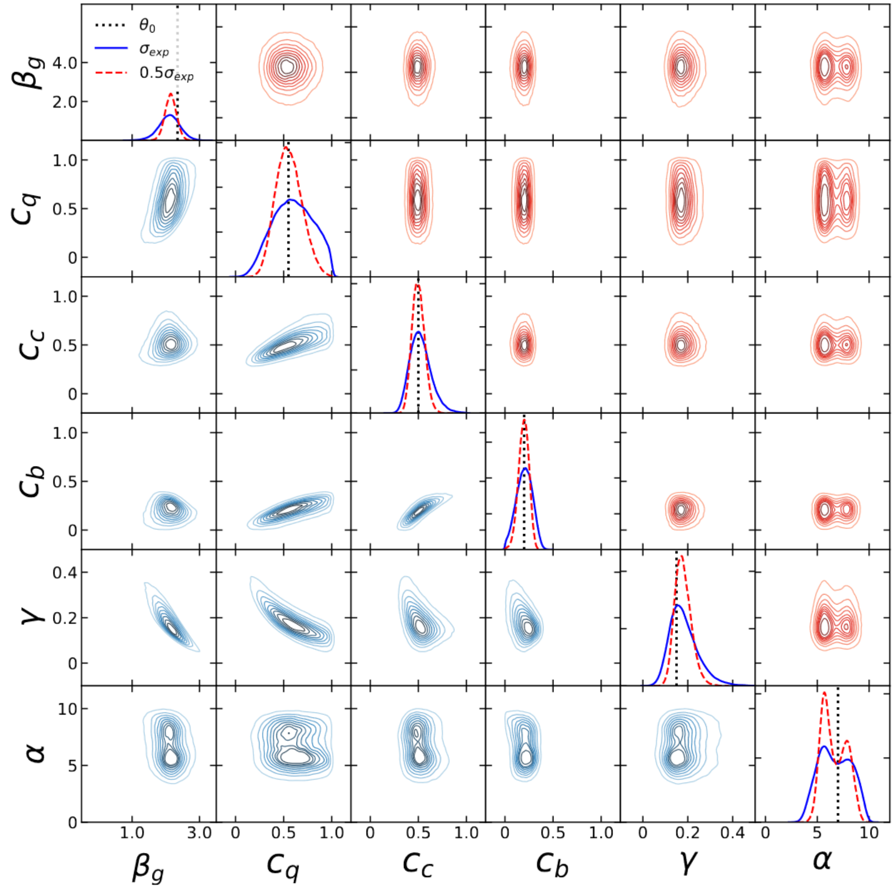
$$P_{inel} = 1 - e^{-\langle N_g \rangle}$$

Medium-induced radiation spectra taken from HT: Guo, Wang PRL 2000; Zhang, Wang, Wang, PRL 2004; Zhang, Hou, GYQ, PRC 2019; Zhang, GYQ, Wang, PRD 2019.

- **Elastic + Inelastic:** $P_{tot} = 1 - e^{-\Gamma_{tot}\Delta t} = P_{el} + P_{inel} - P_{el}P_{inel}$

He, Luo, Wang, Zhu, PRC 2015; Cao, Luo, GYQ, Wang, PRC 2016, PLB 2018; etc.

Closure test



	$\boldsymbol{\theta}_0$	with $\sigma_{\rm exp}$	with $0.5\sigma_{\rm exp}$
β_g	2.35	(1.565, 2.614)	(1.862, 2.49)
C_q	0.55	(0.266, 0.928)	(0.344, 0.789)
C_c	0.5	(0.362, 0.725)	(0.398, 0.61)
C_b	0.2	(0.063, 0.331)	(0.102, 0.278)
γ	0.15	(0.095, 0.303)	(0.125, 0.245)
α	7.0	(4.349, 9.146)	(5.01, 8.561)

Start with a pre-set point $\boldsymbol{\theta}_0$ to calculate R_{AA} of hadrons, which serves as the middle points of pseudo-data (the error bars are taken from the experiments data).

Confirm that the posterior distributions from Baysian analysis do agree with the pre-set value $\boldsymbol{\theta}_0$.

Halving the error bars of the pseudo-data can improve the precision of the extracted parameters.