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Information field based global Bayesian inference of the jet transport coefficient

Man Xie (SCNU)

Poster #32

Gradient tomography of dijets in heavy-ion collisions

Yayun He (SCNU)

Xin-Nian Wang

Lawrence Berkeley National Laboratory

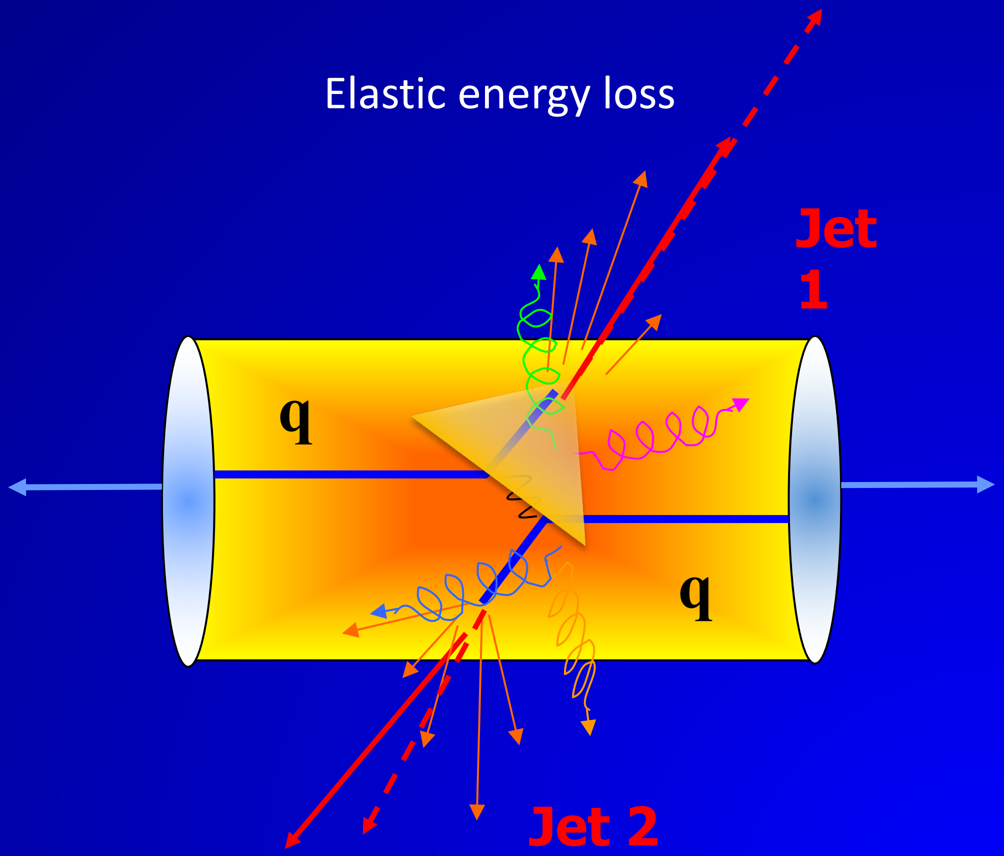
Parton energy loss and jet transport

$$\frac{dE_{rad}}{dx} \approx E\frac{2C_A\alpha_s}{\pi}\hat{q}(x)\int dz\frac{d\ell_\perp^2}{\ell_\perp^4}zP(z)\sin^2\frac{\ell_\perp^2(x-x_0)}{4z(1-z)E} \propto \alpha_s\hat{q}L$$

(High-twist approach)

$$\frac{dE_{el}}{dx} = \int\frac{d^3k}{(2\pi)^3}dq_\perp^2 f(k)\frac{q_\perp^2}{2k}\frac{d\sigma}{dq_\perp^2} \approx \langle\frac{1}{2\omega}\rangle\hat{q}$$

Elastic energy loss



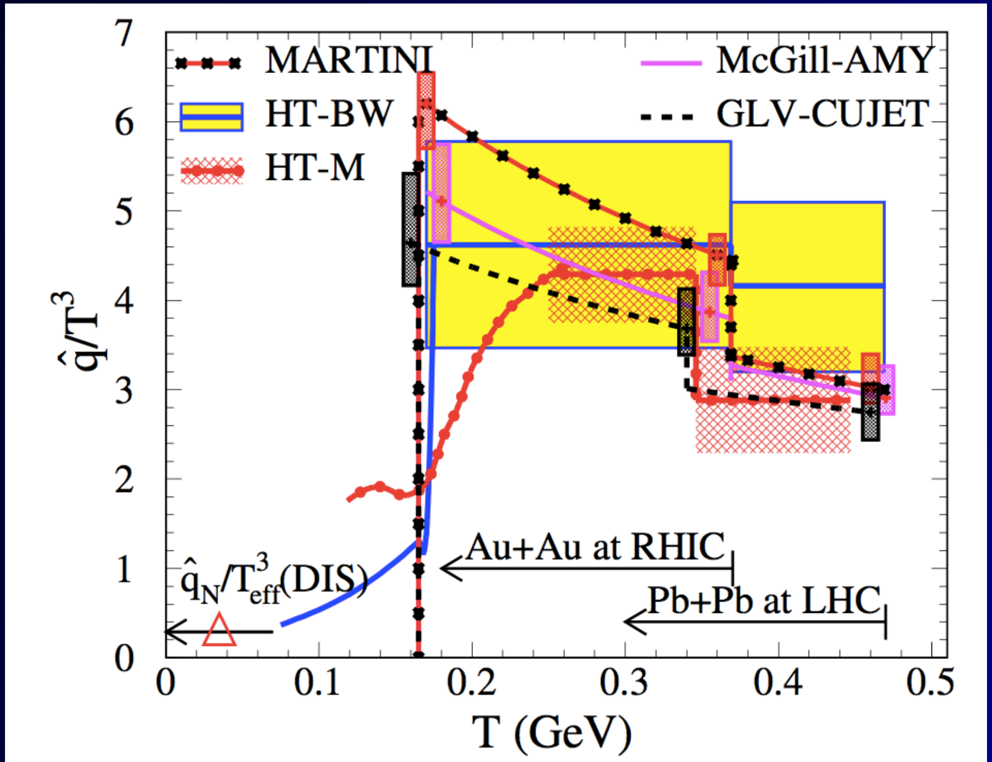
Jet transport coefficient:

$$\hat{q}(y) = \frac{4\pi^2\alpha_s C_R}{N_c^2-1}\rho(y)xG(x)|_{x\approx 0} = \frac{\langle q_\perp^2\rangle}{\lambda}$$

Jet Quenching at RHIC & LHC

JET Collaboration:

e-Print: 1312.5003



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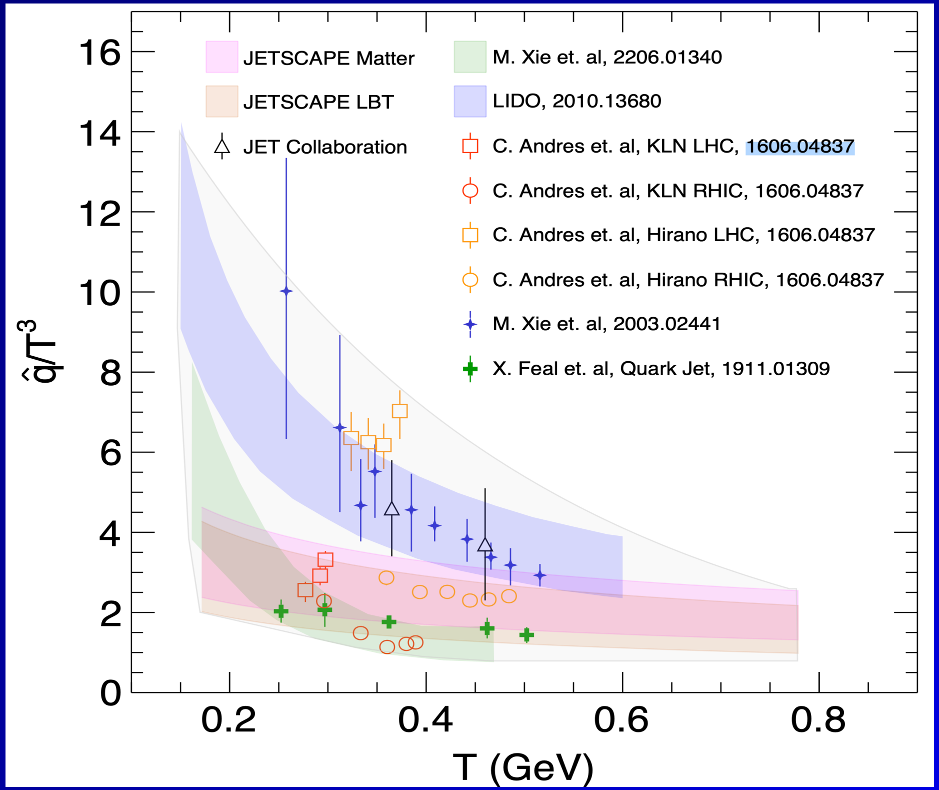
Apolinario, Lee & Winn



$$\hat{q} \approx \begin{cases} 1.2 \pm 0.3 \\ 1.9 \pm 0.7 \end{cases} \mathrm{GeV}^2/\mathrm{fm} \;\; \text{at} \;\; \begin{array}{l} \mathrm{T{=}370\ MeV,} \\ \mathrm{T{=}470\ MeV,} \end{array}$$

