Global constraint on the jet transport coefficient from single hadron, dihadron and γ-hadron spectra in high-energy heavy-ion collisions

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Collaborate with Wei-Yao Ke, Han-Zhong Zhang and Xin-Nian Wang

[arXiv: 2206.01340]

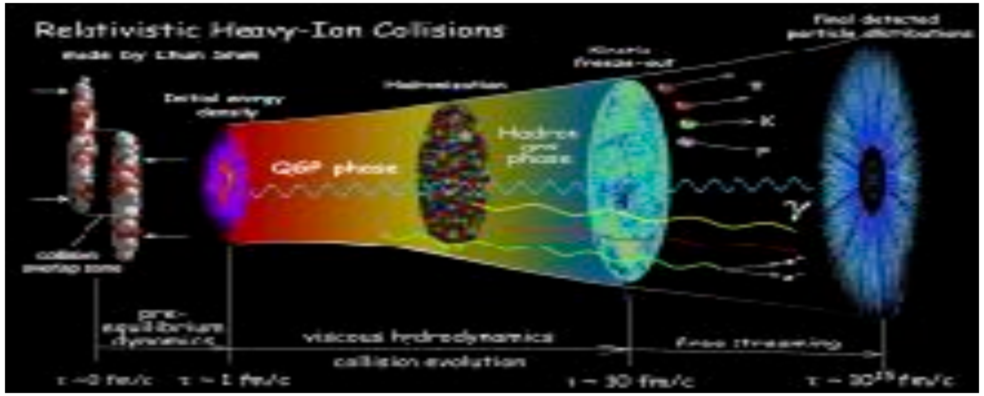
中国物理学会高能物理分会第十一届全国会员代表大会暨学术年会

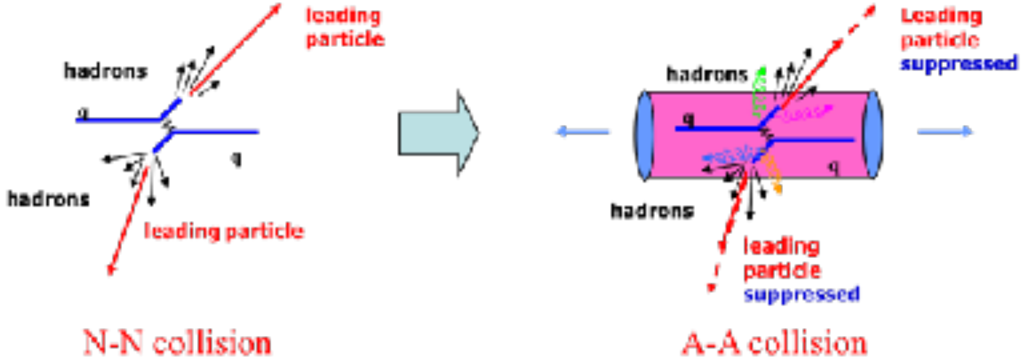
2022/8/10

Outline

- Motivation
- NLO pQCD parton model and JQ-mFFs
- Bayesian inference of $\hat{q}(T)$ with information field method
  1. Prior of unknown function in an IFT method;
  2. The posterior distribution.
- Constraining the T dependence of $\hat{q}(T)$
  1. Combined analysis using both R_{AA} and I_{AA} ;
  2. Progressive constraining power from peripheral to central collisions.
- Validation and predictions
- Summary

Motivation





- Quark-gluon plasma (QGP) has been created in high-energy HIC.
- Jet quenching is an extremely useful tool to explore the properties of QGP.
  [X.-N. Wang and M. Gyulassy, PRL 68, 1480 (1992)]

- The energetic jet losses a large amount of its energy via radiating gluon induced by multiple scatterings, leading to the suppression of the yield of jets and high-p_T hadrons.
- Jet energy loss in QGP medium: $\Delta E \propto \hat{q}$.
- Jet transport parameter: hard parton's transverse momentum broadening squared per unit length.

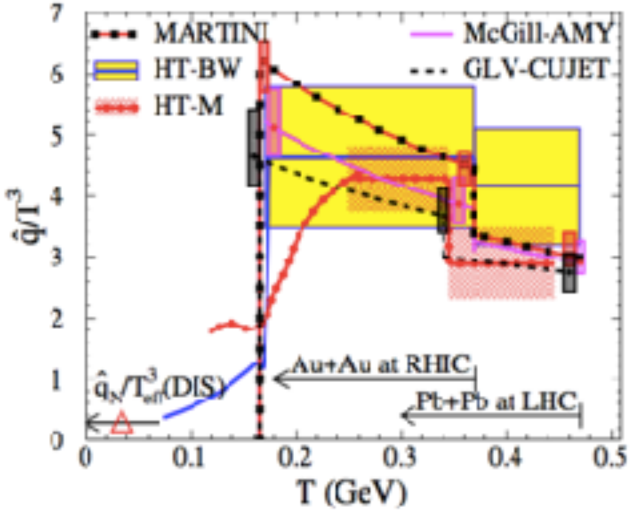
$$\hat{q} = \rho \int dq_\mathrm{T}^2 \frac{d\sigma}{dq_\mathrm{T}^2} q_\mathrm{T}^2$$

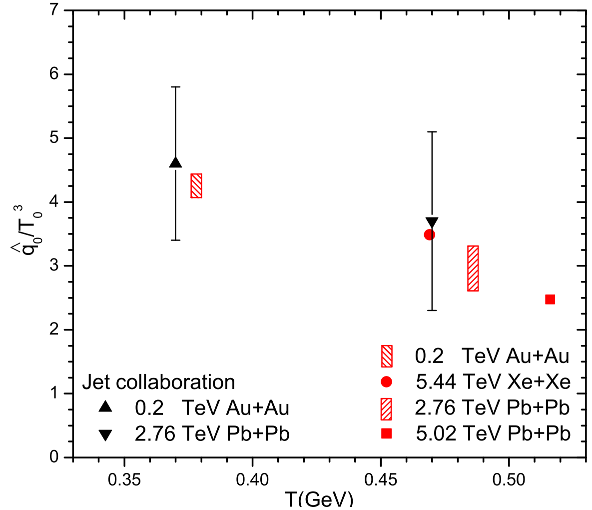
[BDMPS, NPB 483 (1997) 291]

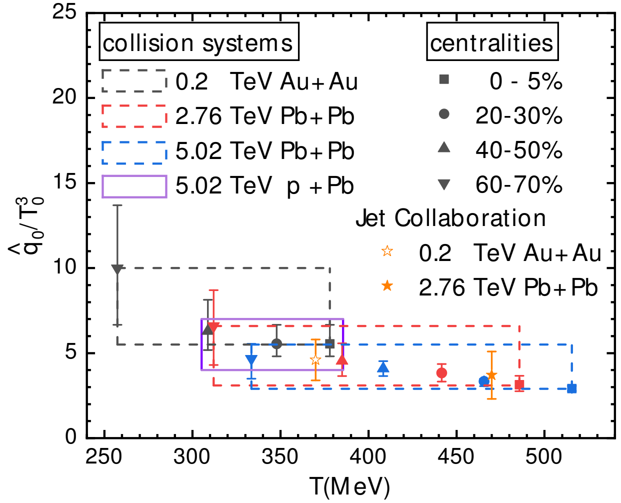
Motivation

- $\hat{q}$ depends on the local T in the jet trajectory: $\dfrac{\hat{q}}{T^3} = \dfrac{\hat{q}_0}{T_0^3}\dfrac{p \cdot u}{p_0}$.

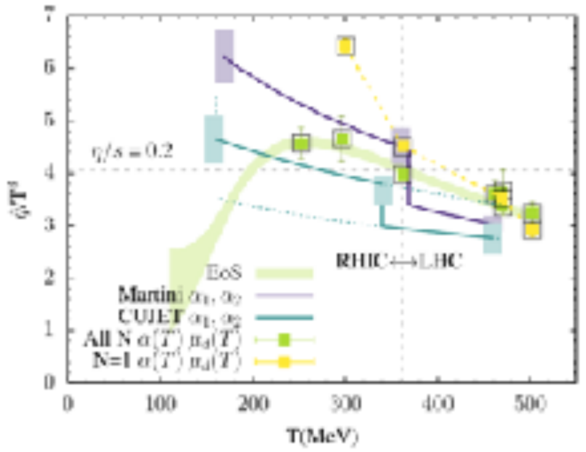
[X. Chen, T. Hirano, E. Wang, X.-N. Wang, H. Z. Zhang, Phys. Rev. C84 (2011) 034902]

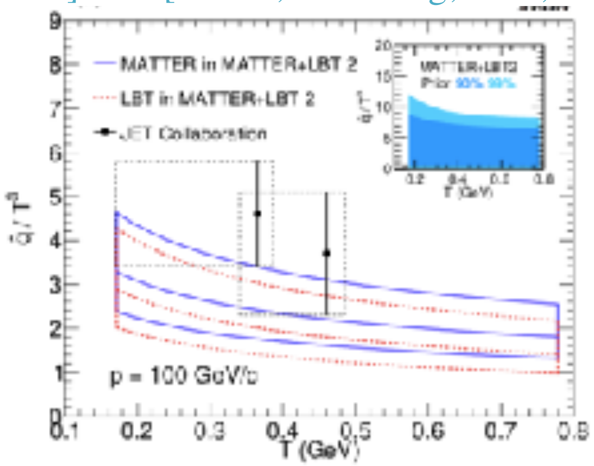






[The JET collaboration, PRC 90. 014909] [**M Xie**, HZ Zhang, et al., EPJC (2019) 79:589; PRC103(2021)3,034911]





- $\hat{q}$ constant assumption is too simple, additional T dependence.
- Discrete extraction from different systems.
- Complex parametrisation form leads to relatively large uncertainty.

[Xabier Feal, .et al., PLB 816 (2021) 136251] [JETSCAPE], PRC 104 (2021) 2, 024905]

Motivation

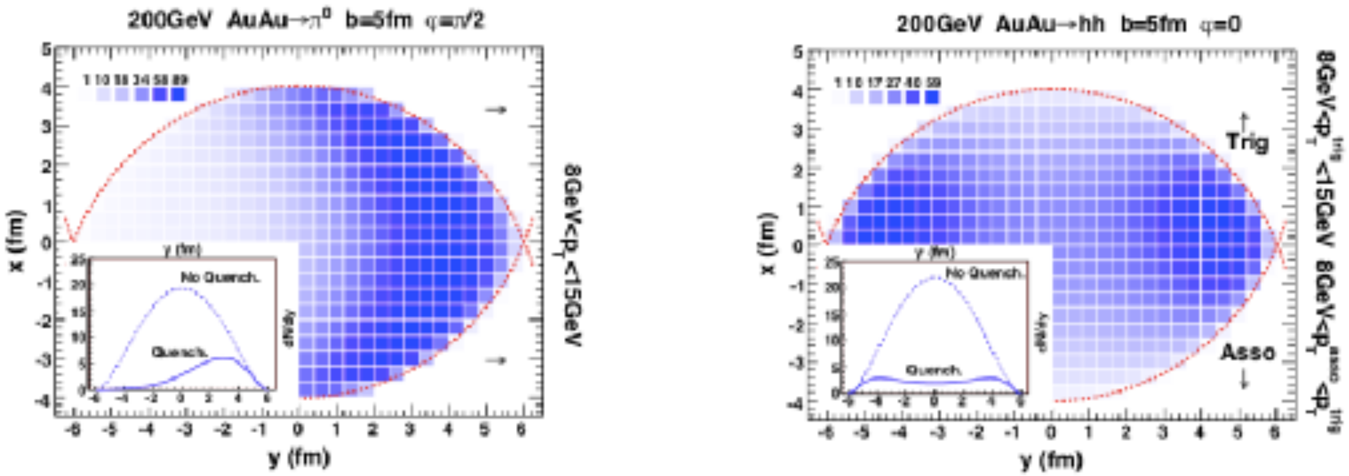
Aim: to constrain the T dependence of $\hat{q}$.

Data:

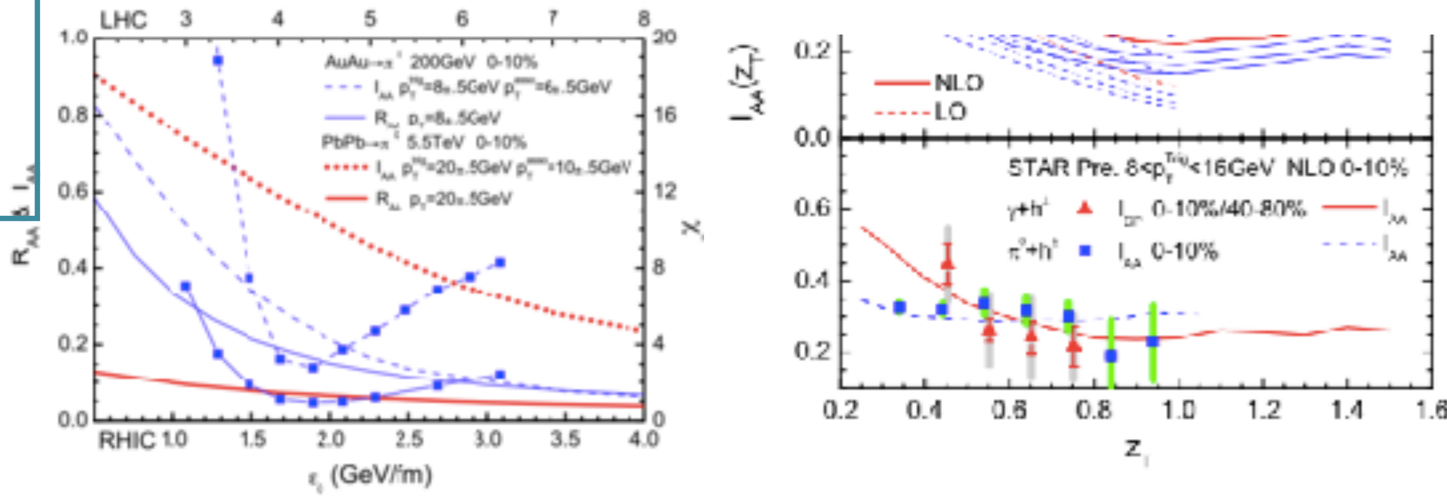
combined global analysis of $R_{AA}^{h}, I_{AA}^{hh}, I_{AA}^{\gamma h}$;
both RHIC and LHC energies;
a wide range of centralities.

Analysis method:

Bayesian inference method;
$\hat{q}(T)$ prior of unknown function in an information field.

