Heavy ion physics with machine learning

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Shandong Institute of Advanced Technology

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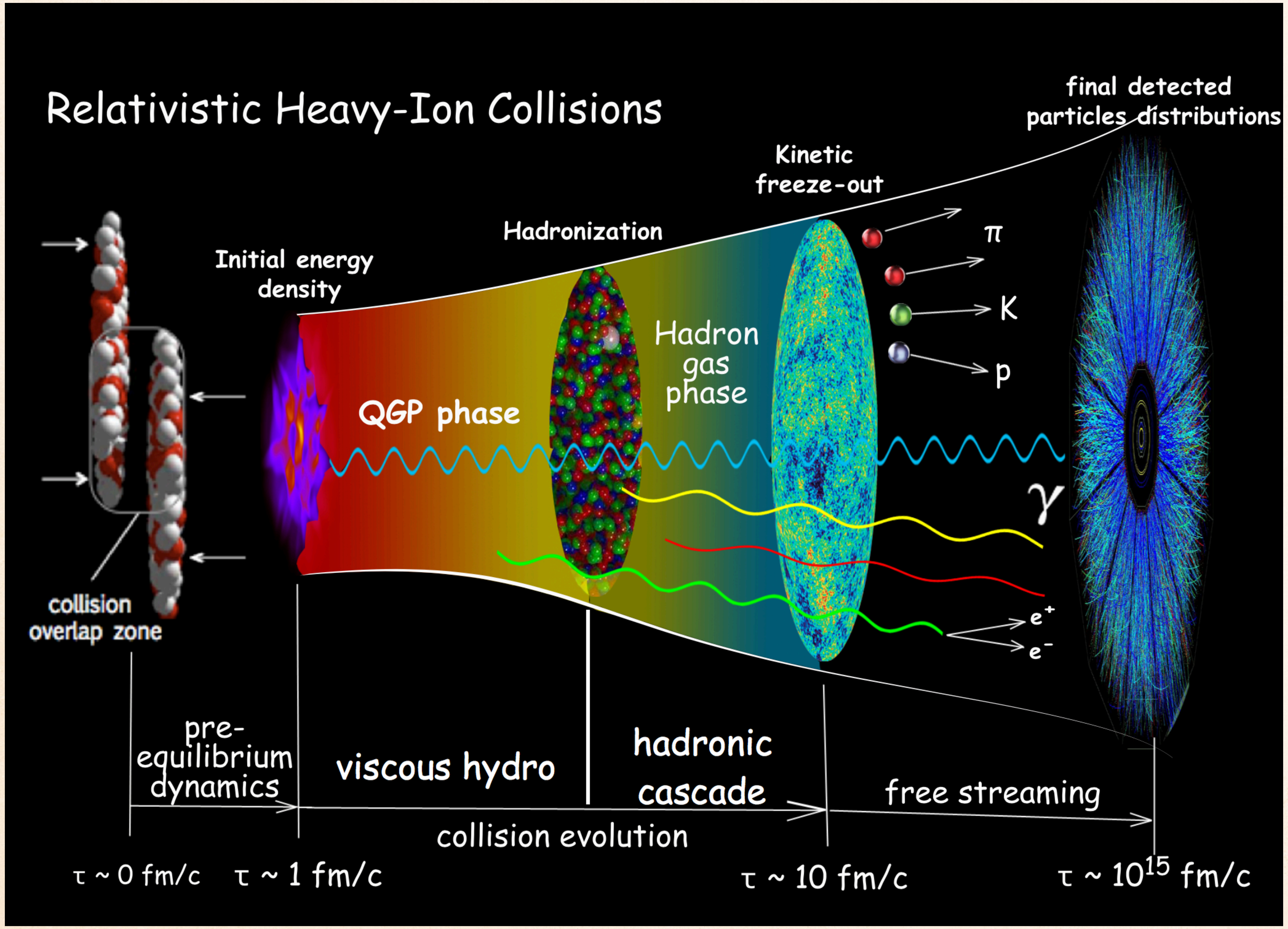
Hiroshima, Japan

Heavy ion collisions



- Multi-stages process
- Soft & hard probes
- Various inverse problems
- ML can contribute a lot!

Outline

- Bayesian analysis:
    - QGP Properties—EoS, Viscosities η/s, ξ/s, Jet transport $\hat{q}$, Diffusion coeff. D_S, Quasi-parton mass
- Unsupervised learning
    - Harmonic flows
- Supervised learning
    - Initial states: Impact parameter, nuclear deformation, α-cluster
    - EoS, Heavy flavor in-medium potential
    - Jet quenching

Bayesian analysis

$$P(y \mid x)\, P(x) = P(x \mid y)\, P(y)$$

$$P(y|x) = \frac{P(x|y)\,P(y)}{P(x)}$$

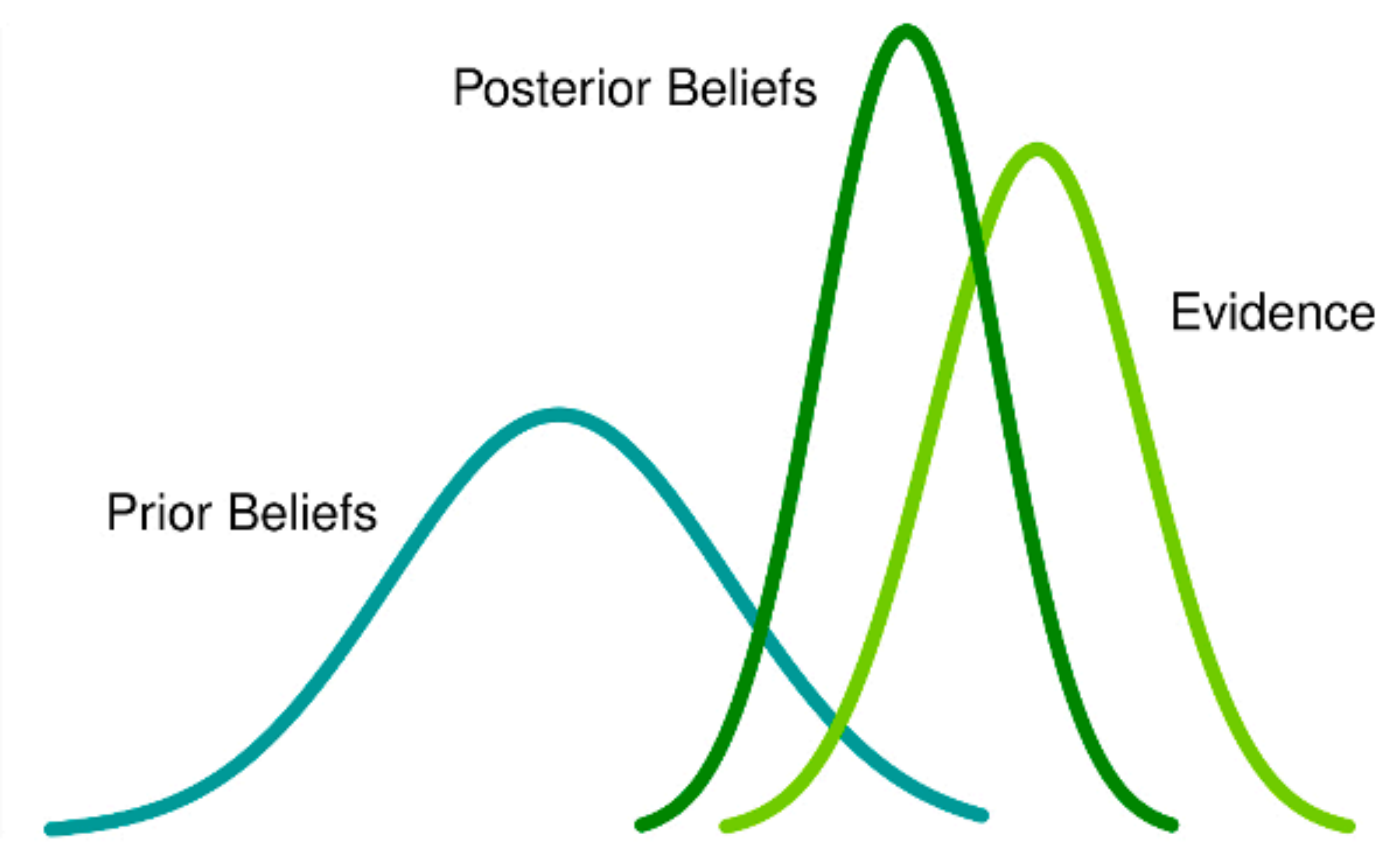
$$P(y \mid x) \propto P(x \mid y)\, P(y)$$

x: data (observables designed by experts)
y: model parameters

P(y | x): Posterior distribution
P(x | y): Likelihood

P(y): a prior

$P(x) = \int P(x|y)\,P(y)\,dy$: evidence



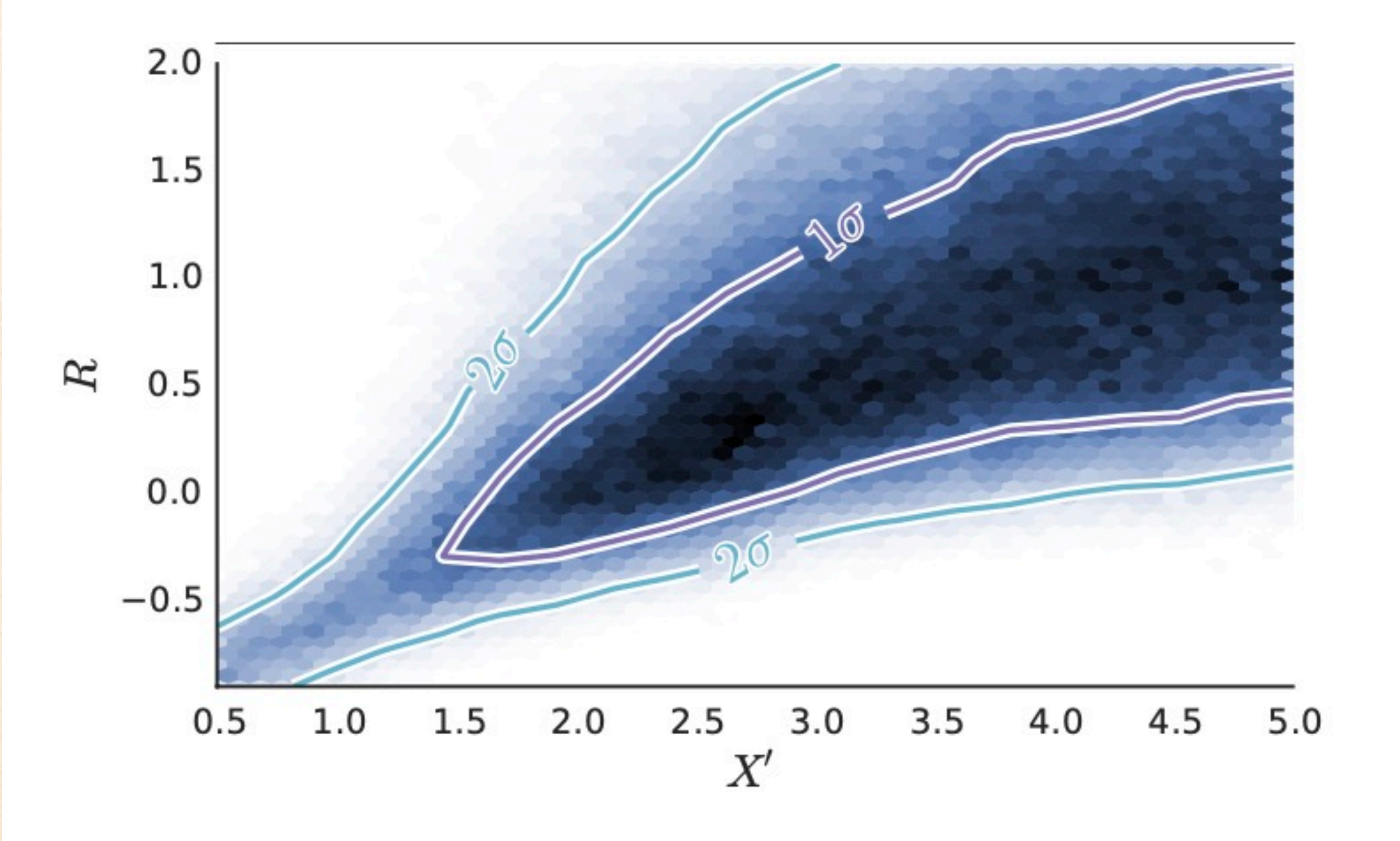
Infer the parameters with prior knowledge and reasonable likelihood given the data!

Bayesian analysis for EoS

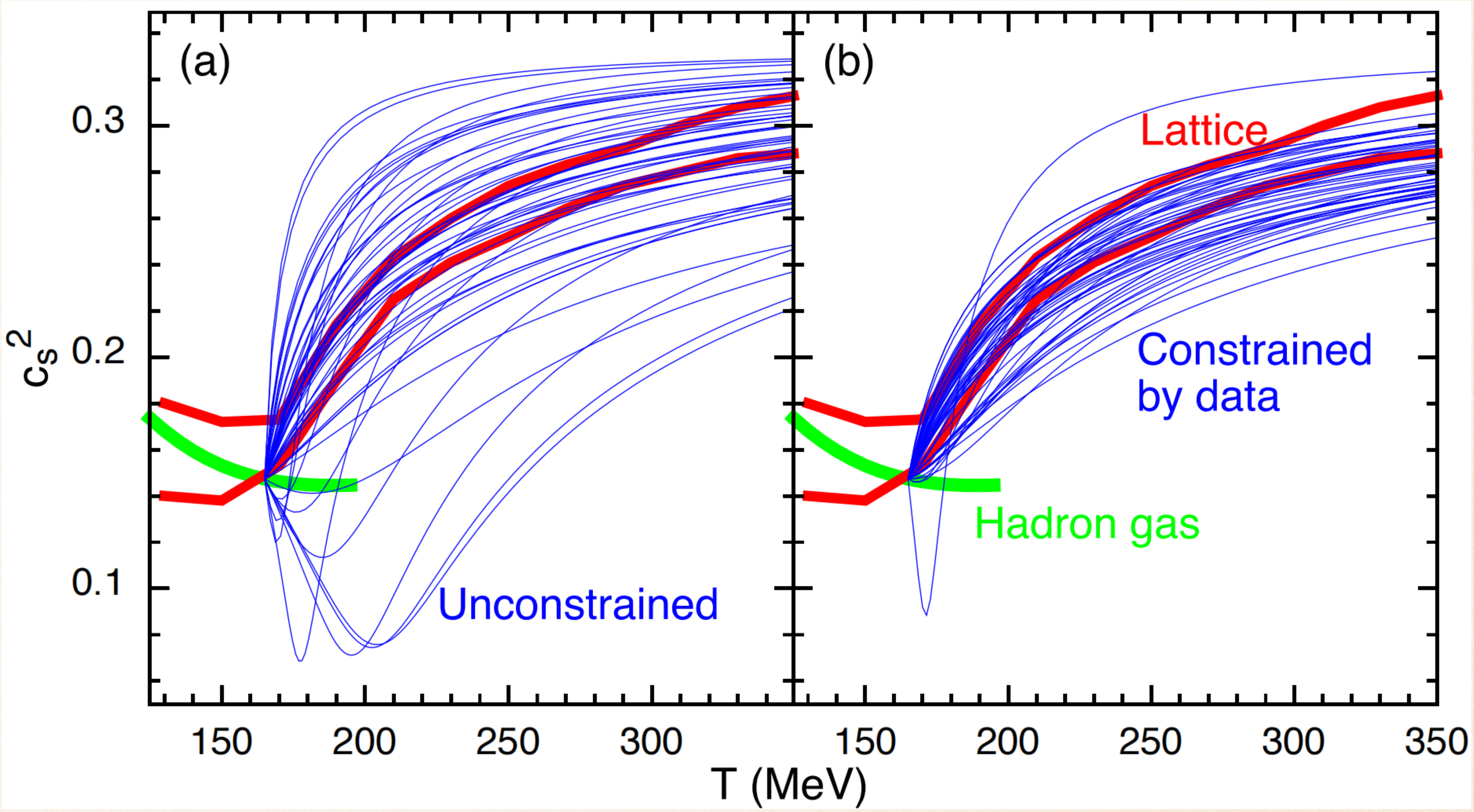
hydro+cascade model

$$c_s^2(\epsilon) = c_s^2(\epsilon_h) + \left(\frac{1}{3} - c_s^2(\epsilon_h)\right) \frac{X_0 x + x^2}{X_0 x + x^2 + X'^2},$$
$$X_0 = X' R c_s(\epsilon) \sqrt{12}, \quad x \equiv \ln \epsilon/\epsilon_h,$$

Stiffer just above T_c



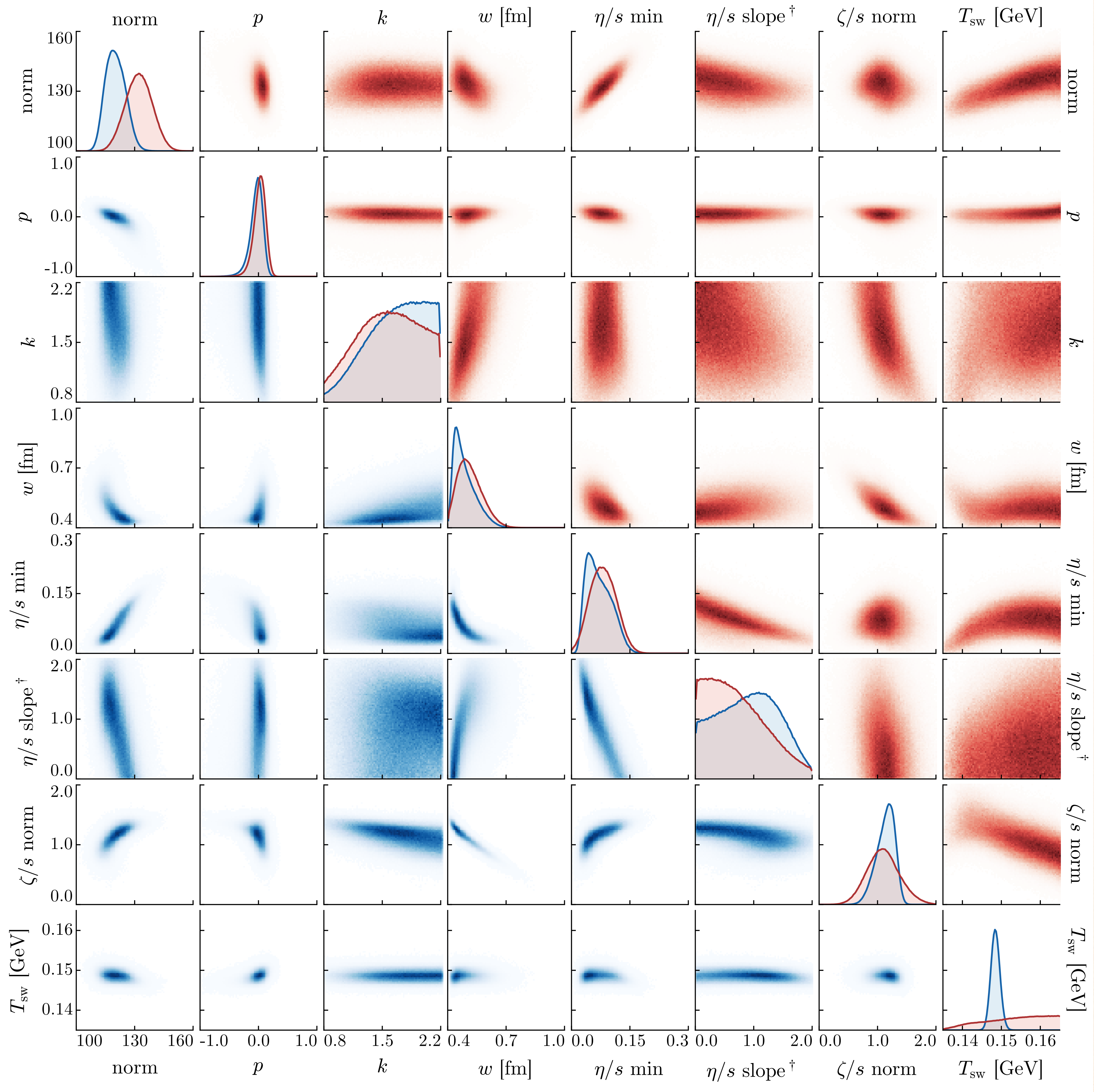
Softer



Spectra of pions, kaons and protons, elliptic flow and femtoscopic source sizes

Scott Pratt, Evan Sangaline, Paul Sorensen, and Hui Wang, PRL114, 202301 (2015)

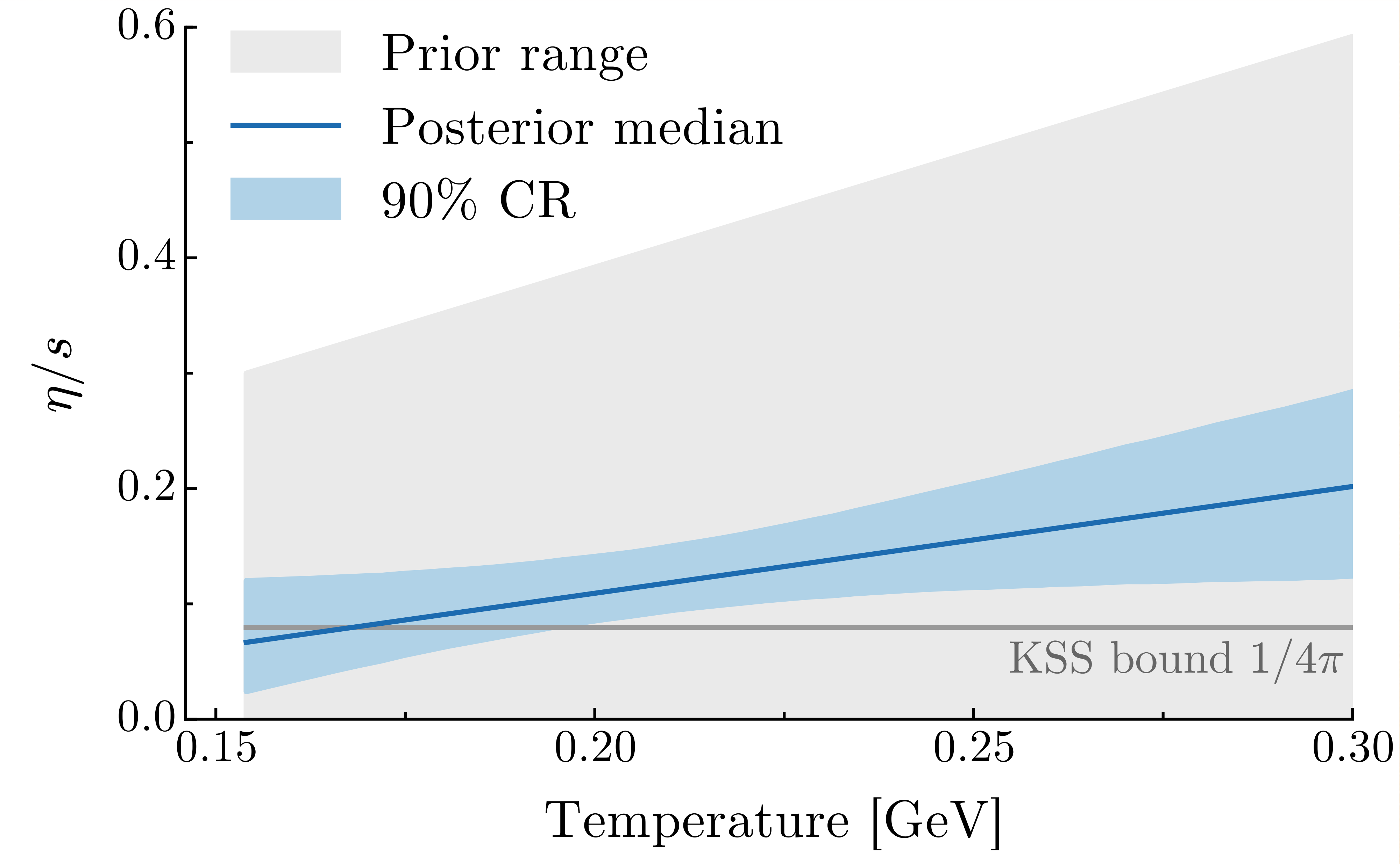
Global fitting with Bayesian analysis



Trento + iEBE-VISHNU + UrQMD   ALICE Pb+Pb 2.76 TeV

TABLE II. Experimental data to be compared with model calculations.

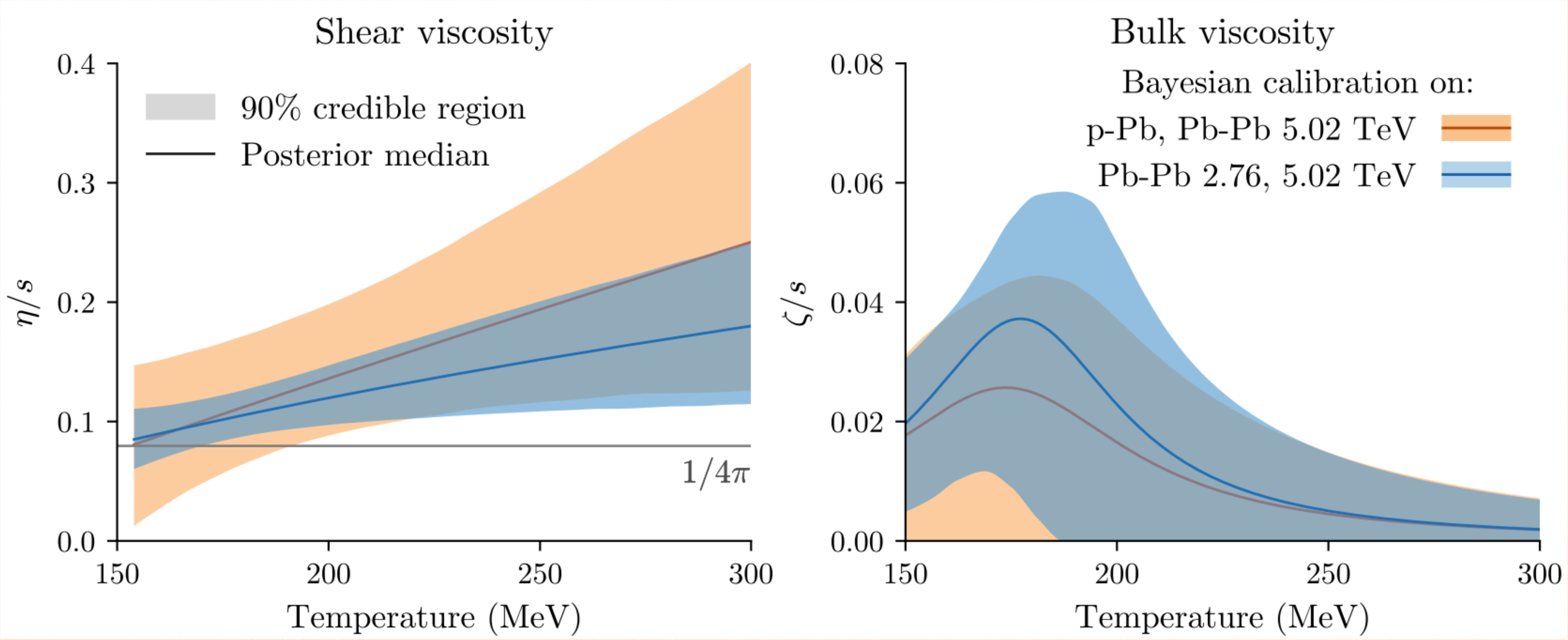
Observable	Particle species	Kinematic cuts	Centrality classes	Ref.
Yields dN/dy	$\pi^\pm$, $K^\pm$, $p\bar{p}$	$\lvert y\rvert < 0.5$	0–5, 5–10, 10–20, . . . , 60–70	[108]
Mean transverse momentum $\langle p_T\rangle$	$\pi^\pm$, $K^\pm$, $p\bar{p}$	$\lvert y\rvert < 0.5$	0–5, 5–10, 10–20, . . . , 60–70	[108]
Two-particle flow cumulants $v_n\{2\}$ $n = 2, 3, 4$	all charged	$\lvert\eta\rvert < 1$ $0.2 < p_T < 5.0$ GeV	0–5, 5–10, 10–20, . . . , 40–50 $n = 2$ only: 50–60, 60–70	[109]



J. E. Bernhard, J. Scott Moreland, S. A. Bass, J. Liu, U. Heinz, PRC 94.024907(2016)

Shear and bulk viscosities

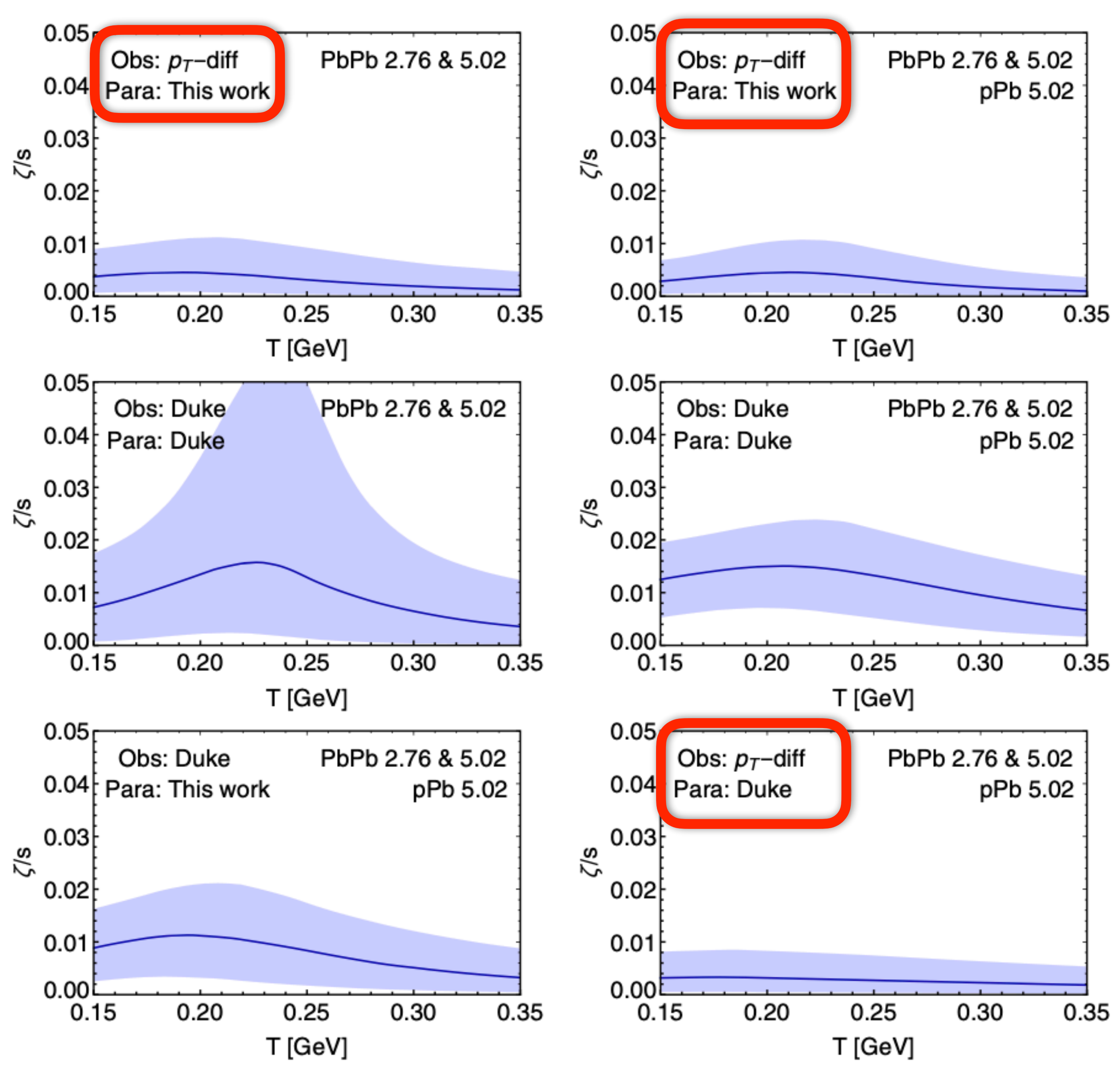
p-Pb data included



"Strongly supports the existence of hydrodynamic flow in small systems at ultrarelativistic energies"

J. E. Bernhard, J. S. Moreland, S. A. Bass, Nature Physics 15, 1113–1117 (2019)
J. S. Moreland, J. E. Bernhard, S. A. Bass, Phys. Rev. C 101, 024911 (2020)

pT-differential observables included



"QGP bulk viscosity is small and even consistent with zero"