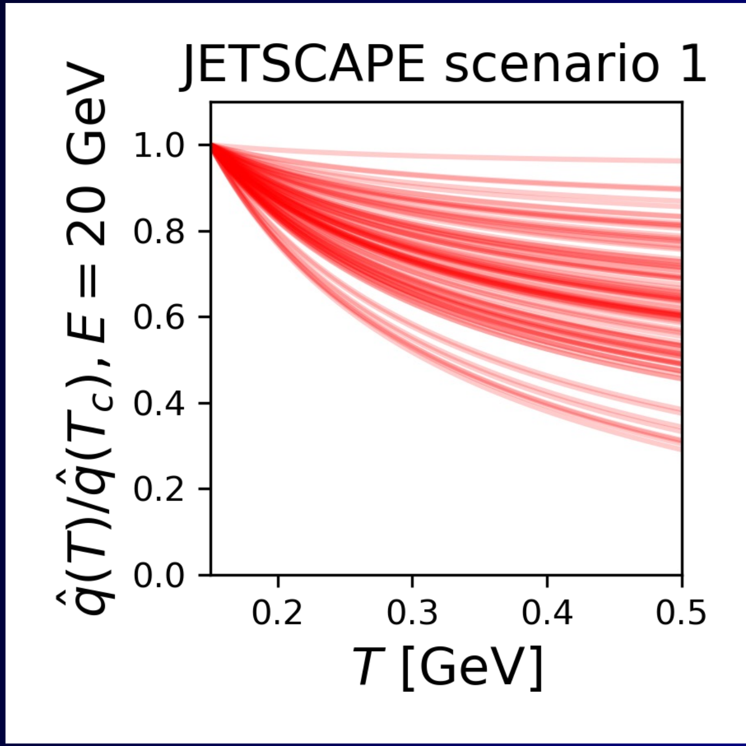
Information Field approach to Bayesian Inference

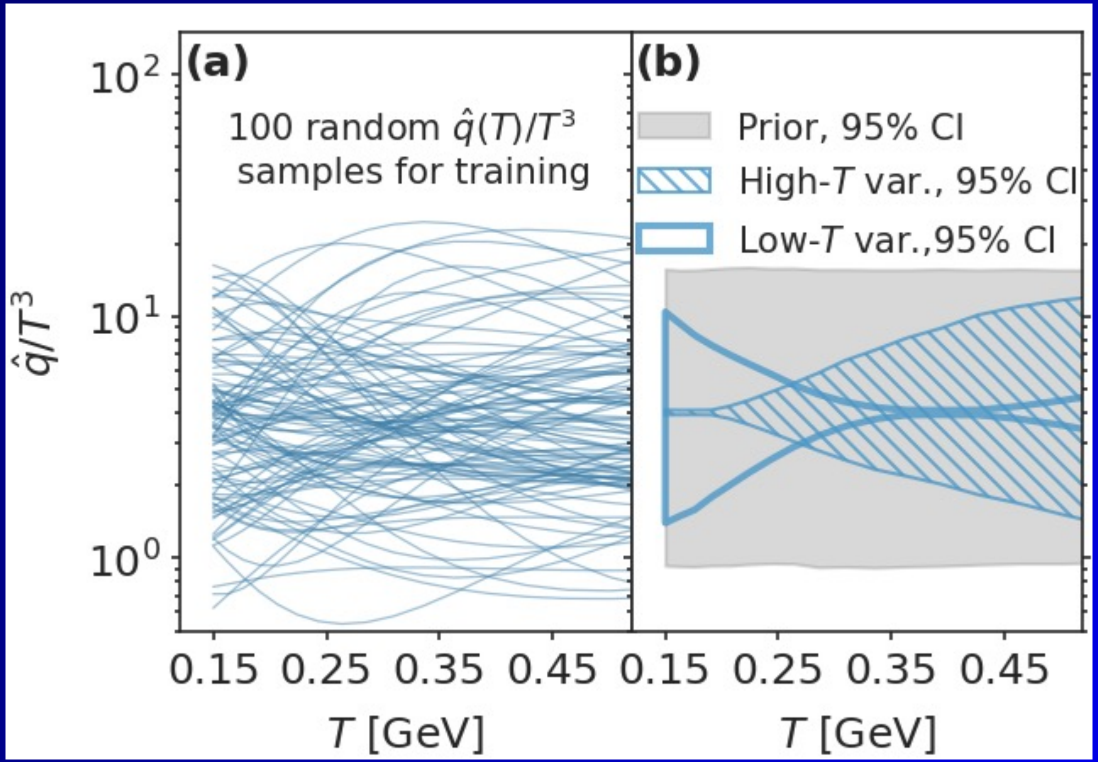
non-parametric representation of an unknown function