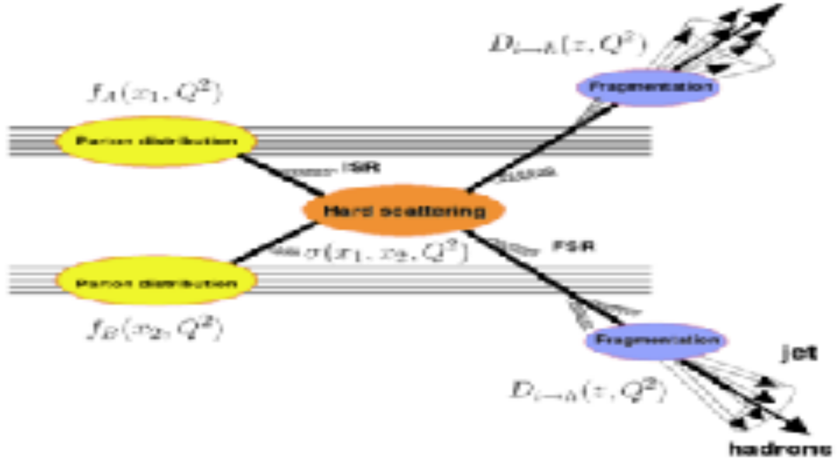


[HZ Zhang J.F. Owens, EK Wang and XN Wang, *Phys. Rev. Lett.* 98 (2007) 212301



[HZ Zhang J.F. Owens, EK Wang and XN Wang, *Phys. Rev. Lett.* 103 (2009) 032302]

pQCD parton model



In p-p collisions：

Single inclusive hadron： [J.F.Owens, Rev. Mod. Phys 59,465(1987)]

$$\frac{d\sigma^h_{pp}}{dyd^2p_\mathrm{T}} = \sum_{abcd}\int dx_a dx_b f_{a/p}(x_a,\mu^2) f_{b/p}(x_b,\mu^2)\frac{1}{\pi}\frac{d\sigma_{ab\to cd}}{d\hat{t}}\frac{D_{h/c}(z_c,\mu^2)}{z_c} + \mathcal{O}(\alpha_s^3)$$

di-hadron：

$$\frac{d\sigma^{hh}_{pp}}{dy_h^c d^2p_\mathrm{T}^{h_c} dy_h^d d^2p_\mathrm{T}^{h_d}} = \sum_{abcd}\int dz_c dz_d f_{a/p}\left(x_a,\mu^2\right) f_{b/p}\left(x_b,\mu^2\right)\frac{x_a x_b}{\pi z_c^2 z_d^2}\frac{d\sigma_{ab\to cd}}{d\hat{t}}$$
$$\times D_{h/c}\left(z_c,\mu^2\right) D_{h/d}\left(z_d,\mu^2\right)\delta^2\left(\vec{p}^{\,c}_\mathrm{T} + \vec{p}^{\,d}_\mathrm{T}\right) + \mathcal{O}\left(\alpha_s^3\right)$$

γ-hadron：

$$\frac{d\sigma^{\gamma h}_{pp}}{dy_\gamma d^2p_\mathrm{T}^\gamma dy_h d^2p_\mathrm{T}^h} = \sum_{abd}\int dz_d f_{a/p}\left(x_a,\mu^2\right) f_{b/p}\left(x_b,\mu^2\right)\frac{x_a x_b}{\pi z_d^2}\frac{d\sigma_{ab\to\gamma d}}{d\hat{t}}$$

only consider direct photon

$$\times D_{h/d}\left(z_d,\mu^2\right)\delta^2\left(\vec{p}^{\,\gamma}_\mathrm{T} + \frac{\vec{p}^{\,h}_\mathrm{T}}{z_d}\right) + \mathcal{O}\left(\alpha_e\alpha_s^2\right)$$

[**M Xie**, XN Wang and HZ Zhang, PRC103(2021)3,034911]

$$D_{pp}^{\text{trig}}\left(z_\mathrm{T}\right) = p_\mathrm{T}^{\text{trig}}\frac{d\sigma_{pp}/dy^{\text{trig}}\,dp_\mathrm{T}^{\text{trig}}dy^{\text{assoc}}\,dp_\mathrm{T}^{\text{assoc}}}{d\sigma_{pp}/dy^{\text{trig}}dp_\mathrm{T}^{\text{trig}}}, z_\mathrm{T} = p_\mathrm{T}^{\text{assoc}}/p_\mathrm{T}^{\text{trig}}.$$

$f_{a/p}(x_a,\mu^2)$: CT14 PDF

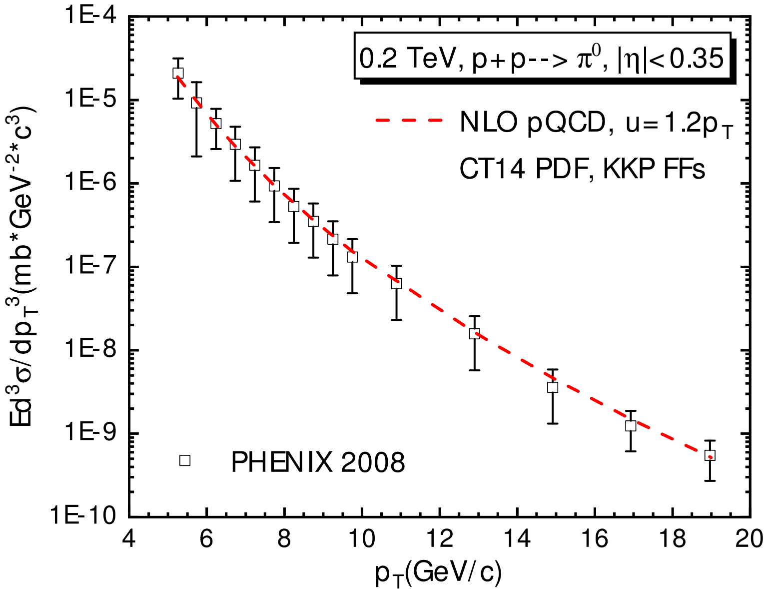
[CT14, Phys. Rev. D 95, 034003 (2017)]

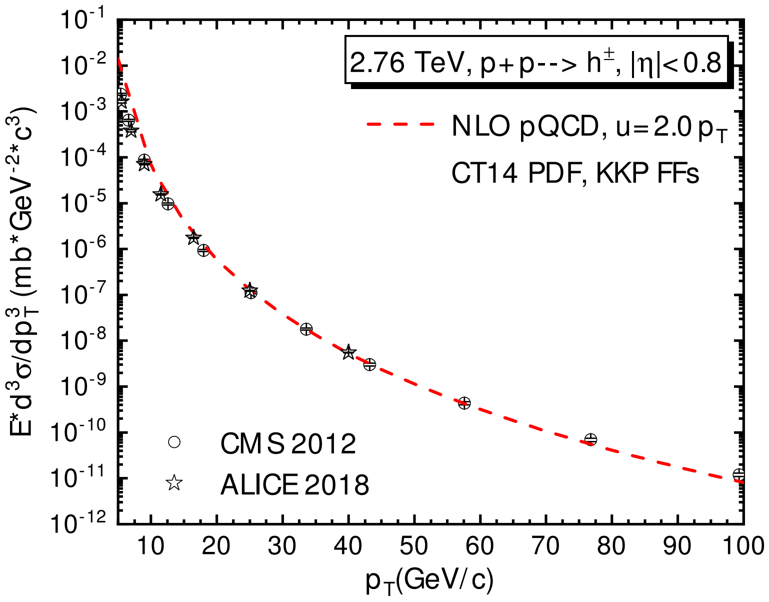
$D_{h/d}(z_d,\mu^2)$: KKP FFs

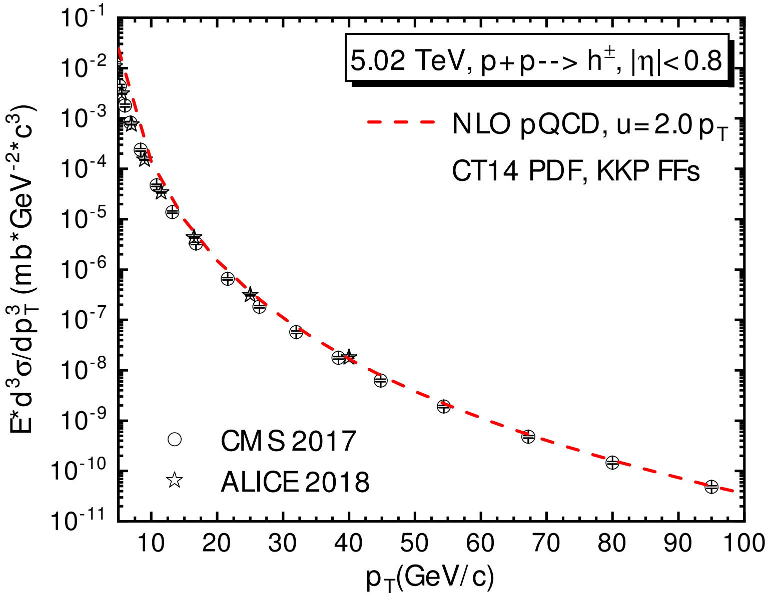
[KKP, Nucl. Phys. B 582,514(2000)]

p-p baselines

Single inclusive hadron：







Good agreement with data.

Data from

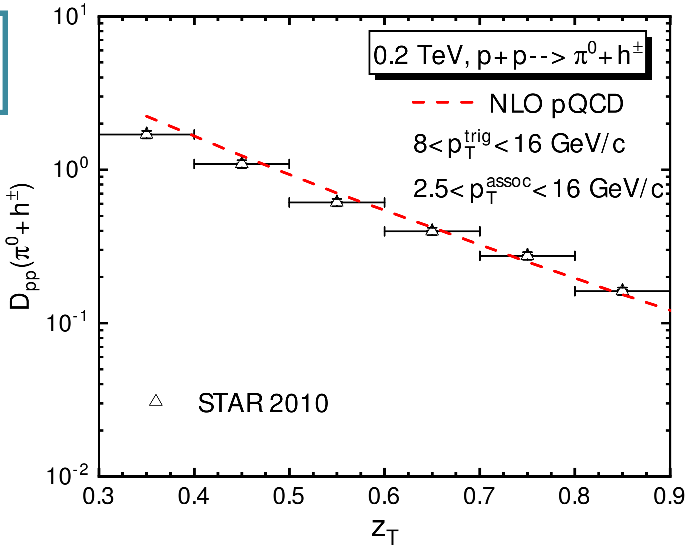
[PHENIX, Phys. Rev. Lett. 101, 232301 (2008)]

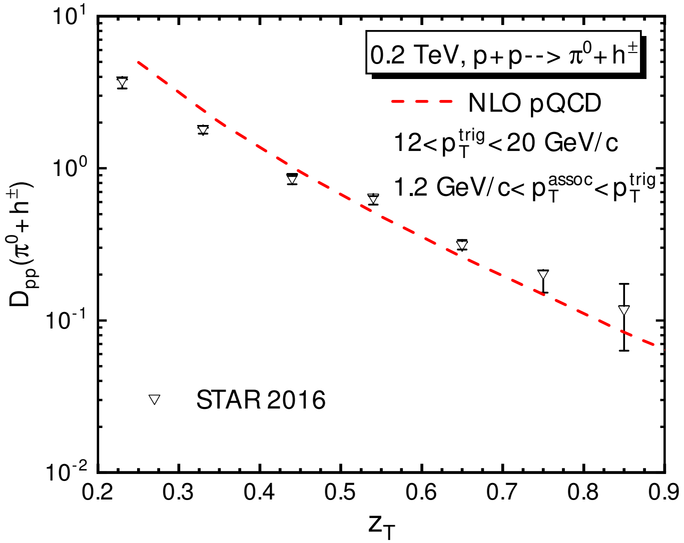
[CMS, Eur. Phys. J. C 72, 1945 (2012), JHEP 04, 039]

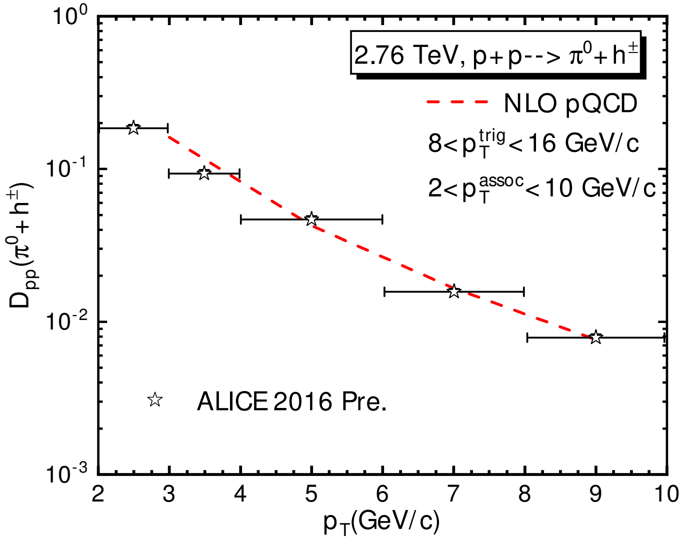
[ALICE, JHEP 11, 013]

p-p baselines

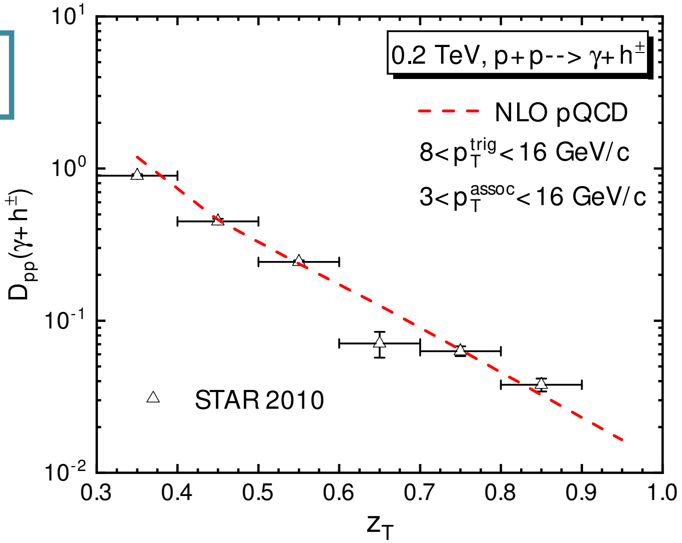
di-hadron：

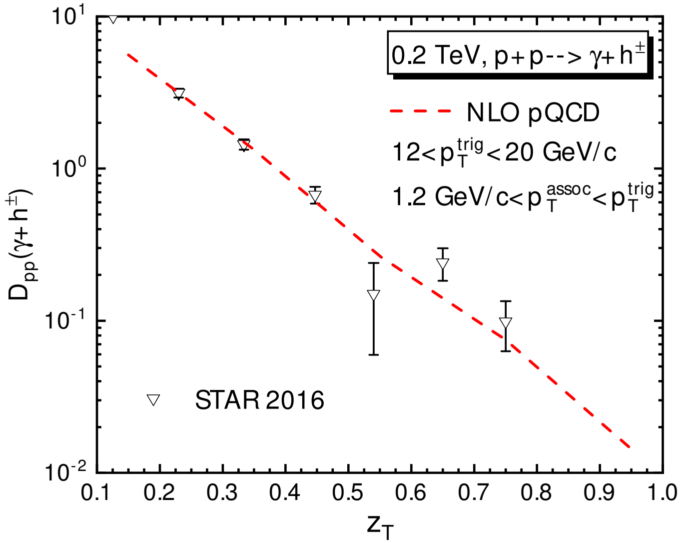






γ-hadron:



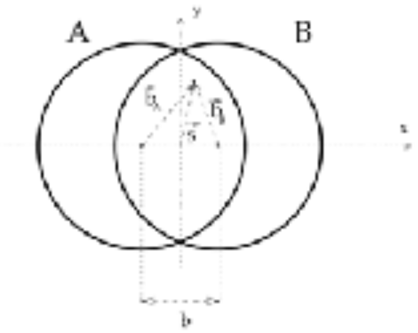


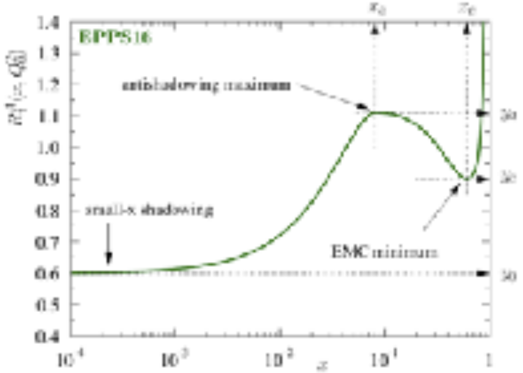
NLO pQCD parton model can give a good description of all the Exp. data of single hadron, γ-hadron, and di-hadron productions at large p_T in p-p collisions.