G. Nijs, Wilke. Schee, U. Gürsoy, and R. Snellings, PRL126, 202301 (2021)

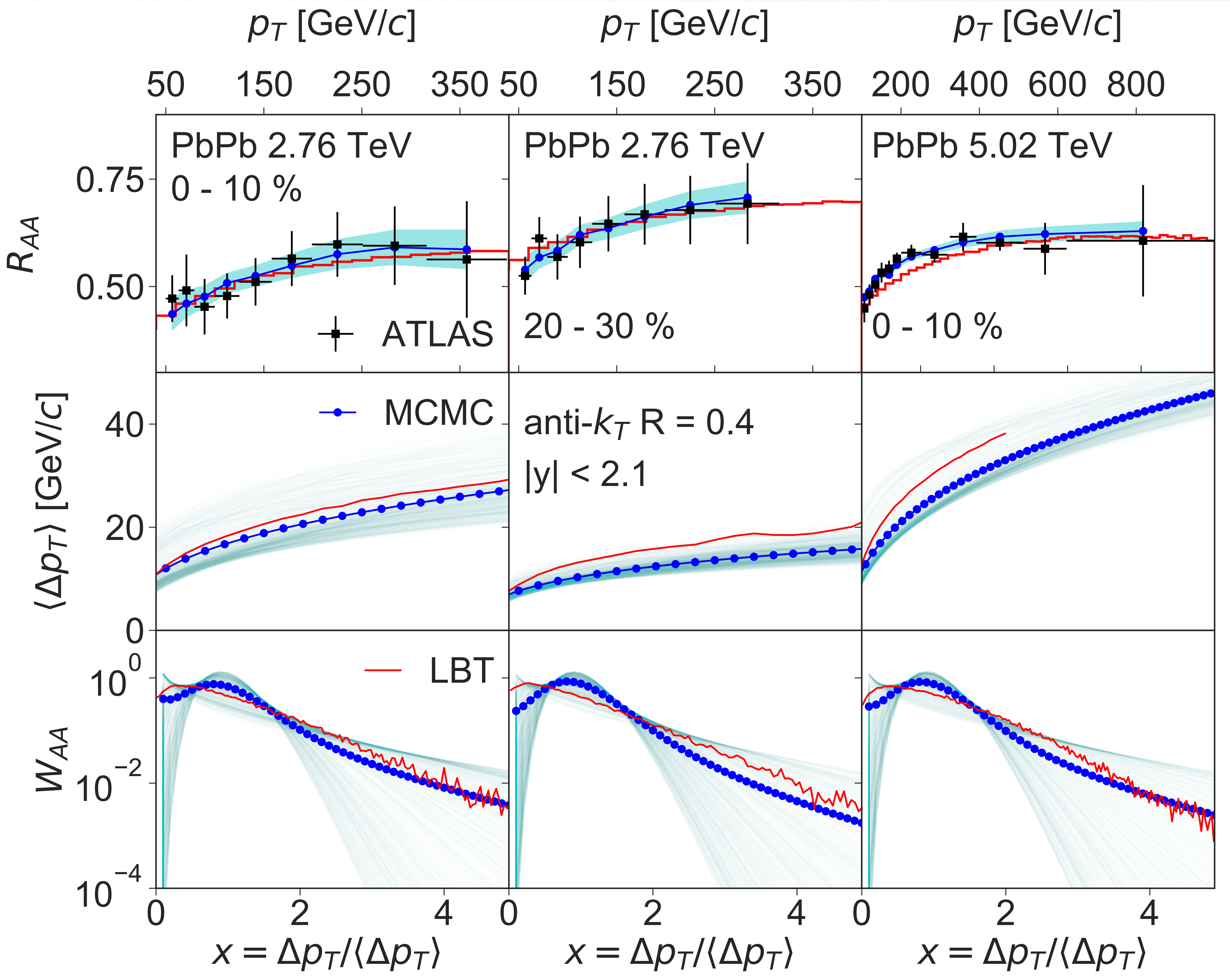
Bayesian analysis jet energy loss distribution

$$R_{AA}(p_T) \approx \frac{1}{d\sigma_{pp}^{\rm jet}(p_T)} \int d\Delta p_T d\sigma_{pp}^{\rm jet}(p_T + \Delta p_T) \times W_{AA}(\Delta p_T, p_T + \Delta p_T, R).$$

$$W_{AA}(x) = \frac{\alpha^\alpha x^{\alpha-1} e^{-\alpha x}}{\Gamma(\alpha)} \qquad x = \Delta p_T / \langle \Delta p_T \rangle$$

$$\langle \Delta p_T \rangle (p_T) = \beta p_T^\gamma \log(p_T)$$

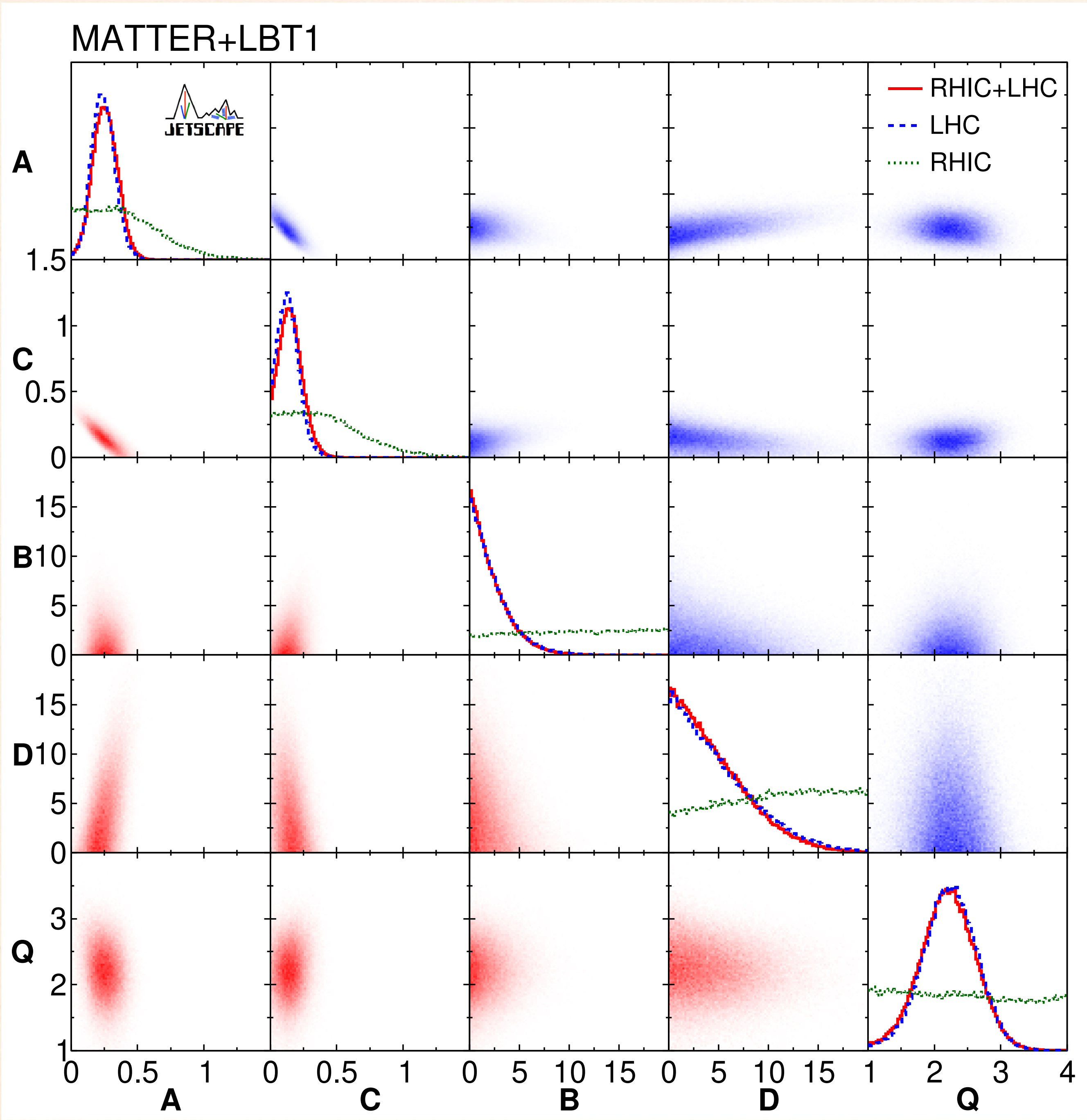
single inclusive jets

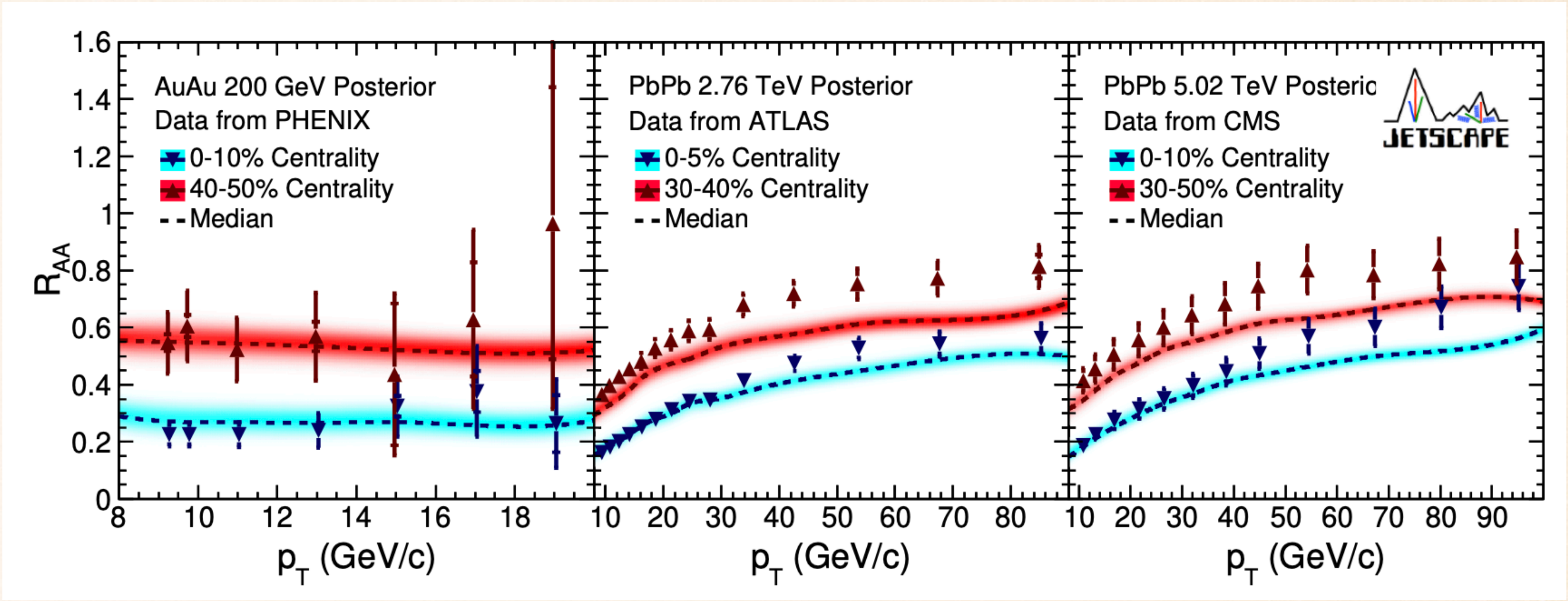


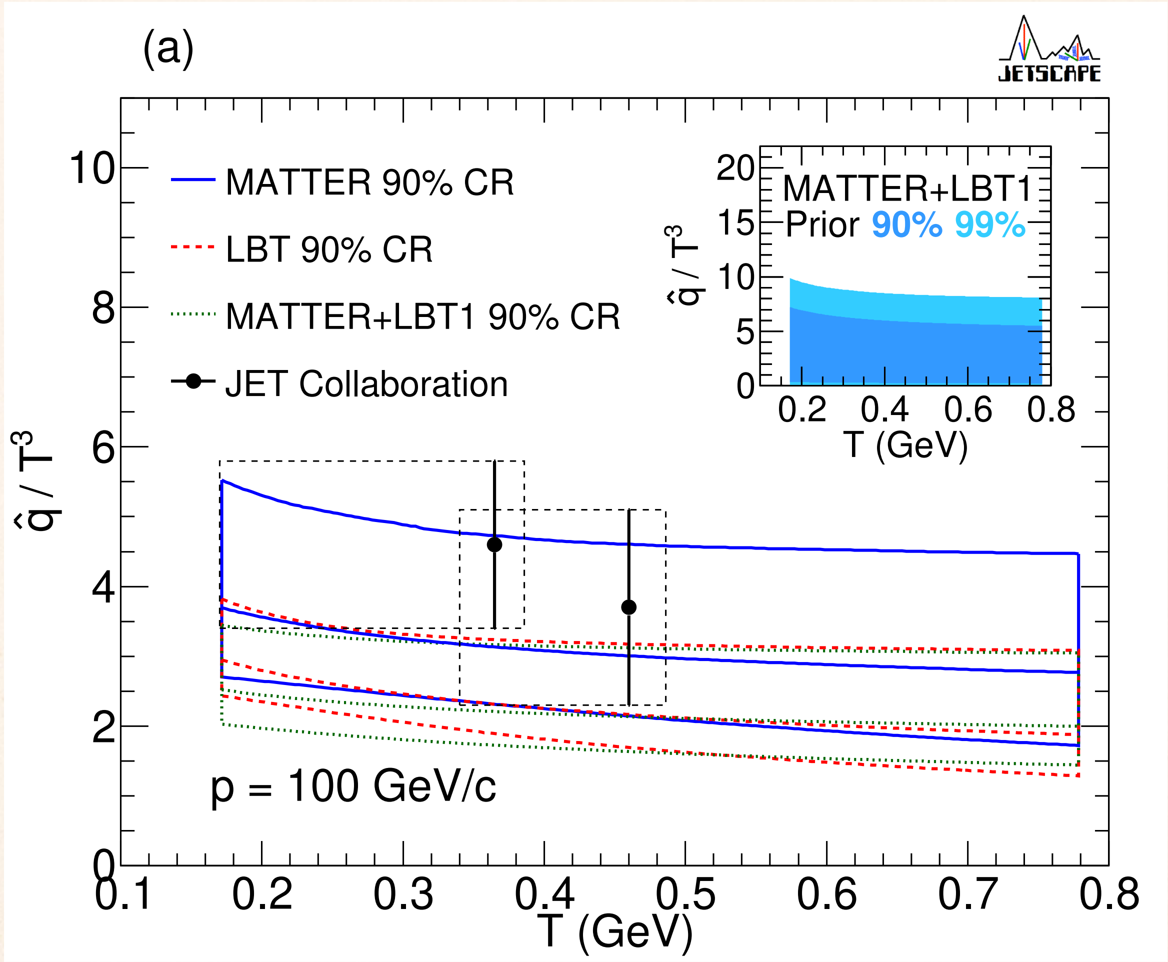
Yayun He, L.G. Pang and X.N. Wang, PRL122, 252302 (2019)

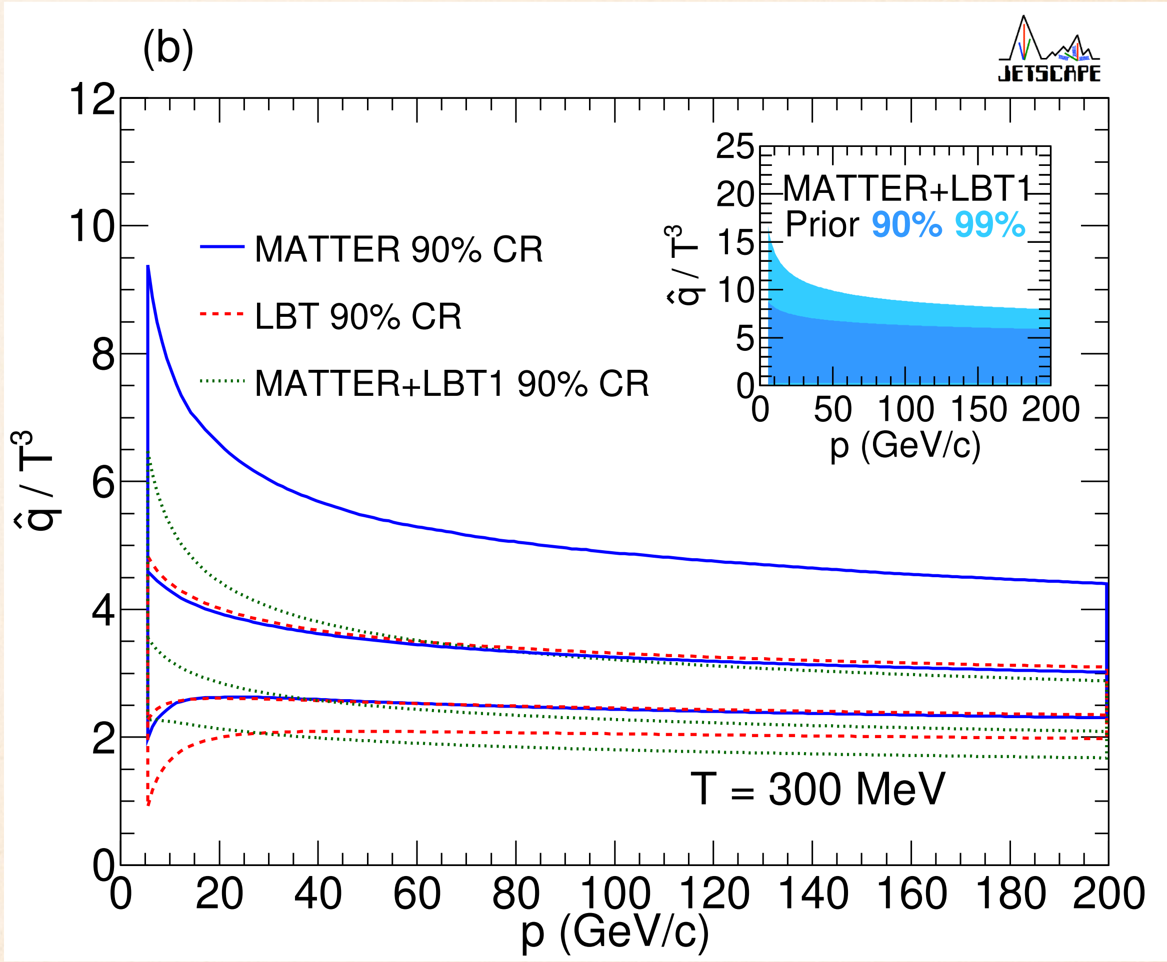
J. Wu, W. Ke and X.N. Wang, arXiv: 2304.06339

Bayesian analysis jet transport $\hat{q}$







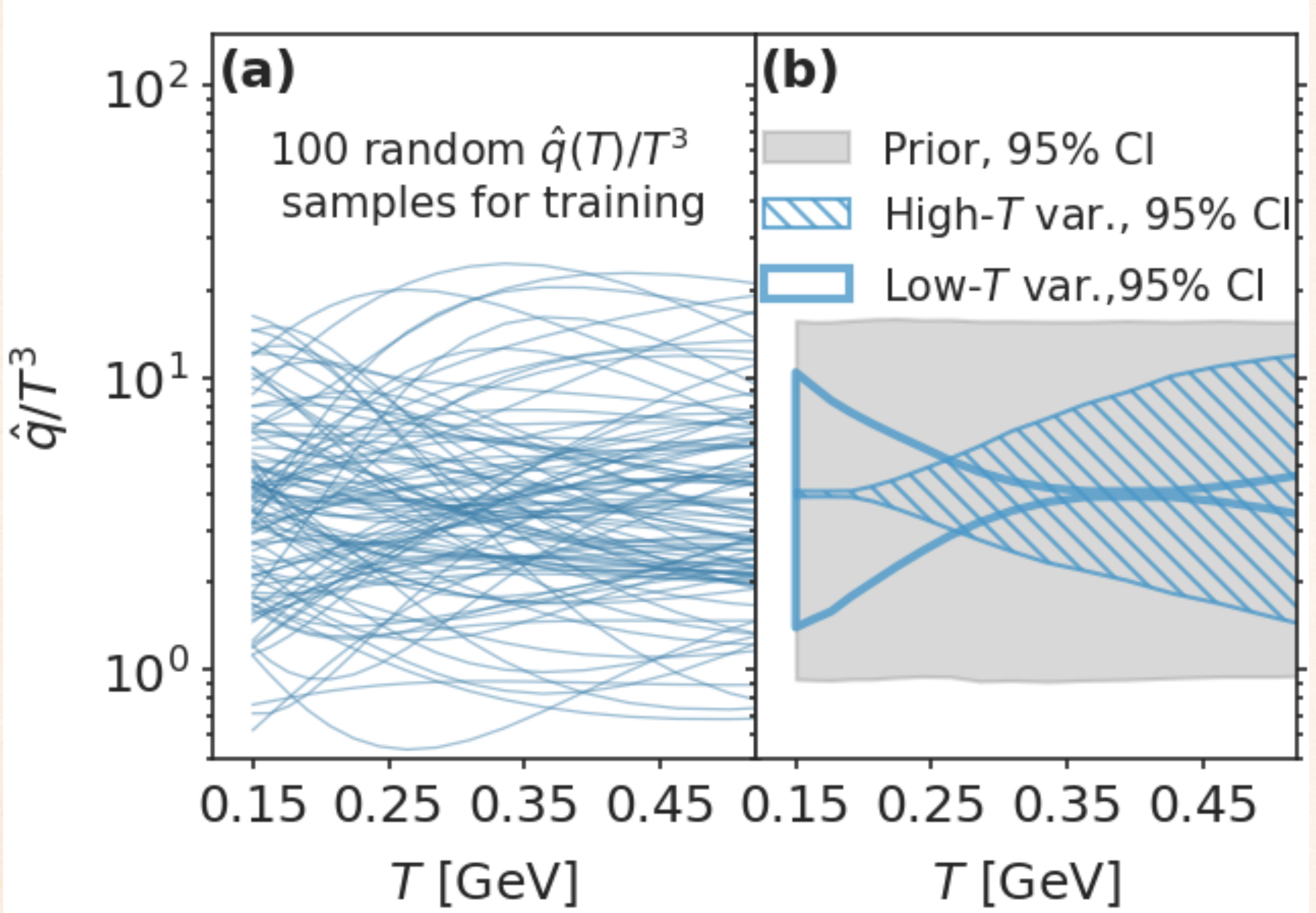


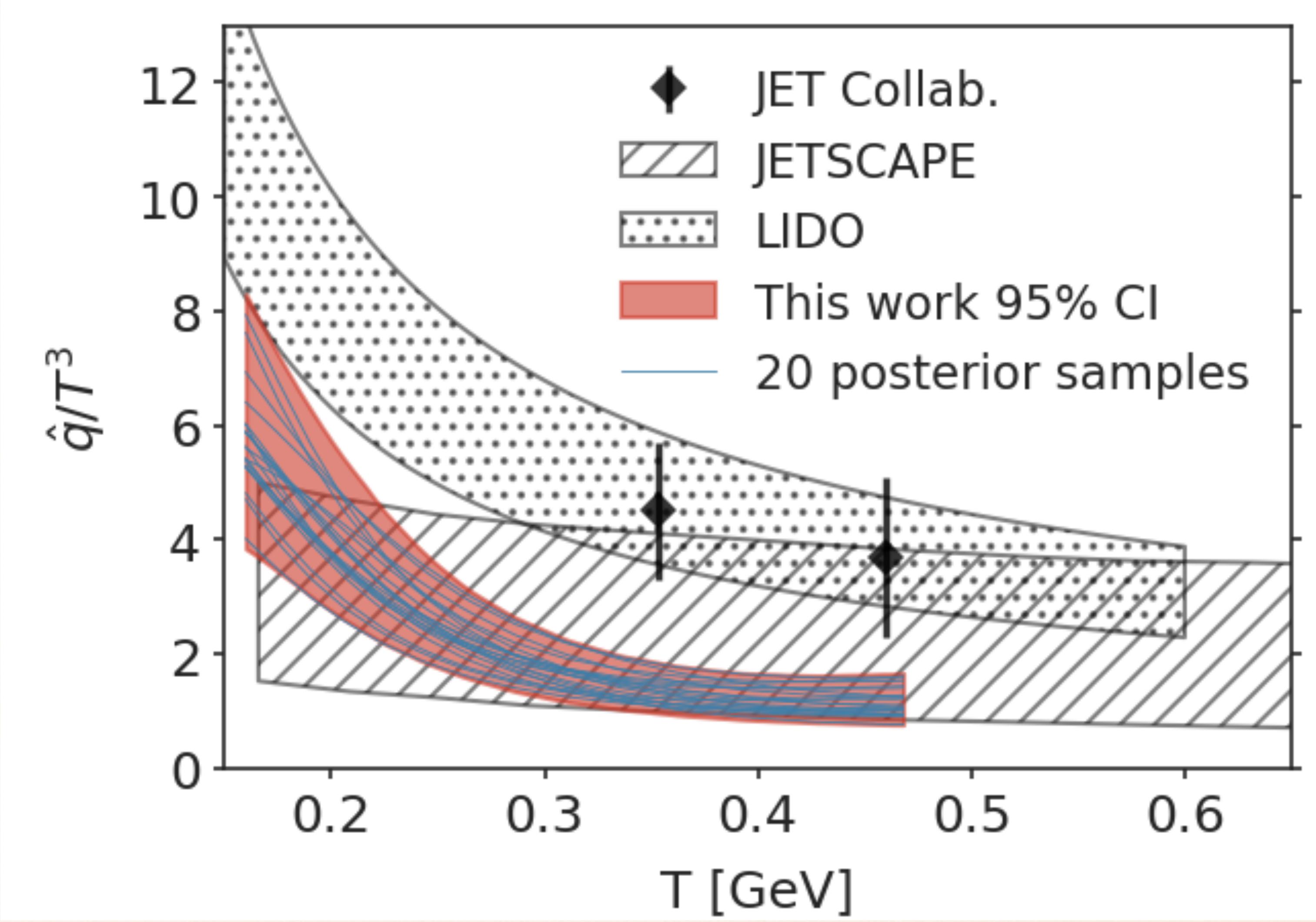
$$\frac{\hat{q}\left(E,T\right)|_{A,B,C,D}}{T^3} = 42C_R\frac{\zeta(3)}{\pi}\left(\frac{4\pi}{9}\right)^2\left\{\frac{A\left[\ln\left(\frac{E}{\Lambda}\right)-\ln(B)\right]}{\left[\ln\left(\frac{E}{\Lambda}\right)\right]^2}+\frac{C\left[\ln\left(\frac{E}{T}\right)-\ln(D)\right]}{\left[\ln\left(\frac{ET}{\Lambda^2}\right)\right]^2}\right\}$$

S. Cao *et al.* (JETSCAPE Collaboration), PRC 104, 024905 (2021)

Information field approach for $\hat{q}$

single inclusive, dihadron and gamma-hadron spectra





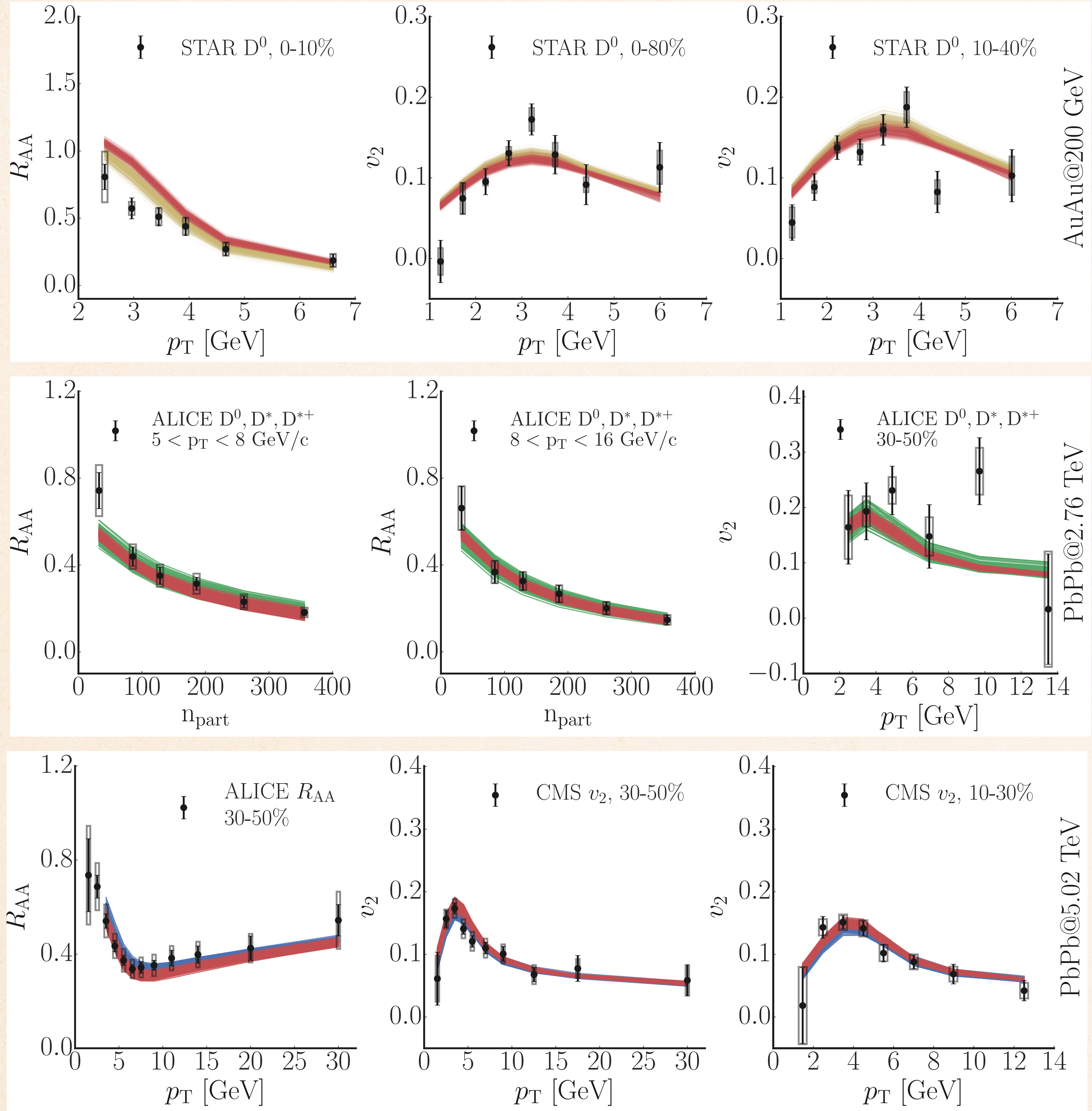
$\langle F(x)\rangle = \mu(x), \quad \langle \delta F(x)\delta F(x')\rangle = C(x,x')$ $\quad C(x,x') = \sigma^2 \exp\left[-(x-x')^2/2l^2\right]$

non-parametric representation
of an unknown function with short correlation

Strong-T dependence
Weak E-dependence

Man Xie, Weiyao Ke, Hanzhong Zhang, Xin-Nian Wang, arXiv: 2206.01340, 2208.14419

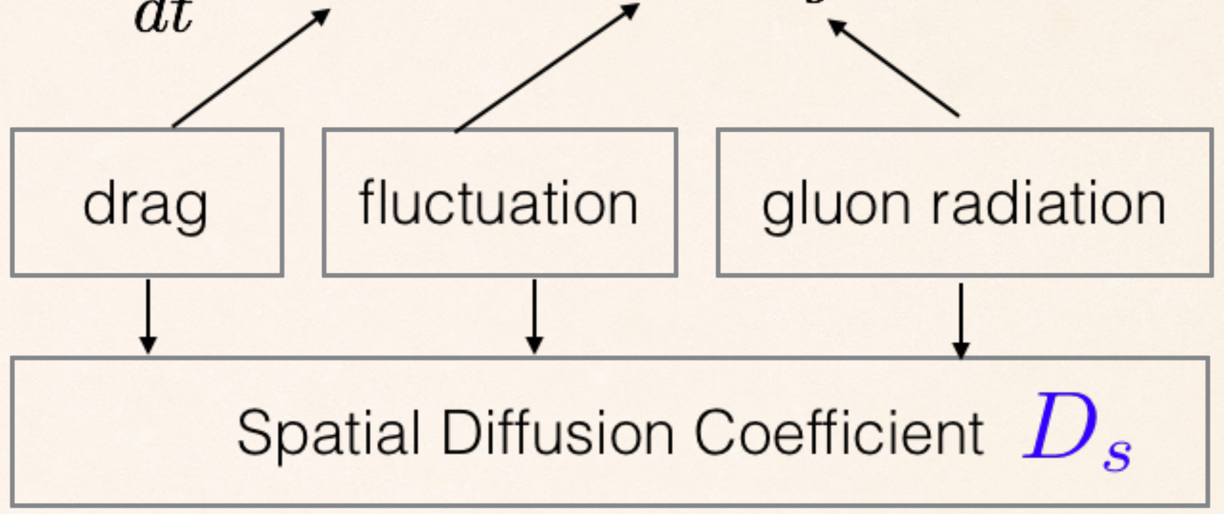
Bayesian analysis heavy quark diffusion coefficients



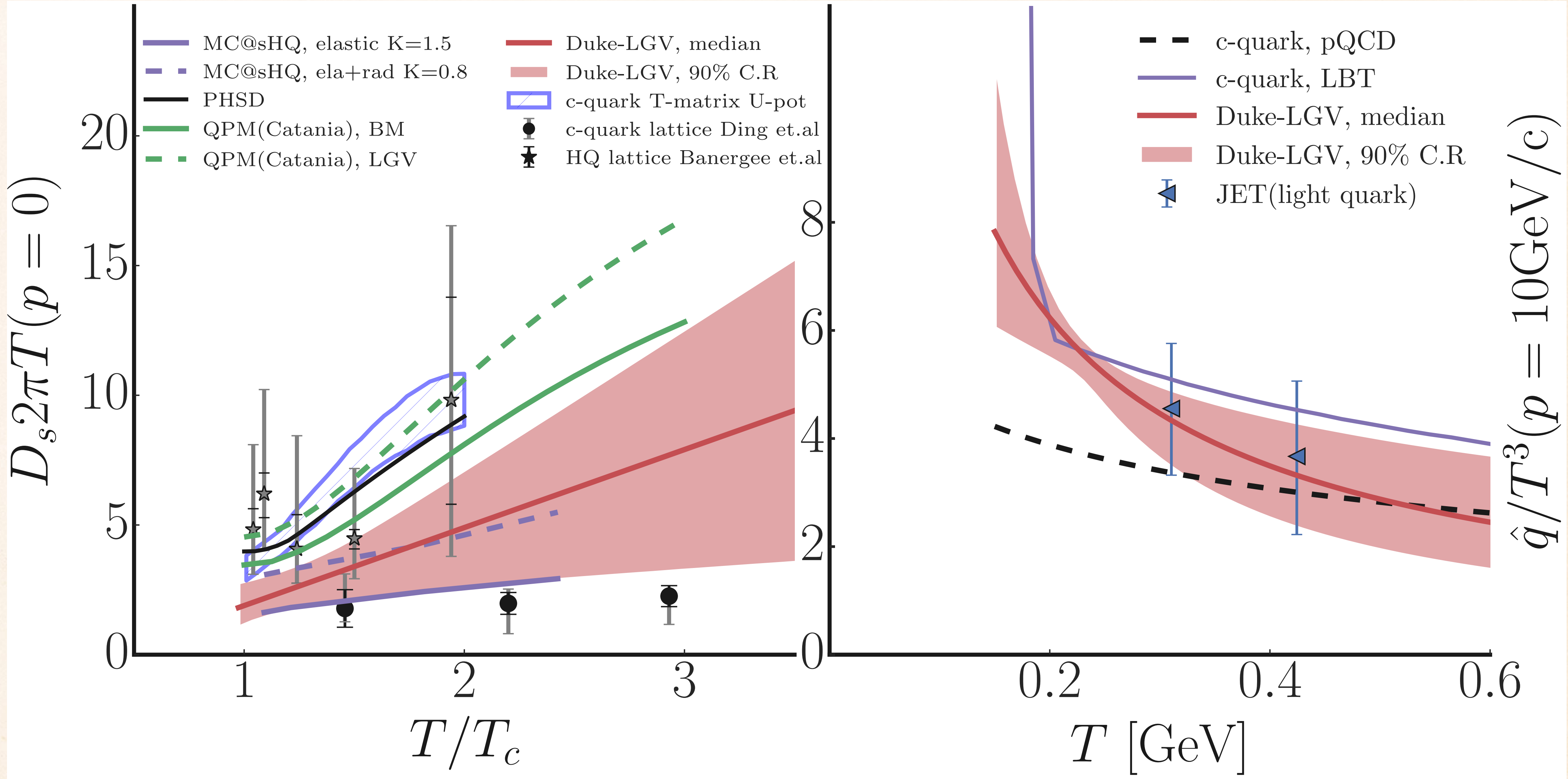
simultaneously describe the R_{AA} and v_2 at both RHIC and the LHC energies, predict well D-meson v_3