$$\text{Gaussian random field } F(x):$$

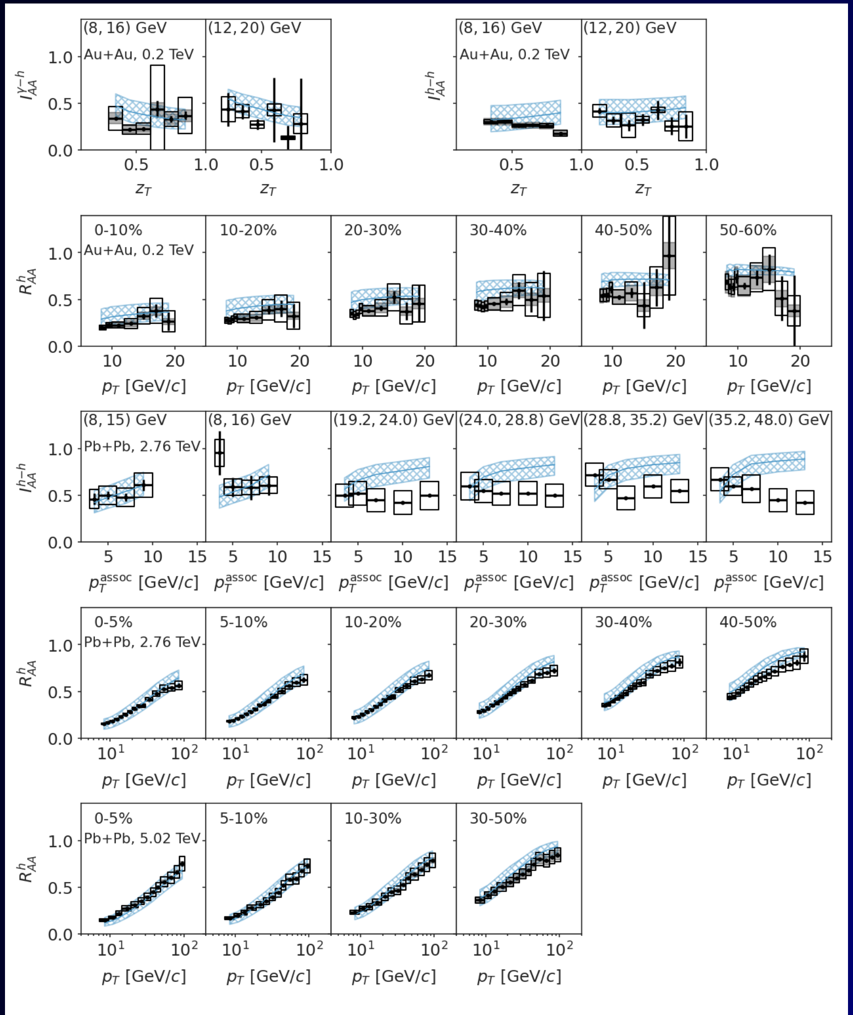
$$\langle F(x)\rangle = \mu(x)$$

$$\langle [F(x)-\mu(x)]\,[F(x')-\mu(x')]\rangle = C(x,x')$$



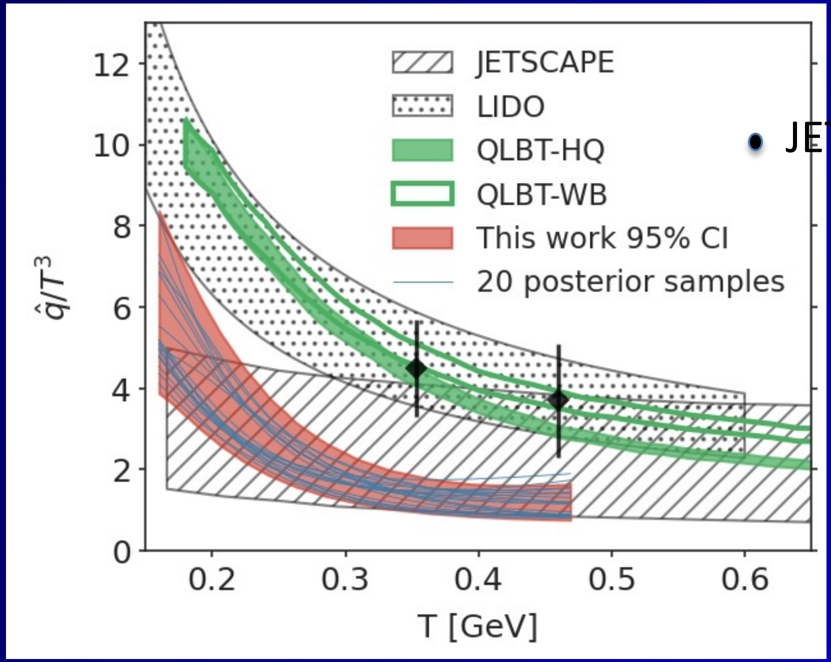


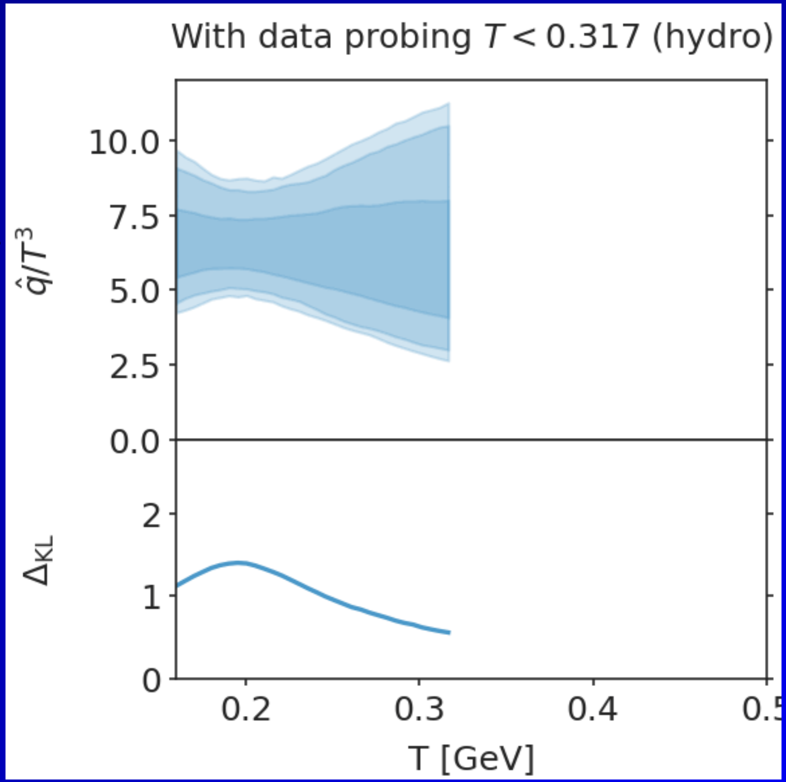
IF-Bayesian inference of jet transport coefficient



The most comprehensive Bayesian analysis of world data on single inclusive, dihadron and gamma-hadron spectra

Strong T-dependence
Weak E-dependence



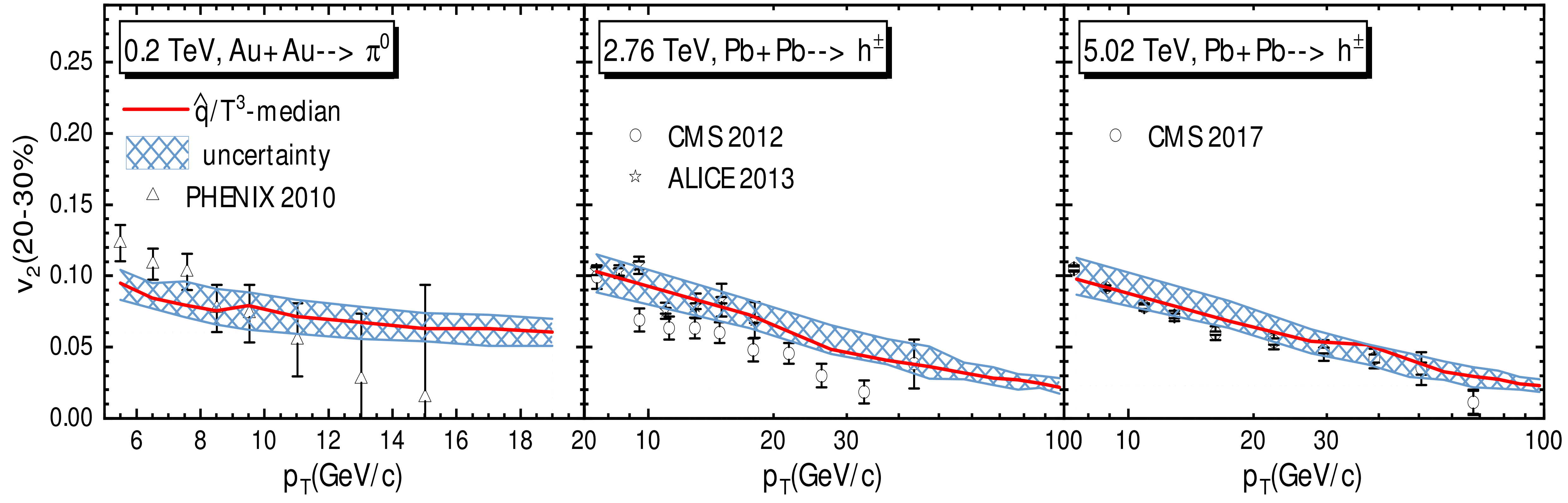


e-Print: 2208.14419
e-Print: 2206.01340

Xie, Ke, Zhang & XNW

BERKELEY LAB

High pT v2



0.2 TeV, Au+Au--> π^0
$\hat{q}/T^3$-median
uncertainty
PHENIX 2010
2.76 TeV, Pb+Pb--> $h^\pm$
CMS 2012
ALICE 2013
5.02 TeV, Pb+Pb--> $h^\pm$
CMS 2017
v_2(20-30%)
p_T(GeV/c)
0.00
0.05
0.10
0.15
0.20
0.25
6
8
10
12
14
16
18
20
10
20
30
100
10
20
30
100

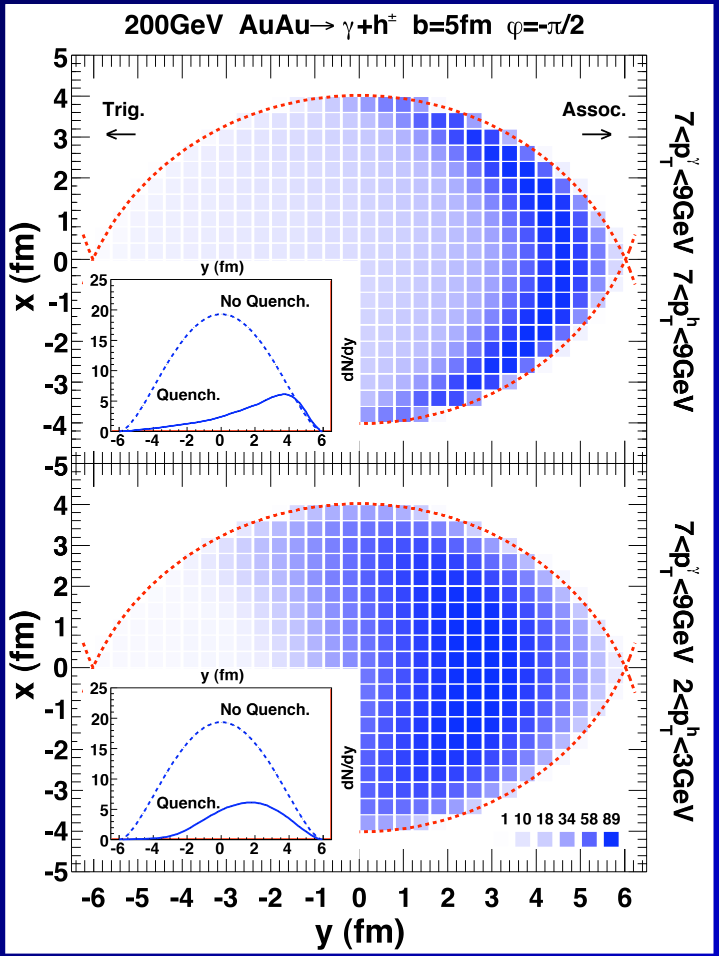
Longitudinal jet tomography with gamma-jet