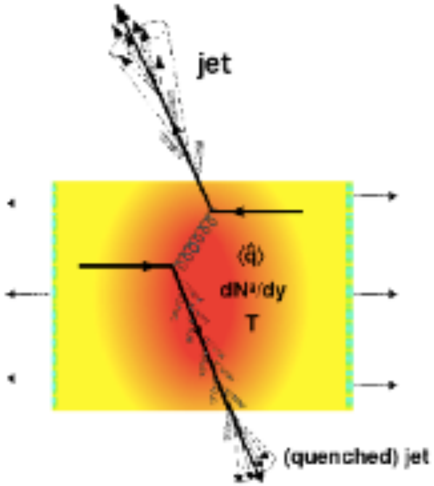
Data from [STAR, Phys. Lett. B 760, 689 (2016), Phys. Rev. C 82, 034909 (2010)]

pQCD parton model

In A-A collisions：







di-hadron：

$$\frac{dN_{AB}^{hh}}{dy_h^c d^2p_{\mathrm{T}}^{h_c} dy_h^d d^2p_{\mathrm{T}}^{h_d}} = \sum_{abcd} \int d^2r dz_c dz_d t_A(\vec{r}) t_B(\vec{r}+\vec{b}) f_{a/A}\left(x_a, \mu^2, \vec{r}\right) f_{b/B}\left(x_b, \mu^2, \vec{r}+\vec{b}\right) \frac{x_a x_b}{\pi z_c^2 z_d^2} \frac{d\sigma_{ab\to cd}}{d\hat{t}}$$
$$\times \tilde{D}_{h/c}\left(z_c, \mu^2, \Delta E_c\right) \tilde{D}_{h/d}\left(z_d, \mu^2, \Delta E_d\right) \delta^2\left(\vec{p}_{\mathrm{T}}^{\,c} + \vec{p}_{\mathrm{T}}^{\,d}\right) + \mathcal{O}\left(\alpha_s^3\right)$$

$t_A(\vec{r})$: nuclear thickness functions, integrating the Woods – Saxon nuclear density distribution;

$f_{a/A}(x_a, \mu^2, \vec{r})$: EPPS16 nPDF [EPPS 16, Eur. Phys. J. C 77, 163 (2017)]

$\tilde{D}_{h/d}(z_d, \mu^2, \Delta E_d)$: medium – modifed FFs

Medium-modified FFs

$$\tilde{D}_{h/d}(z_d,\mu^2,\Delta E_d)=(1-e^{-\langle N_g\rangle})\left[\frac{z_d'}{z_d}D_{h/d}(z_d',\mu^2)+\langle N_g\rangle\frac{z_g{}'}{z_d}D_{h/g}(z_g{}',\mu^2)\right]+e^{-\langle N_g\rangle}D_{h/d}(z_d,\mu^2)$$

[X.-N. Wang, PRC70 (2004) 031901],
[H. Z. Zhang, J.F. Owens, Enke Wang, X.-N. Wang, PRL 98.212301 (2007);103, 032302 (2009)]

$$\frac{\Delta E_d}{E}=\frac{2C_A\alpha_s}{\pi}\int d\tau\int\frac{dl_{\rm T}^2}{l_{\rm T}^4}\int dz\left[1+(1-z)^2\right]\hat{q}_d\left(\tau,\vec{r}+(\tau-\tau_0)\,\vec{n}\right)\sin^2\!\left(\frac{l_{\rm T}^2(\tau-\tau_0)}{4z(1-z)E}\right)$$ High-Twist approach

[W.T. Deng and X.-N. Wang, PRC 81,024902(2010]
[E. Wang and X.-N. Wang, PRL 87, 142301 (2001); 89, 162301 (2002)]

$$\left\langle N_g^d\right\rangle=\frac{2C_A\alpha_s}{\pi}\int_{\tau_0}^{\infty}d\tau\int\frac{dl_{\rm T}^2}{l_{\rm T}^4}\int\frac{dz}{z}\left[1+(1-z)^2\right]\hat{q}_d\left(\tau,\vec{r}+(\tau-\tau_0)\,\vec{n}\right)\sin^2\left[\frac{l_{\rm T}^2\,(\tau-\tau_0)}{4z(1-z)E}\right]$$

[N.B. Chang, W.T. Deng and X.-N. Wang, Phys. Rev. C 89, 03491 (2014)1

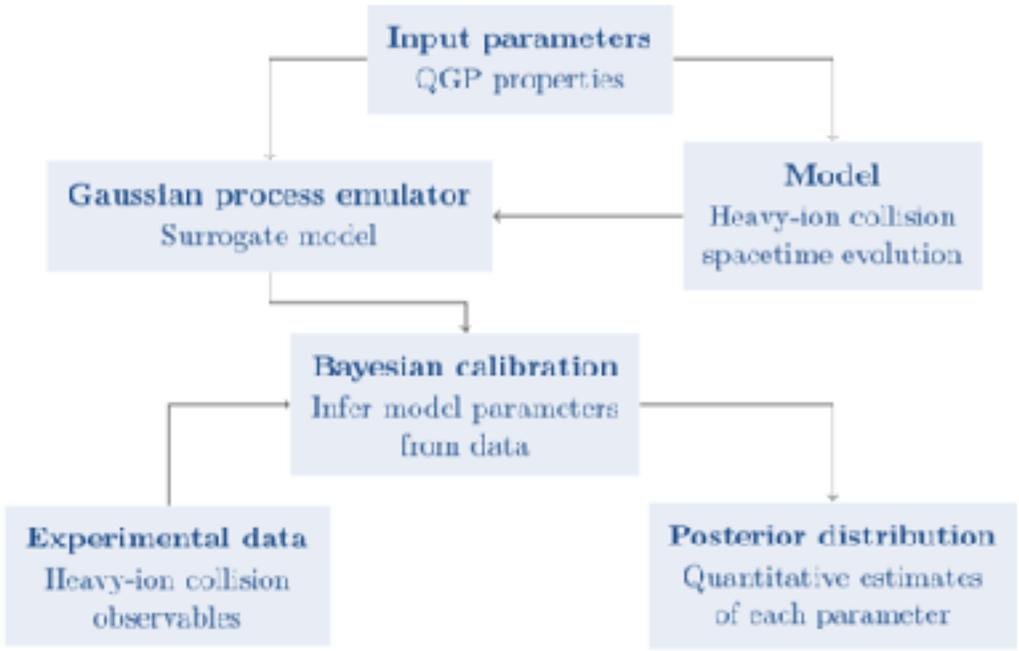
Observables： nuclear modification factor

$$R_{AB}=\frac{dN_{AB}/dyd^2p_{\rm T}}{T_{AB}(\overrightarrow{b})d\sigma_{pp}/dyd^2p_{\rm T}};\qquad I_{AB}\left(z_{\rm T}\right)=\frac{D_{AB}\left(z_{\rm T}\right)}{D_{pp}\left(z_{\rm T}\right)}.$$

Bayesian inference of $\hat{q}(T)$ with parametric form.

[Jonah E. Bernhard, Ph.D. dissertation, arXiv:1804.06569]

Bayesian inference: $\hat{q}_i(x_{1i}, x_{2i}, \ldots, x_{ni})$



$$P(\mathbf{x} \mid \mathbf{y}) \propto P(\mathbf{y} \mid \mathbf{x}) P(\mathbf{x})$$

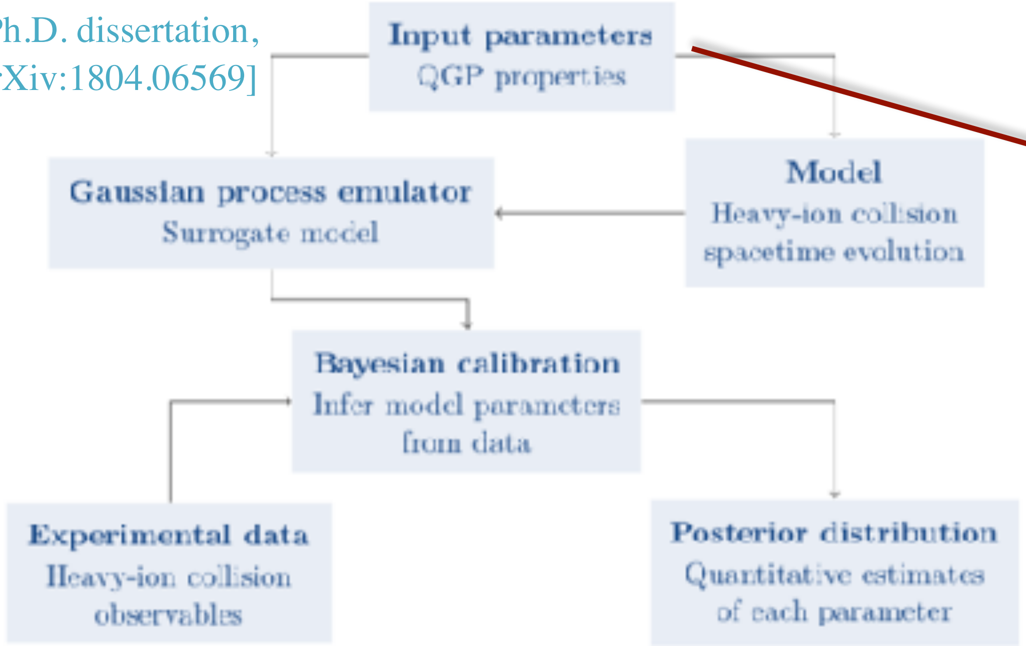
$$P\left(x_1 \mid \mathbf{y}\right) = \int dx_2 \cdots dx_n P(\mathbf{x} \mid \mathbf{y})$$

- Strong prior assumption of parametrization form will result in strong correlation of $\hat{q}$ at different T, e.g. $\hat{q}/T^3 = AT + B$.
- The performance of the emulator can be impaired by non-linear response between model prediction and the input parameter, $\hat{q}/T^3 = (1 + (aT/T_c)^p)^{-1}$. [W. Ke, Ph.D. dissertation, arXiv:2001.02766]
- The number of parameters and complexity increases exponential with the number of control variables (e.g. T, E, Q). [JETSCAPE, PRC 104 (2021) 2, 024905]

Bayesian inference of $\hat{q}(T)$ with information field method

Bayesian inference:

[Jonah E. Bernhard, Ph.D. dissertation, arXiv:1804.06569]



Information field theory (IFT):

[Information Field theory: https://wwwmpa.mpa-garching.mpg.de/~ensslin/research/research_IFT.html]
[Jorsten A. Enßlin *Annalen Phys*. 531 (2019) 3, 1800127]

- Non-parametric way of representing of the unknown function;
- $\hat{q}$ individual variation in different T.

- Parametrization from will result in strong correlation of $\hat{q}$ at different T.
- The performance of the emulator can be impaired by non-linear response between model prediction and the input parameter. [W. Ke, Ph.D. dissertation, arXiv:2001.02766]
- The number of parameters and complexity increases exponential with the number of control variables (e.g. T, E, Q). [JETSCAPE, PRC 104 (2021) 2, 024905]

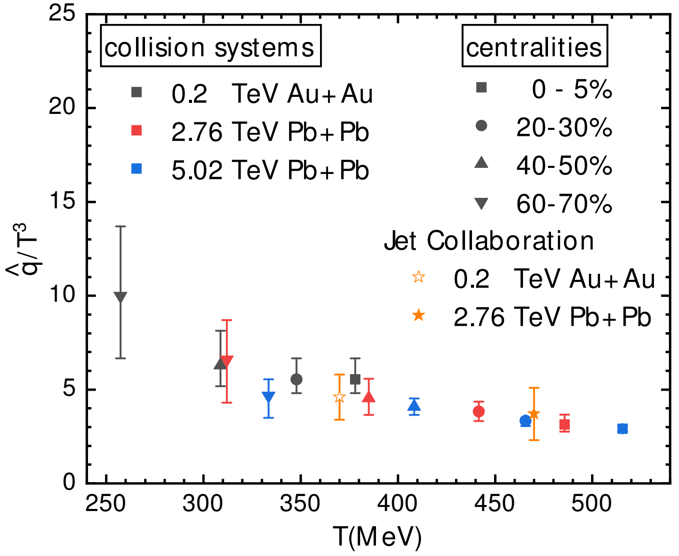
Construction of the functional prior $\hat{q}(T)$

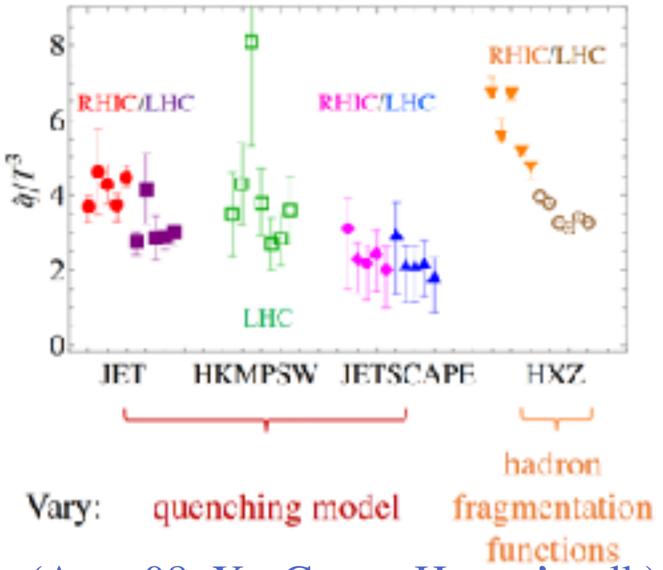
true distribution functional form:

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

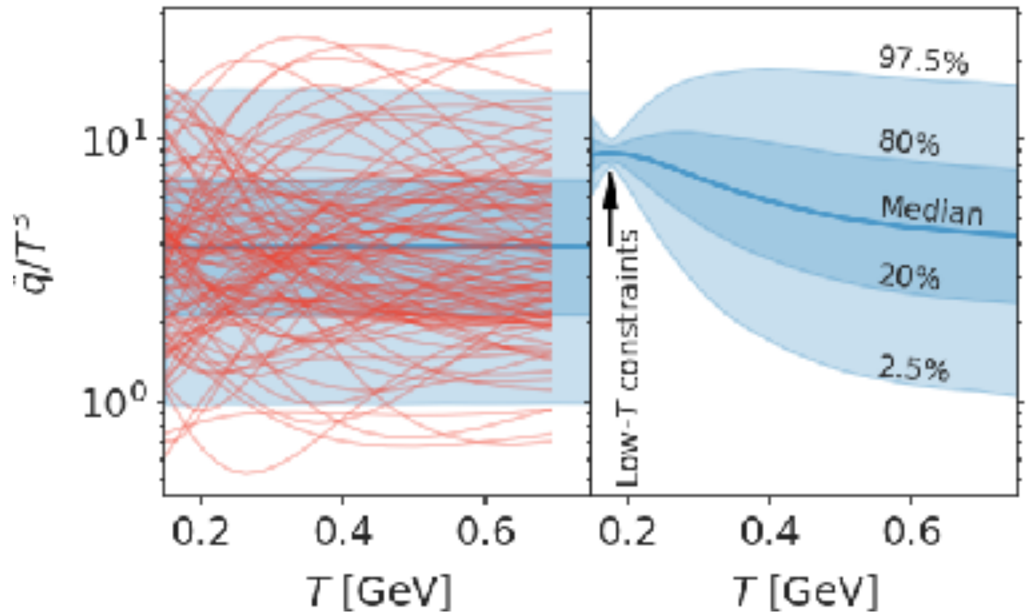
$$F(x) = \ln(\hat{q}/T^3),\ x = \ln(T/\mathrm{GeV})$$ [Y.Y. He, X.-N. Wang, etal, PRC 91,054908(2015)]

$$\mu(x) = C;\ \ C(x,x') = \sigma^2 e^{-\frac{(x-x')^2}{2L^2}}.$$





(Aug. 08, Xu-Guang Huang's talk)



$$T_c < T < 4T_c,\ 0.5 < \hat{q}/T^3 < 20$$

$$\mu(x) = \ln 5,\ \sigma = \ln 2,\ \mathrm{L} = \ln 2$$

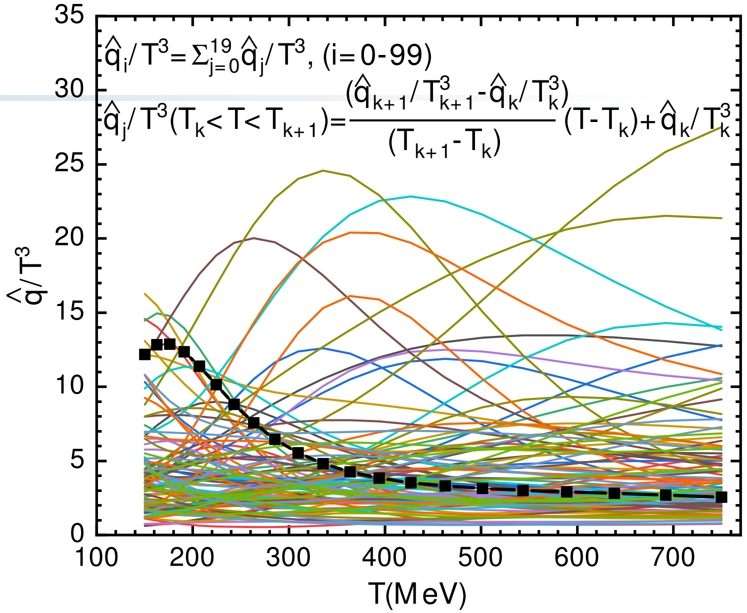
$$T_c = 0.165\ \mathrm{GeV}$$

$\hat{q}(T)$ prior of unknown function in an IFT method

Input parameter matrix

$$\left[\frac{\hat{q}}{T^3}\right]_i = \sum_{j=1}^{20} \theta\left(T - T_j\right) \theta\left(T_{j+1} - T\right) \left(\left[\frac{\hat{q}}{T^3}\right]_{i,j+1} \Delta_j + \left[\frac{\hat{q}}{T^3}\right]_{i,j} \left(1 - \Delta_j\right)\right)$$