Langevin model

$$\frac{d\vec{p}}{dt} = -\eta_D(p)\vec{p} + \vec{\xi} + \vec{f}_g.$$



$$D_s 2\pi T(T,\boldsymbol{p}) = \frac{1}{1+(\gamma^2 p)^2}(D_s 2\pi T)^{\text{linear}} + \frac{(\gamma^2 p)^2}{1+(\gamma^2 p)^2}(D_s 2\pi T)^{\text{pQCD}}.$$



Yingru Xu, J.E. Bernhard, S.A. Bass and M. Nahrgang and S.S. Cao, PRC. 97, 014907 (2018)

EoS from heavy flavor data via QLBT

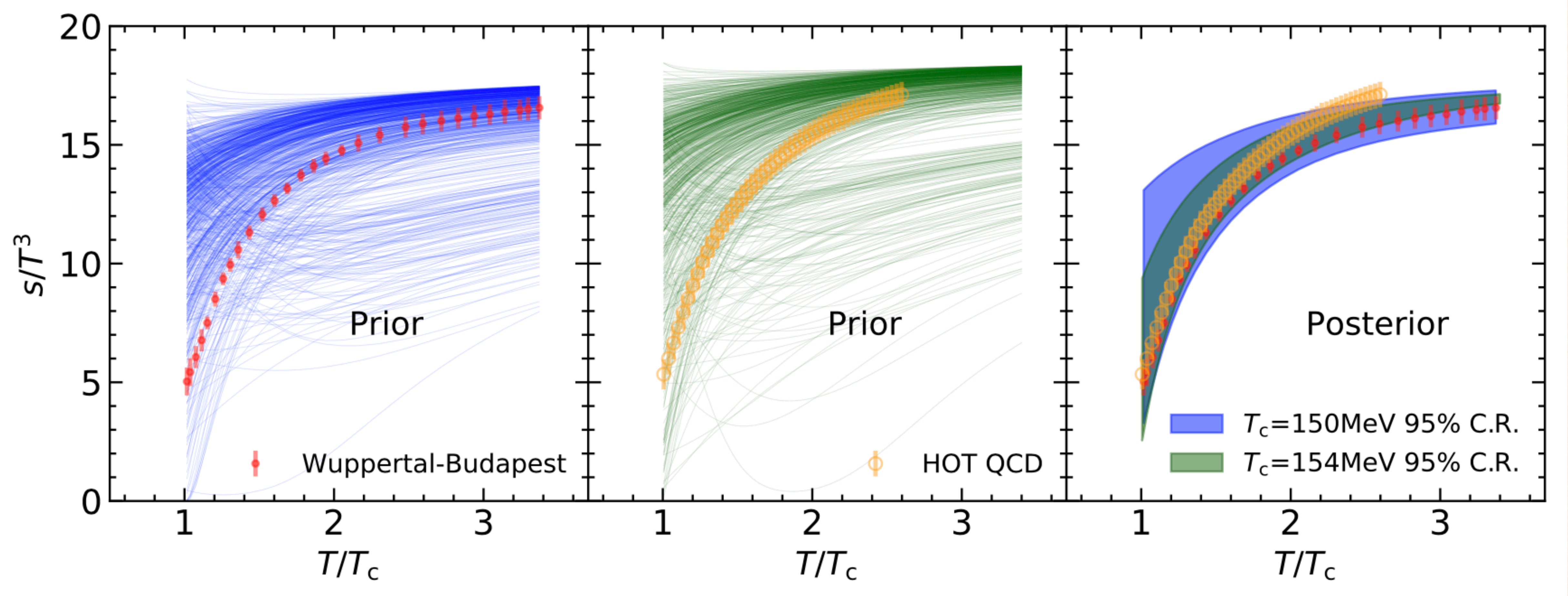
D meson R_{AA} and v_2 at RHIC and the LHC

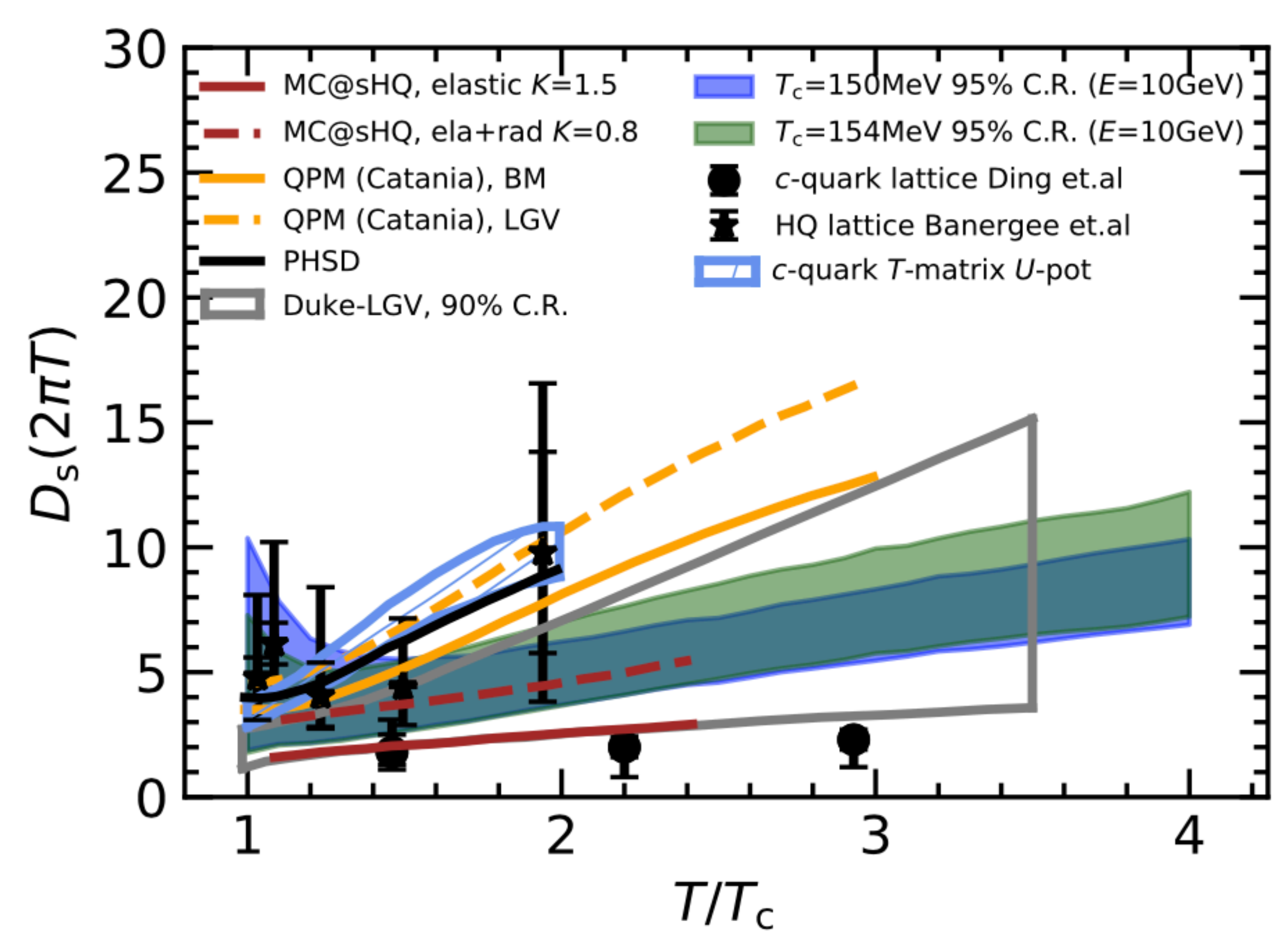
$$m_q^2(T) = \frac{N_c^2 - 1}{8N_c} g^2(T)T^2,$$

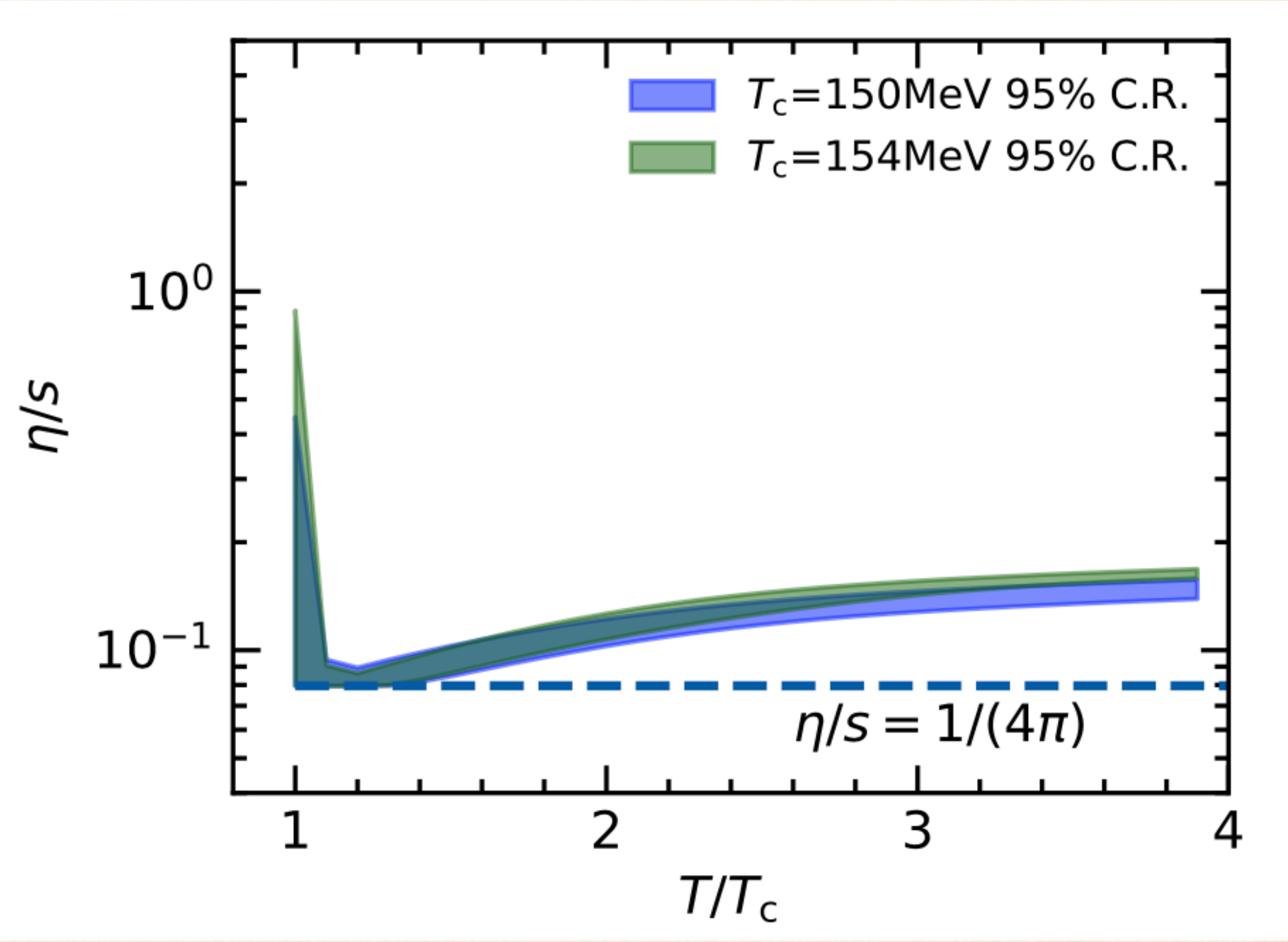
$$m_g^2(T) = \frac{1}{6}\left(N_c + \frac{1}{2}N_f\right) g^2(T)T^2,$$

$$g^2(T) = \frac{48\pi^2}{(11N_c - 2N_f)\ln\left[\frac{(aT/T_c+b)^2}{1+ce^{-d(T/T_c)^2}}\right]}$$

$$g^2(E) = \frac{48\pi^2}{(11N_c - 2N_f)\ln\left[(AE/T_c + B)^2\right]}$$



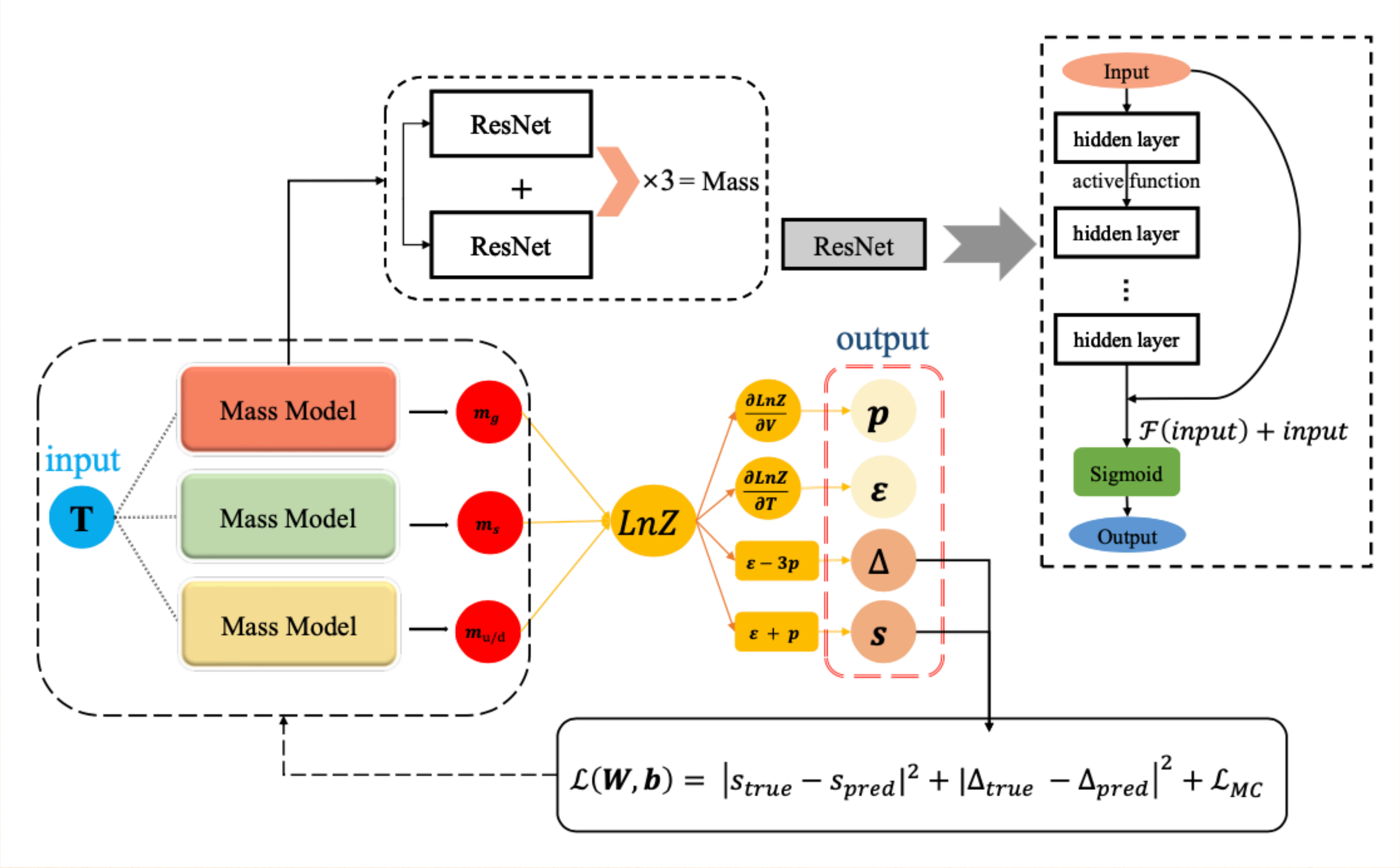




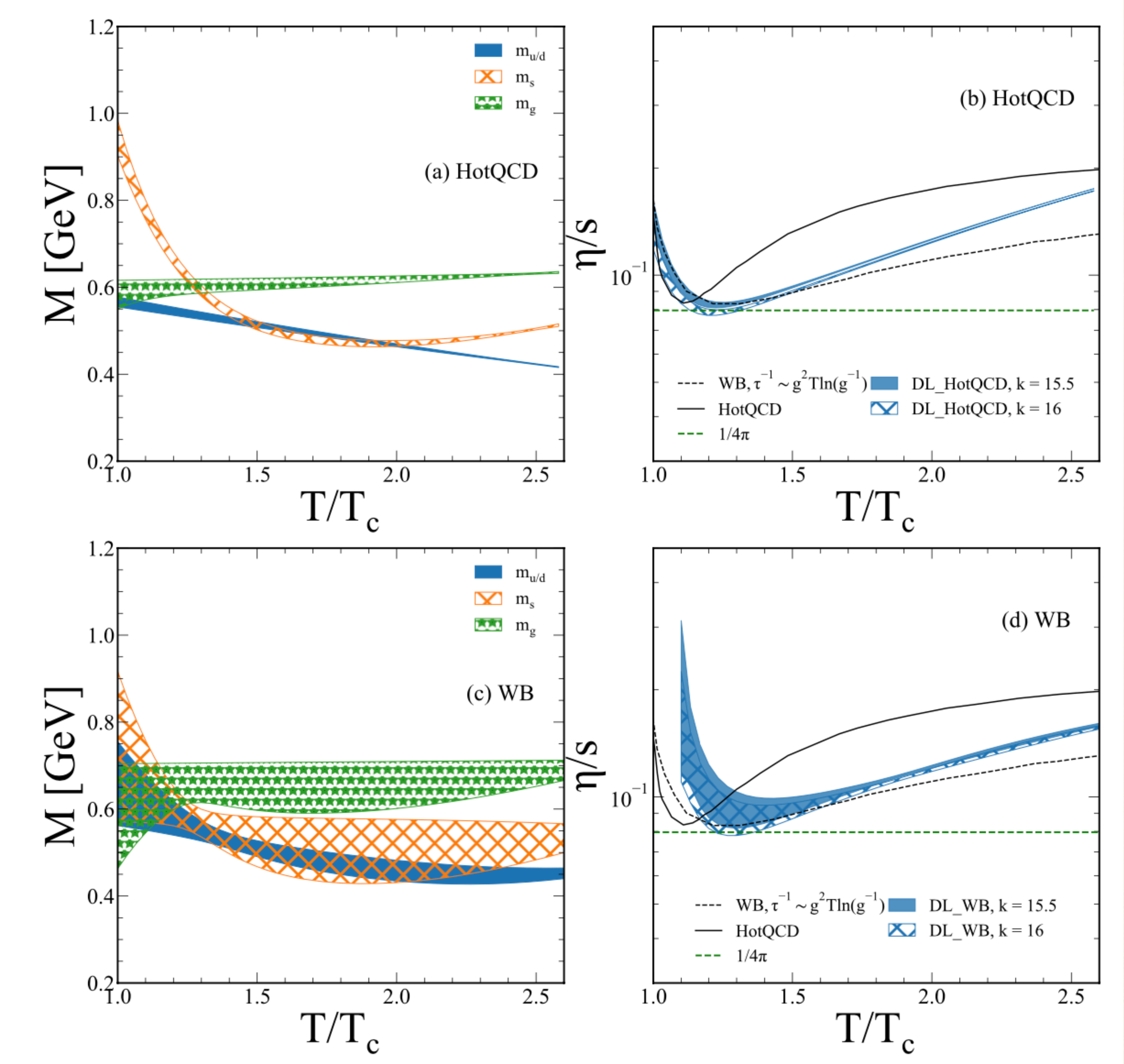
F-L Liu, X-Y Wu, S. Cao, G-Y Qin, and X-N Wang, arXiv:2304.08787

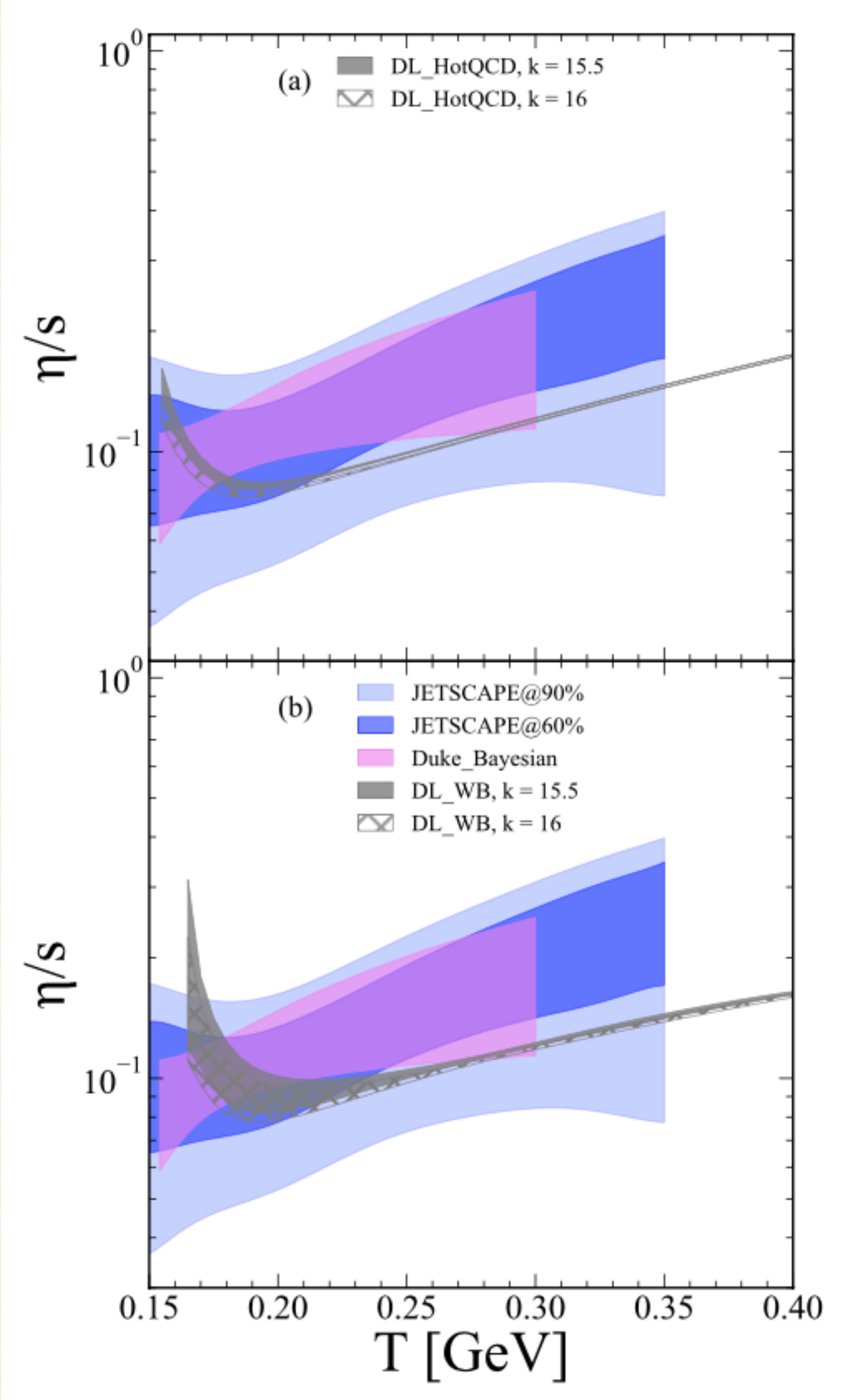
See talk by F. L. Liu, 26 April, Wednesday

Quasi-particle mass from lattice QCD EoS



auto differentiation

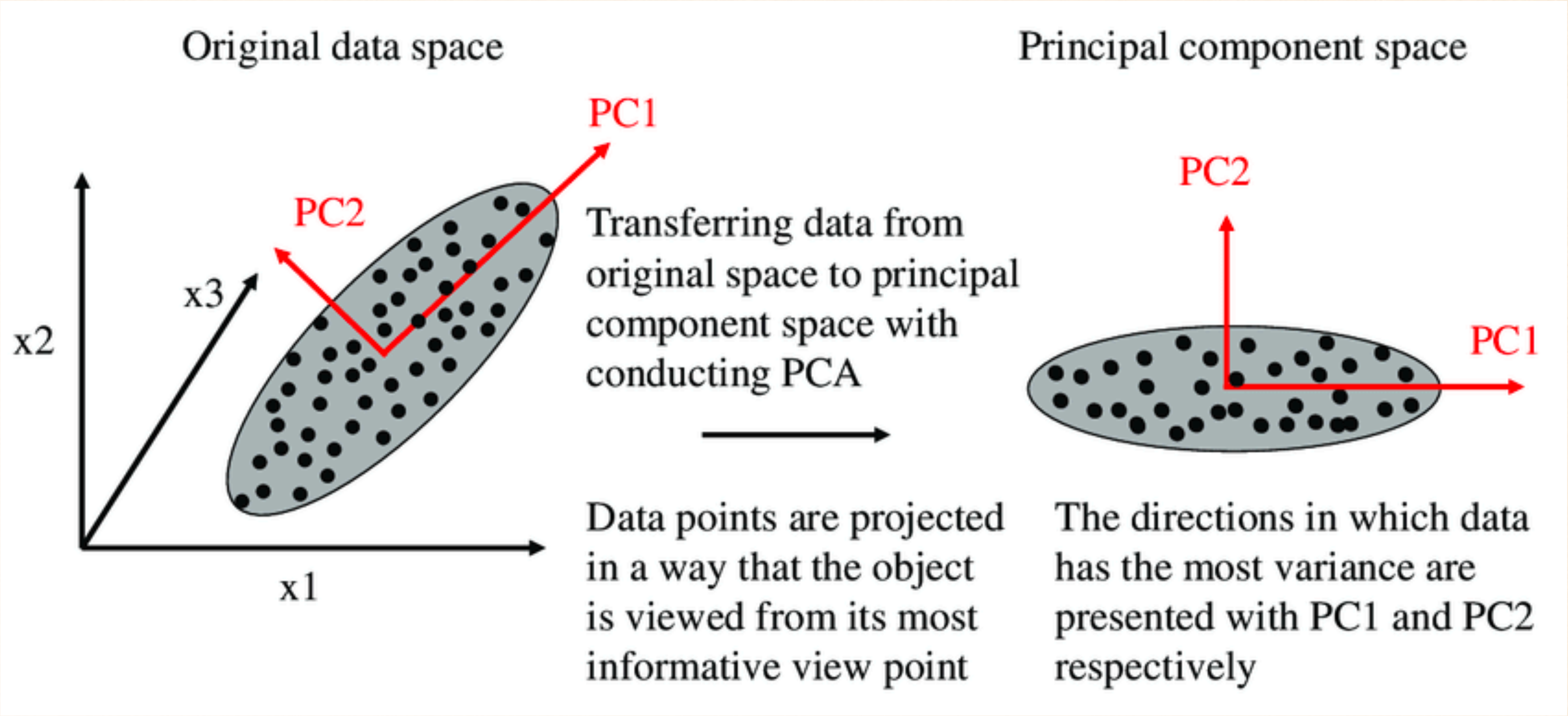


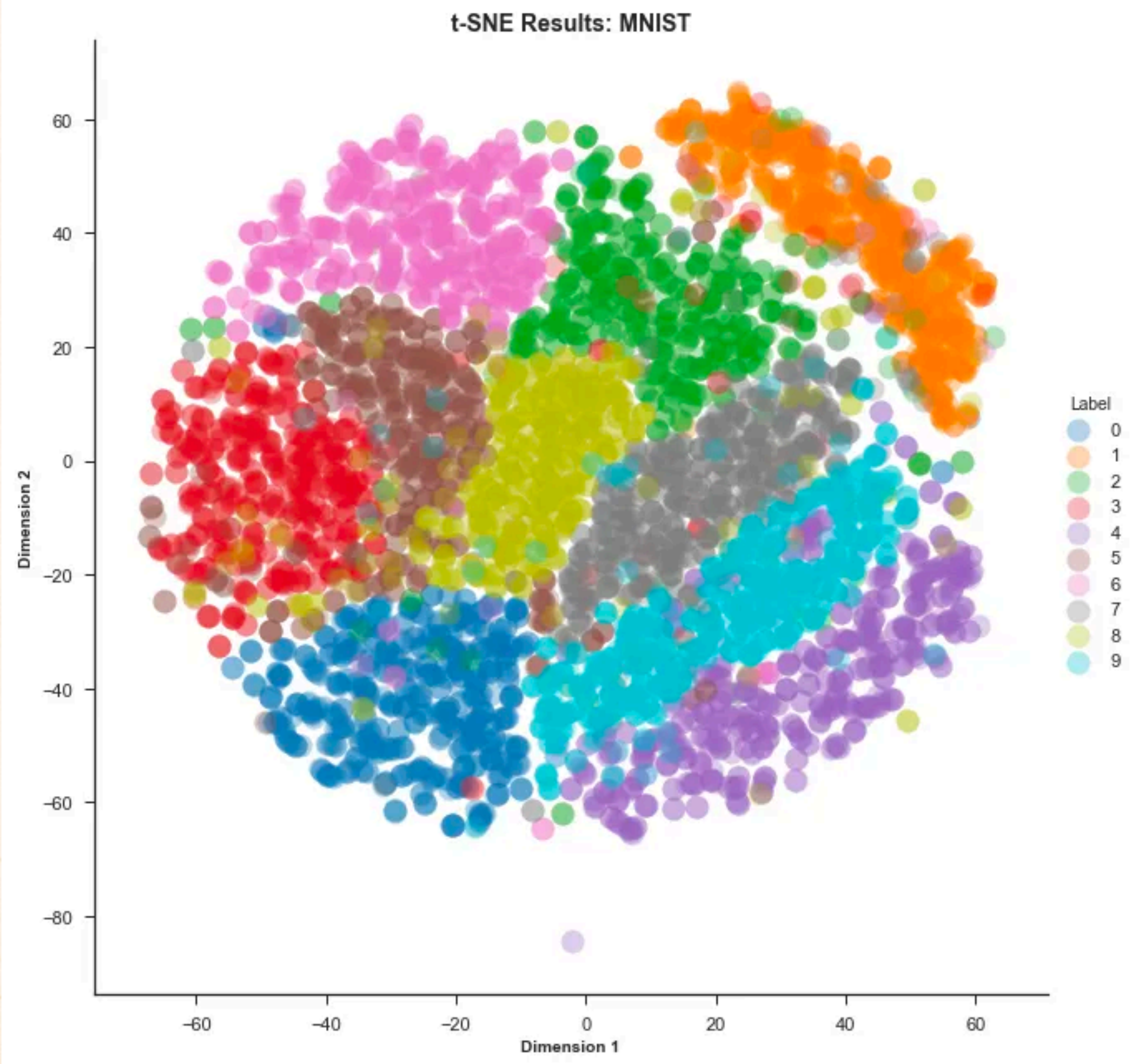


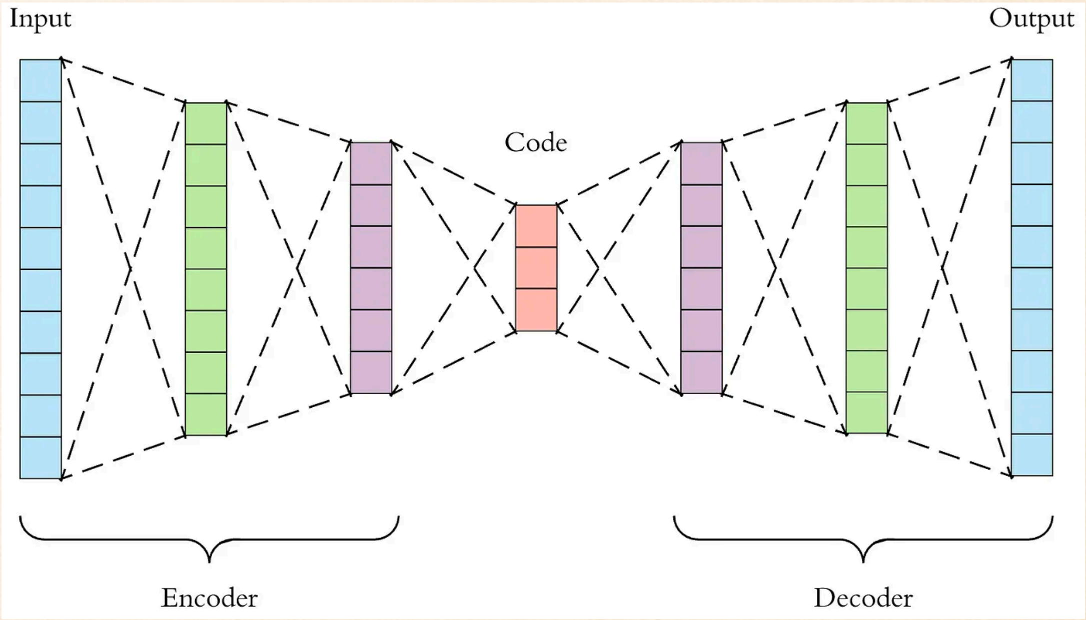
Fu-Peng Li, Hong-Liang Lü, Long-Gang Pang, Guang-You Qin, arXiv:2211.07994

Unsupervised learning

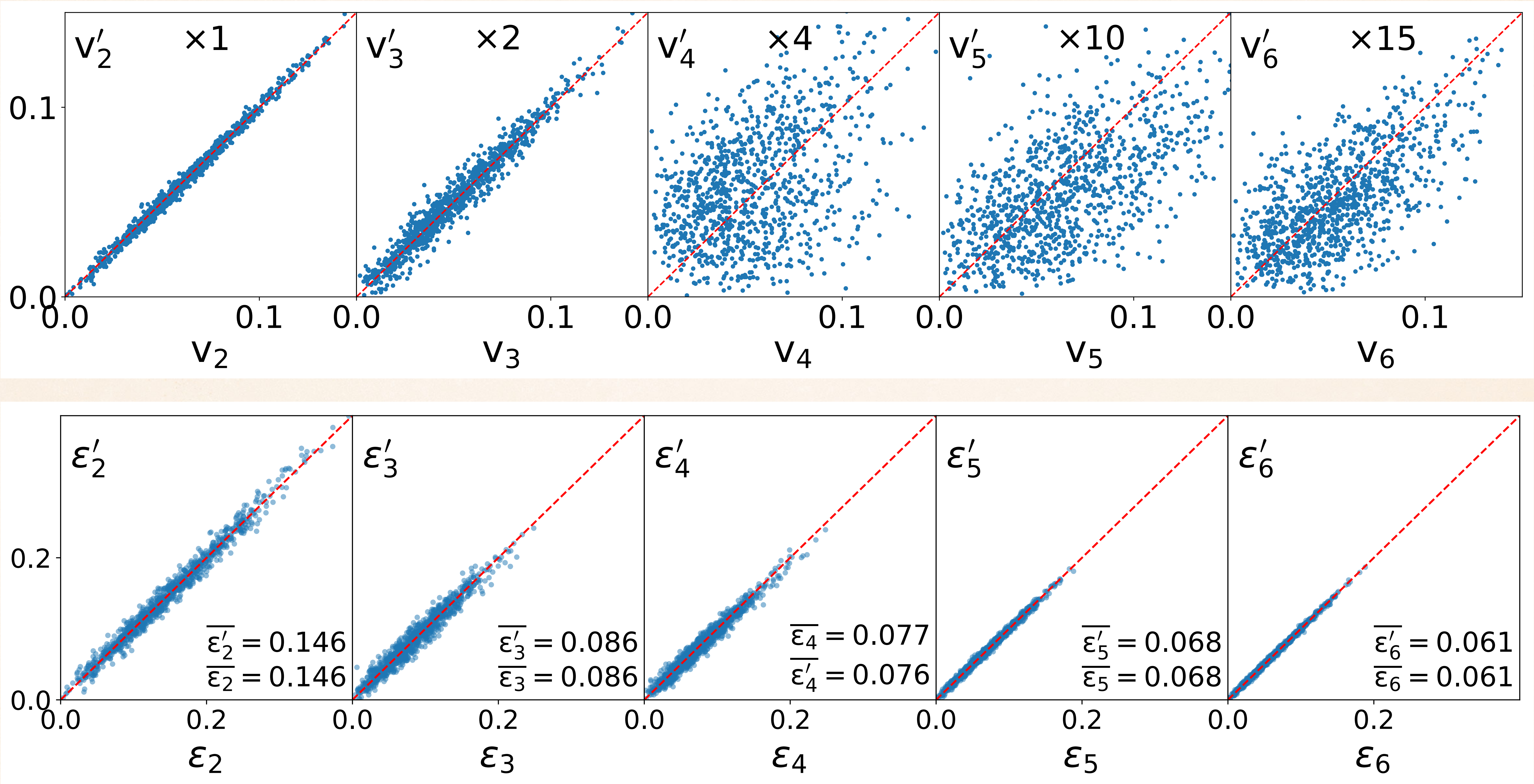
- Principle component analysis (PCA)
- t-SNE: non-linear dimensionality reduction
- Auto Encoder: extract features by minimizing the reconstruction error using bottleneck network
- Generative adversarial network (GAN): generator + discriminator
- K-means clustering for unsupervised classification