Zhang, Owens, Wang and XNW, Phys. Rev. Lett. 103, 032302 (2009)

length dependence
of parton Energy loss

γ-jet asymmetry $x_{\gamma jet}=p_T^{jet}/p_T^{\gamma}$

Can be used to select
propagation length <L>



$p_T^h/p_T^\gamma \sim 1$

$p_T^h/p_T^\gamma \sim 0.3$

Asymmetric-diffusion in nonuniform medium

$$\frac{\partial f}{\partial t} + \frac{\vec{p}_\perp}{E} \cdot \frac{\partial f}{\partial \vec{r}_\perp} = \frac{\hat{q}}{4} \vec{\nabla}^2_{p_\perp} f(\vec{p}, \vec{r})$$

Boltzmann equation under approximation of small angle elastic scattering, no drag:

$$f_s = 3\left(\frac{4E}{\hat{q}t^2}\right)^2 \exp\left[-(\vec{r}_\perp - \frac{\vec{p}_\perp}{2E}t)^2 \frac{12E^2}{\hat{q}t^3} - \frac{p_\perp^2}{\hat{q}t}\right]$$

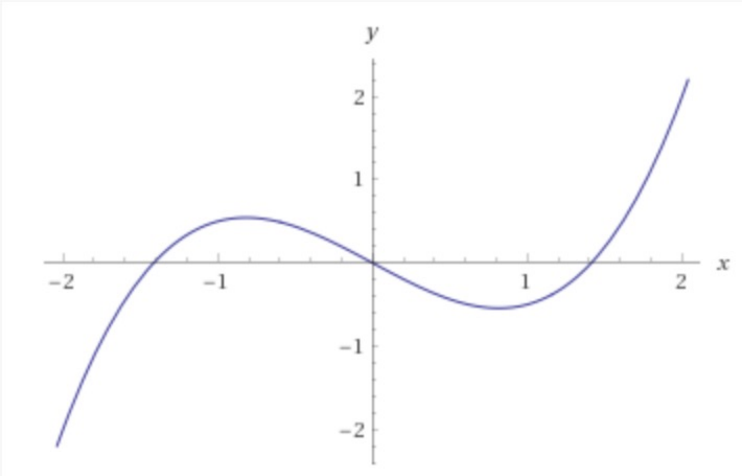
$$\hat{q} = \hat{q}_0 + \vec{x}_\perp \cdot \vec{a}$$

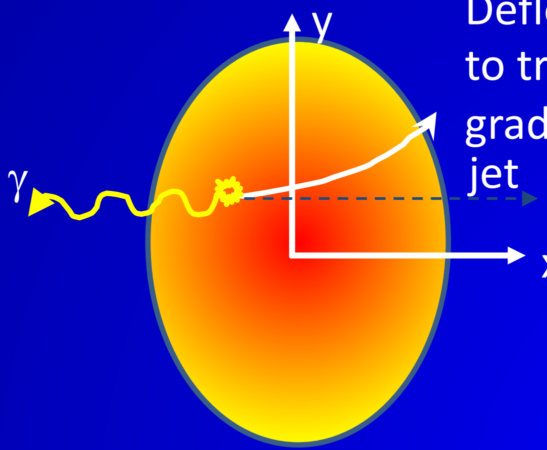
Momentum asymmetry:

$$\delta f(\vec{p}_\perp) = -\frac{t}{3\omega\hat{q}_0} \vec{a} \cdot \vec{p}_\perp \left(1 - \frac{p_\perp^2}{2\hat{q}_0 t}\right) f_s(\vec{p}_\perp, t) + \mathcal{O}(a^2)$$

He, Pang & XNW,
PRL 125 (2020) 12, 122301

Barata, Sadofyev, XNW
Phys. Rev.D 107 (2023) 5, L051503



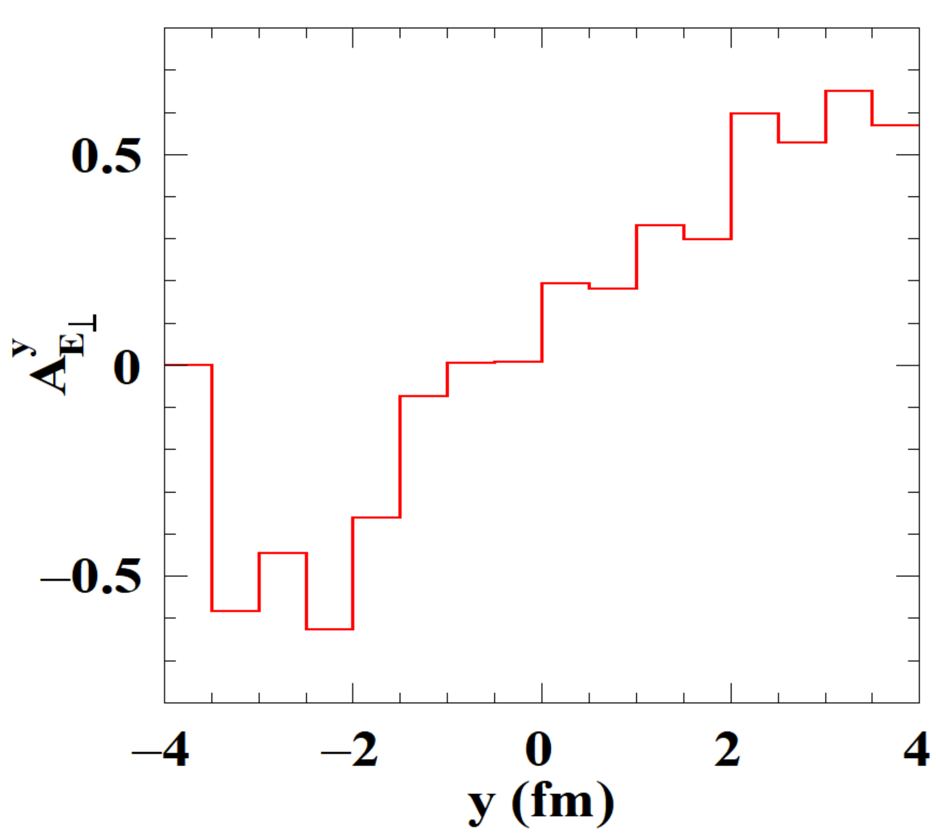


Deflection due to transverse gradient along y
jet

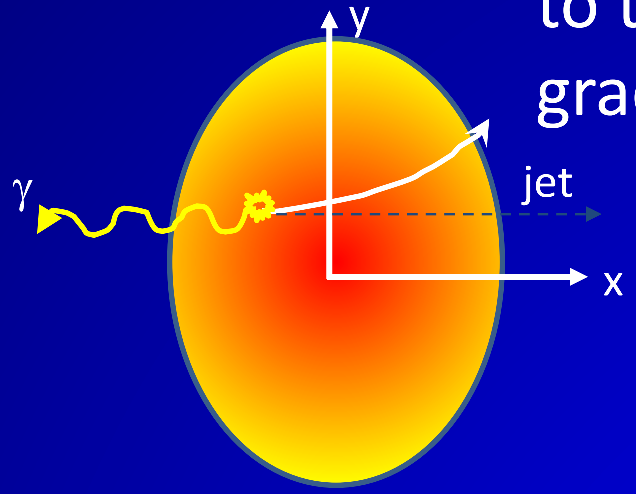
Transverse gradient tomography with gamma-jet

$$A^{\vec{n}}_{E_\perp} = \frac{\int d^3r d^3p f_a(\vec{p},\vec{r})\vec{p}_T\cdot\vec{n}}{\int d^3r d^3p f_a(\vec{p},\vec{r})} = \frac{E_T^{up} - E_T^{dn}}{E_T^{up} + E_T^{dn}}$$