$$\Delta_j = \frac{T - T_j}{T_{j+1} - T_j},\ i = 1 - 100,\ j = 1{,}20.$$

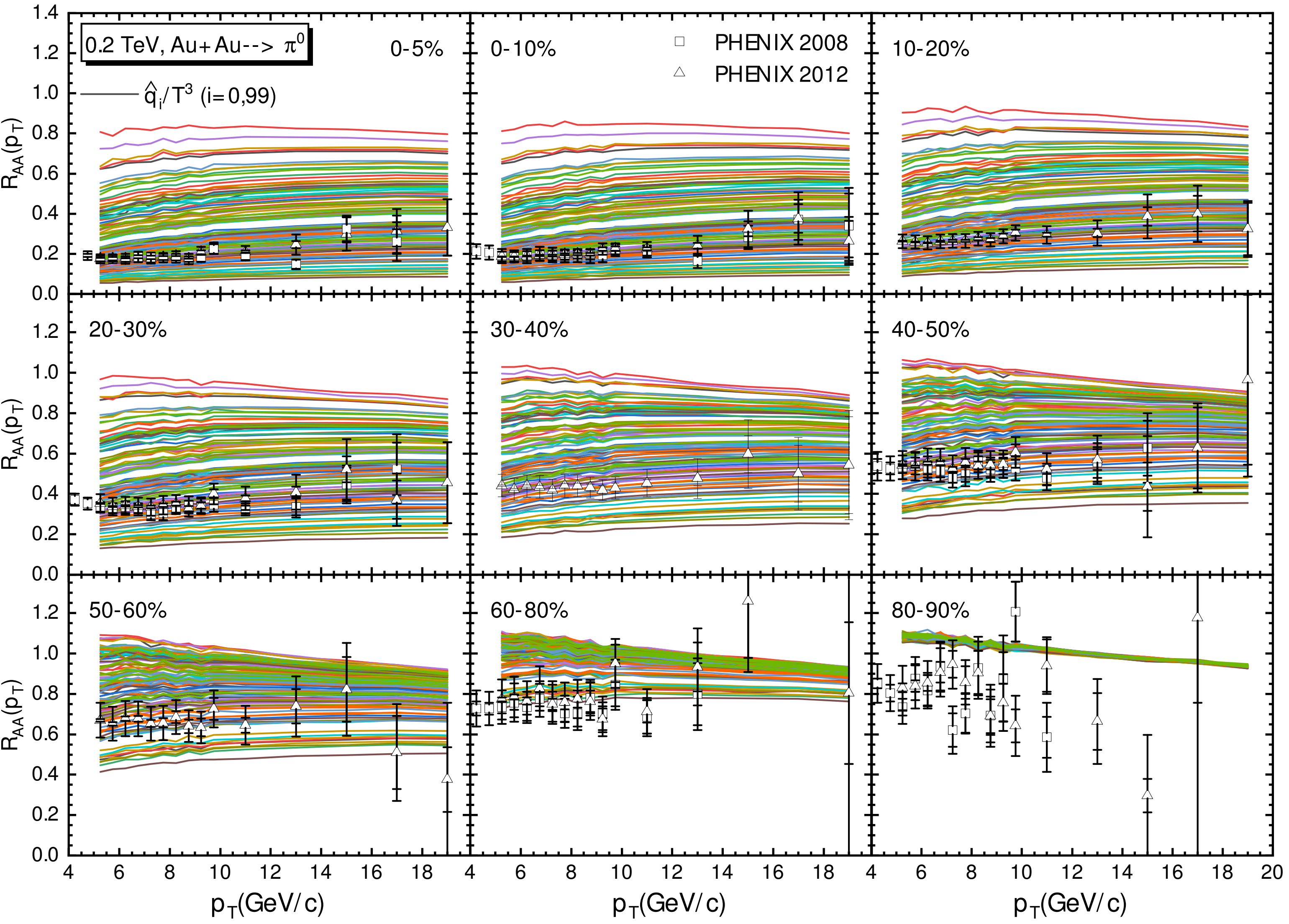


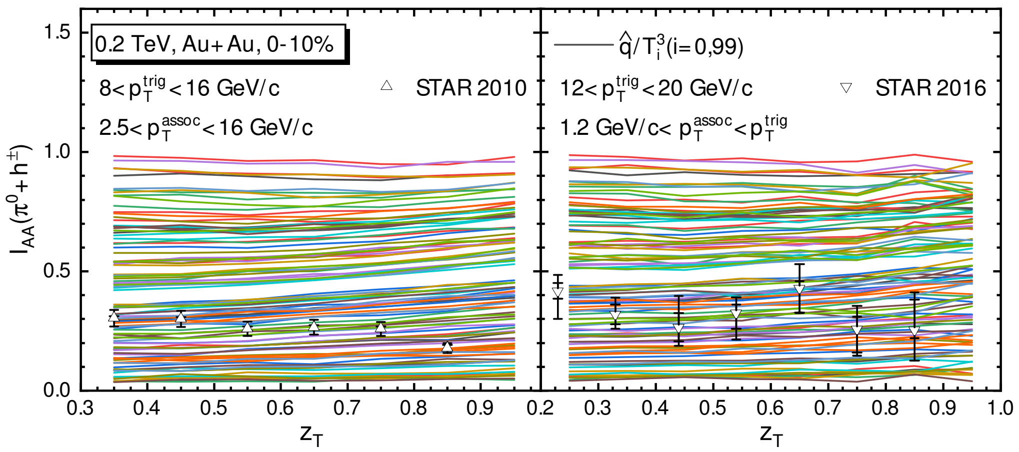
The hydrodynamic evolution of the QGP medium provided by the CLVisc (3+1) D hydrodynamic model.

[L. G. Pang, Q. Wang, X.-N. Wang, Phys.Rev.C 86 (2012) 024911], [L. G. Pang, H. Petersen, X.-N. Wang,Phys.Rev.C 97 (2018) 6, 064918]

- $R_{AA}^{\pi^0}$ in 0-5%, 0-10%, 10-20%, 20-30%, 30-40%, 40-50%, 50-60%, 60-80%, 80-90% Au-Au collisions at 0.2 TeV;
- $R_{AA}^{h^\pm}$ in 0-5%, 5-10%, 10-20%, 20-30%, 30-40%, 40-50%, 50-60%, 60-80%, 70-90% Pb-Pb collisions at 2.76 TeV;
- $R_{AA}^{h^\pm}$ in 0-5%, 5-10%, 10-20%, 10-30%, 20-30%, 30-50%, 50-70% Pb-Pb collisions at 5.02 TeV;
- $I_{AA}^{\gamma h^\pm}$ in 0-10% Au-Au collisions at 0.2 TeV, (2 trigger ranges);
- $I_{AA}^{\pi^0 h^\pm}$ in 0-10% Au-Au collisions at 0.2 TeV, (2 trigger ranges);
- $I_{AA}^{h^\pm h^\pm}$ in 0-5%, 0-10% Pb-Pb collisions at 2.76 TeV, (6 trigger ranges).

Model calculations with 100 prior $\hat{q}(T)$





NLO pQCD calculations:
2500 curves of R_{AA};
200 curves of $I_{AA}^{\gamma h^\pm}$;
800 curves of I_{AA}^{hh}.

Training data $(\hat{q}_{ij}, \mathbf{y}_{ik})$

The posterior distribution

- Prior distribution of the random function: [Jorsten A. Enßlin *Annalen Phys*. 531 (2019) 3, 1800127]

$$P_0[F(x)] = e^{-\frac{1}{2}\int dxdx'\delta F(x)C^{-1}(x,x')\delta F(x')}$$

$$\delta F(x) = F(x) - \mu(x);\ \ C(x,x') = \sigma^2 e^{-\frac{\left(x-x'\right)^2}{2L^2}}.$$

- Posterior distribution : [python library emcee: multi-dimensional Gaussian]

$$P[F(x)] = P_0[F(x)] \times \text{ Likelihood}$$

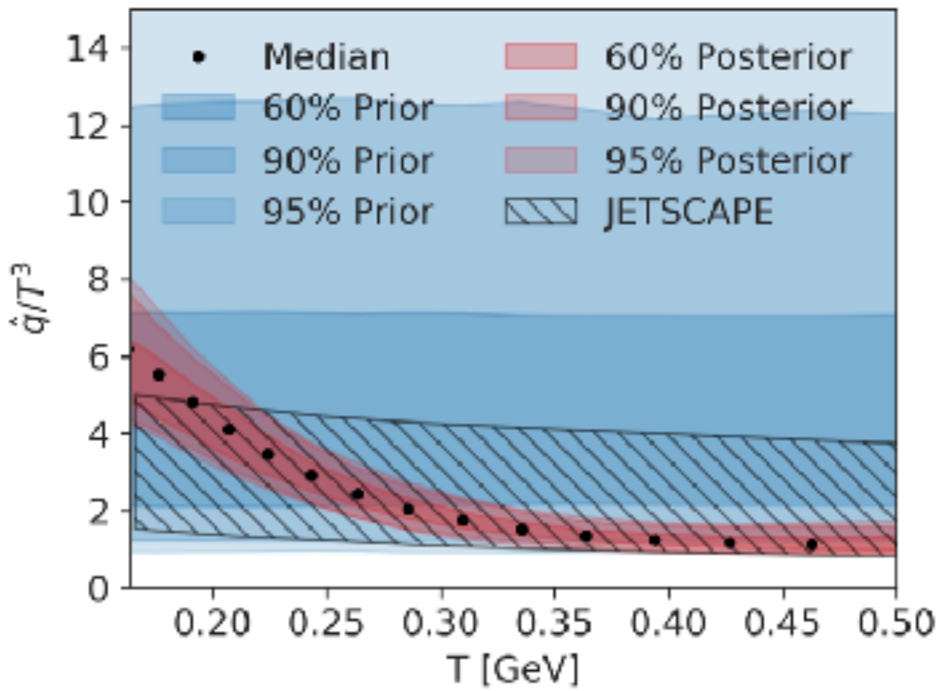
$$= \exp\{-\frac{1}{2}\int dxdx'\delta F(x)C^{-1}(x,x')\,\delta F(x')$$

$$-\frac{1}{2}\left(M'[F] - y_{\text{exp}}\right)^T \Sigma_{\text{error}}^{-1}\left(M'[F] - y_{\text{exp}}\right)\}.$$

- MCMC sampling

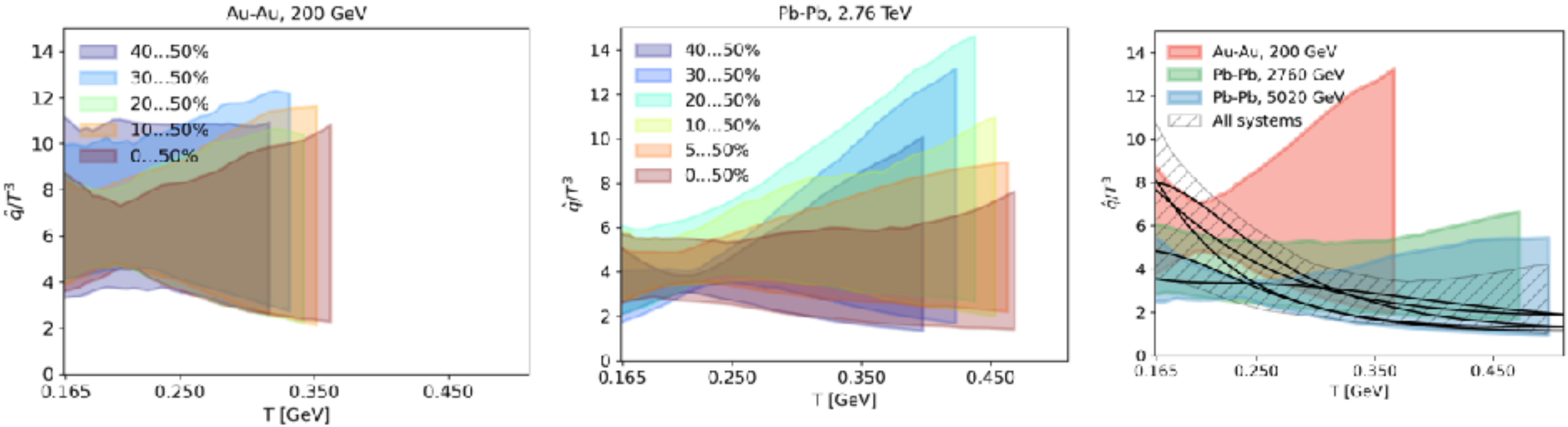
- To marginalise the values of F* at a fixed input x*

$$p(F^*) = \int [\mathscr{D}F]\delta\left(F(x^*) - F^*\right) P[F(x)]$$



Progressive constraining power from peripheral to central collisions

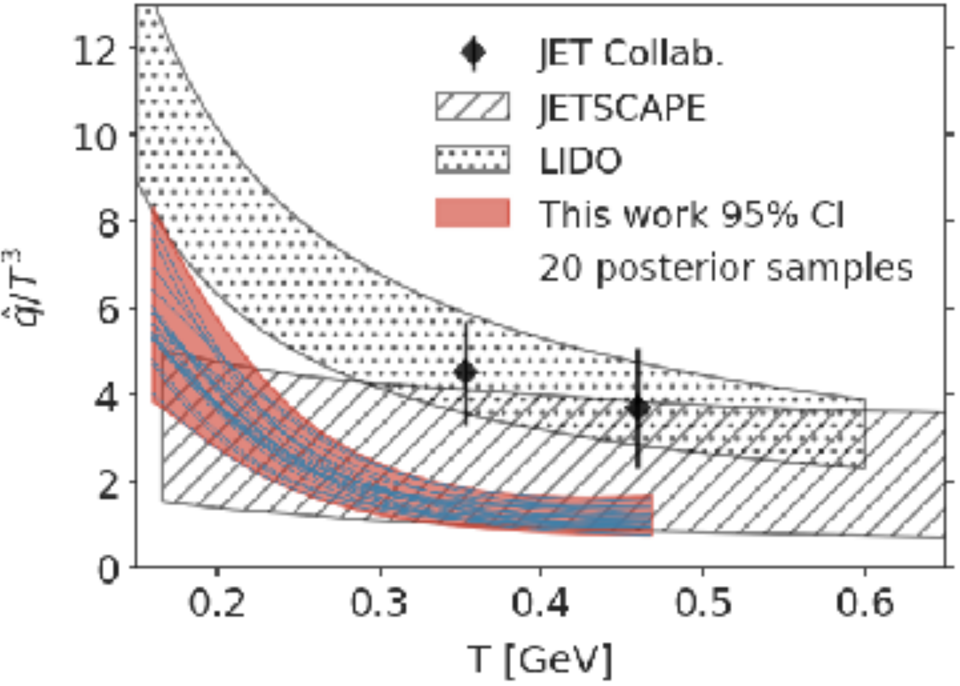
From low-T —> high-T region; From peripheral —> central collisions; From RHIC —> LHC energies.