PCA for orthogonal high order harmonics flows



Reduce the mode mixing between v'_4 and ϵ_2^2…

Ziming Liu, WenBin Zhao and HuiChao Song, EPJC 79, 870 (2019)

PCA for event-by-event fluctuations

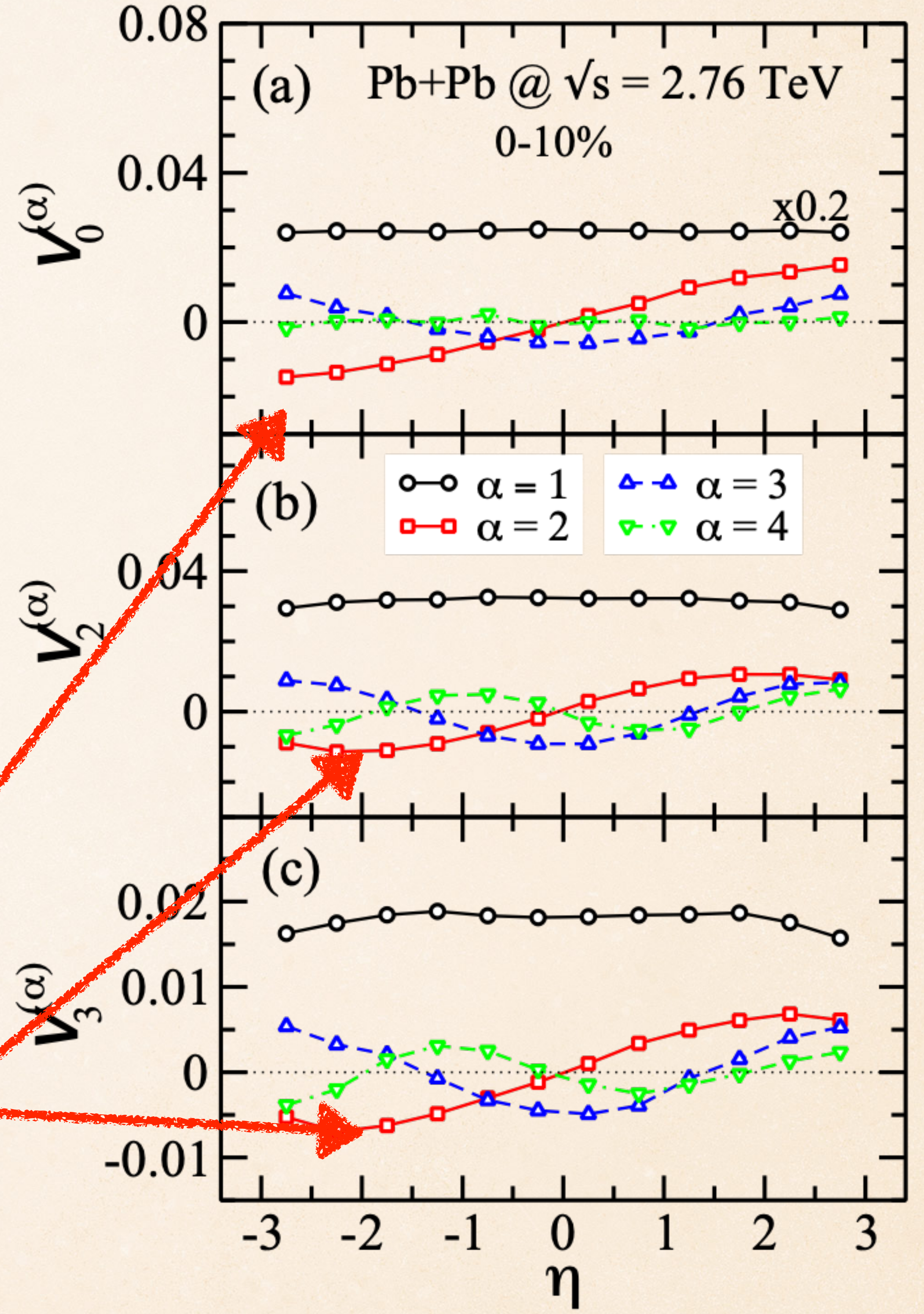
$$\left\langle \frac{dN_{\text{pairs}}}{d\mathbf{p}_1 d\mathbf{p}_2} \right\rangle = \left\langle \frac{dN}{d\mathbf{p}_1} \frac{dN}{d\mathbf{p}_2} \right\rangle + \mathcal{O}(N)$$

$$\frac{dN}{d\mathbf{p}} = \sum_{n=-\infty}^{+\infty} V_n(p) e^{in\varphi}$$

$$\left\langle \frac{dN_{\text{pairs}}}{d\mathbf{p}_1 d\mathbf{p}_2} \right\rangle = \sum_{n=-\infty}^{+\infty} V_{n\Delta}(p_1, p_2) e^{in(\varphi_1 - \varphi_2)}$$

$$V_{n\Delta}(p_1, p_2) = \langle V_n(p_1) V_n^*(p_2) \rangle$$

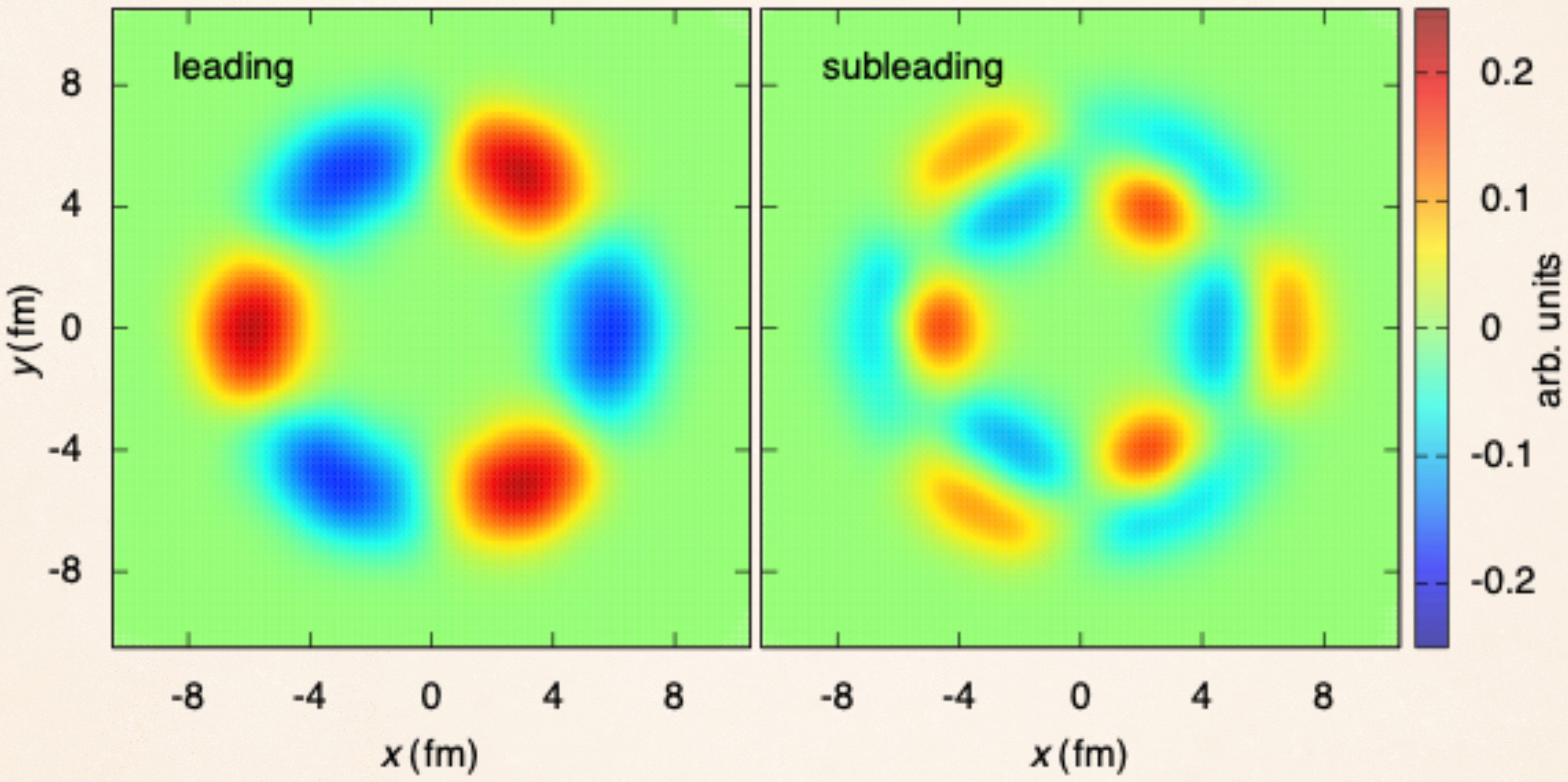
PCA



- small difference between the participant numbers of projectile and target nuclei induced by fluctuations
- small relative angle between n-th harmonic participant planes defined in the projectile and target nuclei

Rajeev S. Bhalerao, Jean-Yves Ollitrault, Subrata Pal, Derek Teaney, PRL 114, 152301 (2015)

Subleading harmonic flow

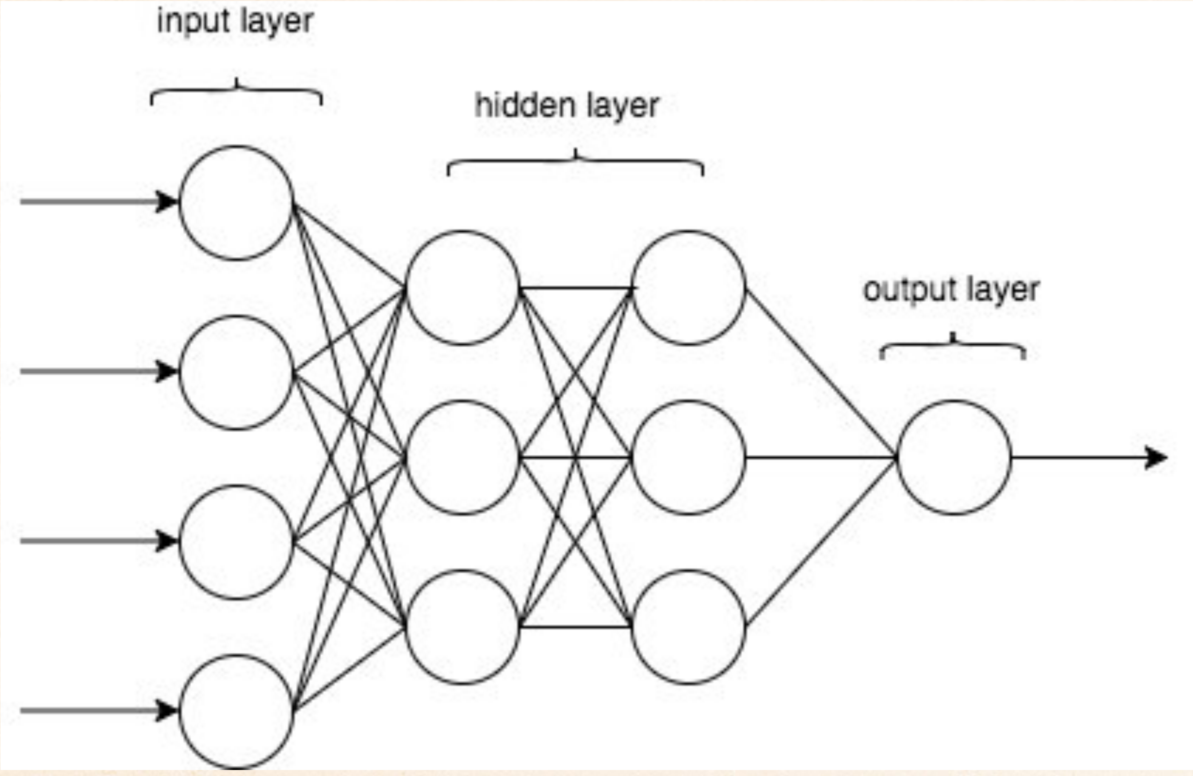


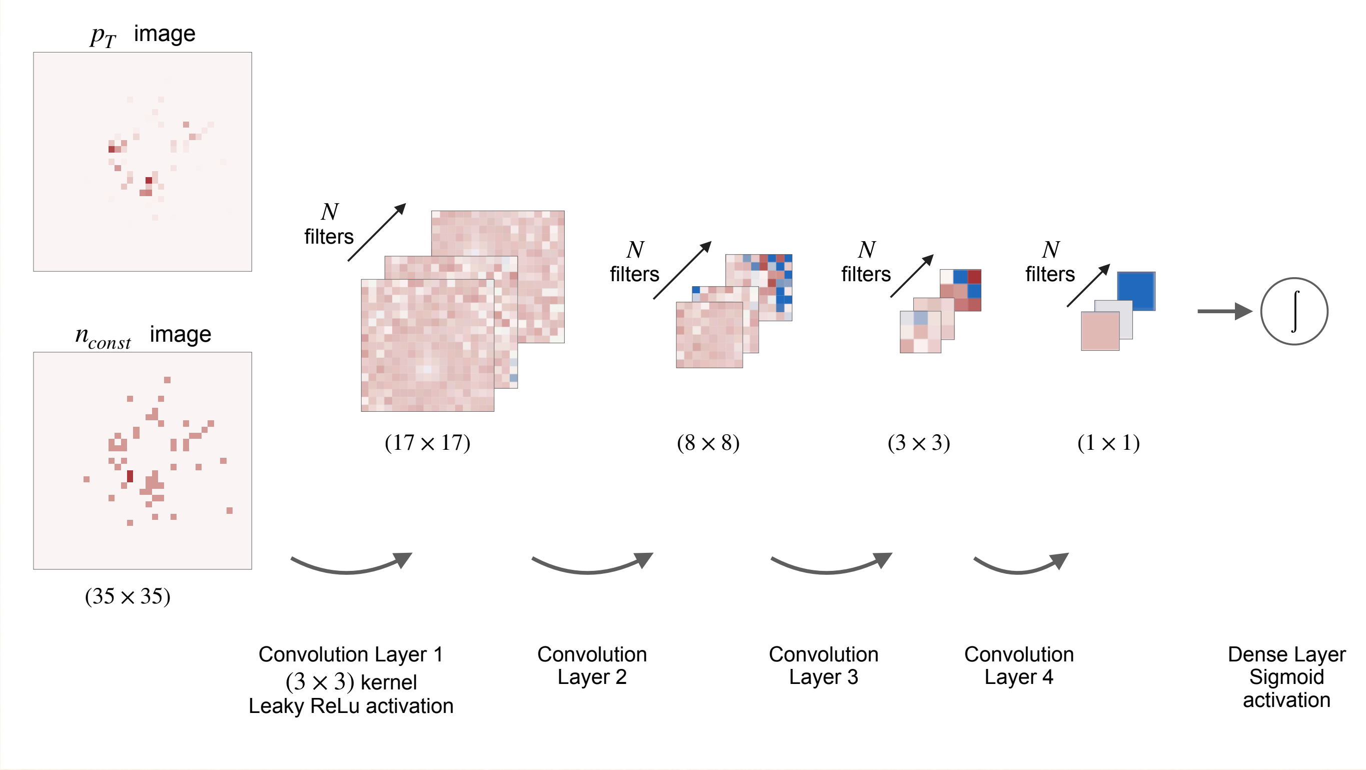
- Leading: triangular components of the initial geometry
- Subleading: radial excitations of this geometry
- Explaining the factorization breaking of v_3

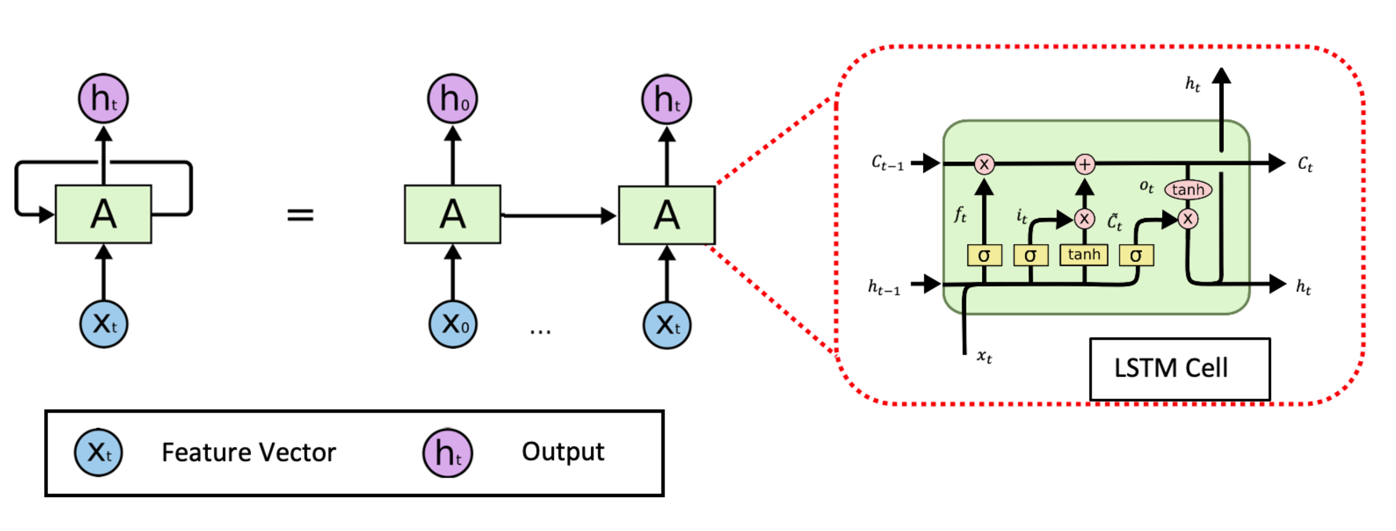
$$1 - r \simeq \frac{1}{2}\left|\frac{V_n^{(2)}(p_1)}{V_n^{(1)}(p_1)} - \frac{V_n^{(2)}(p_2)}{V_n^{(1)}(p_2)}\right|^2$$

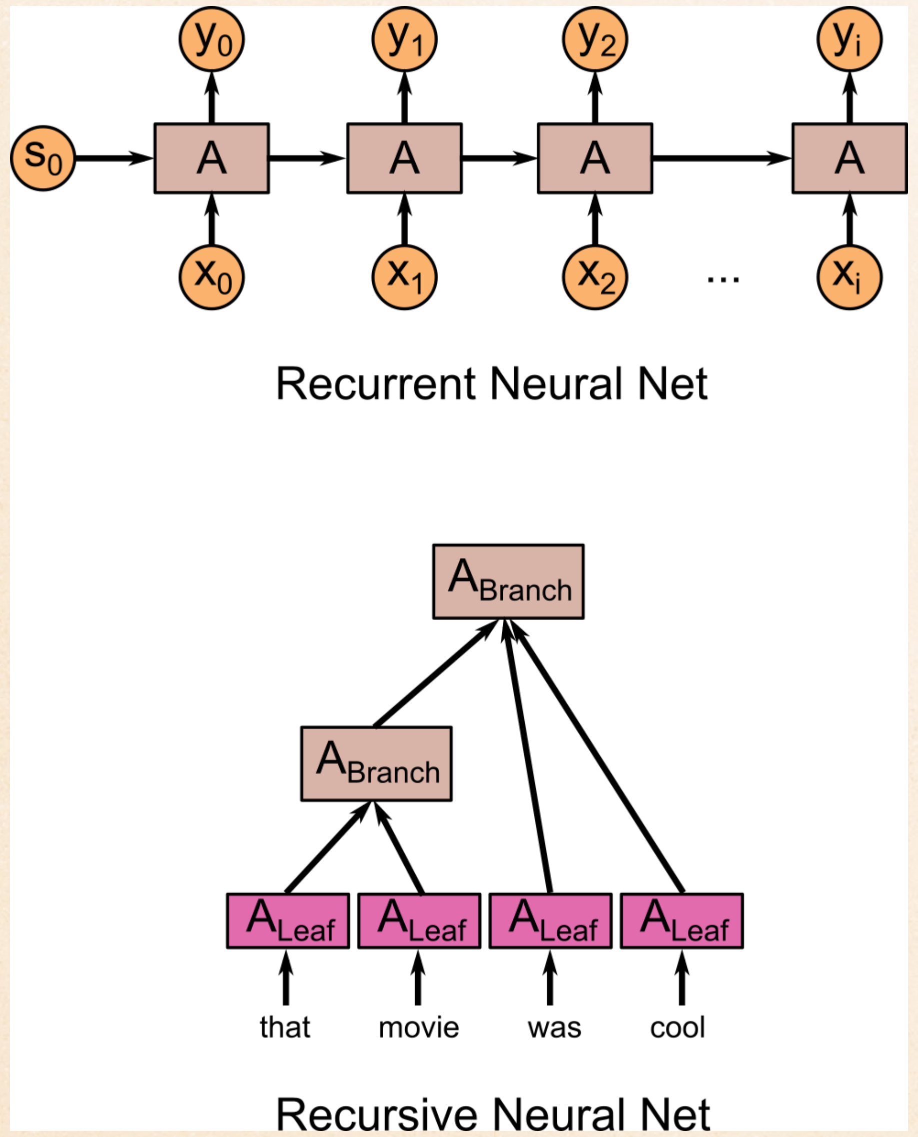
A. Mazeliauskas and D. Teaney, PRC 91, 044902 (2015)

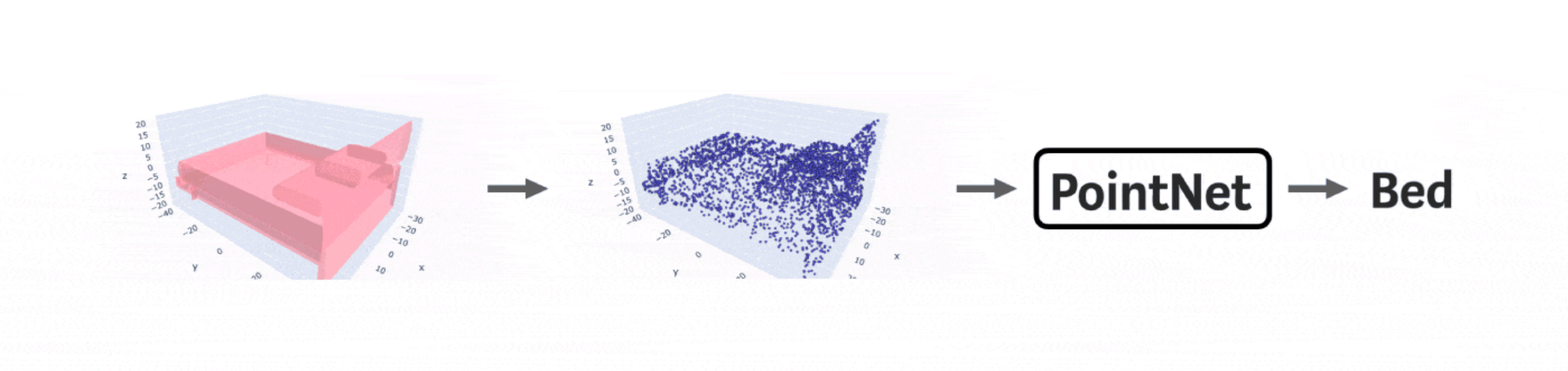
Supervised learning

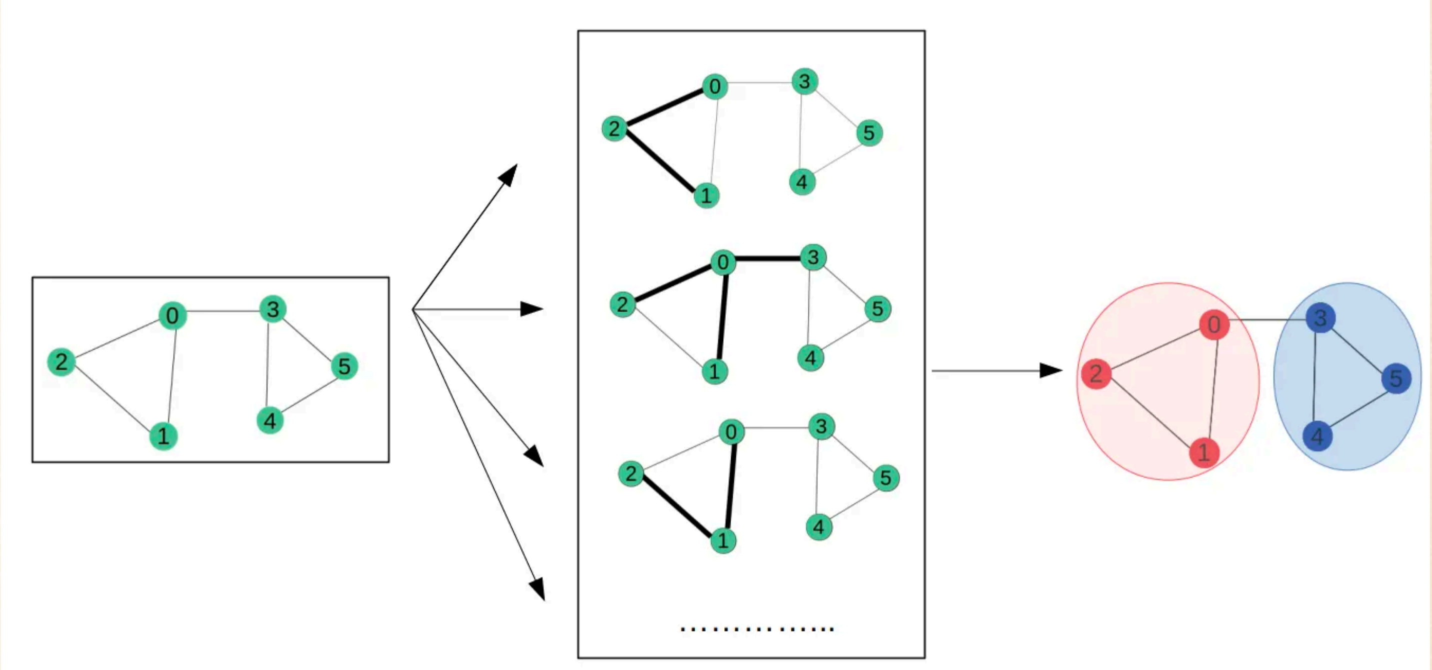






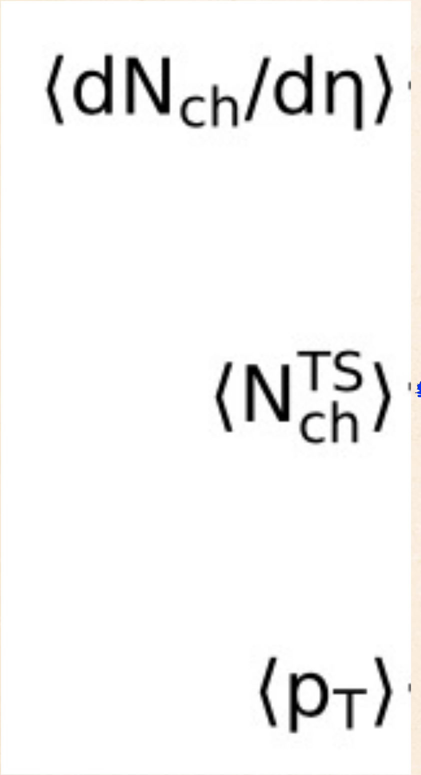




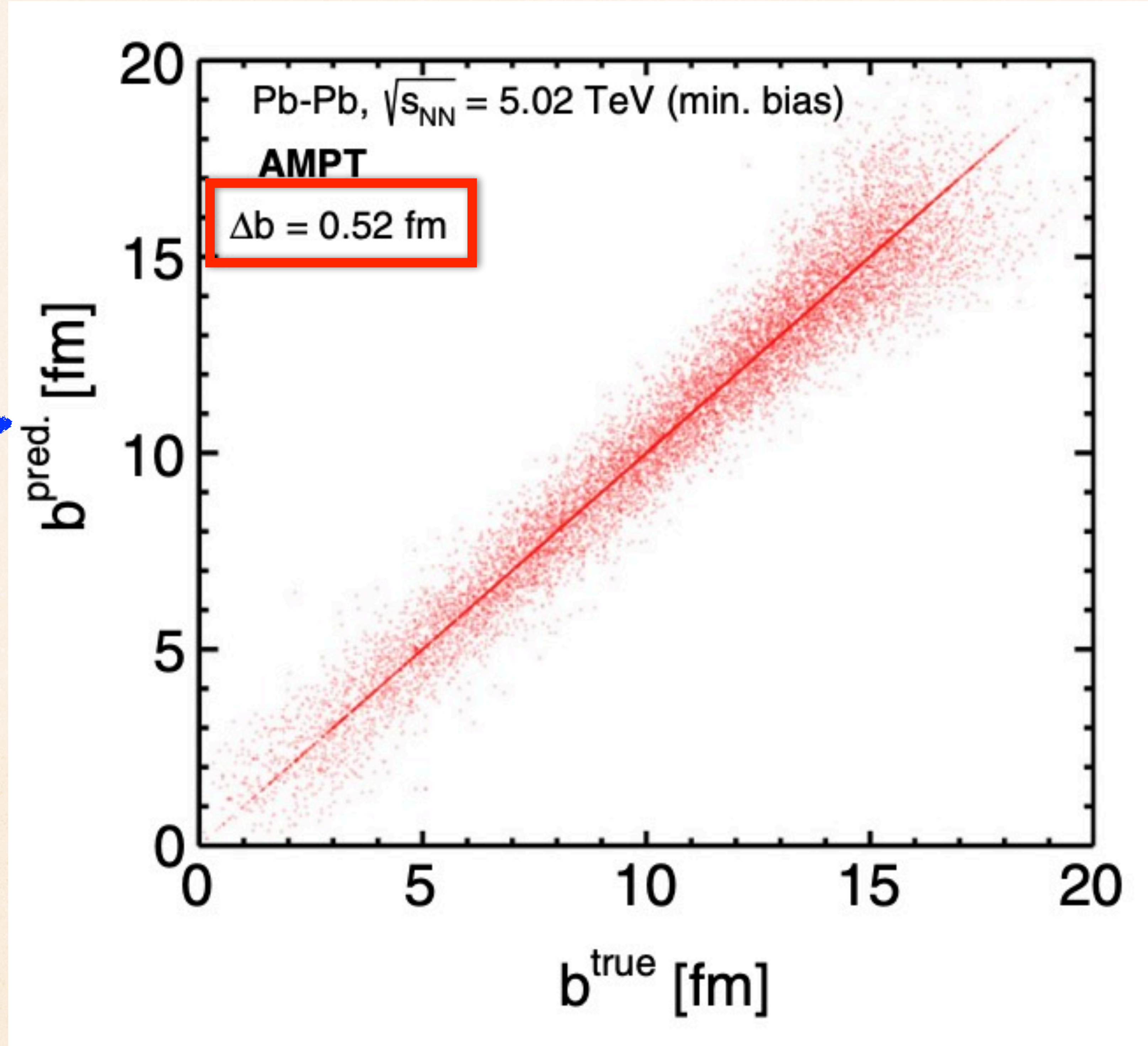


- Various tools suit a lot for heavy ion physics
- A tremendous amount of applications in HEP arXiv:2102.02770

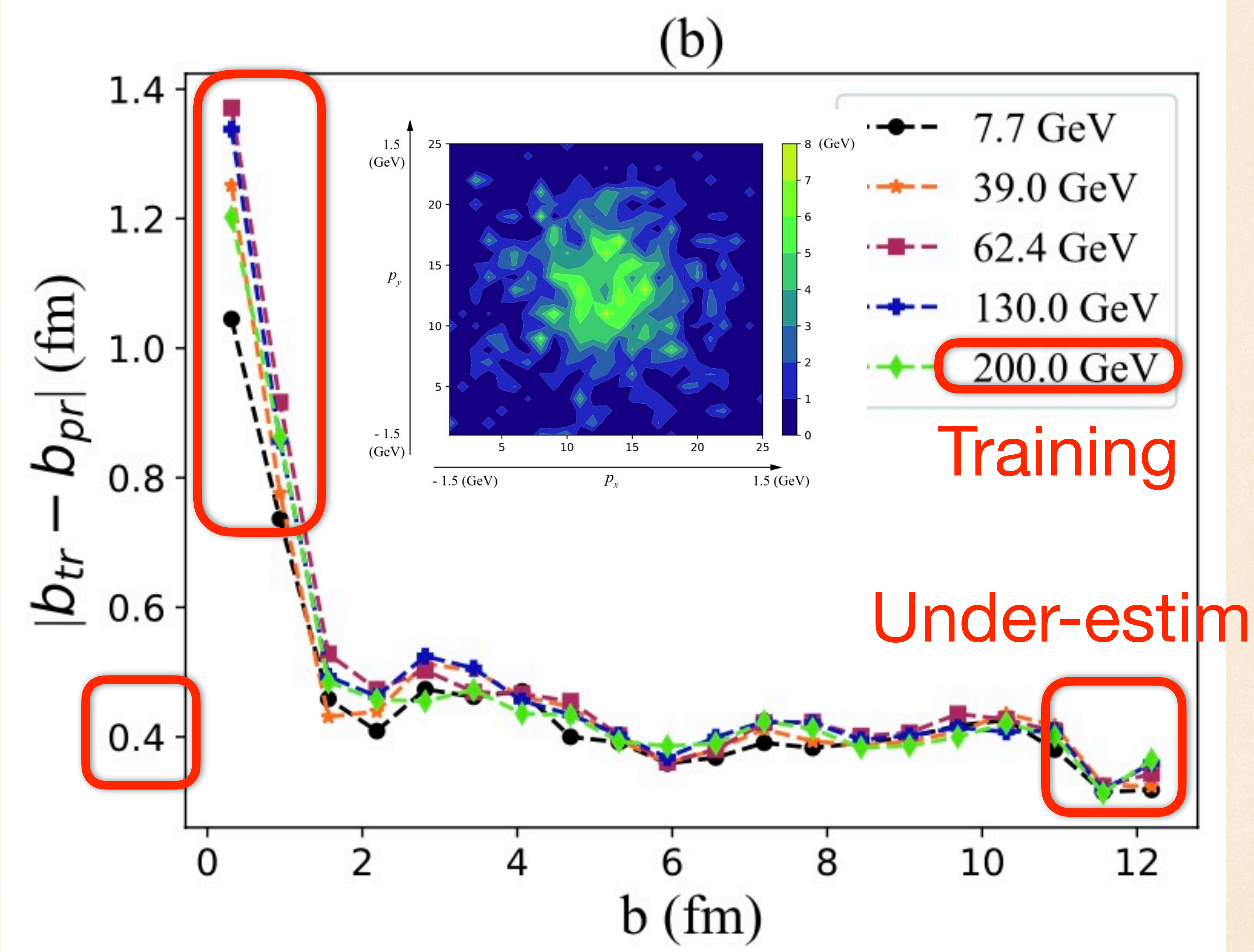
Impact parameter



BDT



Over-estimated!