(p_T>3 GeV/c)



drift due to transverse gradient along y



He, Pang & XNW, *Phys Rev Lett* 125 (2020) 12, 122301

Jet energy loss → propagation length → initial jet position in x: Longitudinal tomography

3D jet tomography

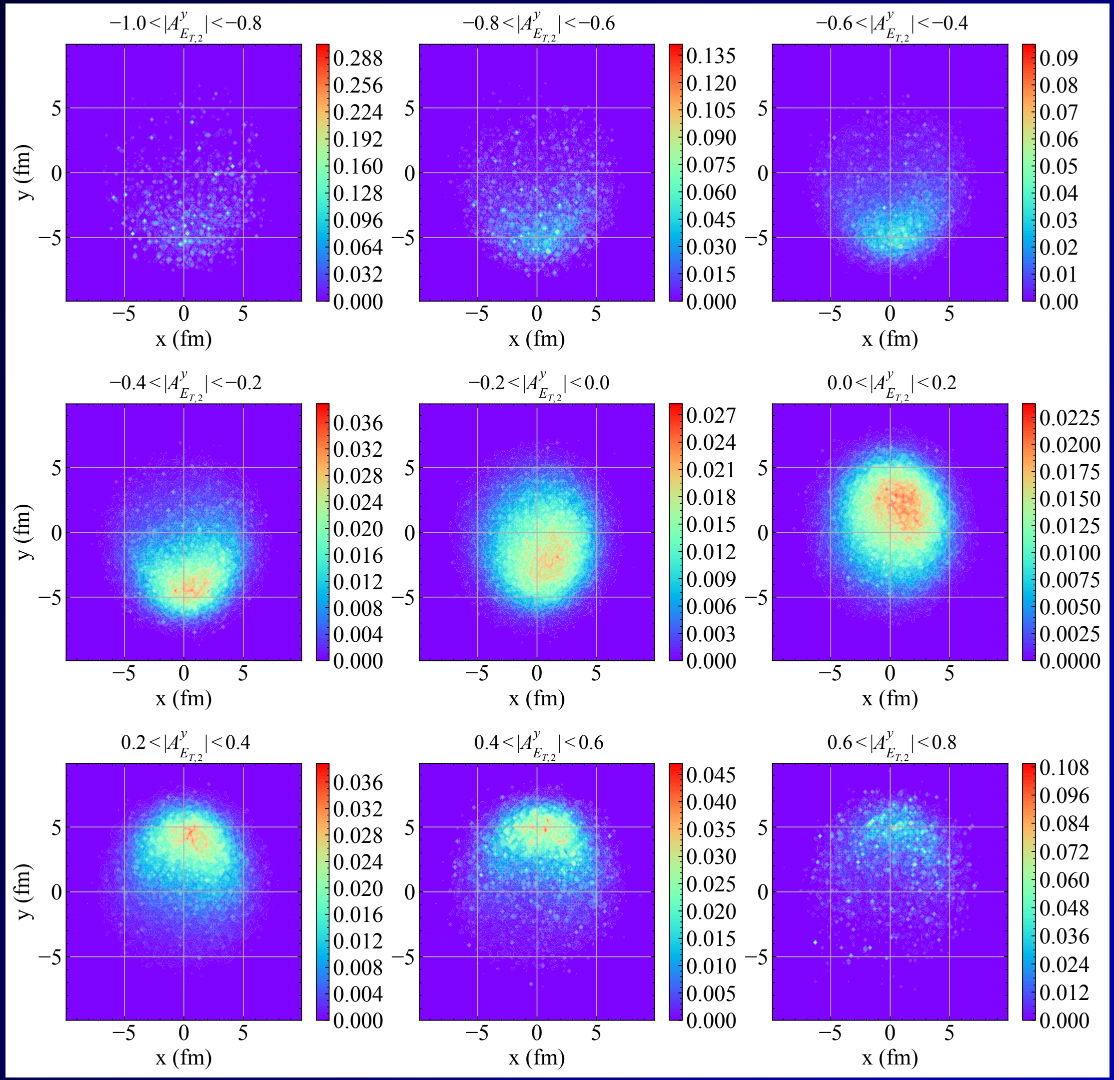
Gradient tomography for dijets

$A_{E_T} = -0.9 \to -0.3$