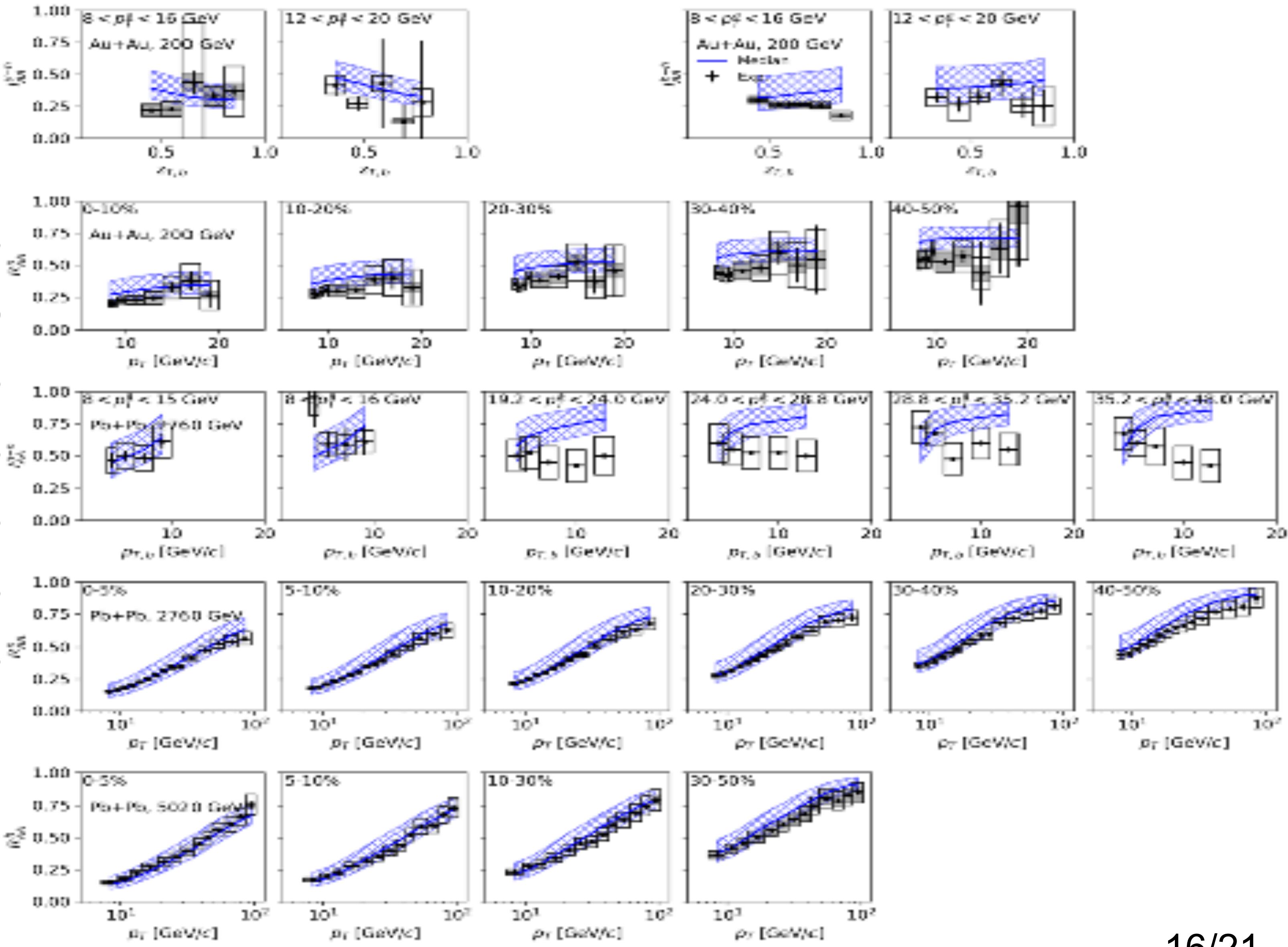


The combined analysis compromises between the relatively large $\hat{q}/T^3$ at low-T as favored by the Au+Au data at the RHIC energy and the small $\hat{q}/T^3$ at high-T as favored by the Pb+Pb data at the LHC energies.

Constrain the T dependence of $\hat{q}(T)$

The 95% credible interval around the median of the ensemble prediction of the emulator.

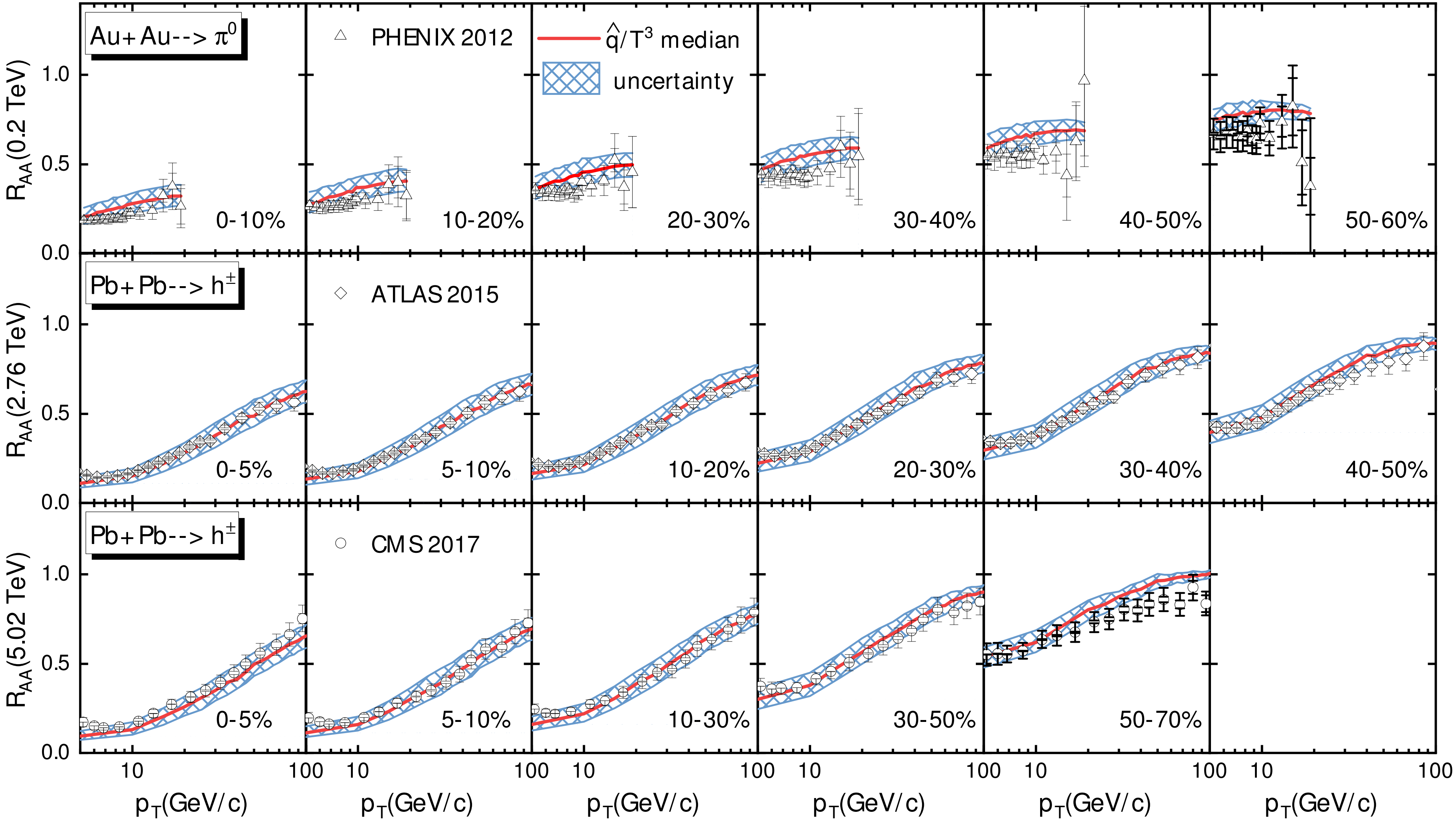




[JET Collaboration: Phys. Rev. C 90, 014909 (2014) ;
JETSCAPE: Phys. Rev. C 104, 024905 (2021) ;
LIDO, W. Ke, X.-N. Wang, JHEP 05041.]