Training

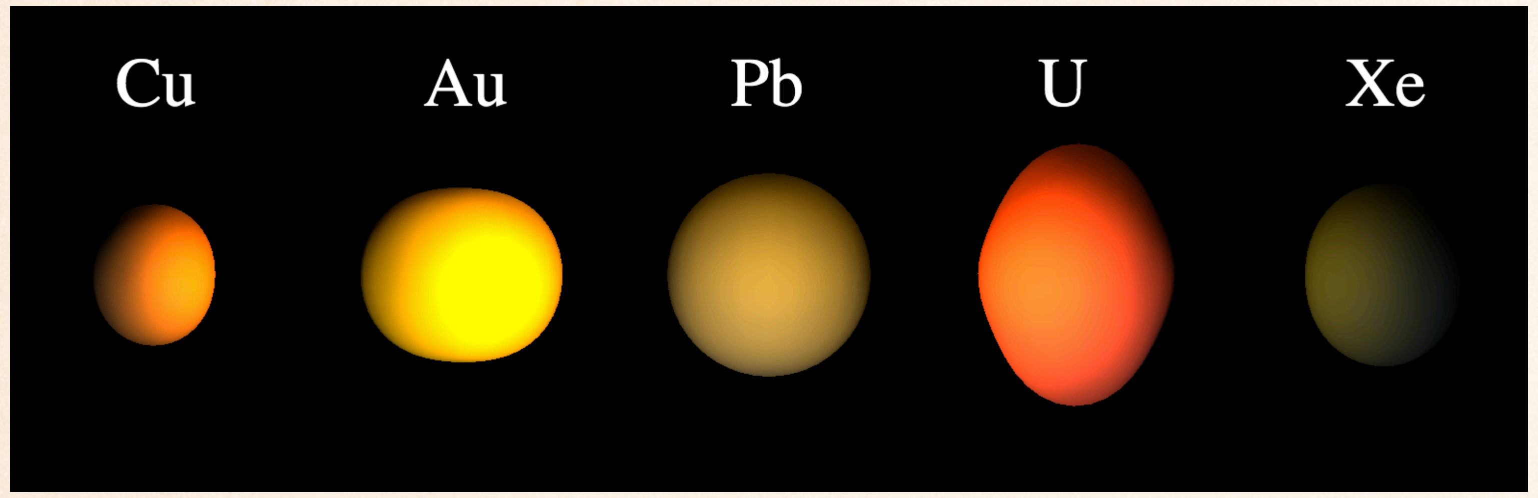
Under-estimated!

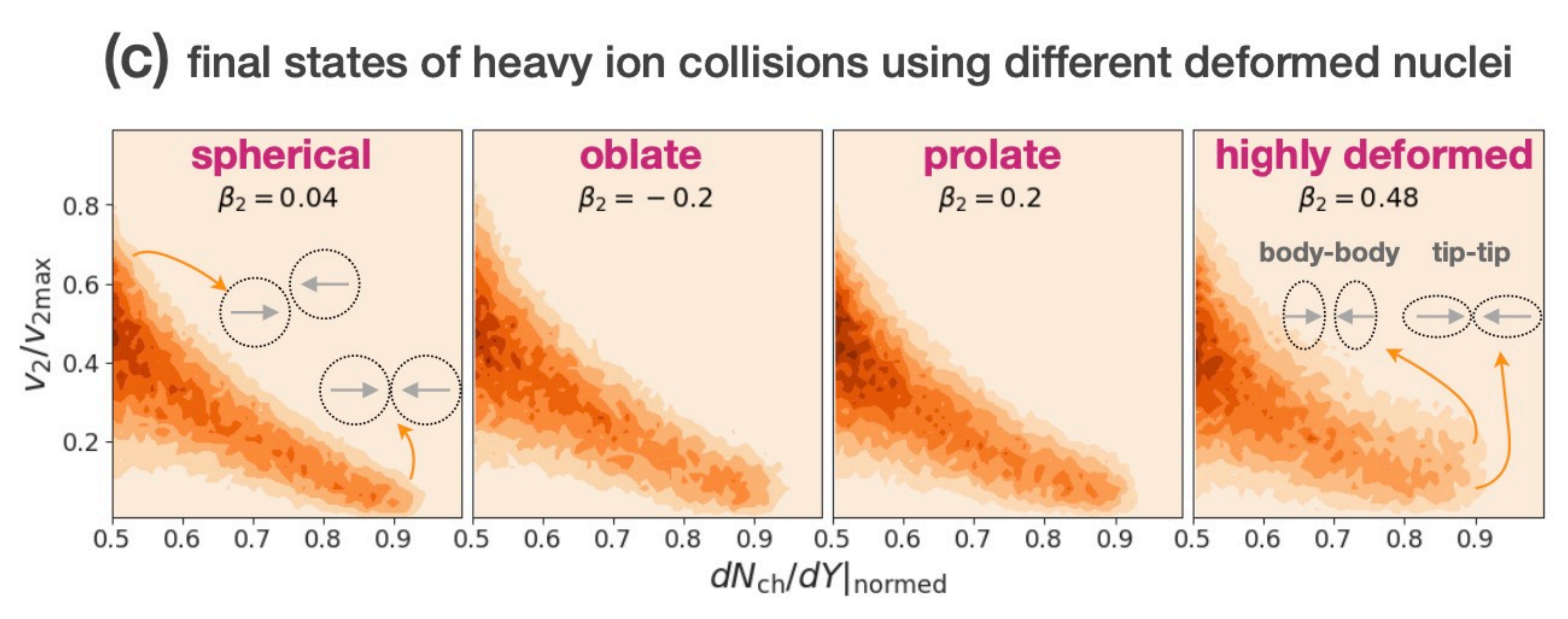
CNN with spectrum in (p_x, p_y) space of charged particles

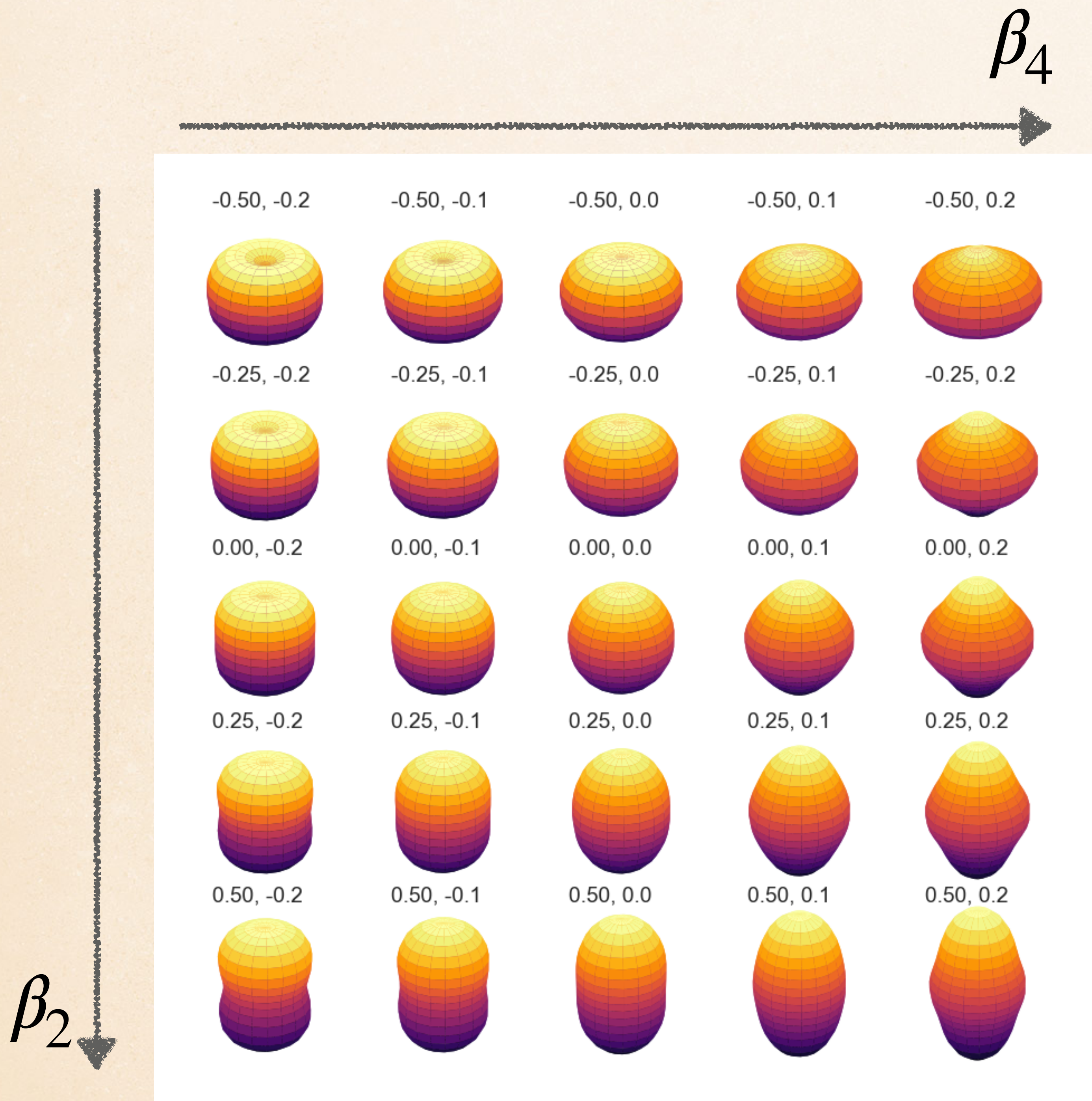
N. Mallick, S. Tripathy, A. N. Mishra, S. Deb, and R. Sahoo, PRD 103, 094031 (2021)

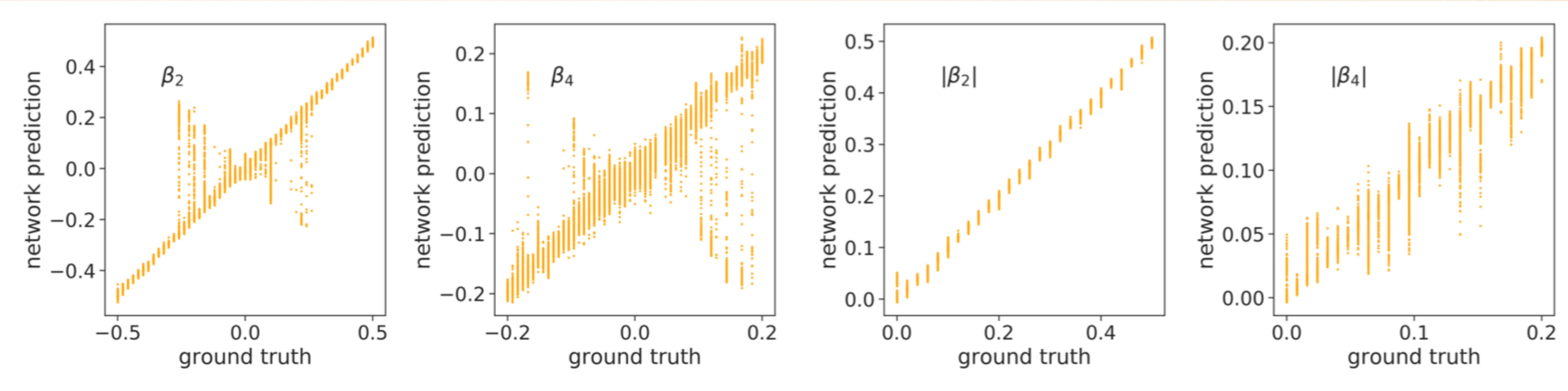
Pei Xiang, Yuan-Sheng Zhao, Xu-Guang Huang, Chin. Phys. C 46, 074110 (2022)

Nuclear shape deformation



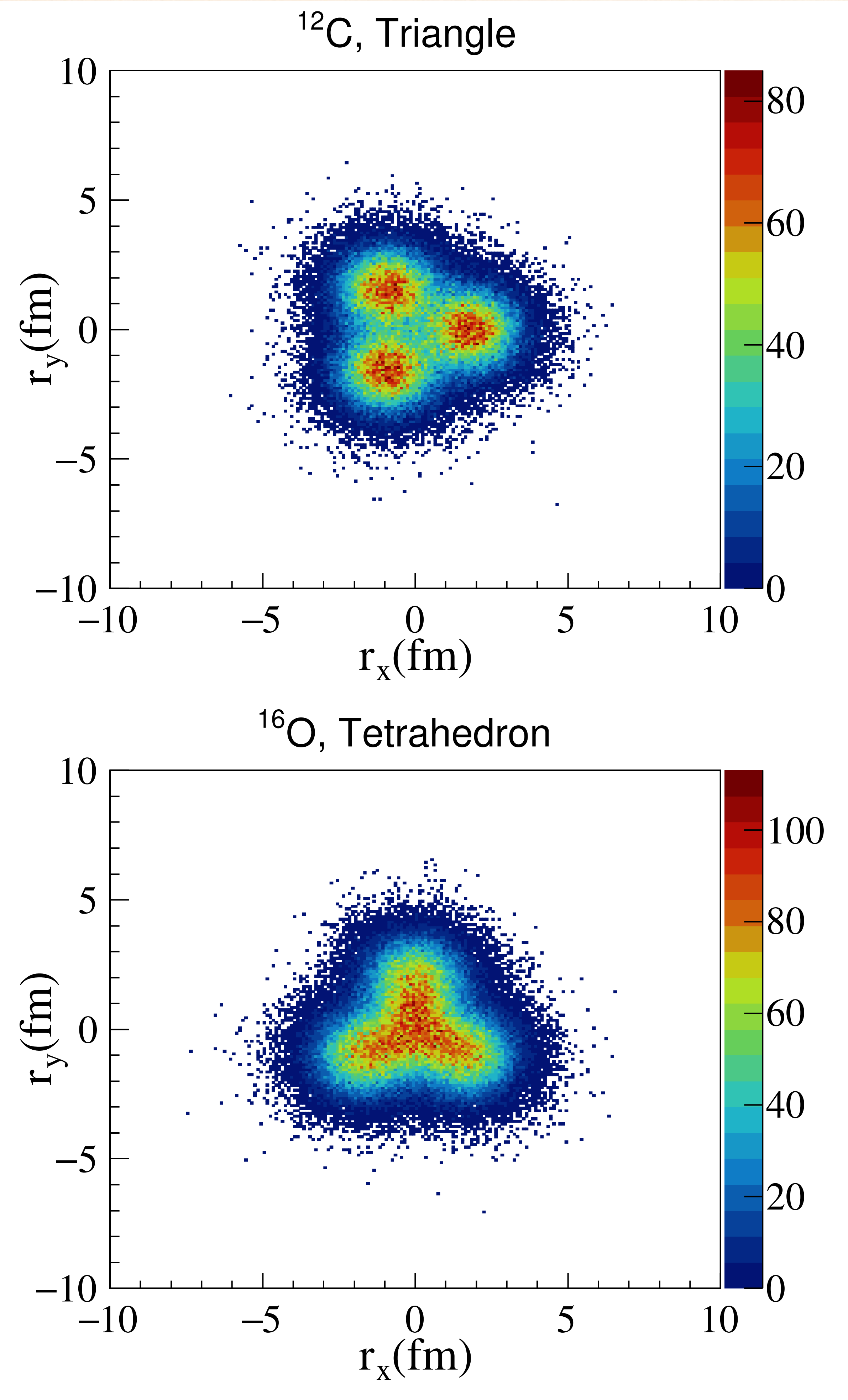


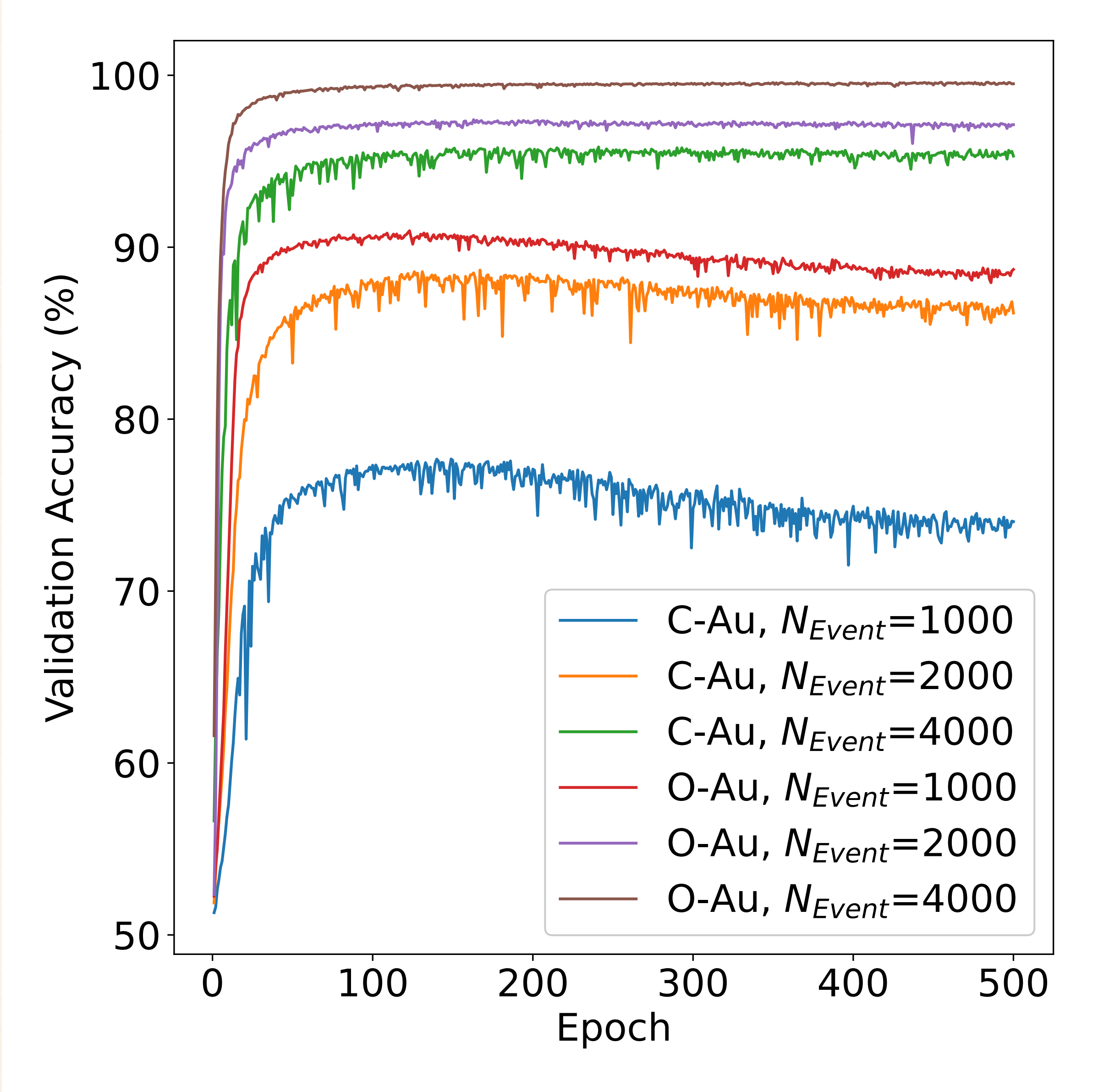


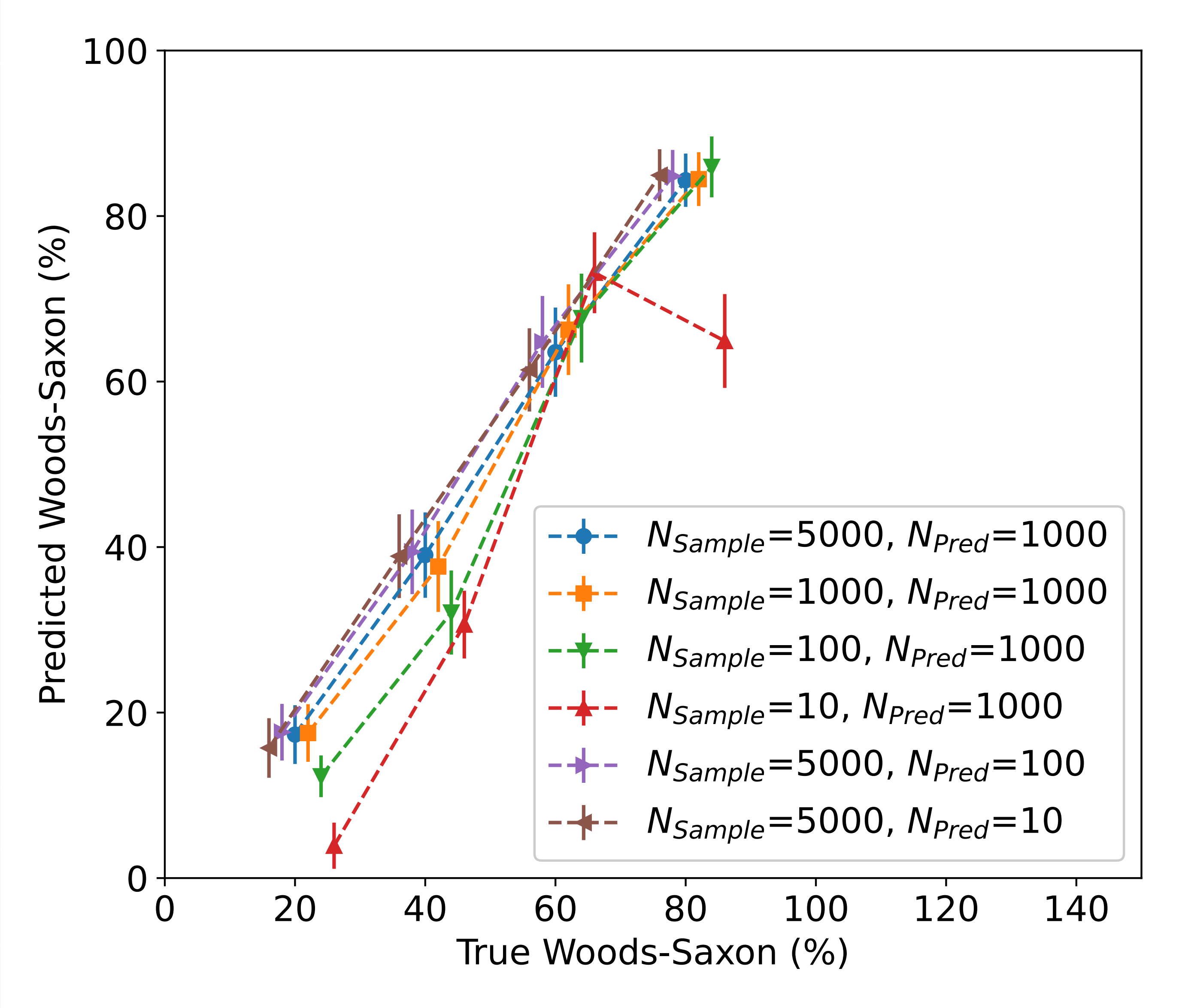


L.-G. Pang, K. Zhou and X.-N. Wang, arXiv:1906.06429

α-cluster v.s. Woods-Saxon in light nuclear

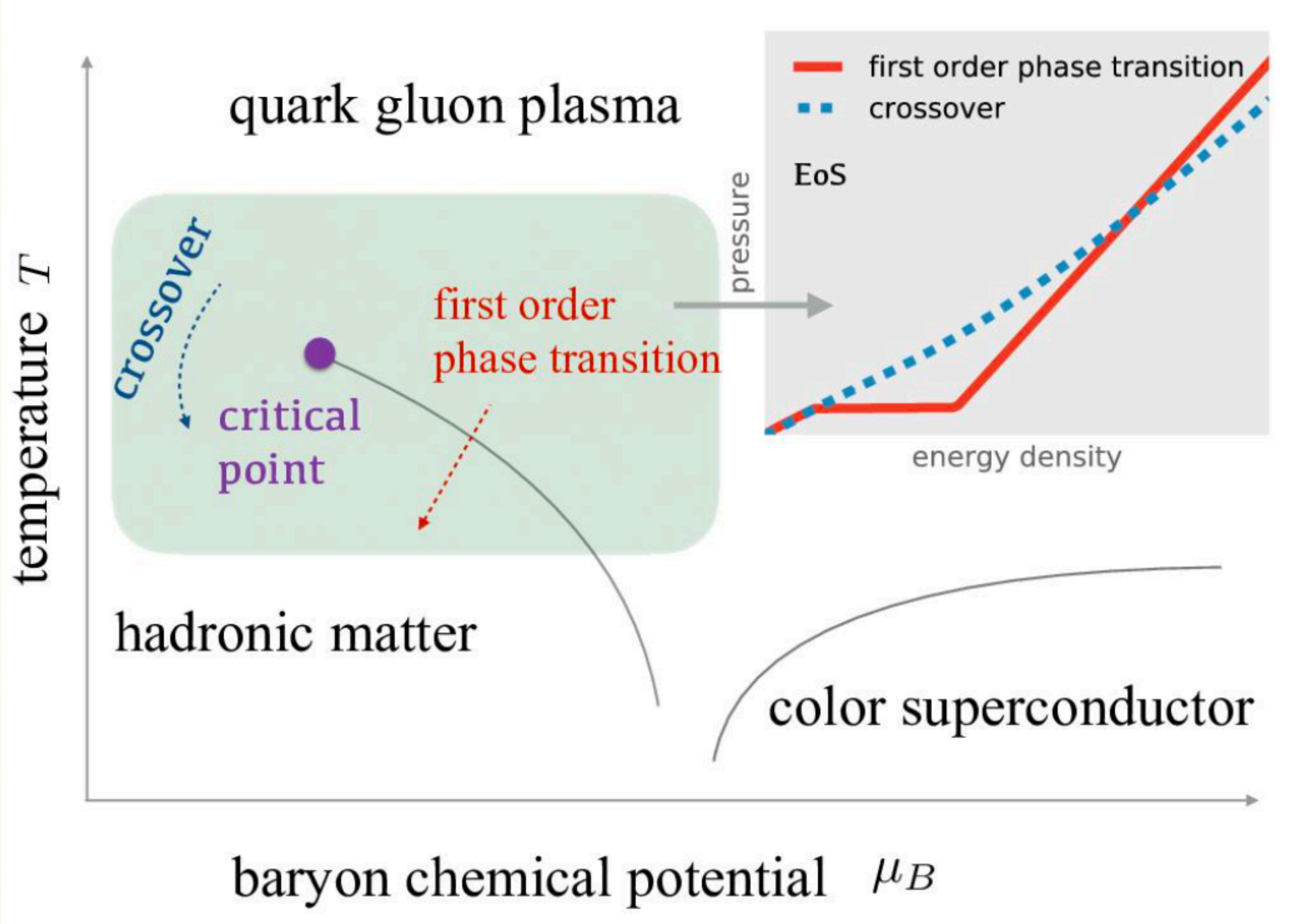


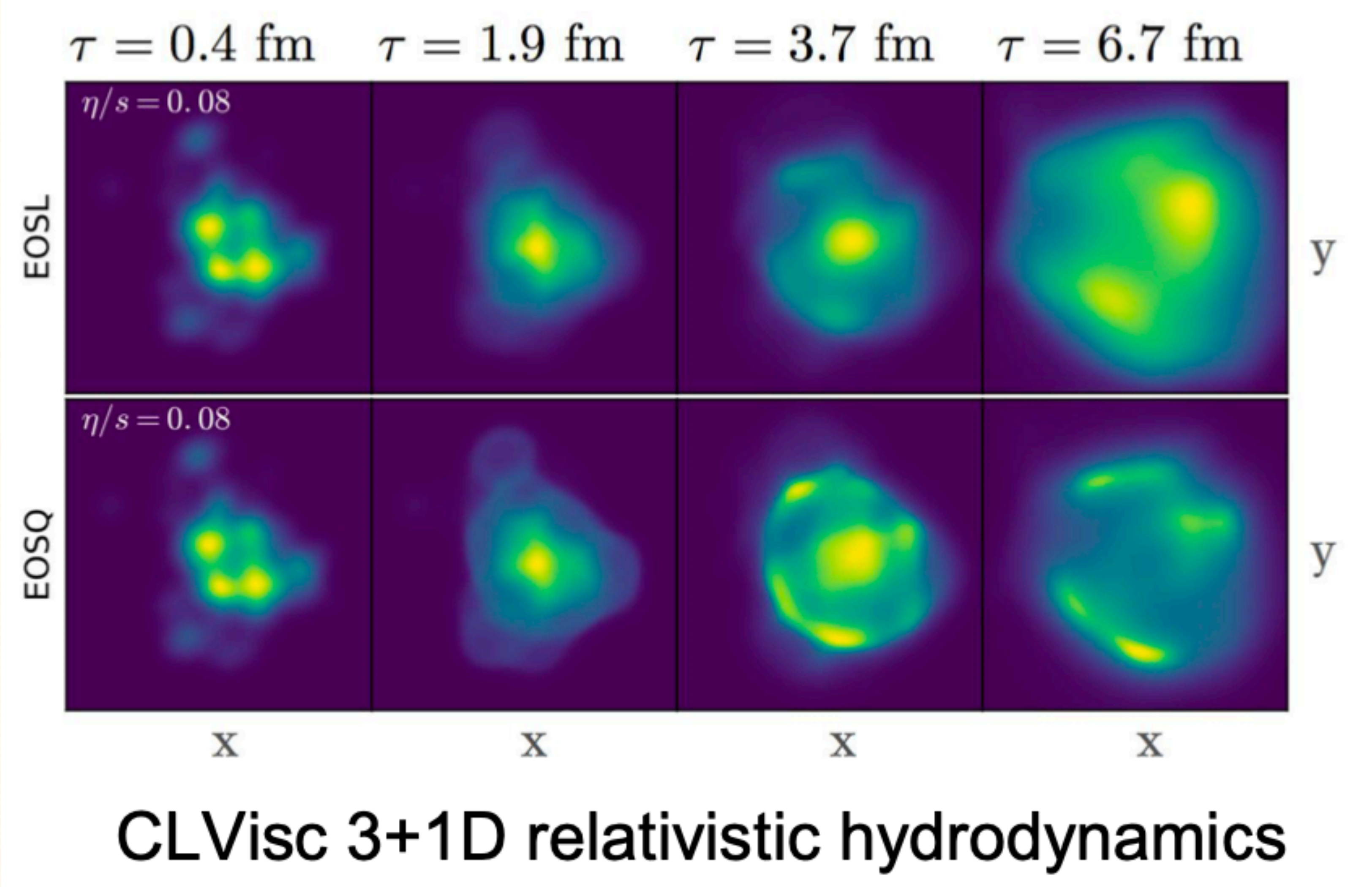


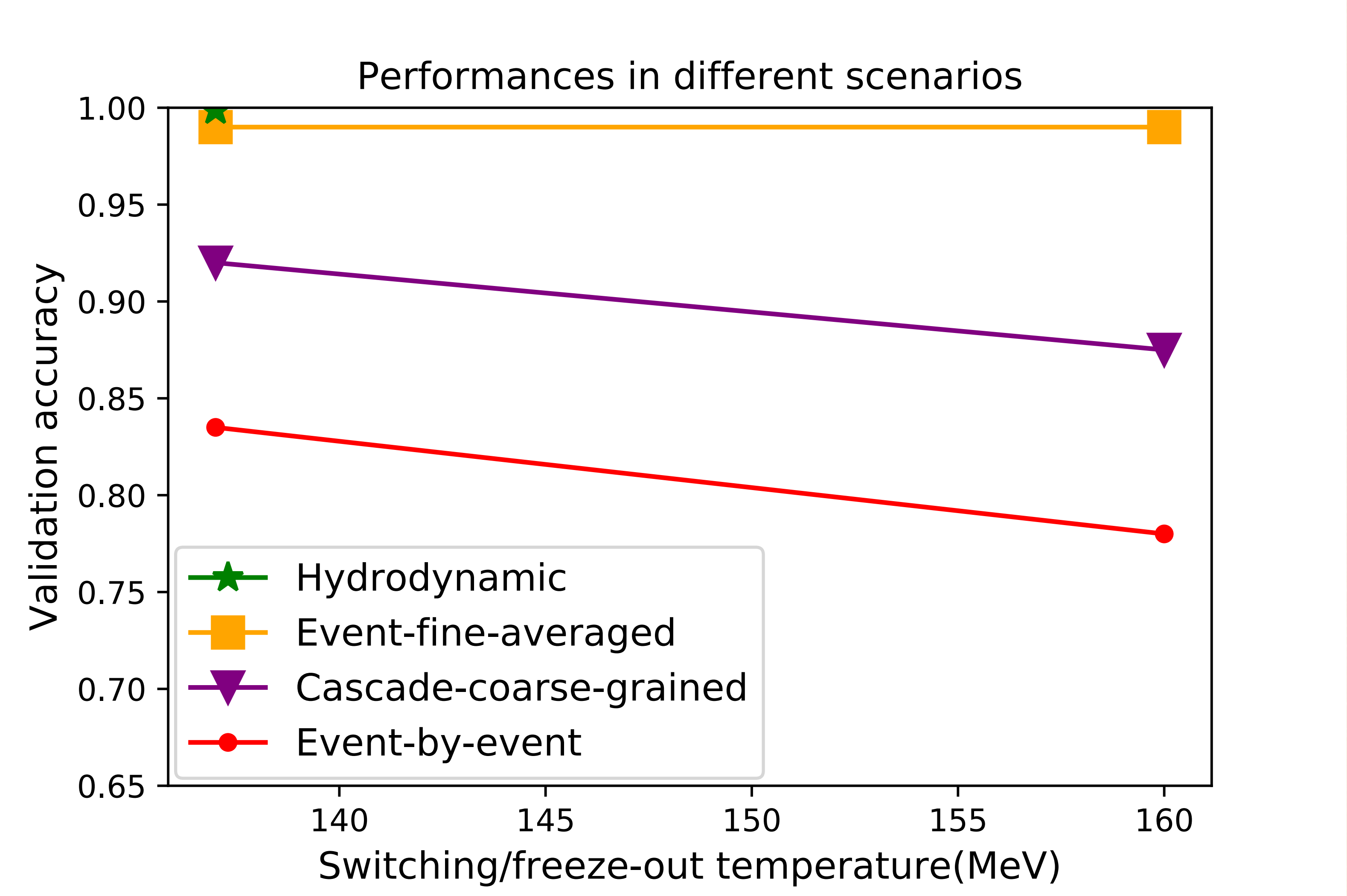


Junjie He, Wan-Bing He, Yu-Gang Ma and Song Zhang, PRC, 104, 044902 (2021)