$A_{E_T} = -0.3 \to 0.3$

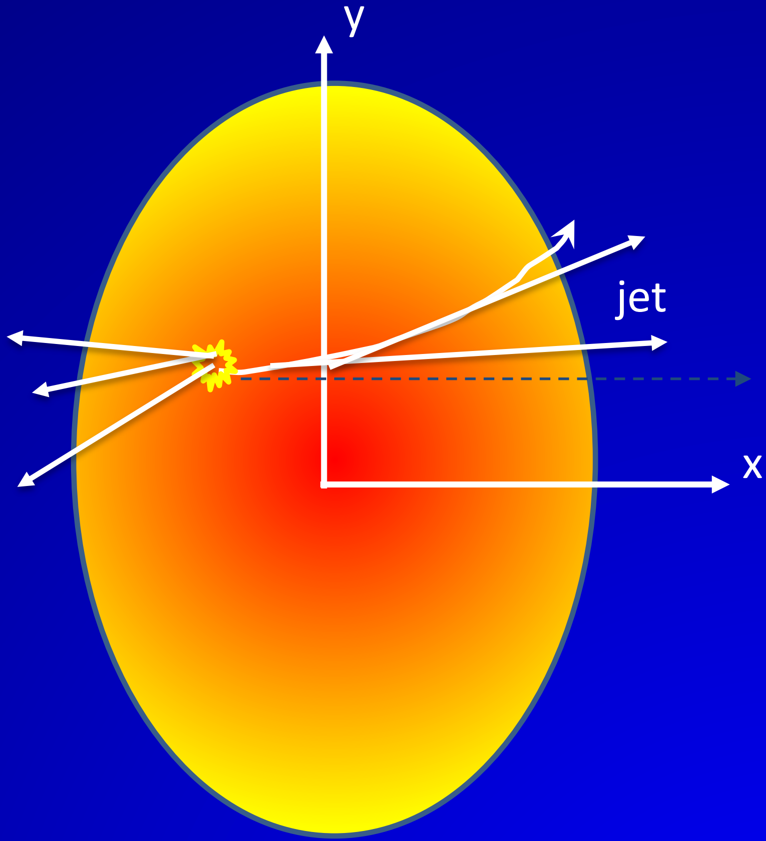
$A_{E_T} = 0.3 \to 0.7$

y



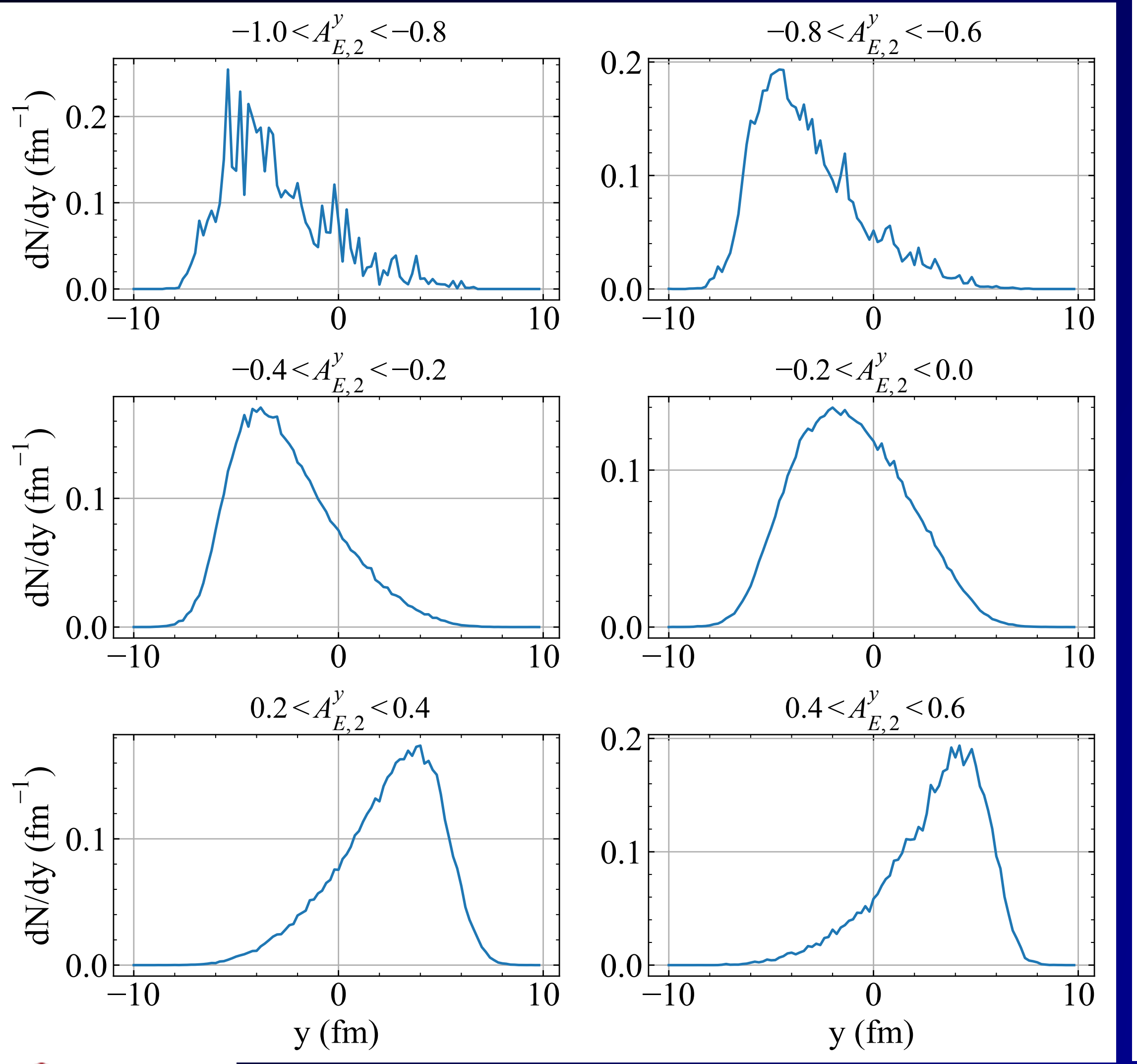
x

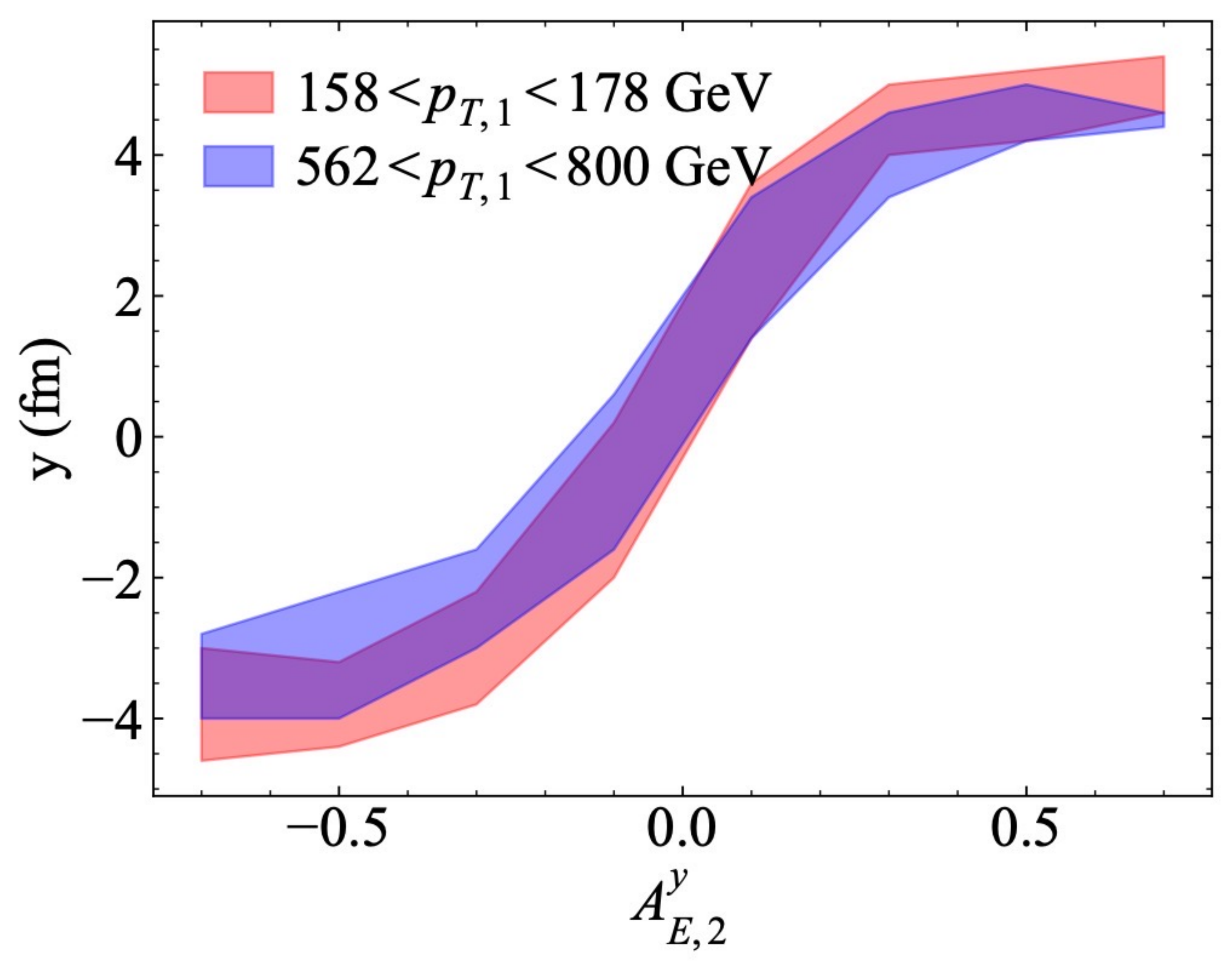
Pb+Pb 0-10% 5.02 TeV



158 < p_{T,1} < 178 GeV

Gradient tomography for dijets

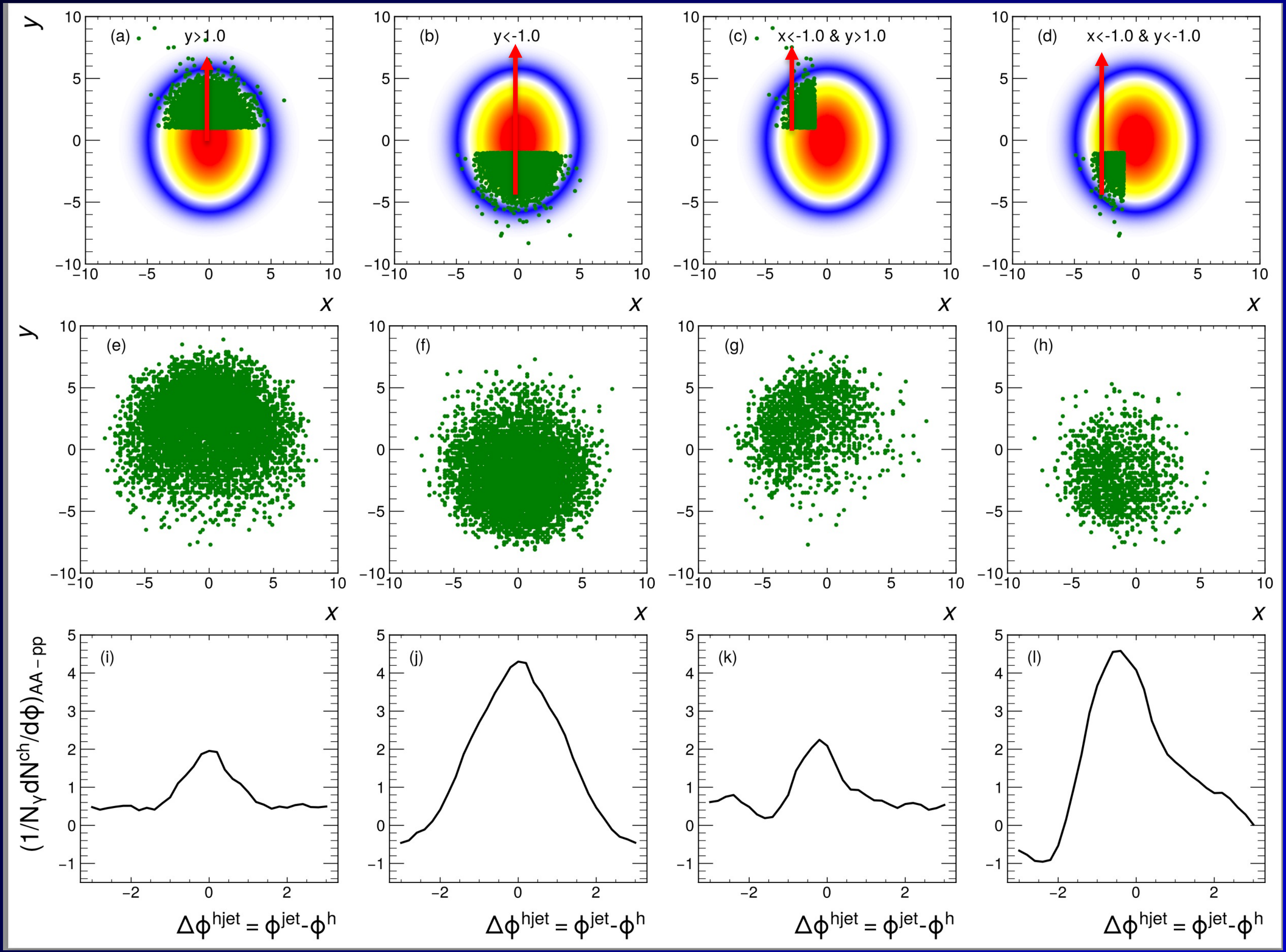




158 < p_{T,1} < 178 GeV