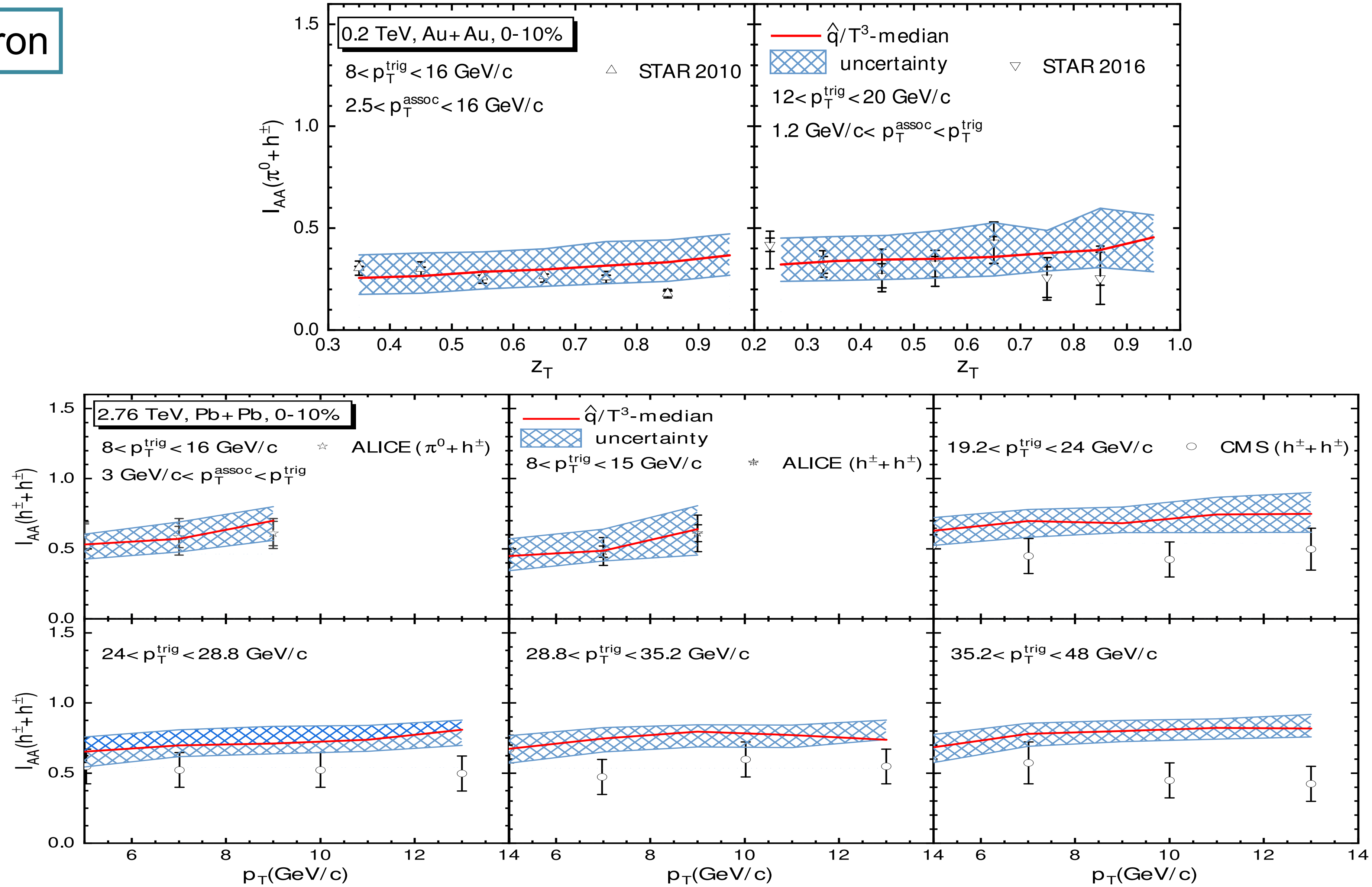
Model validation 90% CL

Single hadron



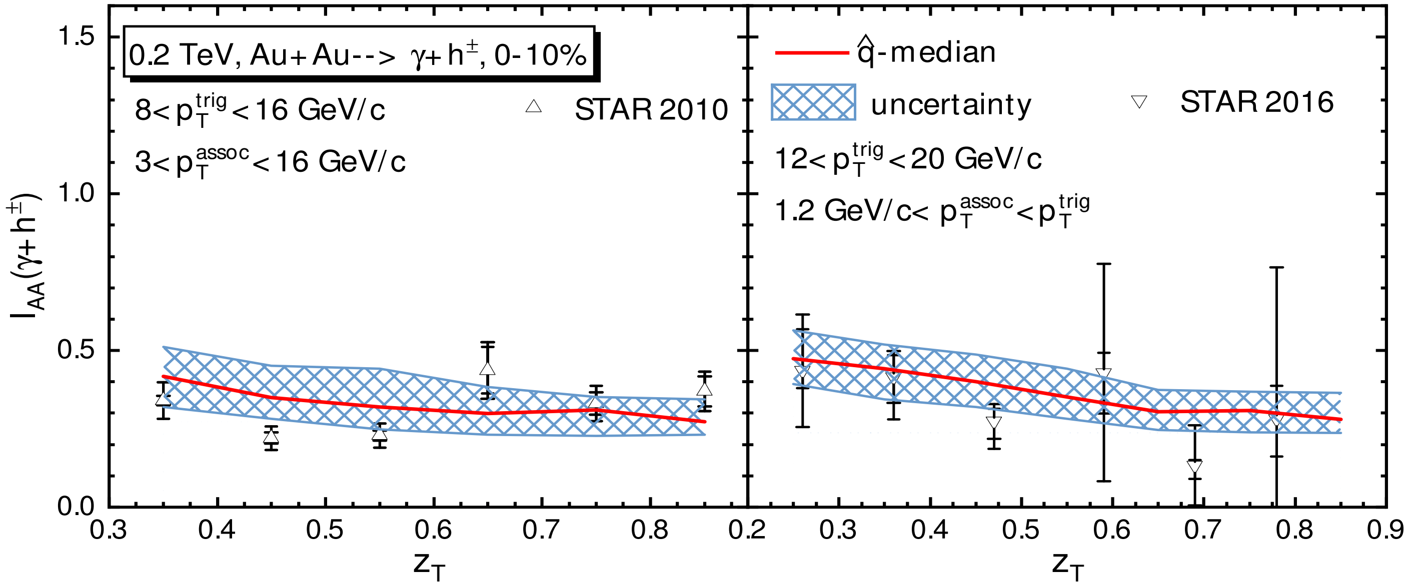
Model validation 90% CL

Di-hadron

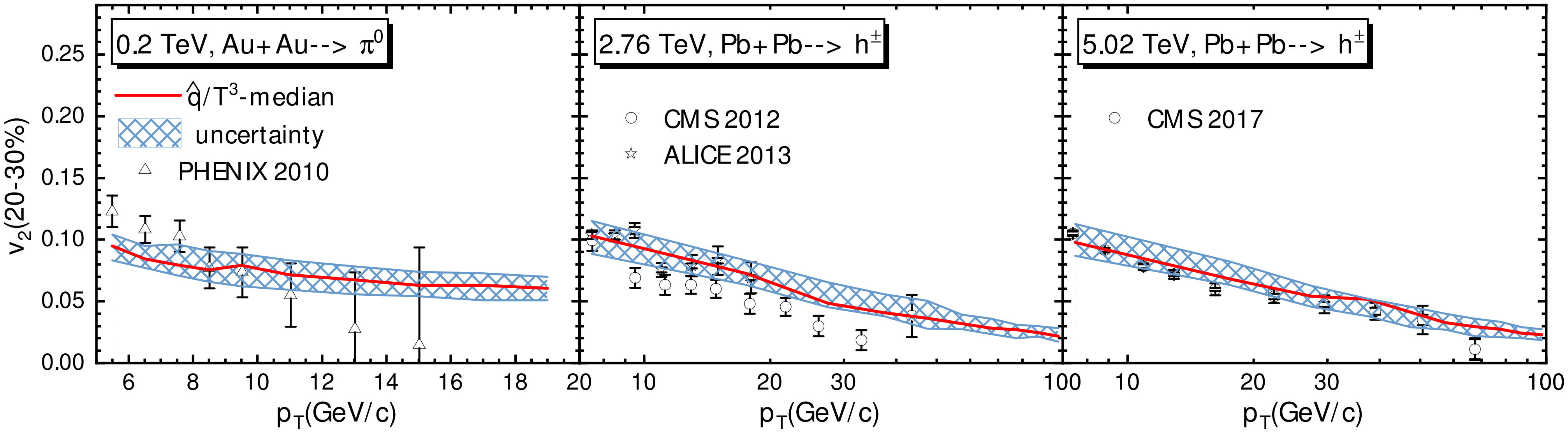


Model validation 90% CL

γ-hadron

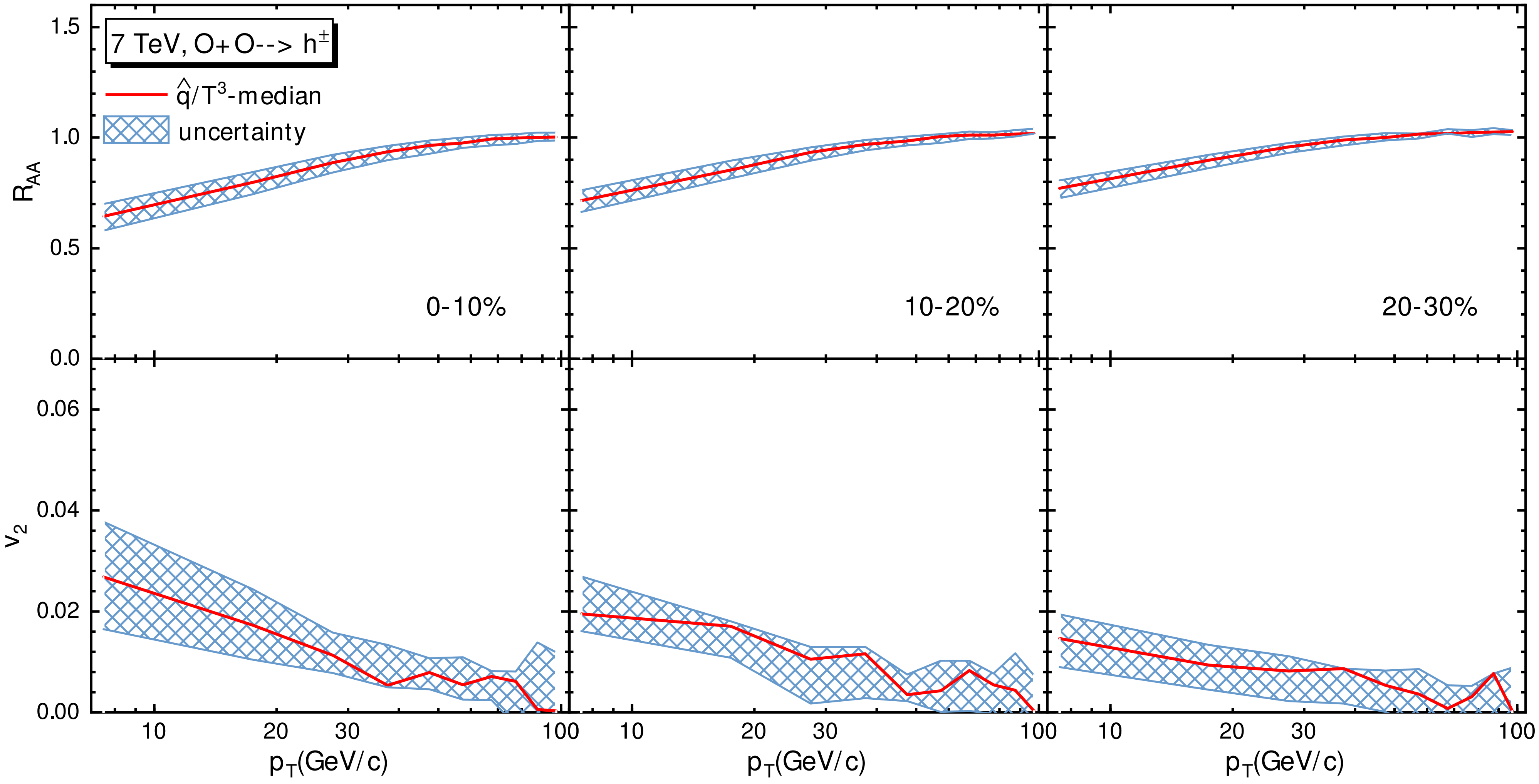


v_2 of single hadorn



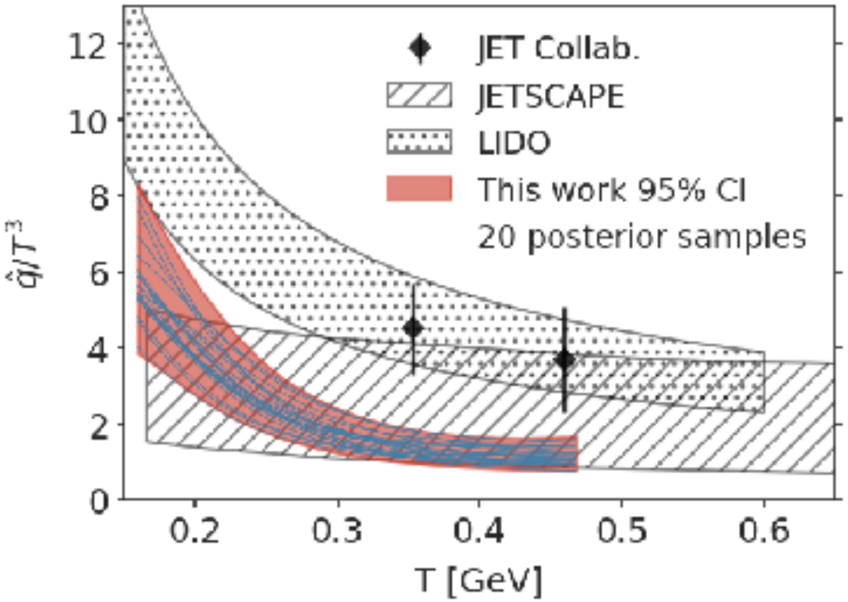
Prediction

O-O collisions at 7 TeV



Summary

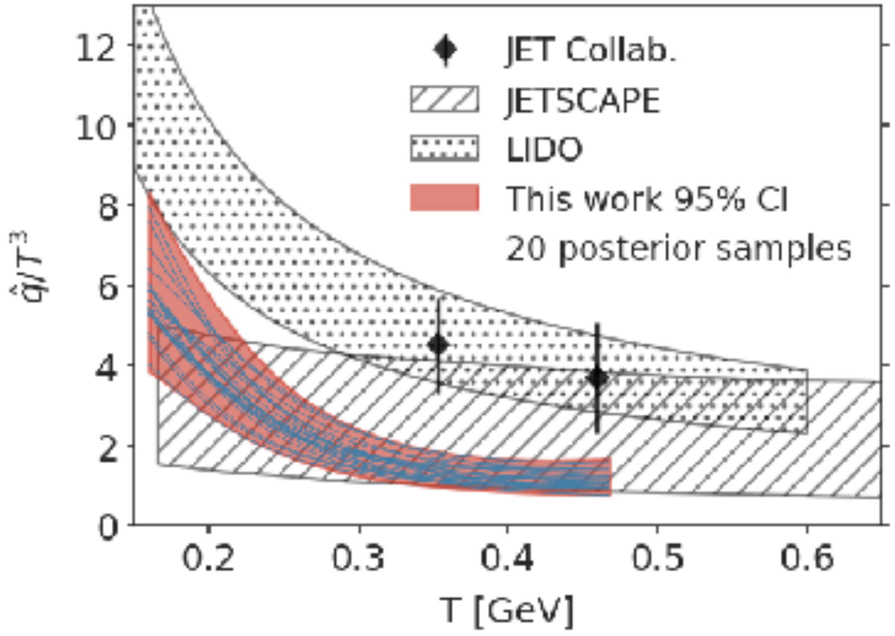
- A first global Bayesian constraint of $\hat{q}(T)$ using combined experimental data of R_{AA} and I_{AA} in HIC at both RHIC and LHC energies with a wide range of centralities.
- The Bayesian inference method combined with the IFT for the prior unknown functions.
- Random field prior: avoid any intrinsic long-range correlations between prior $\hat{q}/T^3$ values at different T regions that are usual present in many explicit forms of parameterizations.
- $\hat{q}/T^3$ decreases with T from 6±2 near T_c to 1.1±0.3 at 3 T_c .
- The extracted $\hat{q}/T^3$(T) describe for single hadron v_2 at large p_T.
- We also predict the R_{AA} and v_2 in O-O collisions at 7 TeV.

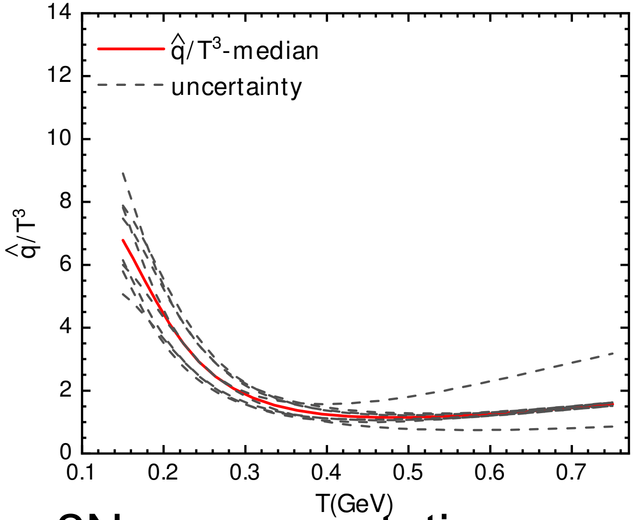


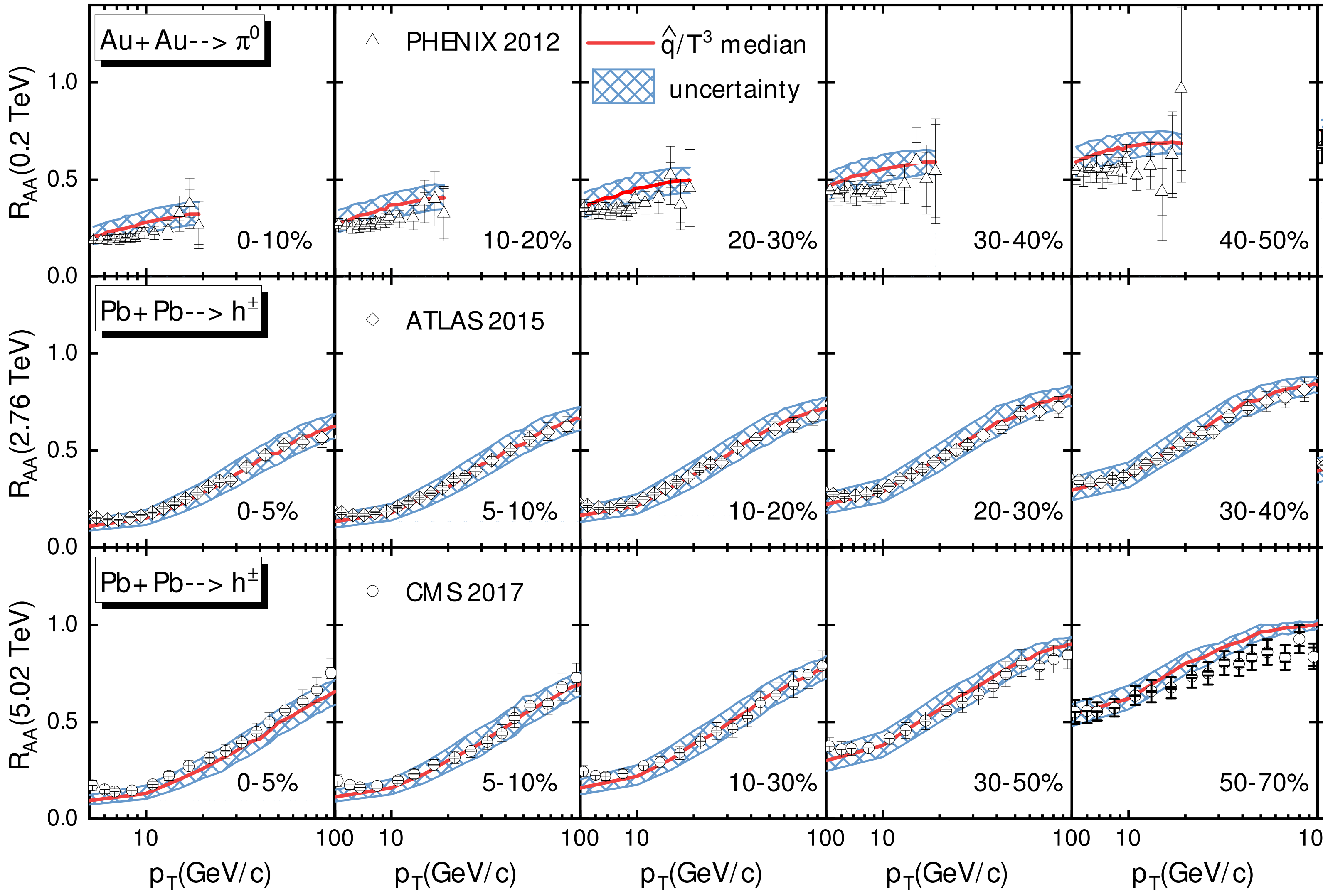
Thank you for your attention!