EoS meter with CNN



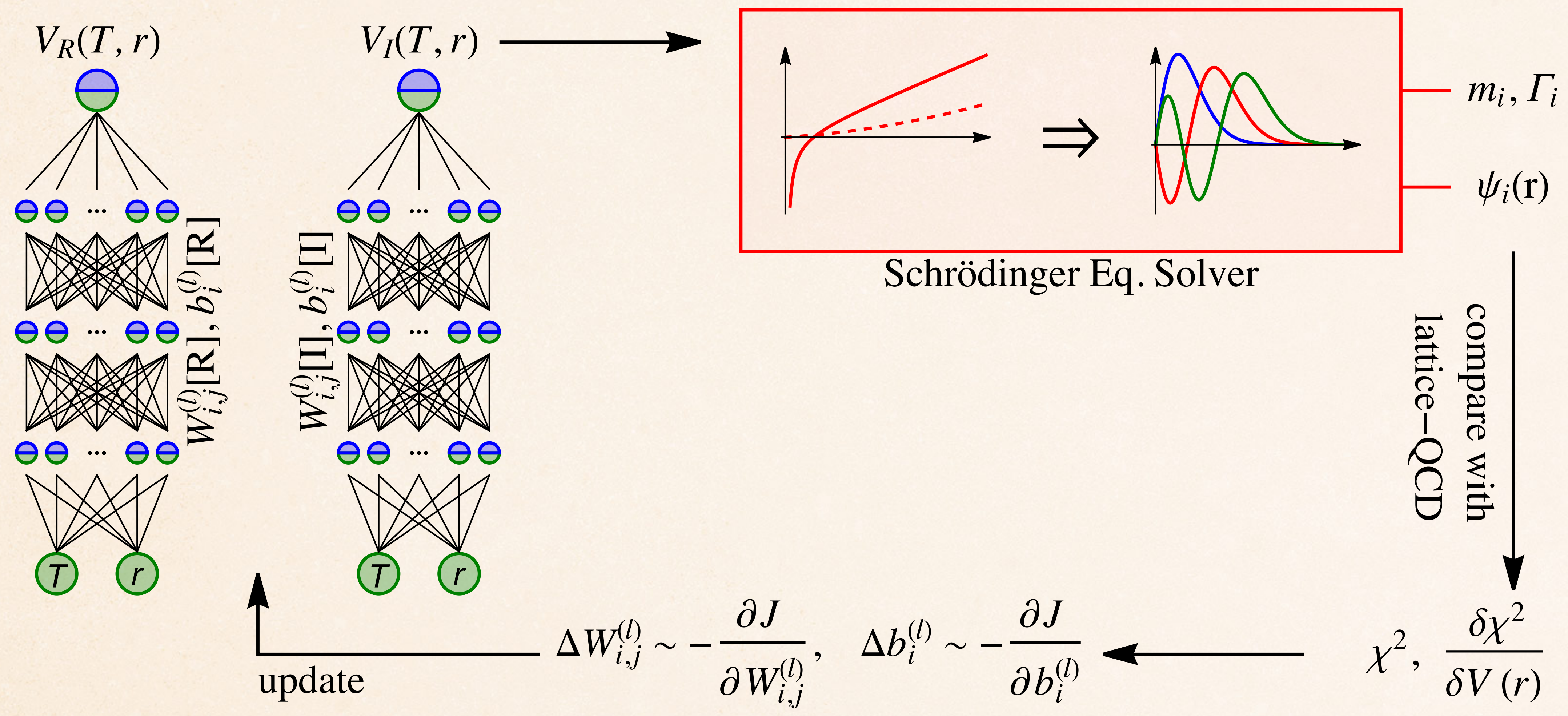


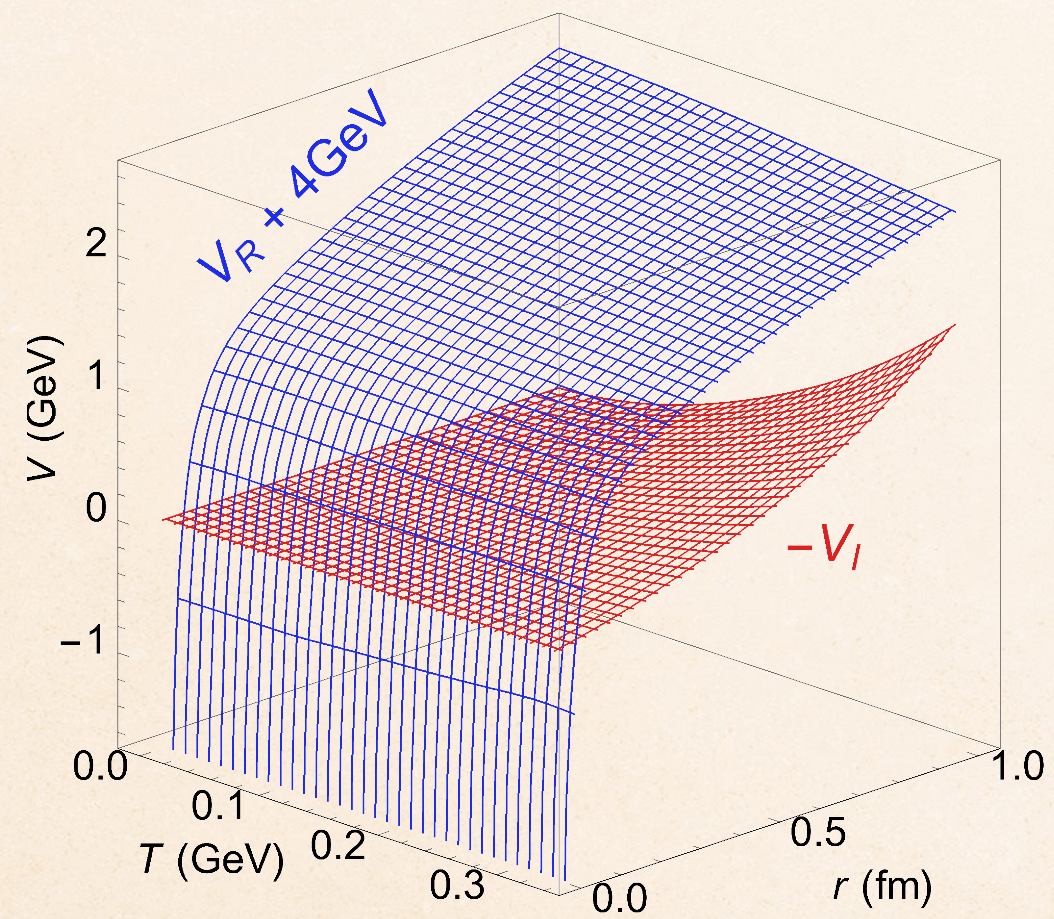


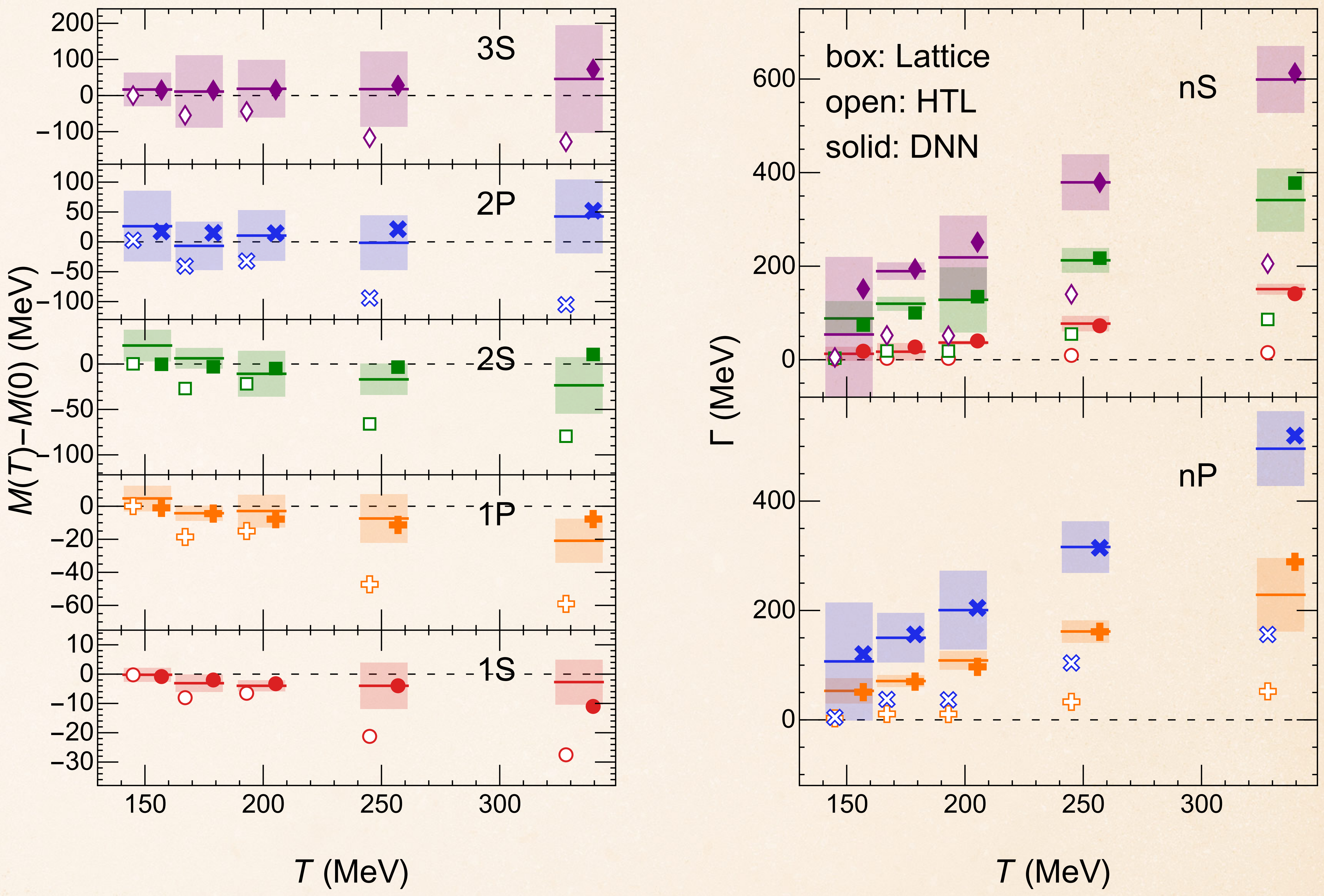
LG. Pang, K. Zhou, N. Su, H. Petersen, H. Stoecker, XN. Wang, Nature Communications 9, 210 (2018)

YLD, K. Zhou, J. Steinheimer, *et al.*, Eur. Phys. J. C, 80, 516 (2020)

Network for heavy quark potential





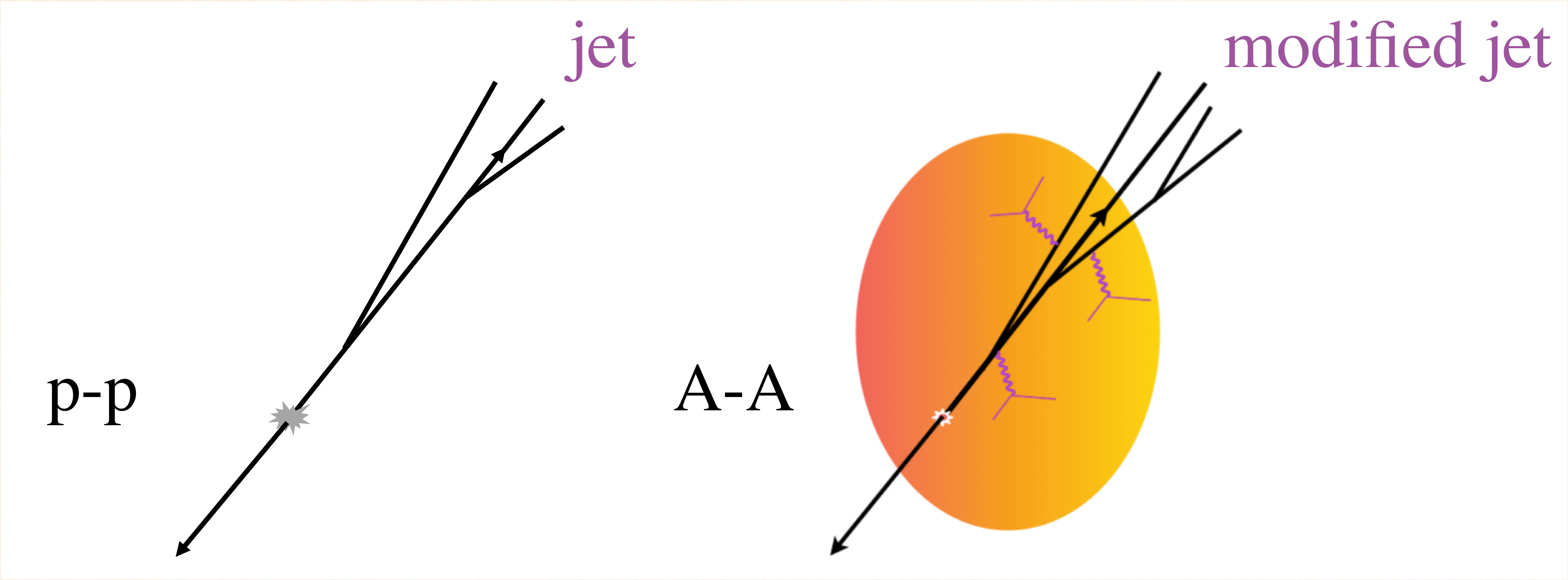


Very mild T dependence of $V_R(T,r)$, for T ≈ 0–334 MeV

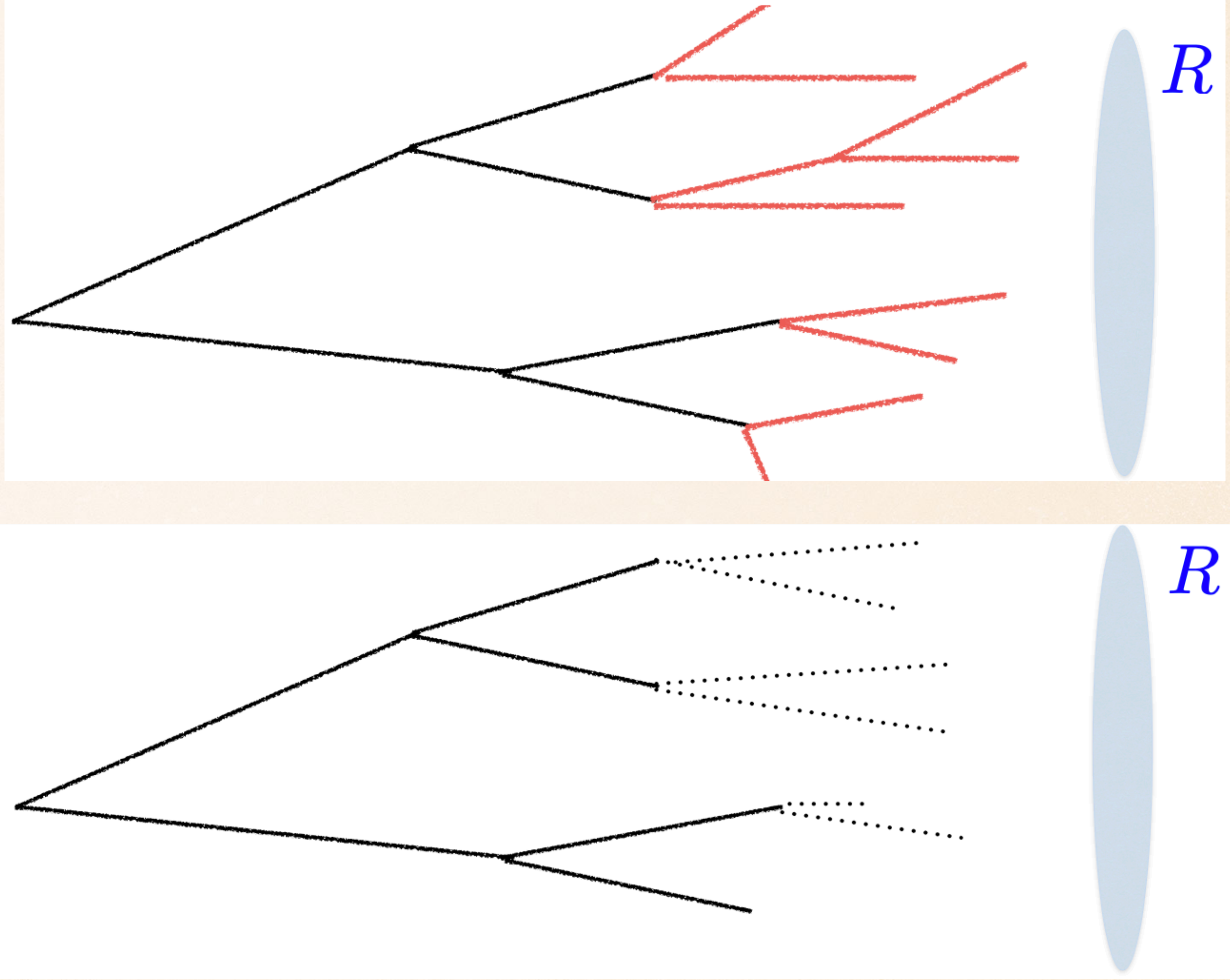
$V_I(T,r)$ shows a rapid increase with T and r, for T=151–334 MeV

S. Shi, K. Zhou, J. Zhao, S. Mukherjee and P. Zhuang, PRD 105, 014017 (2022)

QGP and Jet Modifications



By J. Brewer



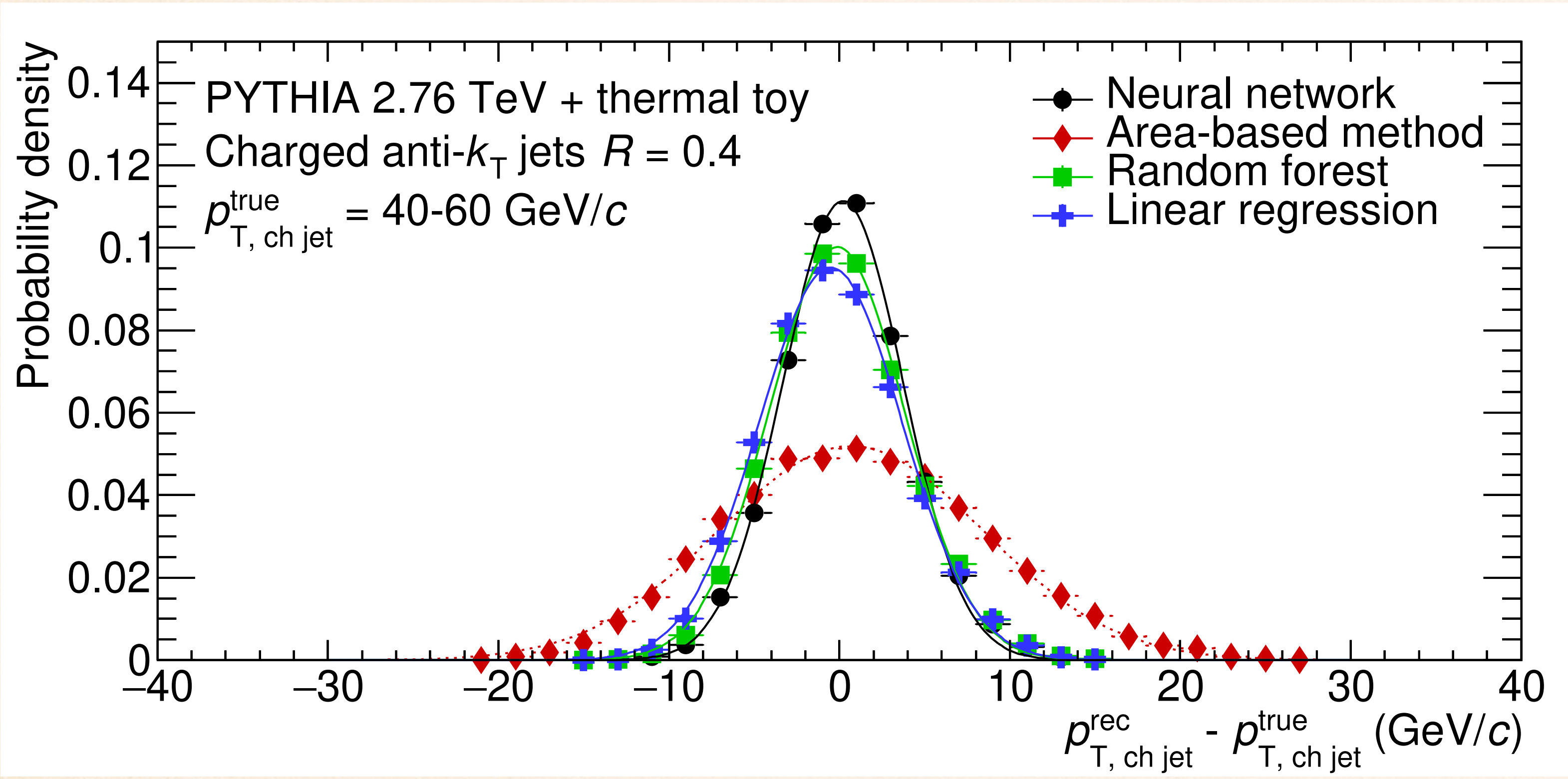
By D. Pablos

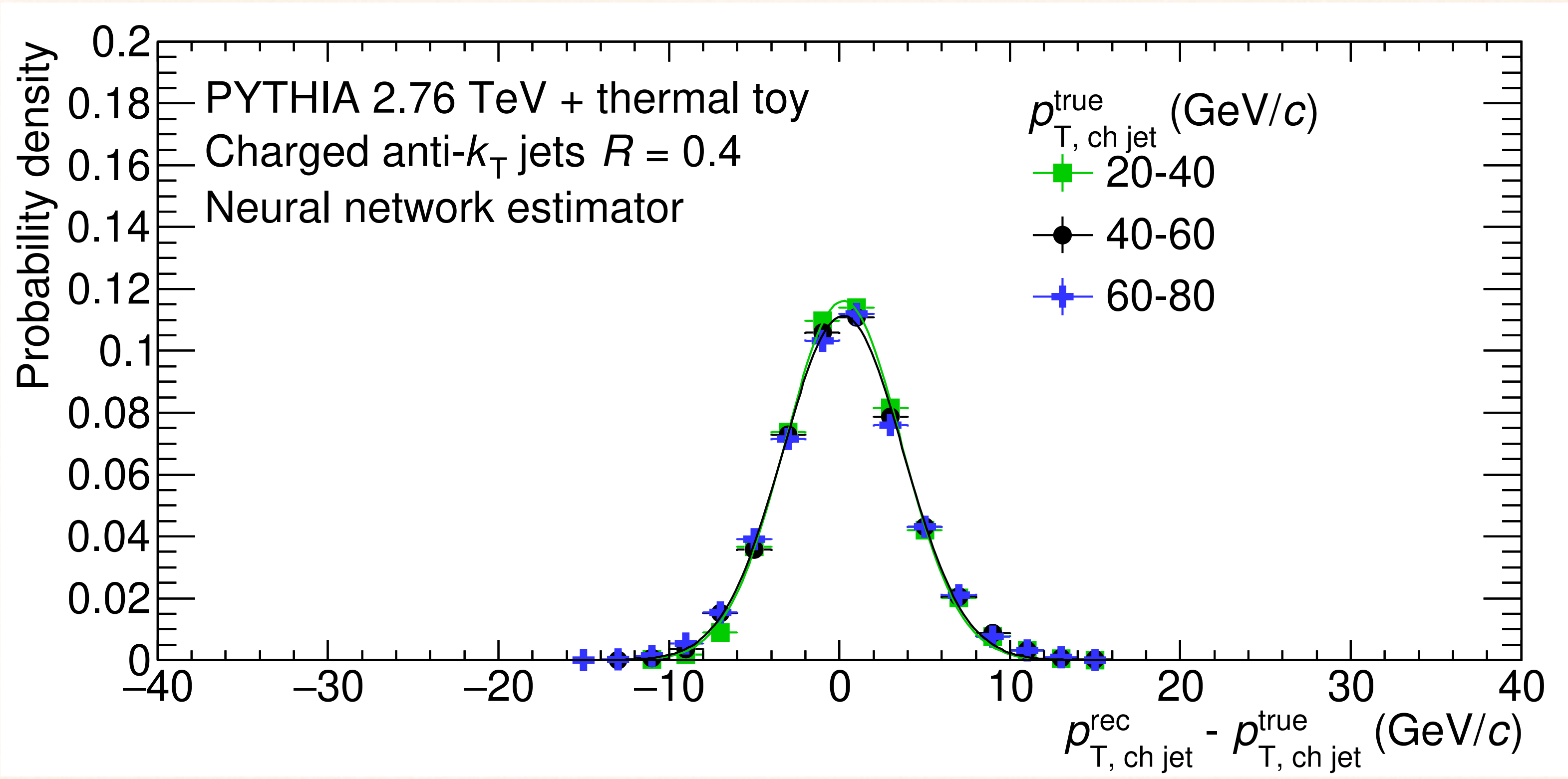
Hypethetical twin jets in vacuum/medium

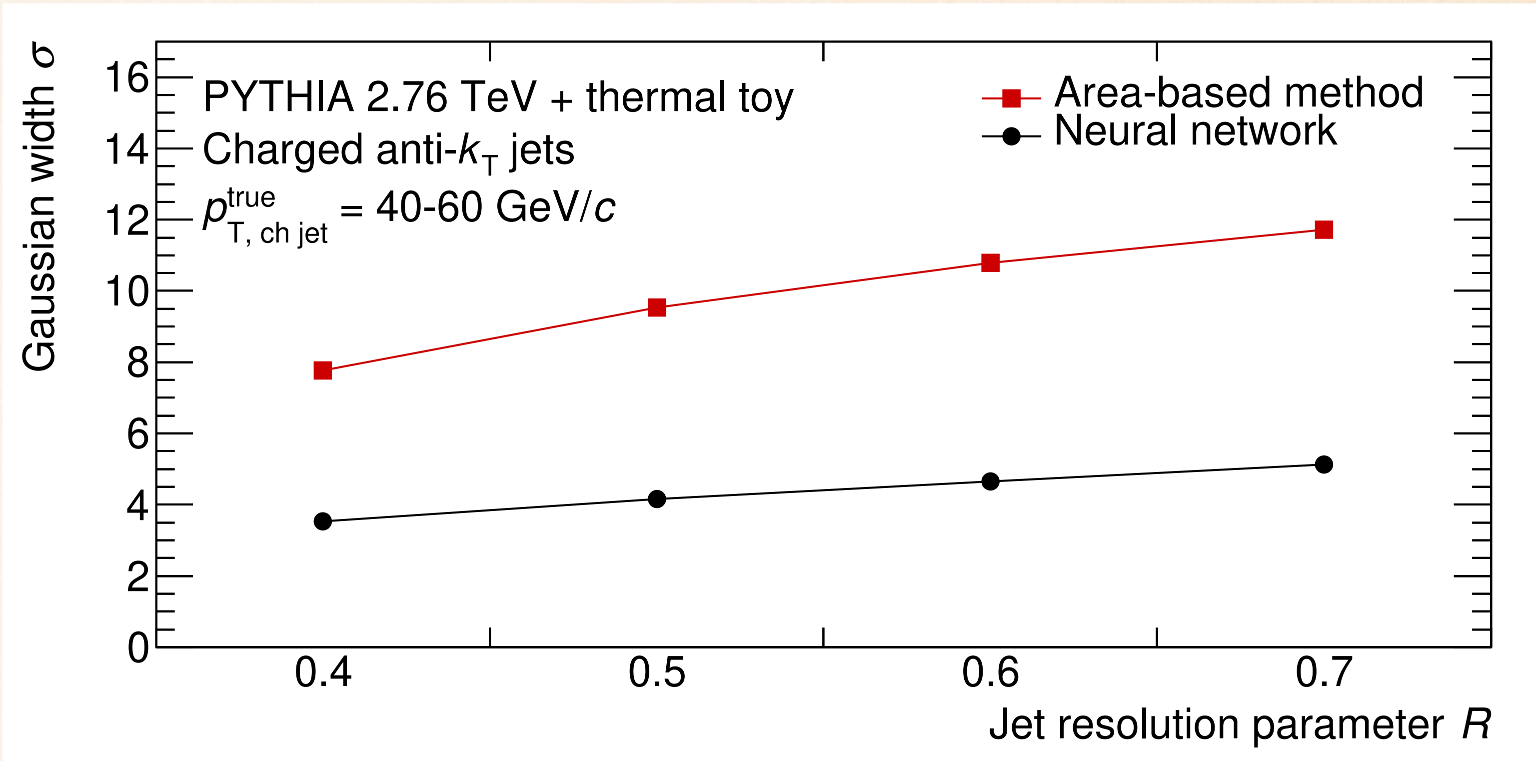
- Jets are powerful probes to QGP
  - QGP: AA collisions at $\sqrt{s}$ with different centralities
  - Jets (dijets, γ/Z-jets): initiator's flavor, energy, position, direction and jet substructures developed at early stages
  - Jet-medium interactions
- Towards more precise probes & jet tomography with ML

Jet Momentum Reconstruction

R. Haake and C. Loizides, PHYS. REV. C 99, 064904 (2019)







$$p^{\mathrm{rec}}_{\mathrm{T,\,ch\,jet}} = p^{\mathrm{raw}}_{\mathrm{T,\,ch\,jet}} - \rho A$$

$$p^{\mathrm{true}}_{\mathrm{T,\,ch\,jet}} = p^{\mathrm{raw}}_{\mathrm{T,\,ch\,jet}} \cdot \sum_i p^{\mathrm{PYTHIA}}_{\mathrm{T,\,const}\,i} \Big/ \sum_i p_{\mathrm{T,\,const}\,i}.$$

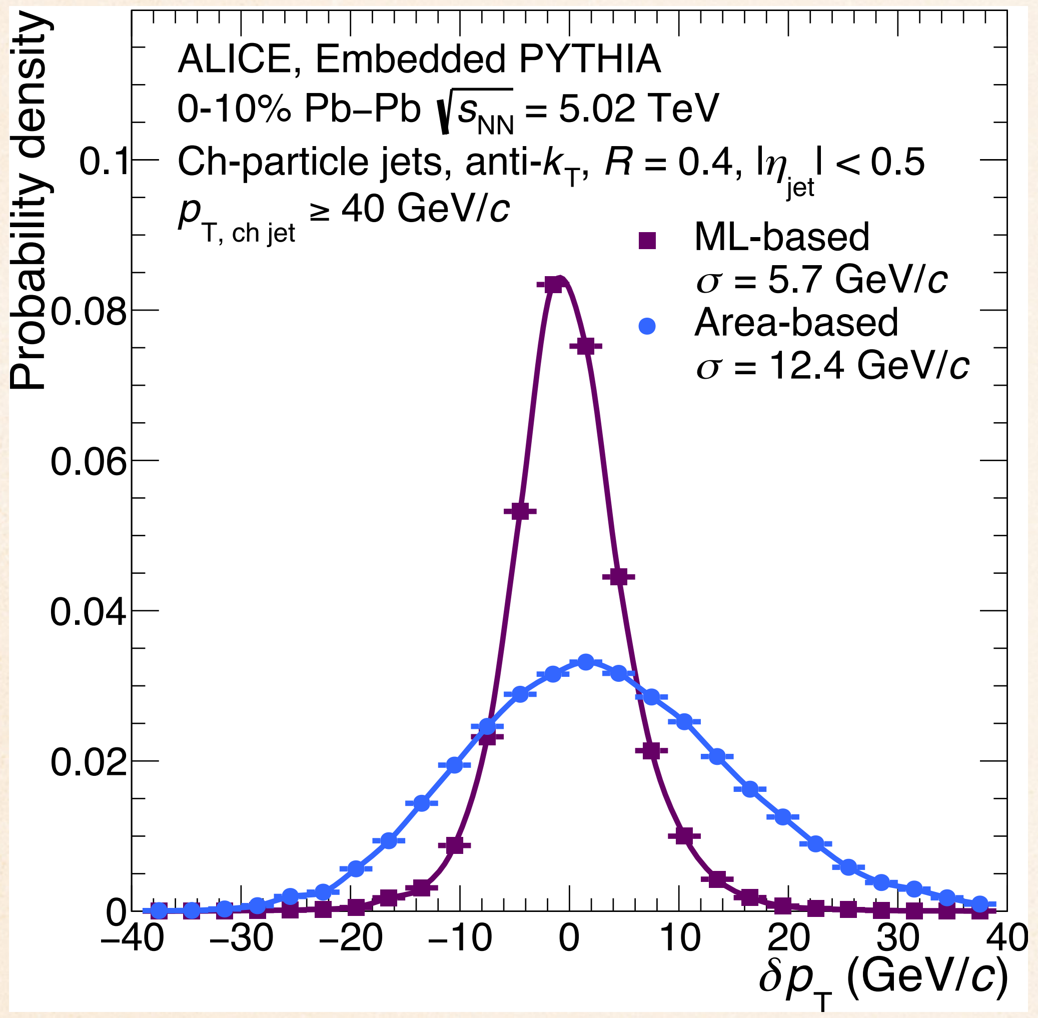
- Pythia jets embedded in a toy thermal model
- Linear Regression, Random Forest (decision trees), Neural Network
- Enable low-p_T large-R jet measurements