Pb+Pb 0-10% 5.02 TeV

Deep learning assisted jet tomography



DL network selection

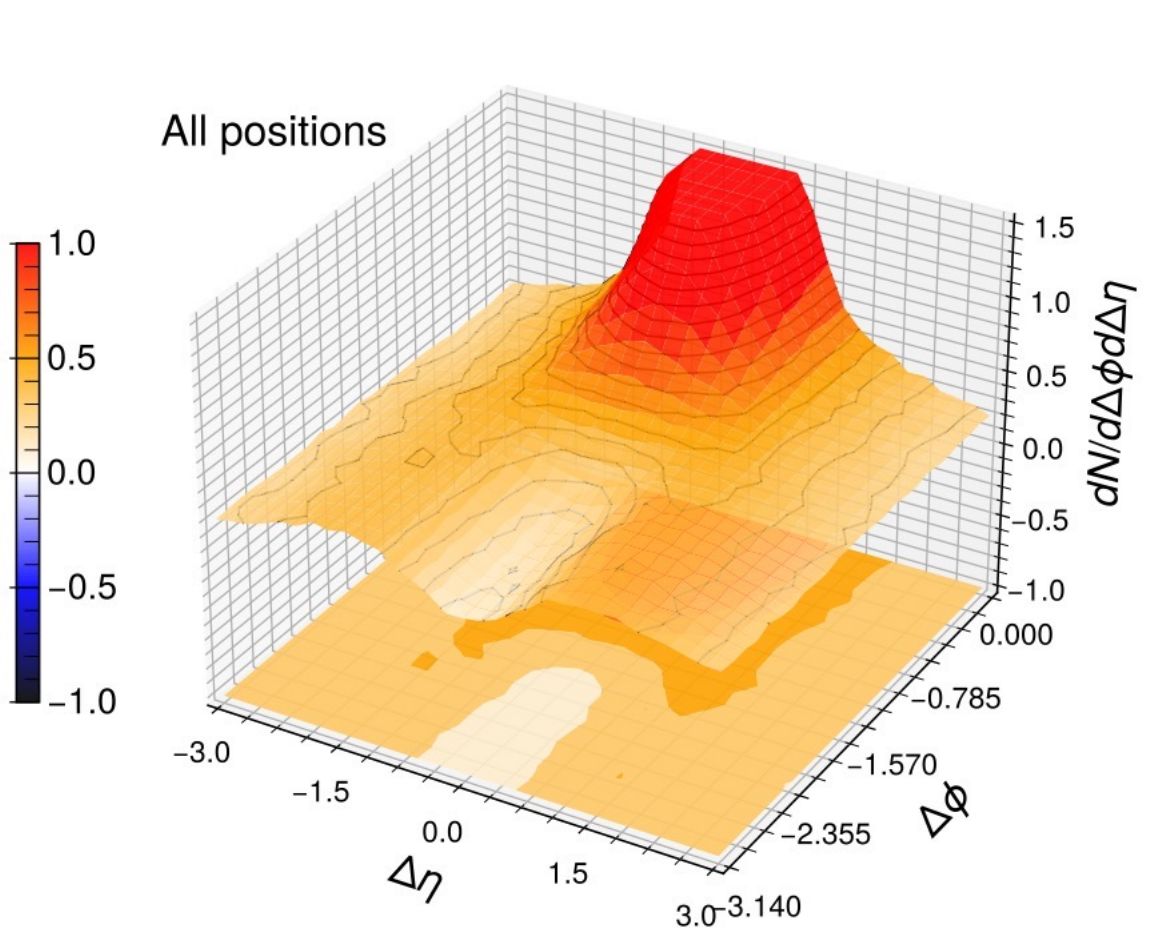
Actual distribution

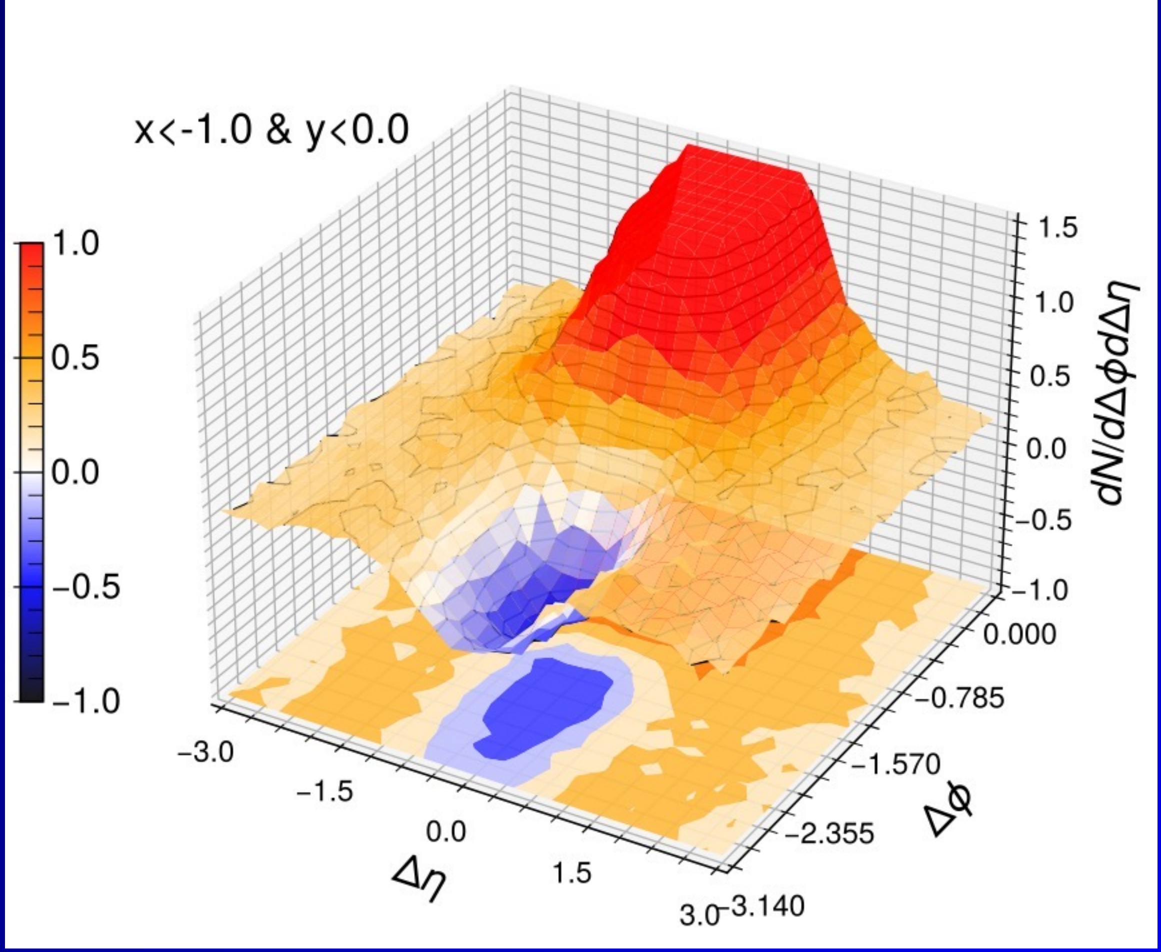
γ-soft hadron correlation

Yang, He, Chen, Ke, Pang and XNW, 2206.02393

p_T^γ=200-250 GeV/c, p_T^{jet}>100 GeV/c, p_T^h=1-2 GeV/c in 0-10% Pb+Pb @ 5.02 TeV