Model validation 90% CL

Single hadron

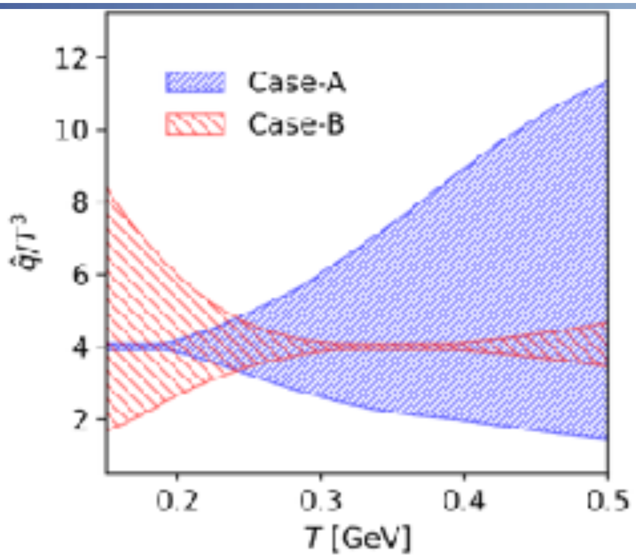




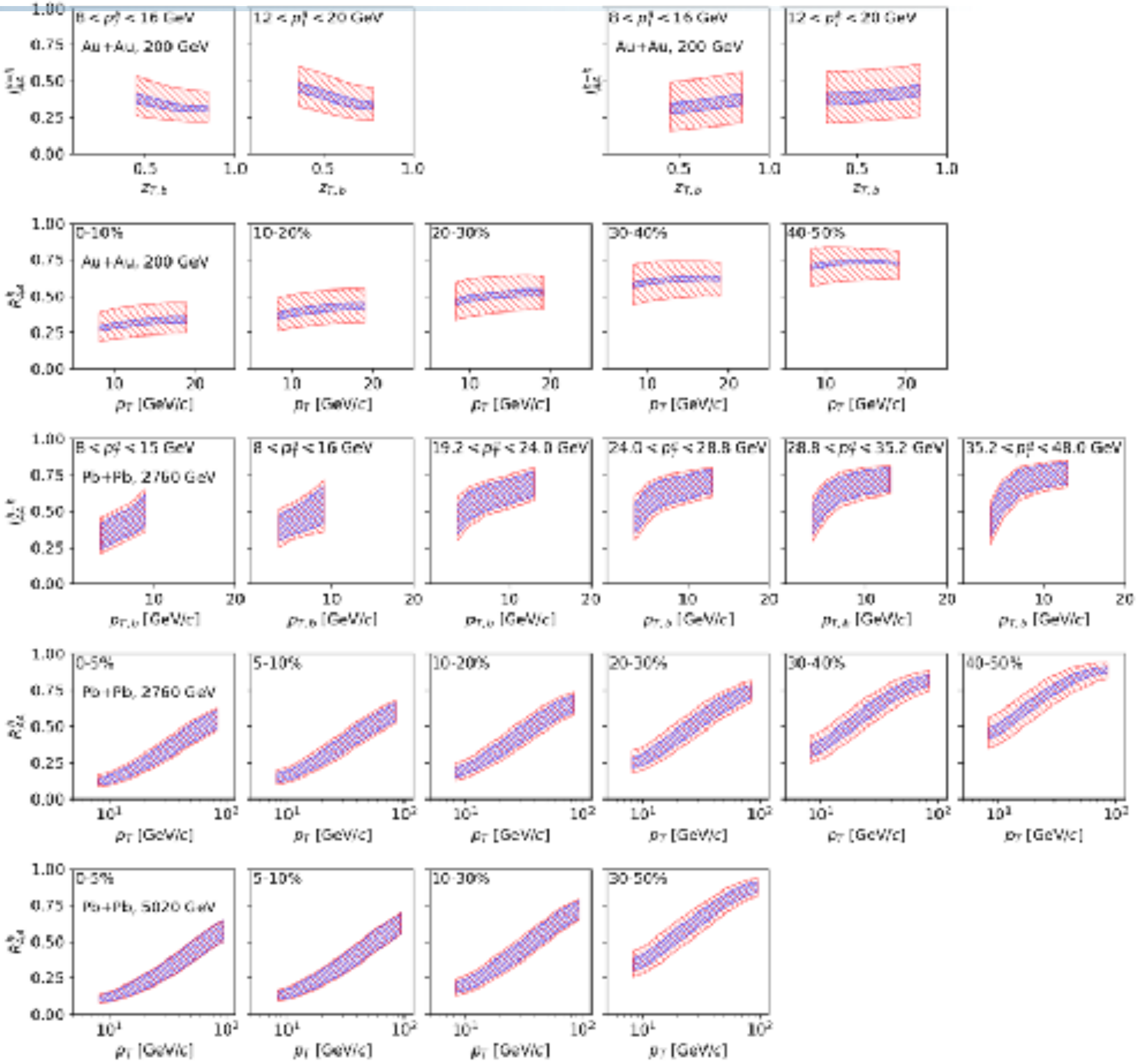


1 + 2Np representative parameter sets: Np=4; 1 median, 8 sets to get uncertainty. [W. Ke, X.-N. Wang, JHEP 05041.]

Sensitivity of the observables to the T dependence of jet transport coefficient

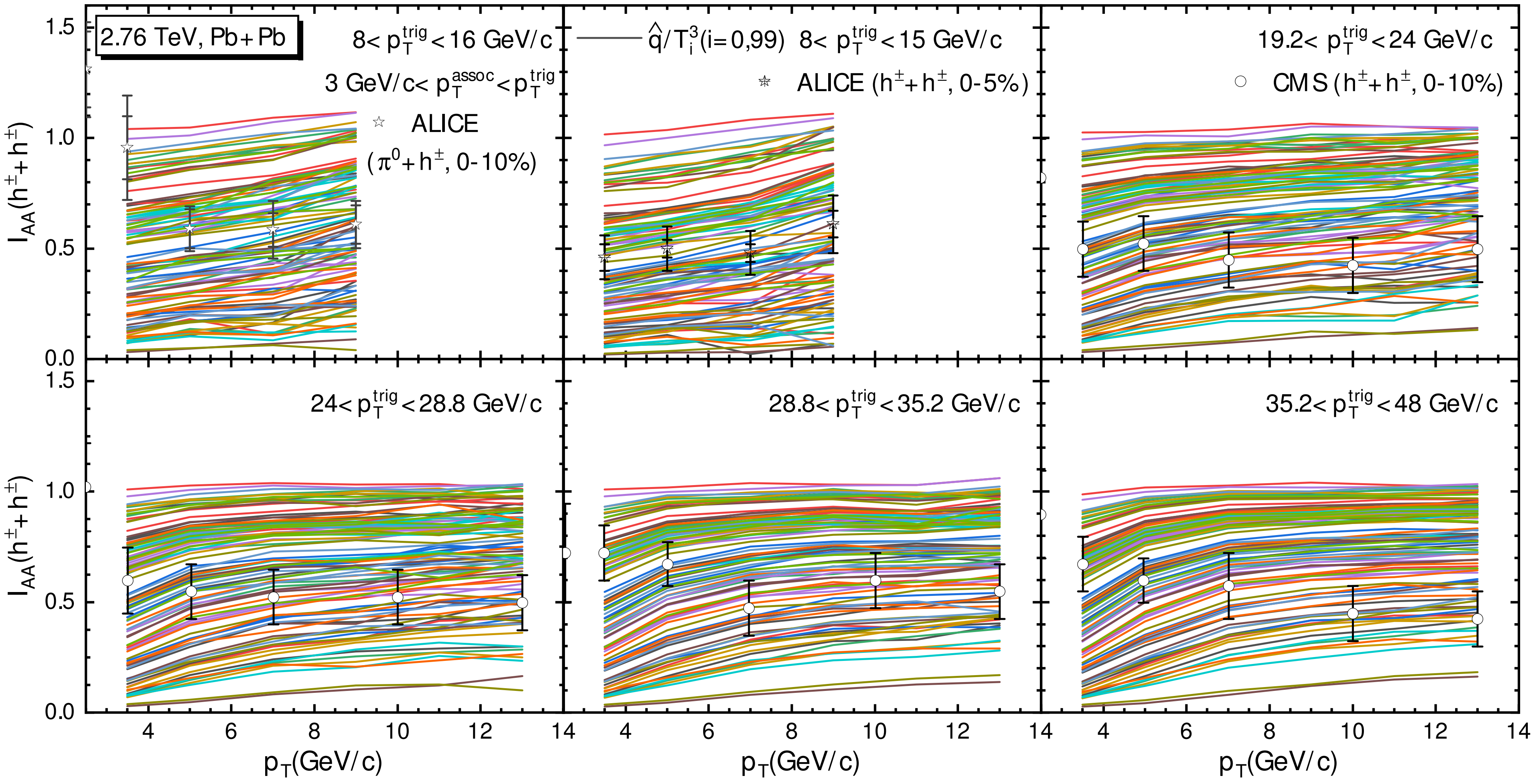


$\text{Case} - \text{A}: \text{ vary high T},$
$0.15 < T < 0.2 \text{ GeV},$
$\hat{q}/T^3 = 4 \pm 0.1;$
$\text{Case} - \text{B}: \text{ vary low T},$
$0.3 < T < 0.4 \text{ GeV},$
$\hat{q}/T^3 = 4 \pm 0.1.$



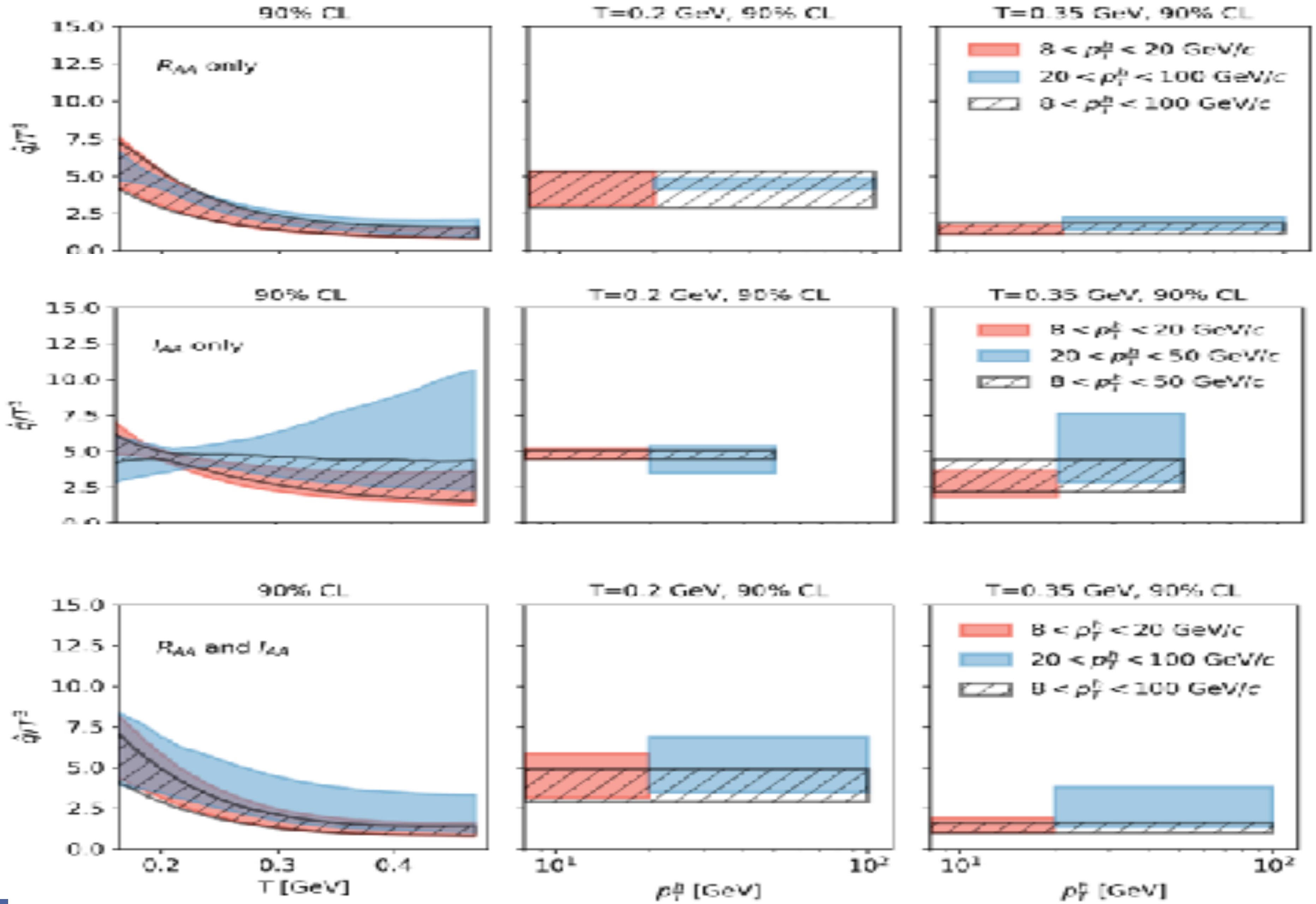
- At RHIC, observables are more sensitive to $\hat{q}$ in low-T.
- In central collisions and at higher beam energy, observables are more sensitive to $\hat{q}$ in the high-T region.
- $\hat{q}$ are more sensitive to di-h, gam-h.

Di-hadron at LHC with 100 prior $\hat{q}(T)$



- I_{AA} with high trigger suggest a larger $\hat{q}$.
- Explore p_T-dependence in the future.

Test transverse momentum sensitivity



- R_{AA} are almost p_T-independence
- I_{AA} with high trigger p_T suggest a larger $\hat{q}$.
- Explore p_T-dependence in the future.

Training model emulators with random function realization

- Training data $(\hat{q}_{ij}, \mathbf{y}_{ik})$, $i = 1 - 100,\ j = 1{,}20$;

  k = each observable points, including R_{AA} and I_{AA} in each centralities an at each p_{T} (z_{T}) point.
- Reduce dimensionality: $N_{\text{feature}} \ll N_{\text{observables}}$.

  Principal Component Analysis (PCA):

  transform the high-dimensional observables into the “feature” space.

  [Scikit-Learn: scikit-learn: Machine learning in Python, http://scikit-learn.org.]
  [M. E. Tipping and C. M. Bishop, “Mixtures of Probabilistic Principal Component Analyzers”,
  Neural Computation **11**, 443–482 (1999).]

- Training the mapping from $\hat{q}$ to each one of the $N_{feature}$ principal components using an Gaussian emulators. [C. E. Rasmussen and C. K. I. Williams, Gaussian Processes for Machine Learning (MIT Press, Cambridge, MA, 2006), http://gaussianprocess.org/gpml.]

- To predict observables at new input $\hat{q}$, one transforms the “interpolated” principal components back to the observables space using the inverse PCA transformation.

The posterior distribution

- prior distribution of the random function: $P_0[F(x)] = e^{-\frac{1}{2}\int dxdx'\delta F(x)C^{-1}(x,x')\delta F(x')}$

[Jorsten A. Enßlin *Annalen Phys*. 531 (2019) 3, 1800127]

$$\delta F(x) = F(x) - \mu(x) \quad C(x,x') = \sigma^2 e^{-\frac{(x-x')^2}{2L^2}}.$$

$P[F(x)] = P_0[F(x)] \times$ Likelihood

[python library emcee: multi-dimensional Gaussian¶ https://emcee.readthedocs.io/en/stable/tutorials/quickstart/#quickstart

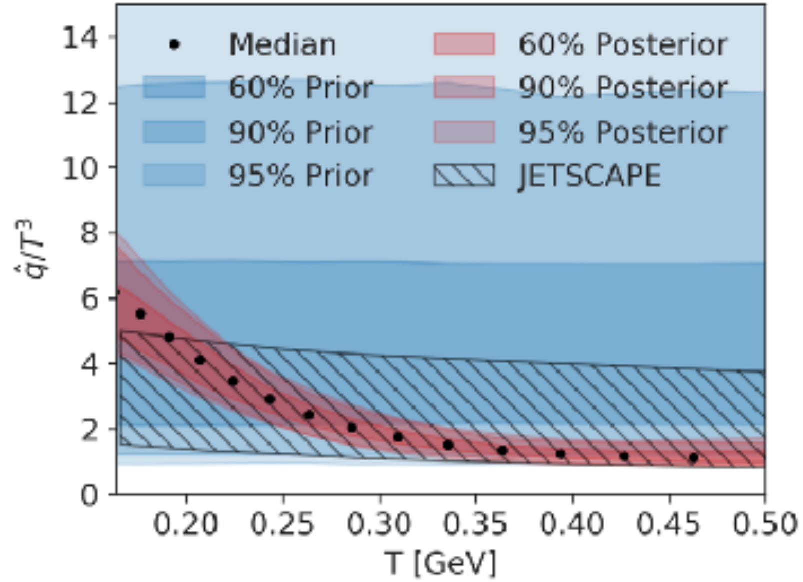
$$= \exp\left\{-\frac{1}{2}\int dxdx'\delta F(x)C^{-1}(x,x')\,\delta F(x') - \frac{1}{2}\left(M'[F] - y_{\mathrm{exp}}\right)^T \Sigma_{\mathrm{error}}^{-1}\left(M'[F] - y_{\mathrm{exp}}\right)\right\}.$$