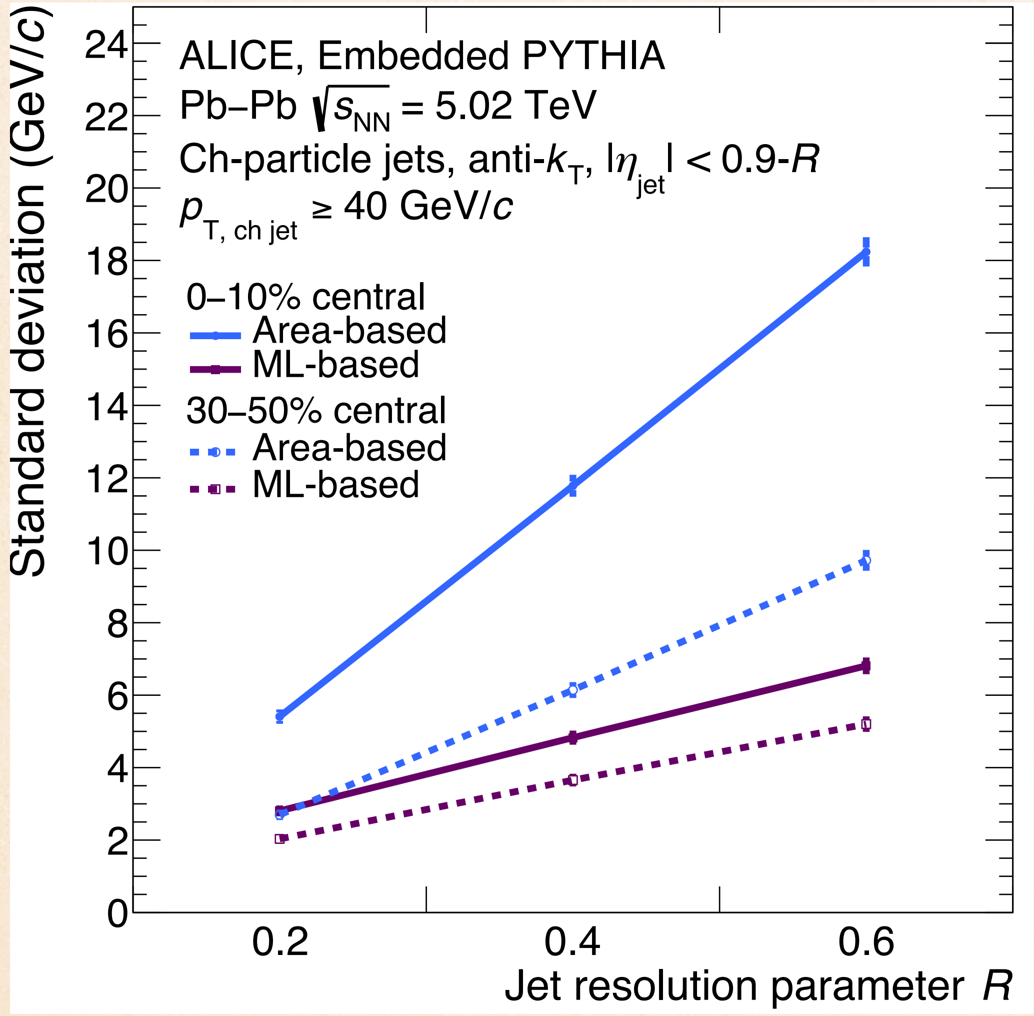
In order to find a suitable combination of input parameters, the analysis was repeated for a large variety of parameter sets. The number of parameters used is kept small to avoid a dependence on data subtleties. Eventually, the following input parameters prove to be useful, discriminative features:

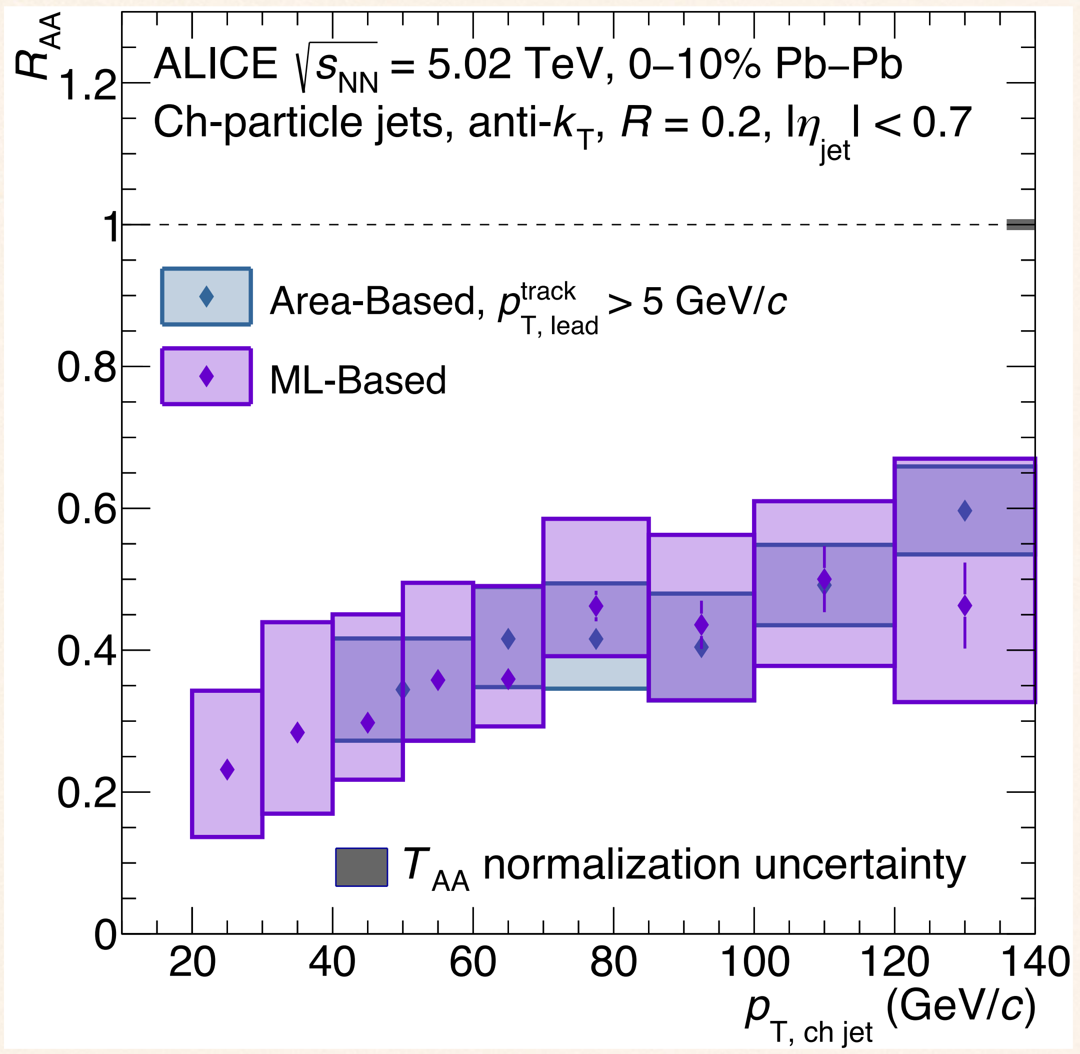
(1) The uncorrected jet momentum as reconstructed by the jet finding algorithm,
(2) the jet transverse momentum, corrected by the established area-based method,
(3) several jet shape observables, namely jet mass, radial moment, momentum dispersion, and LeSub,
(4) the number of constituents within the jet,
(5) mean and median of all constituent transverse momenta,
(6) the transverse momenta of the first ten leading, i.e., hardest, particles within the jet.

Jet Momentum Reconstruction in ALICE

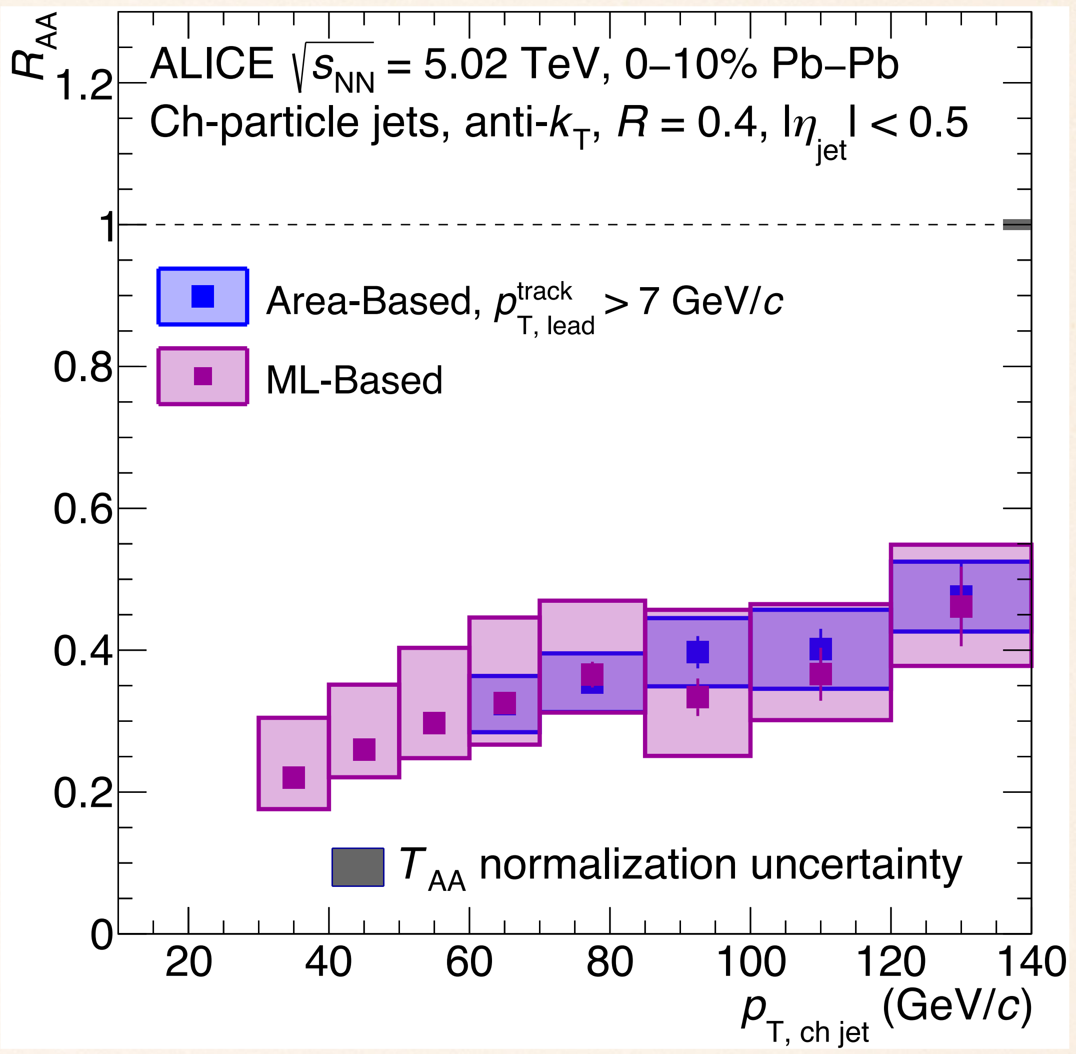
ALICE: arXiv.2303.00592



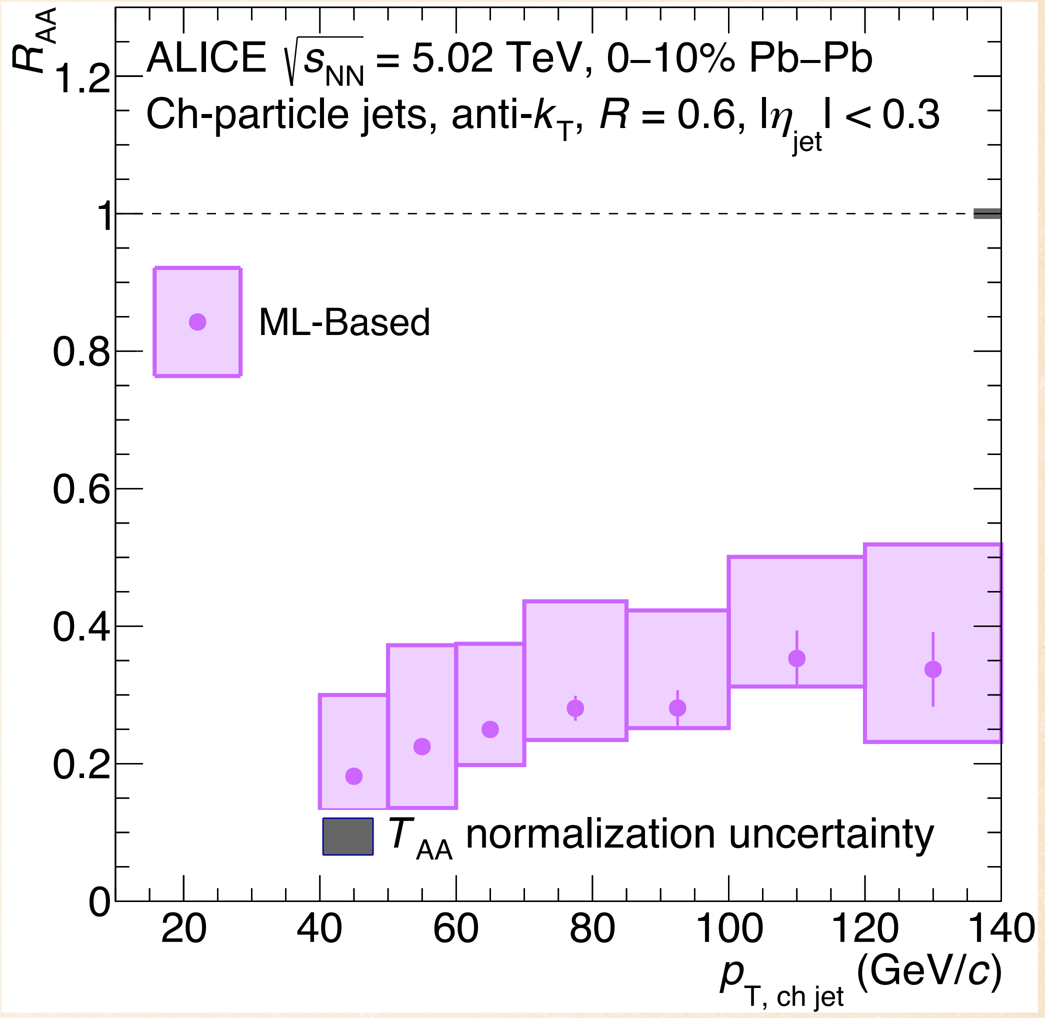




R=0.2



R=0.4



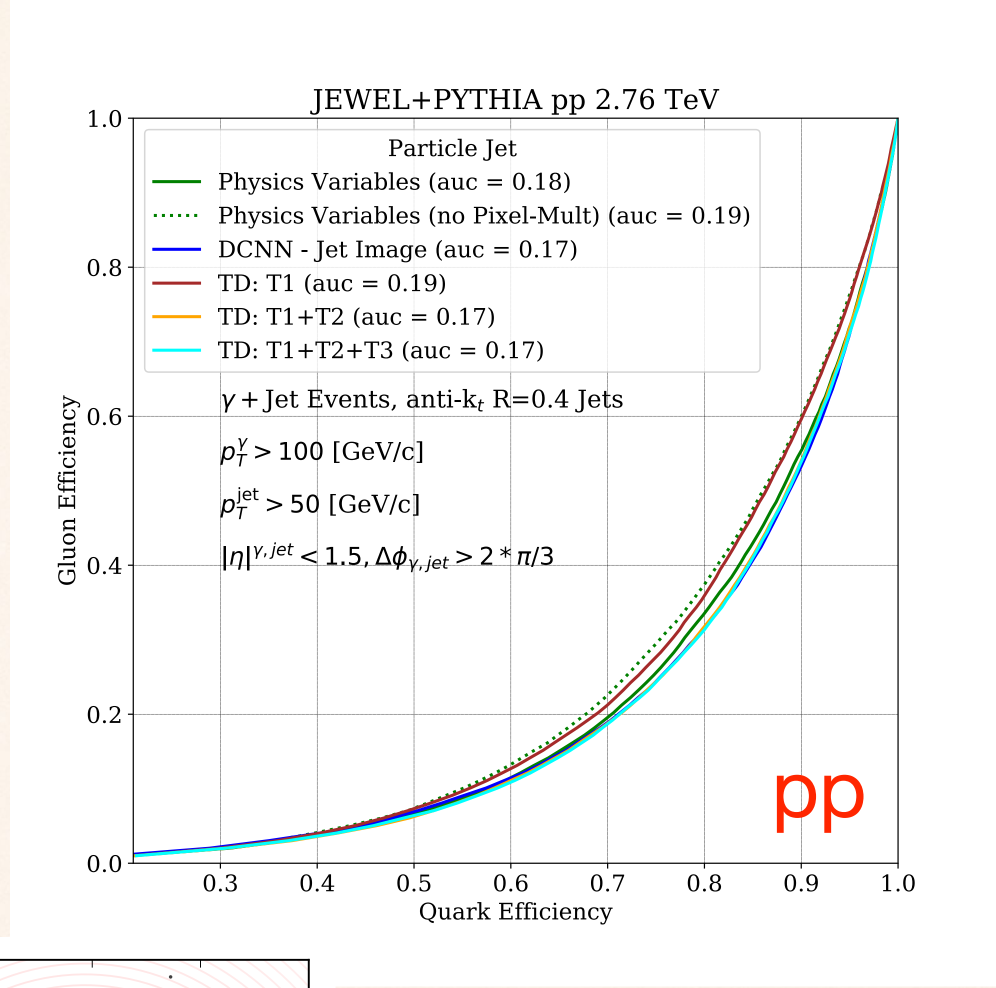
R=0.6

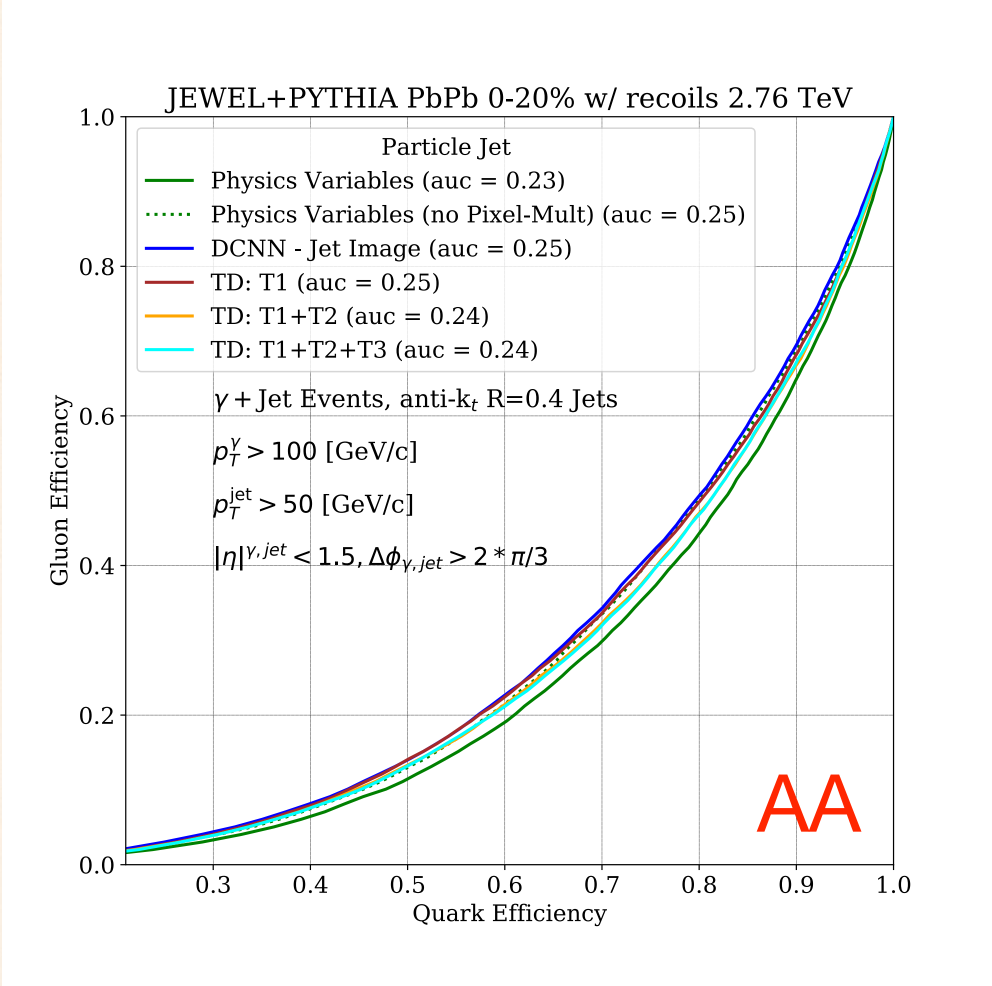
- Jet p_T correction with ML- VS. area-based approach in ALICE
- More precise jet p_T resolution with the ML-based method for low-p_T jets at large R

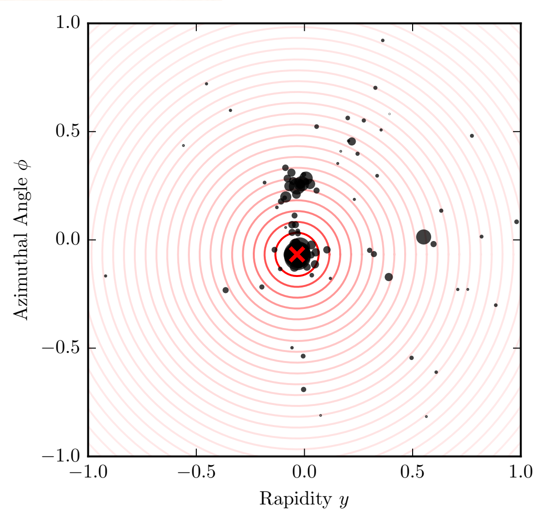
Classification of Quark/Gluon Jets

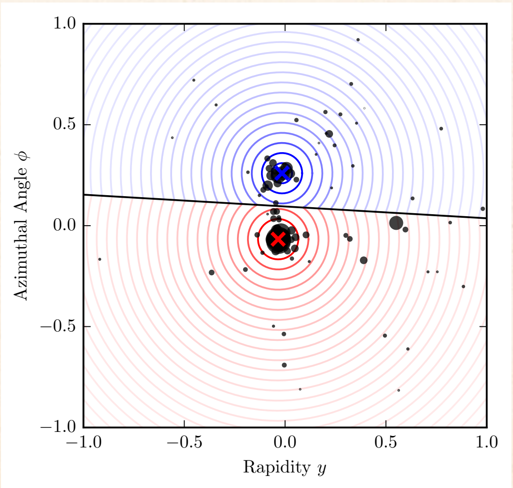
Y.-T. Chien, R. K. Elayavalli, arXiv:1803.03589

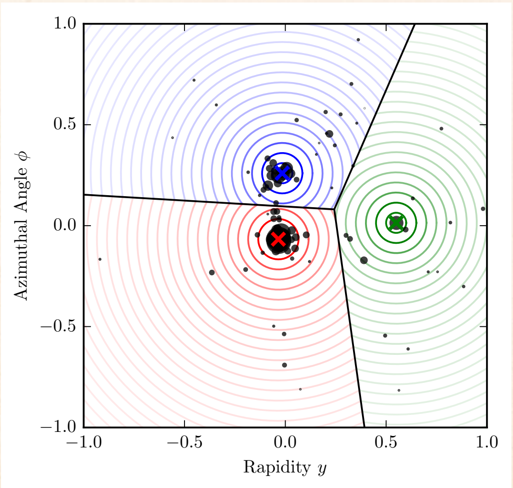
- Jewel jets in pp and AA
- DNN with Jet mass, two radial moments including the girth, p_T^D, and the pixel multiplicity
- CNN on jet images (η,ϕ)
- DNN with Telescoping deconstruction framework exploiting subjet kinematics – p_T, mass
- “Quark gluon discrimination performance worsens in heavy ion jets due to significant soft event activity affecting the soft jet substructure”