Enhanced DFW signal with ML jet tomography



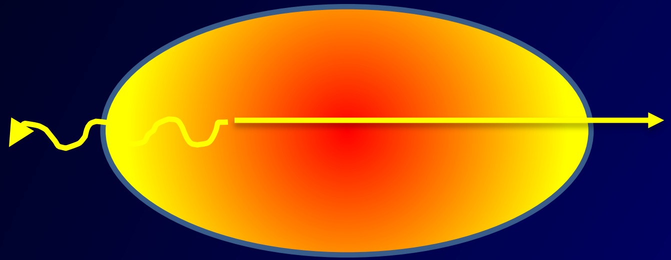


p_T^{γ}=200-250 GeV/c, p_T^{jet}>100 GeV/c, p_T^{h}=1-2 GeV/c in 0-10% Pb+Pb @ 5.02 TeV

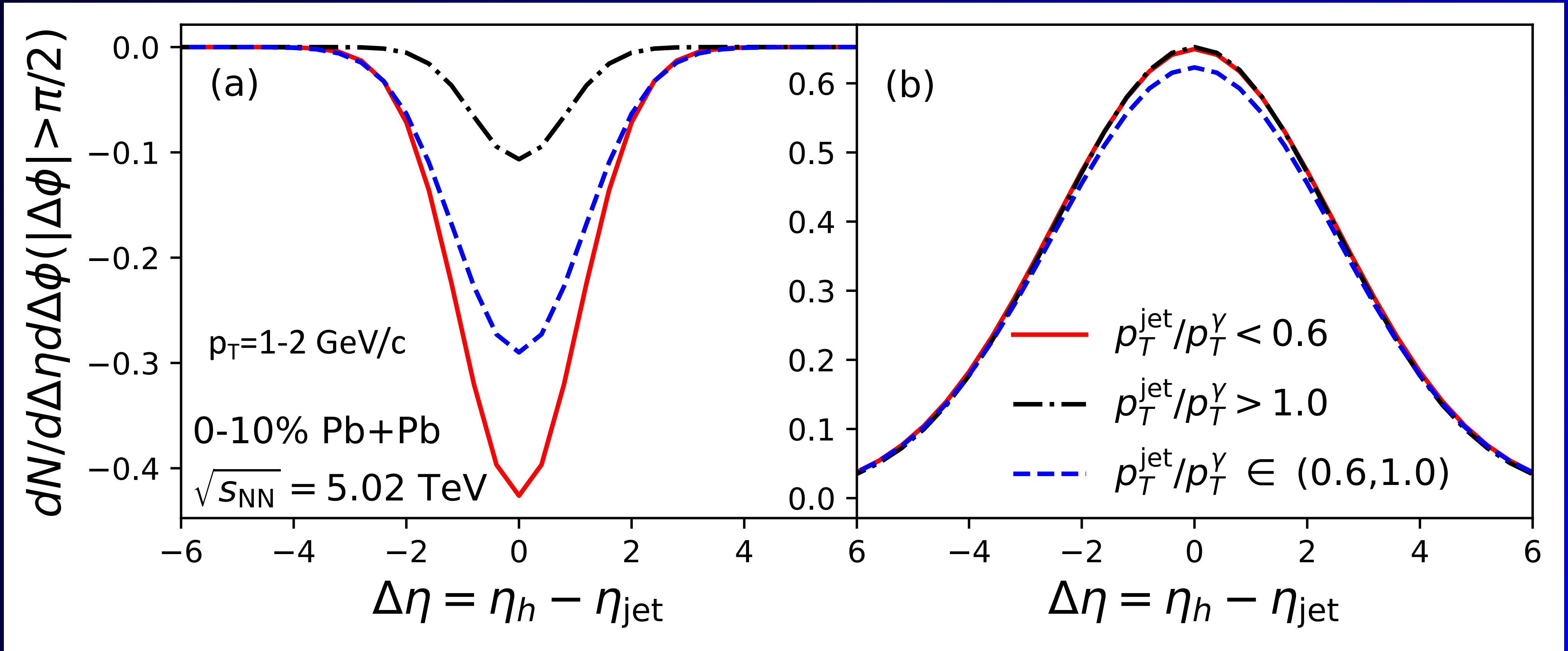
Summary

- Information-Field based Bayesian inference provides unbiased nonparametric priors
  - Reduce correlation between errors at different T
  - qhat has stronger T dependence
- Parton propagation in nonuniform medium leads to asymmetric pT broadening
- Gradient jet tomography provides unparalleled information about initial production position for jet studies

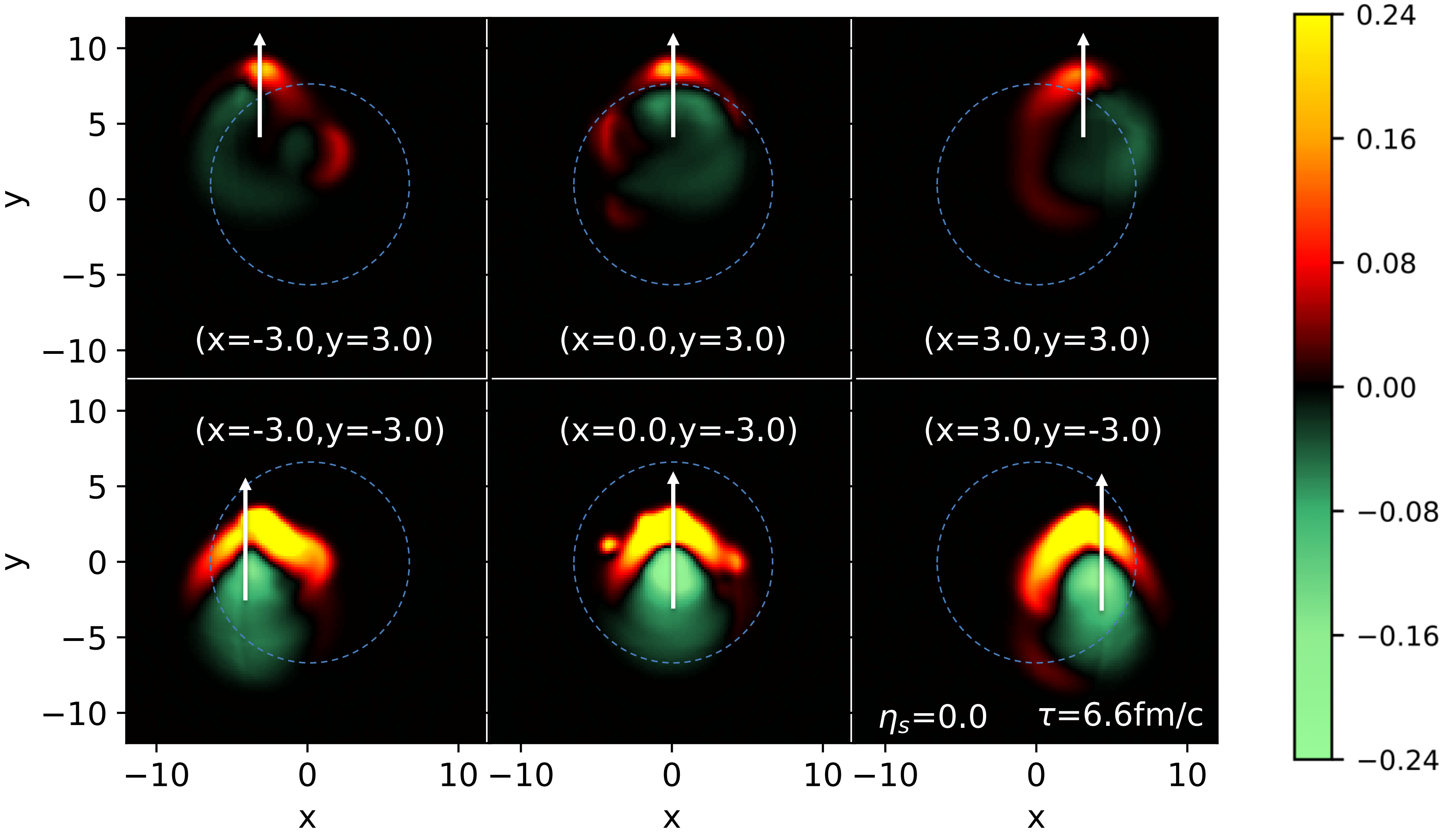
γ/jet asymmetry and diffusion wake



Larger γ/jet asymmetry → more energy loss
→ long propagation length → larger diffusion wake



Jet trajectories & Mach cone shapes



p_T^{γ}=200-250 GeV/c, p_T^{jet}>100 GeV/c in 0-10% Pb+Pb @ 5.02 TeV