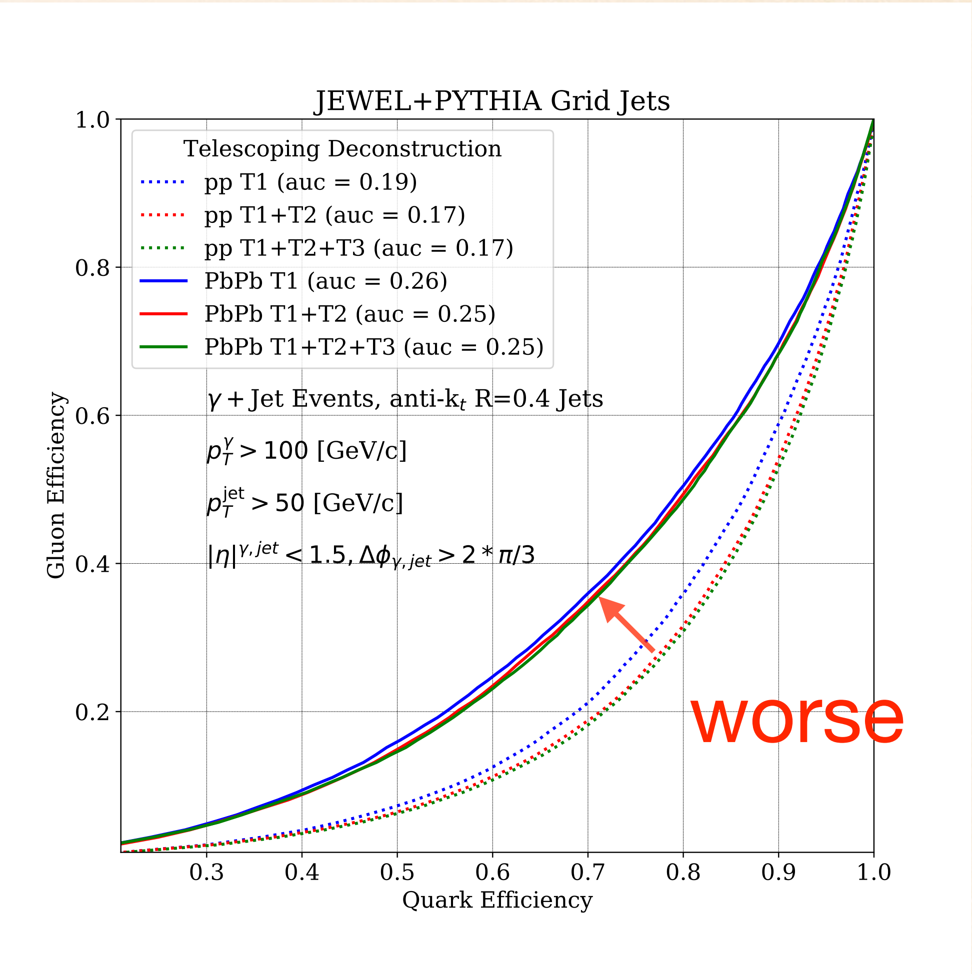










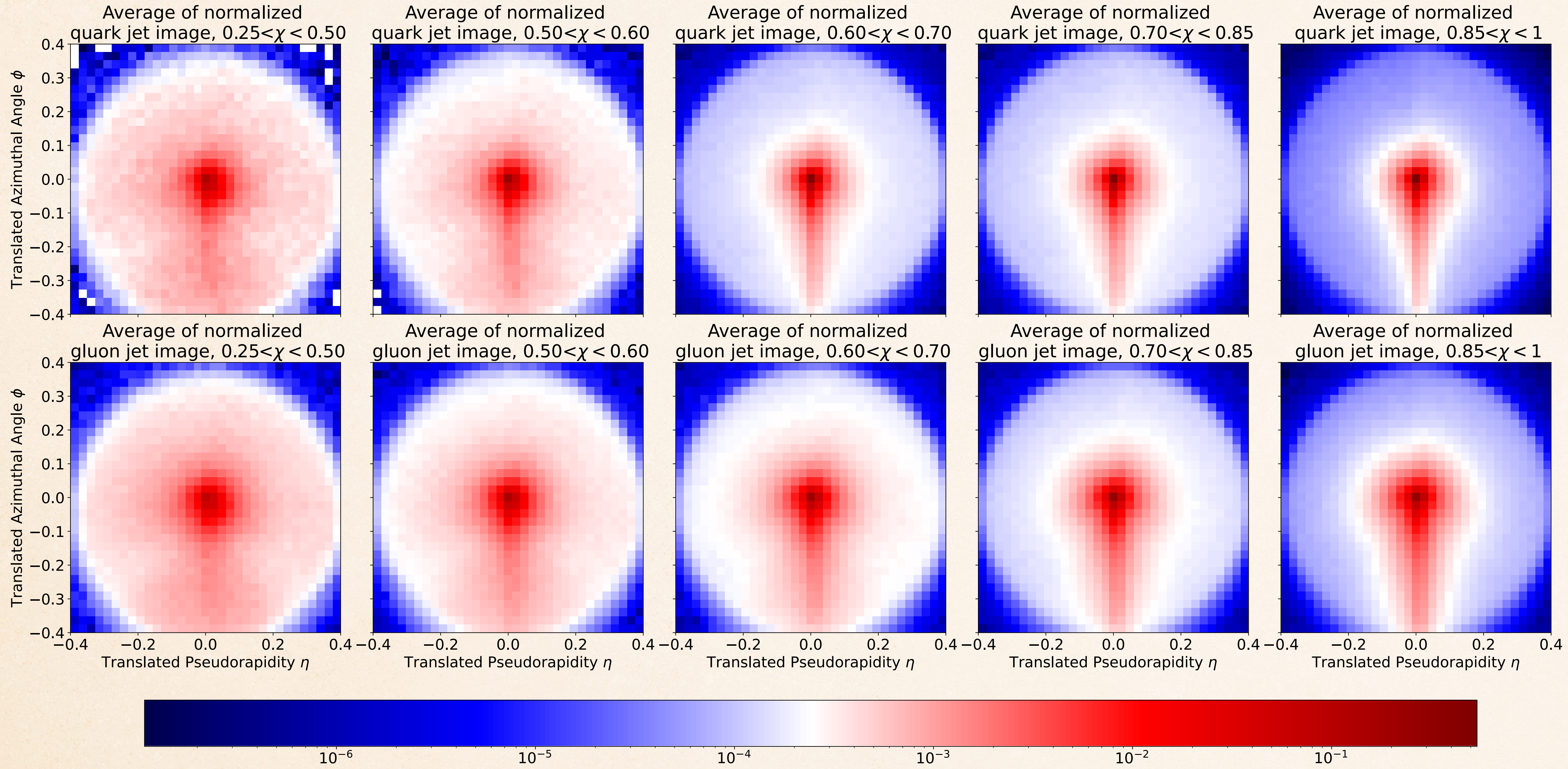


Classification of Quark/Gluon Jets

Hybrid model

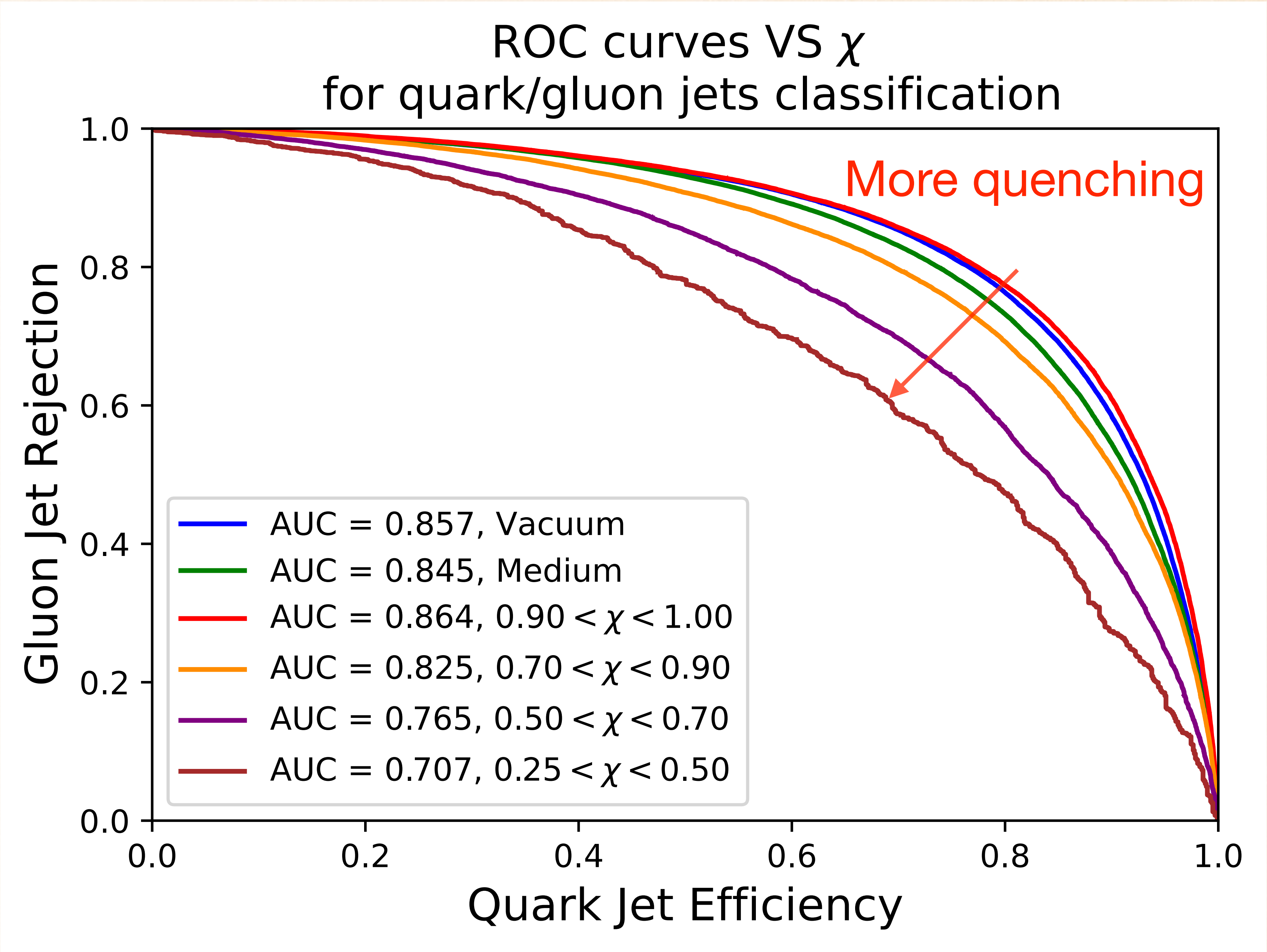
More quenching

YLD, D. Pablos and K. Tywoniuk, PoS(PANIC2021)224



Quark

Gluon

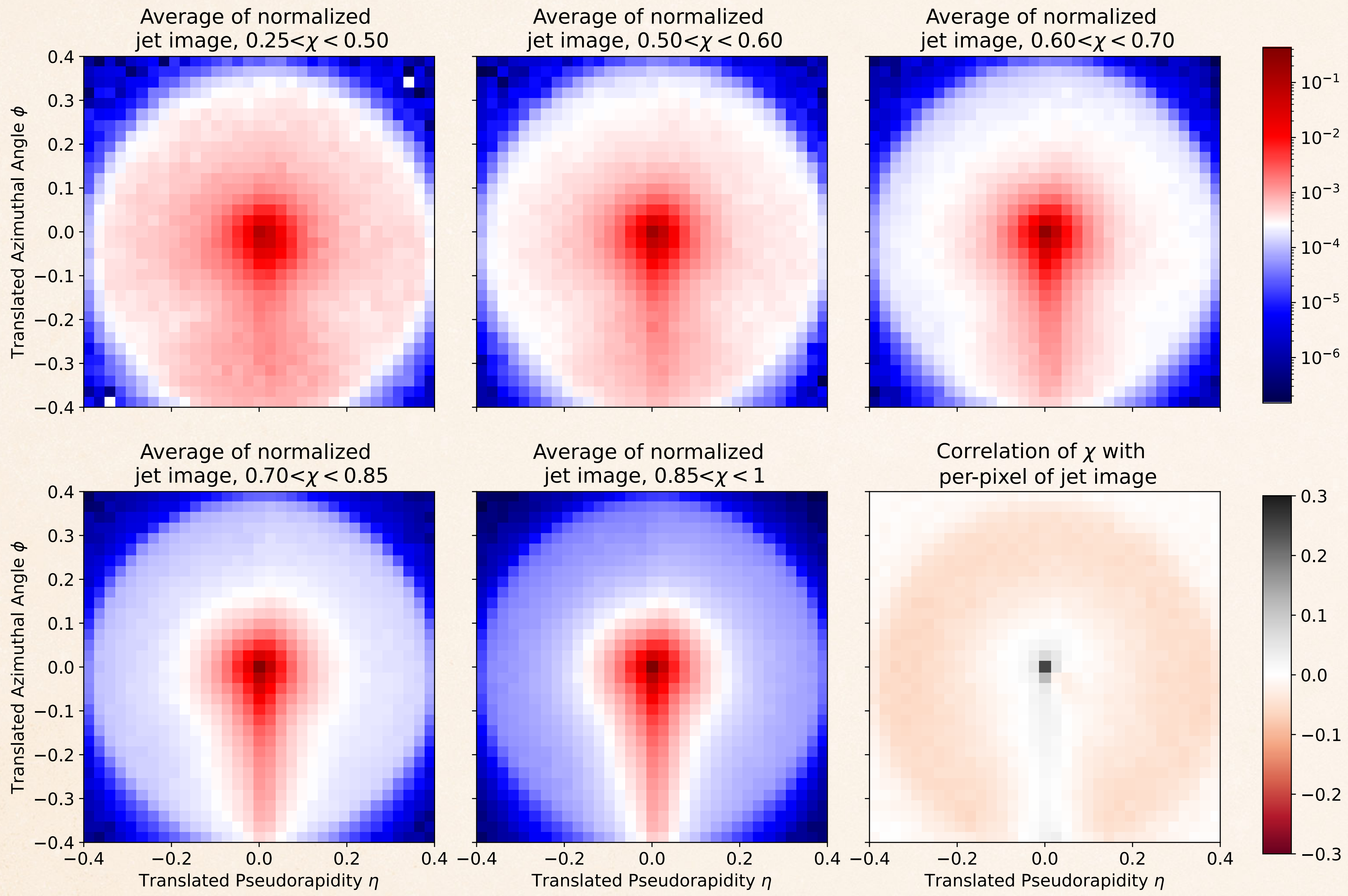


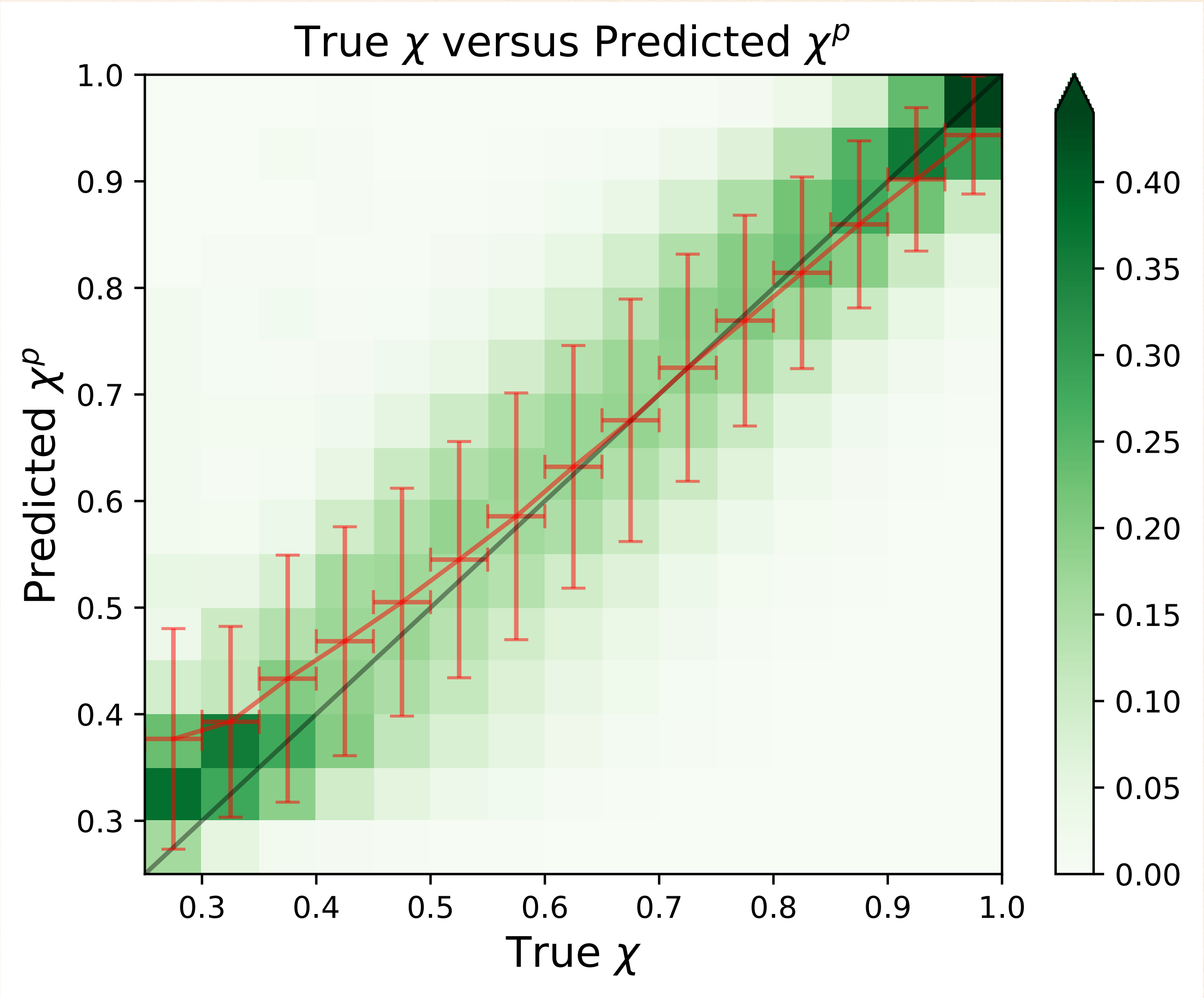
- Same qualitative characteristics: more soft particles at large angles within the jet cone
- The quenching smears the difference of substructures of quark/gluon jets
- The greater the energy loss is, the more difficult it is to classify

Prediction of Jet Energy Loss

YLD, D. Pablos and K. Tywoniuk, JHEP03(2021)206

Hybrid model





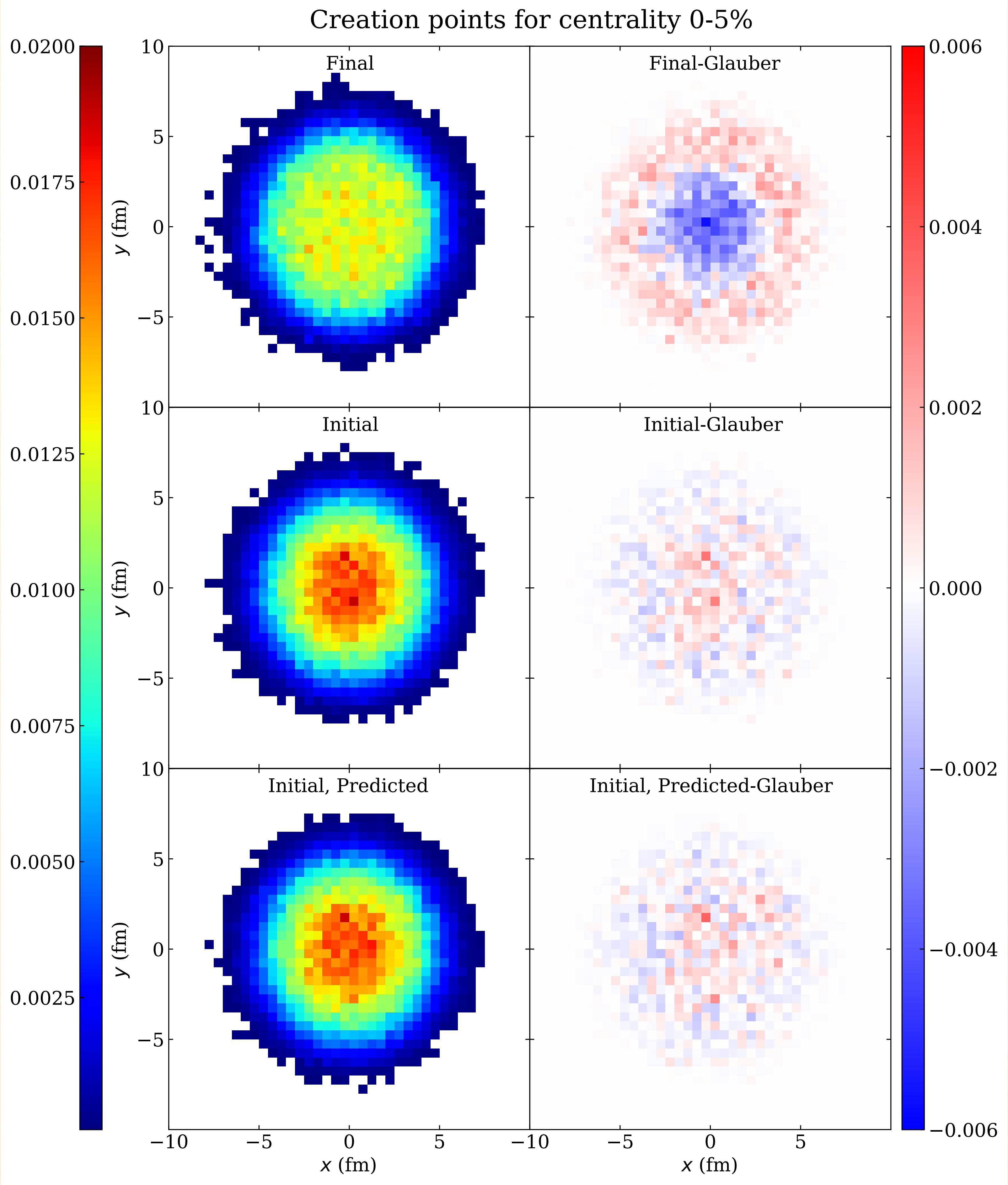
Input (size)	Output	Network	Loss
FF (10)	χ_{jh}	FCNN	0.0058
Jet shape (8)	χ_{jh}	FCNN	0.0033
FF, jet shape (18)	χ_{jh}	FCNN	0.0032
FF, jet shape, features (25)	χ_{jh}	FCNN	0.0028
Jet image & FF, jet shape, features (25)	χ_{jh}	API: CNN&FCNN	0.0028

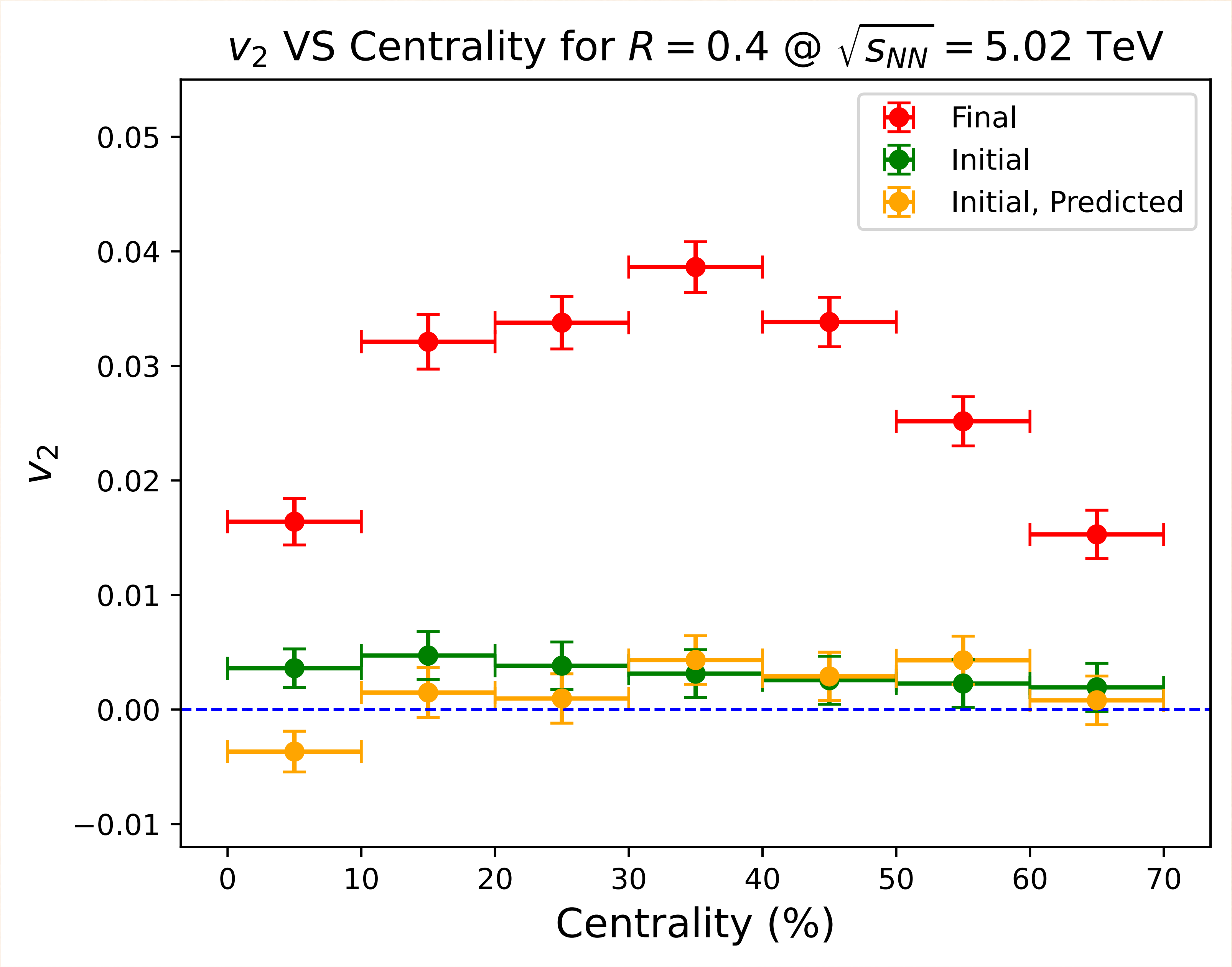
- Regression analysis of jet energy loss between the twin jets
- Jet quenching increases the number of soft particles at large angles
- Well predicted for a wide range of χ

Interpretability!

Genuine Configuration Profile

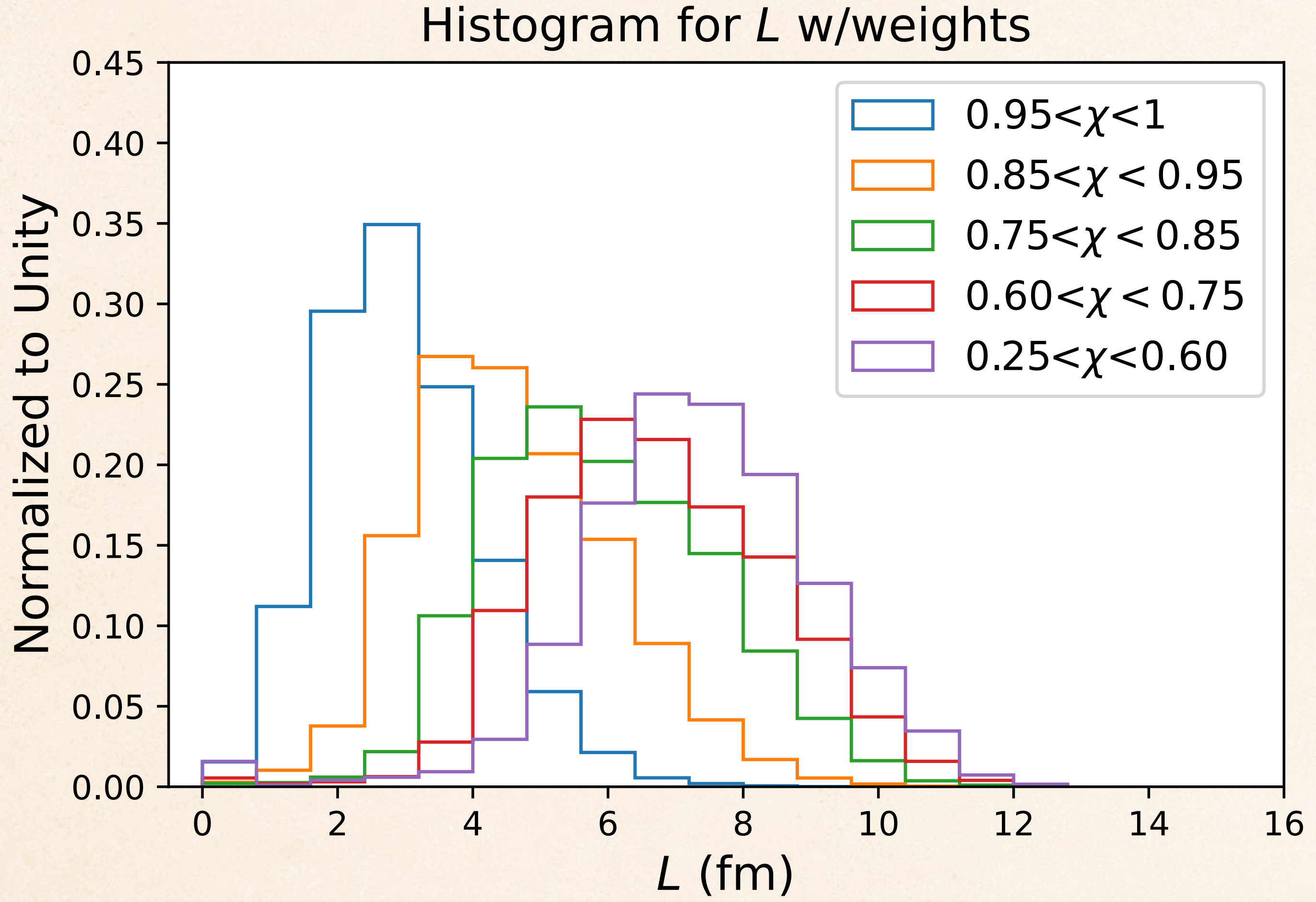
YLD, D. Pablos and K. Tywoniuk, JHEP03(2021)206

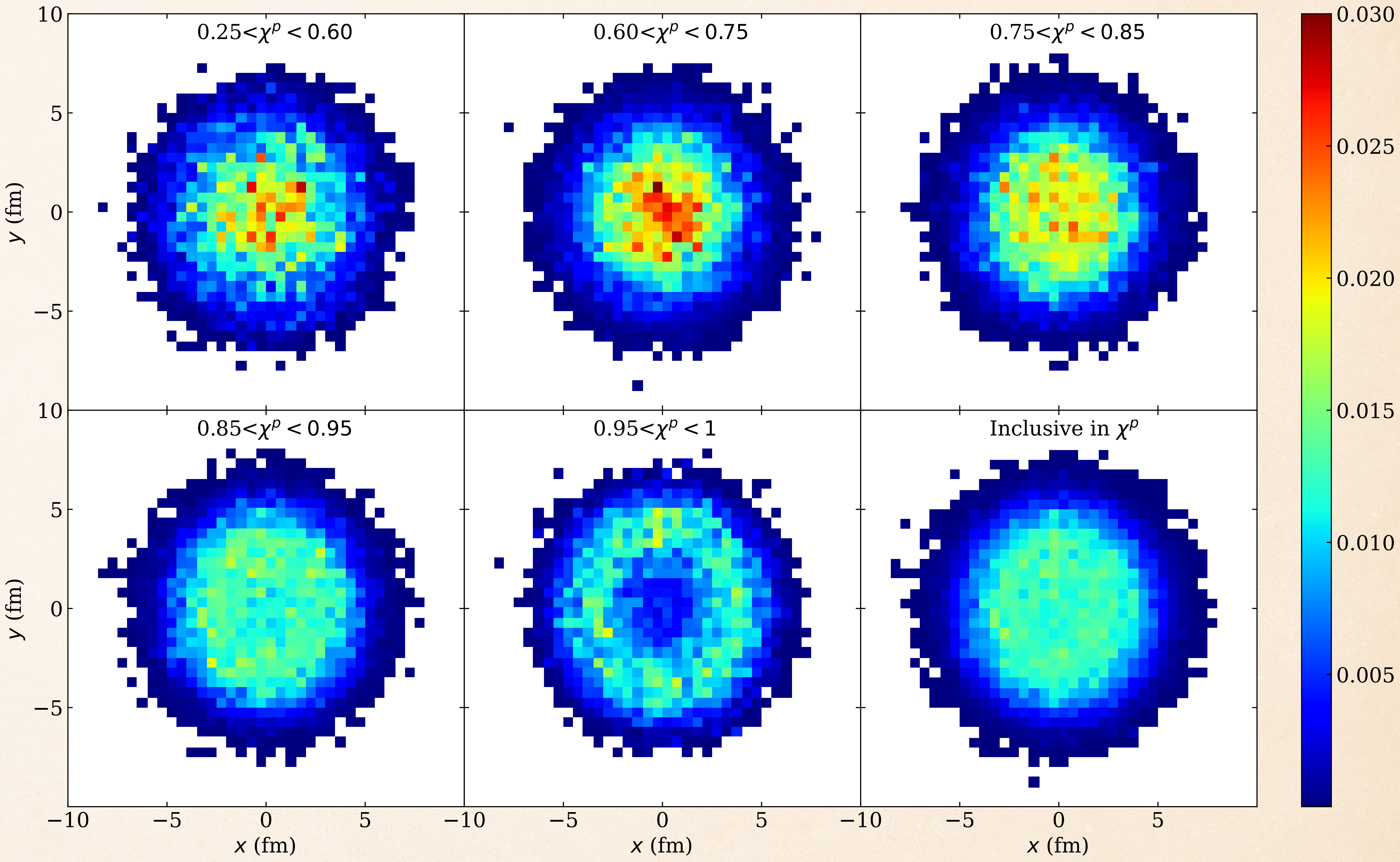




- Initial Energy Selection (IES) "removes" final state interactions (selection bias), since we record "all" jets
- IES provides access to the genuine jet creation point (path length) distribution and possible initial-state jet anisotropy

Towards jet tomography



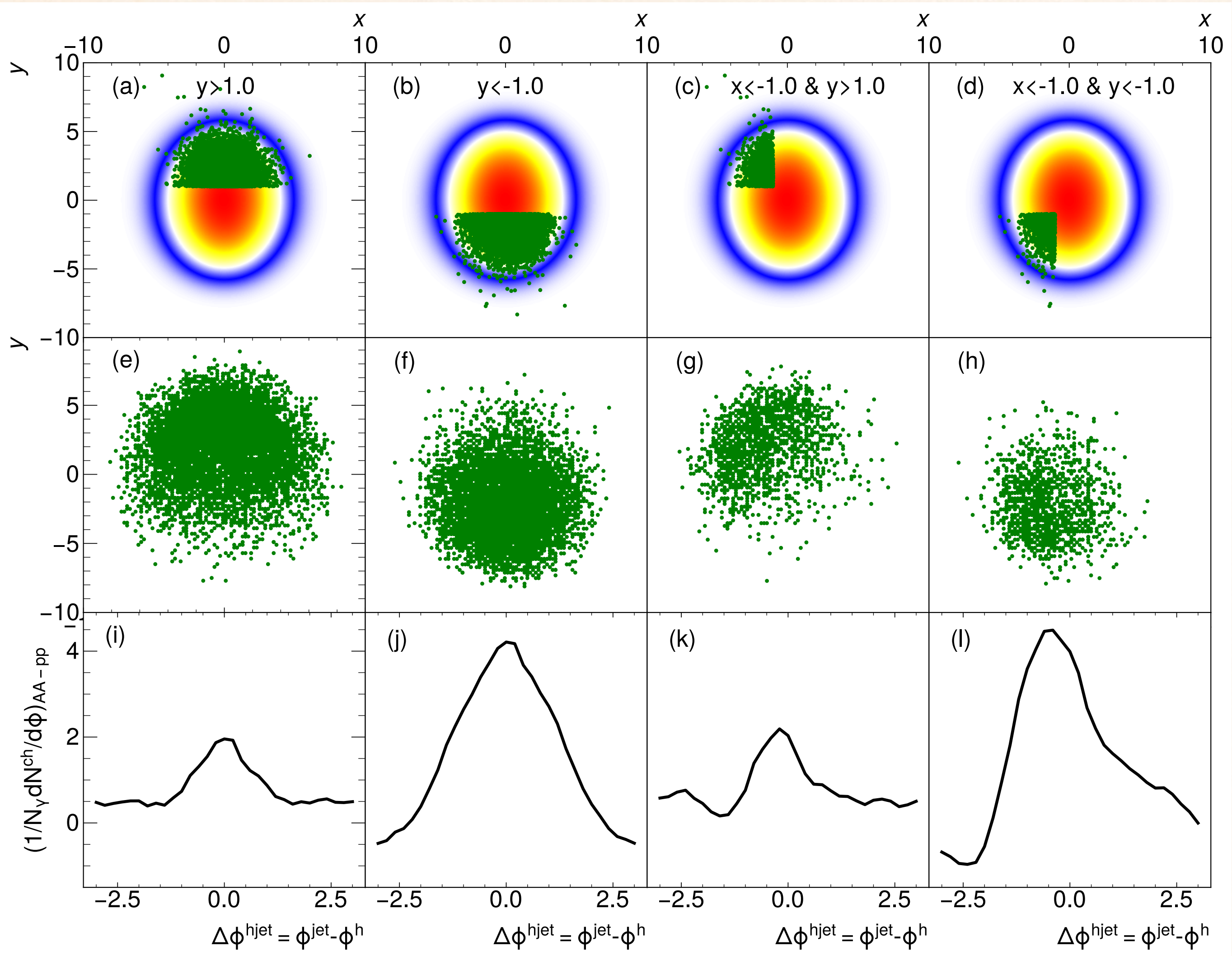


- Strong correlation between L and χ
- Selecting jets with different χ will naturally select jets that traversed different L
- Great potential to make tomographic application!

Prediction of Jet Production Positions

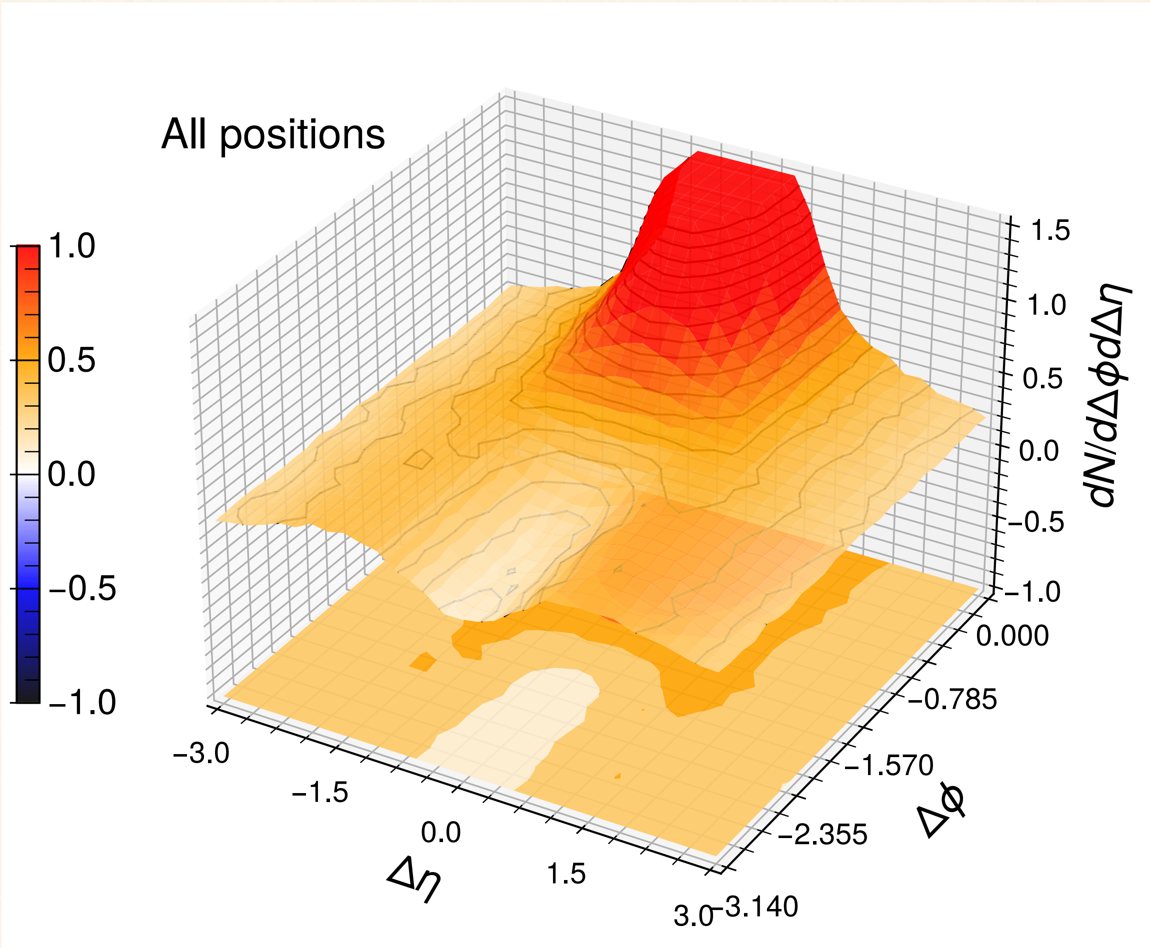
Z. Yang, Y. He, W. Chen, *et al.*, arXiv:2206.02393

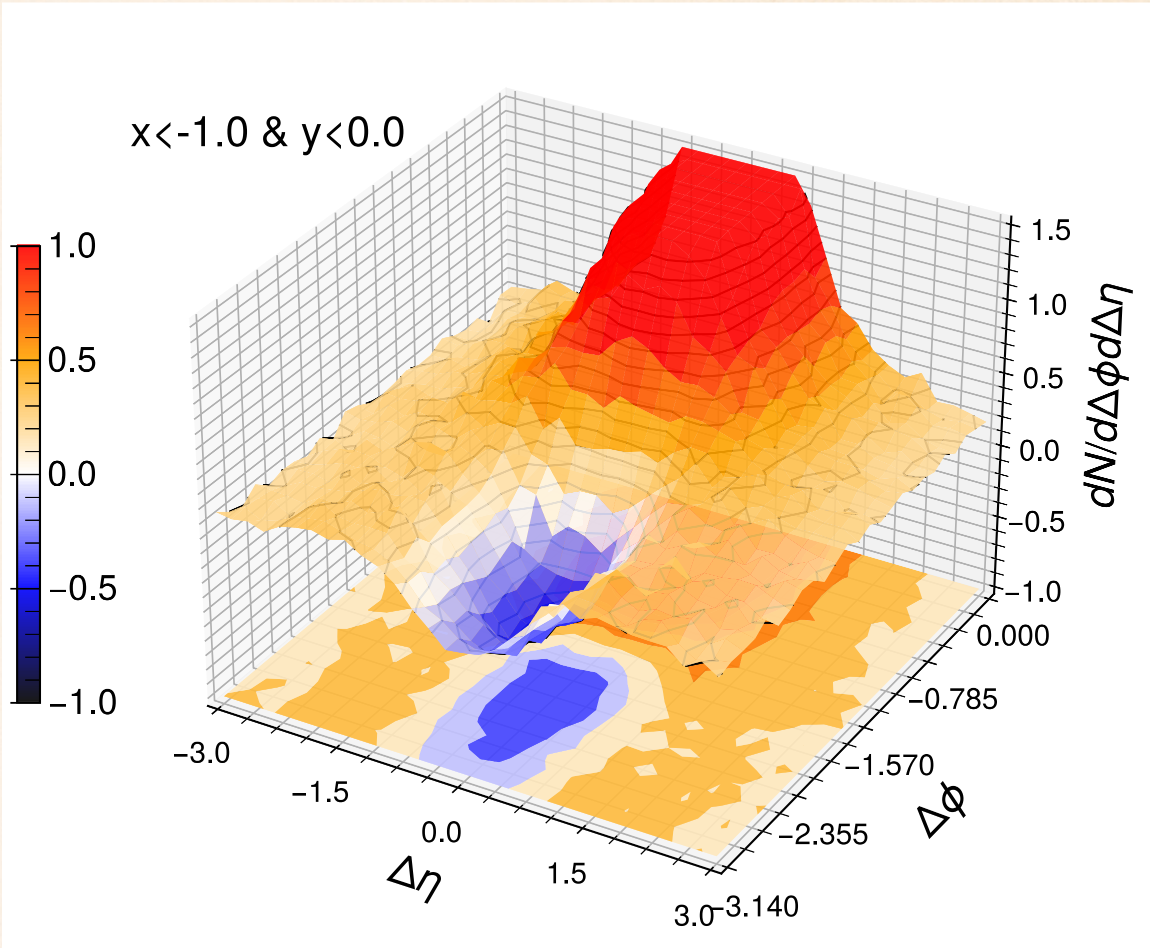
Jet $p_y > 0$



Network selection

Actual distribution





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

- Point cloud network employs hadrons' momentum, mass and γ/jet info to predict jet production position (x, y)
- Select jets by their positions and directions to have a larger yields of soft hadron from medium response and induced radiation
- Diffusion Wake signal amplified by DL jet tomography

See talk by L. G. Pang, 24 April, Monday

Summary

- Bayesian analysis for various QGP properties: EoS, η/s, ξ/s, $\hat{q}$, D_S…
- Discover novel subleading harmonic modes with PCA
- Various neural networks with different representations of data are applicable in the study of heavy ion collisions (e.g., DNN, CNN, RNN, RecNN, Point Cloud, Graph NN, PCA…)
- Reveal initial geometry/condition better
- First application on jet exp. data - Jet p_T reconstruction in ALICE
- Towards jet tomography (jet energy loss, production points)

Outlook

- Model independence
- Interpretability
- Applicability to more realistic environment
- Better performance from state-of-the-art neural networks? Quantum machine learning?
- Novel applications:
  - Information field approach to more quantities, e.g., η/s, ξ/s, D_S…
  - Extract jet traversed length in QGP?
  - Unfold vacuum twin jet properties apart from jet energy? Apple to apple comparison