$M'[F]$: model result

y_{exp} : experimental data

$\Sigma_{\mathrm{error}}^{-1}$: the uncertainty covariance matrix, $\Sigma_{\mathrm{error}} = \mathrm{diag}[\sigma_1^2, \sigma_2^2, \ldots]$

combining experimental, theoretical, and emulator uncertainties,

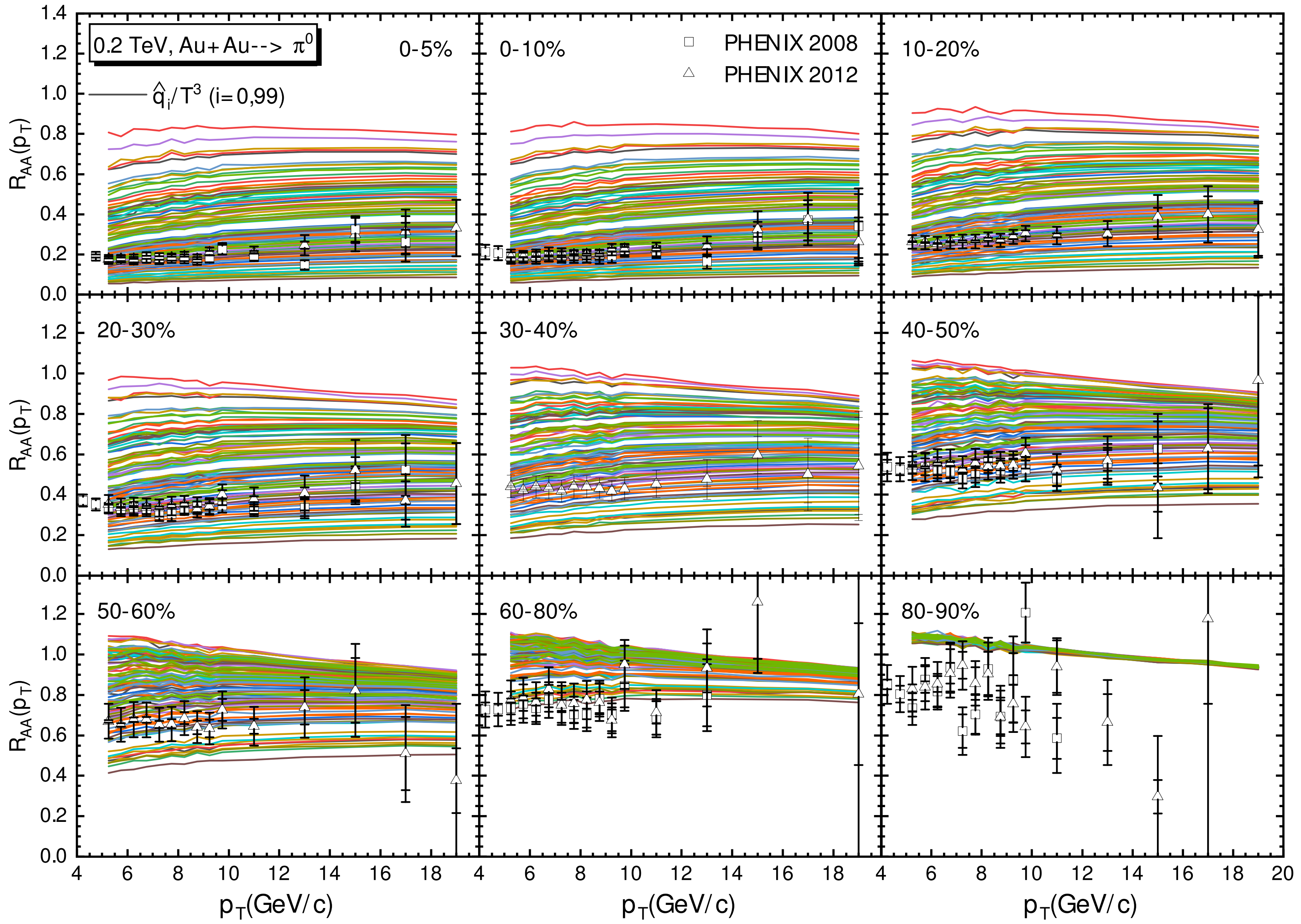


- Markov-Chain-Monte-Carlo (MCMC) sampling

- To marginalize the values of F* at a fixed input x*, one in principle have to perform a path integral

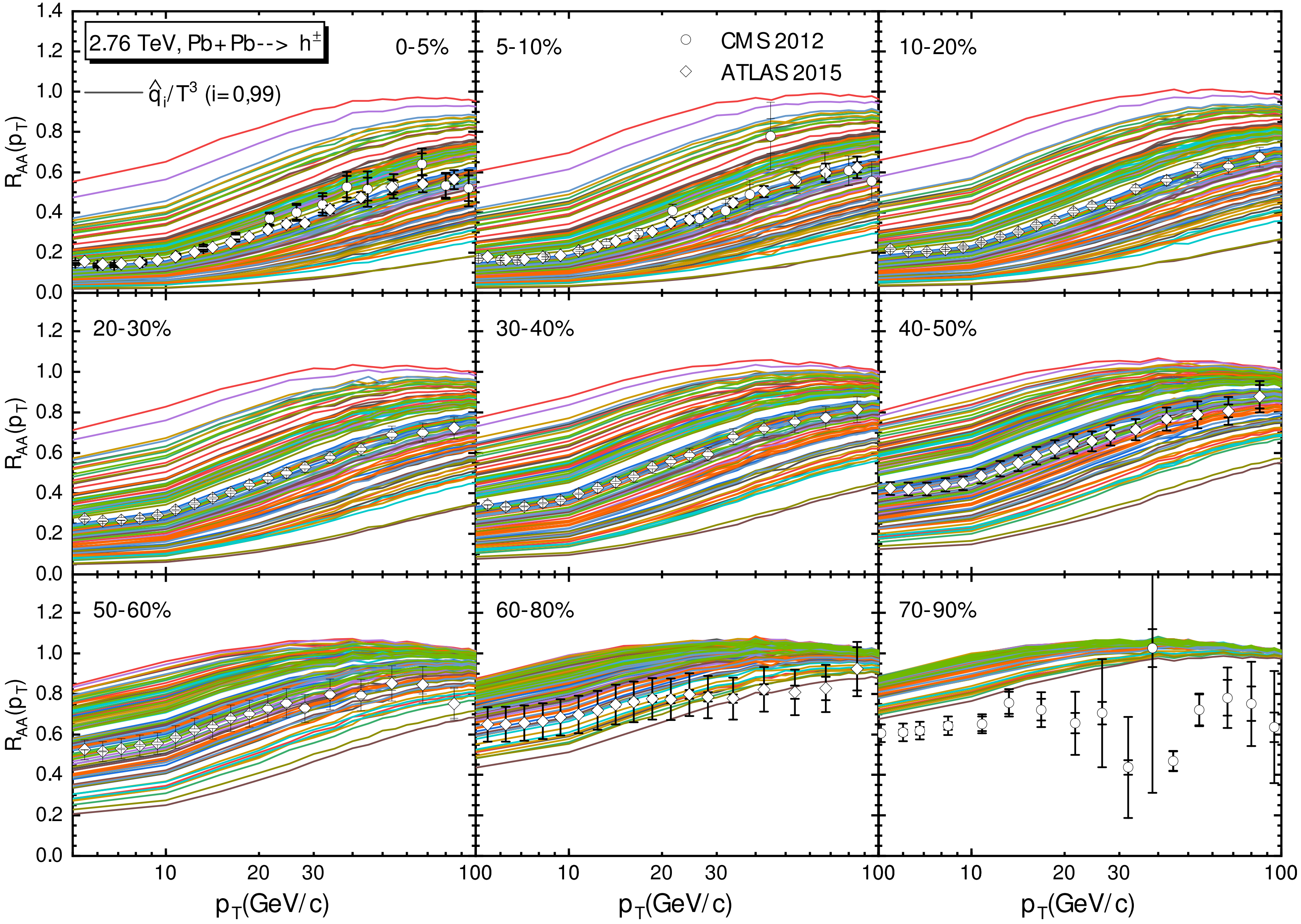
$$p(F^*) = \int [\mathscr{D}F]\delta\left(F(x^*) - F^*\right) P[F(x)] \qquad \left(P\left(x_1 \mid \mathbf{y}\right) = \int dx_2 \cdots dx_n P(\mathbf{x} \mid \mathbf{y})\right)$$

Back-Up



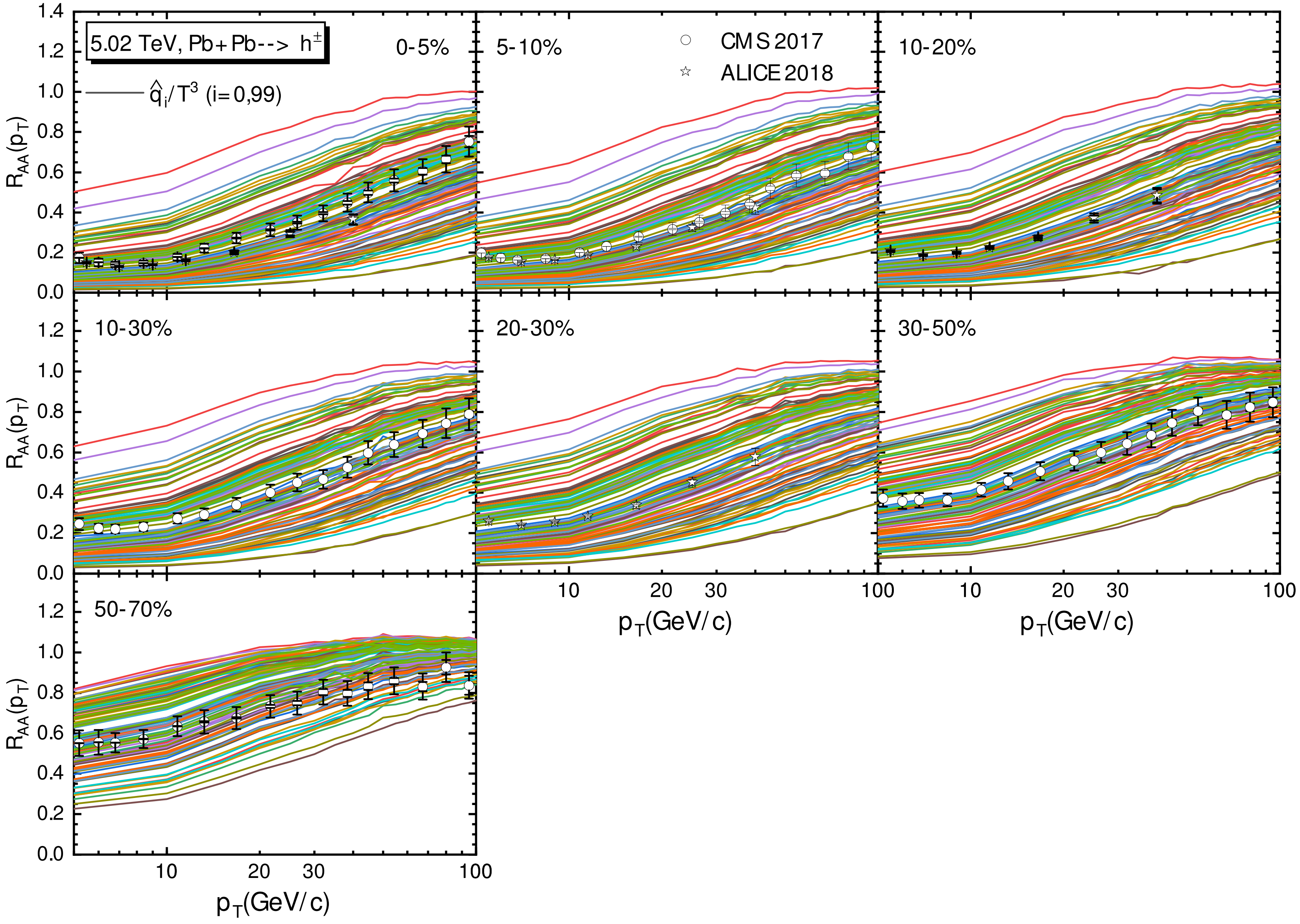
0.2 TeV, Au+Au--> π^0
$\hat{q}_i/T^3$ (i=0,99)
PHENIX 2008
PHENIX 2012
0-5%
0-10%
10-20%
20-30%
30-40%
40-50%
50-60%
60-80%
80-90%
$R_{AA}(p_T)$
p_T(GeV/c)

Back-Up



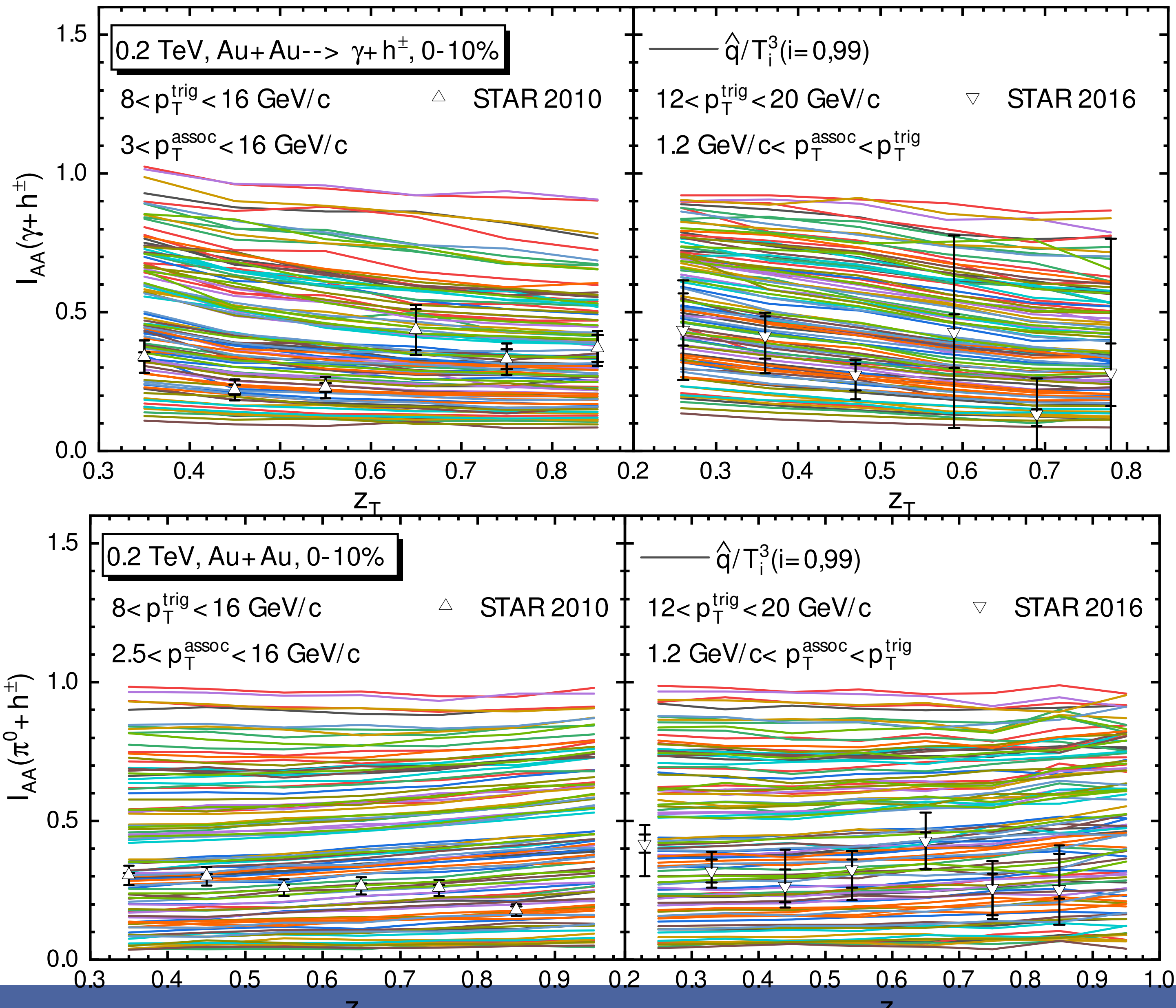
2.76 TeV, Pb+Pb--> h±
$\hat{q}_i/T^3$ (i=0,99)
CMS 2012
ATLAS 2015
0-5%
5-10%
10-20%
20-30%
30-40%
40-50%
50-60%
60-80%
70-90%
$R_{AA}(p_T)$
p_T(GeV/c)

Back-Up



5.02 TeV, Pb+Pb--> h±
$\hat{q}_i/T^3$ (i=0,99)
CMS 2017
ALICE 2018
0-5%
5-10%
10-20%
10-30%
20-30%
30-50%
50-70%
$R_{AA}(p_T)$
p_T(GeV/c)

Back-Up



0.2 TeV, Au+Au--> γ+h±, 0-10%
8<p_T^trig<16 GeV/c
3<p_T^assoc<16 GeV/c
STAR 2010
q̂/T_i^3(i=0,99)
12<p_T^trig<20 GeV/c
1.2 GeV/c< p_T^assoc<p_T^trig
STAR 2016
I_AA(γ+h±)
z_T
0.2 TeV, Au+Au, 0-10%
8<p_T^trig<16 GeV/c
2.5<p_T^assoc<16 GeV/c
STAR 2010
q̂/T_i^3(i=0,99)
12<p_T^trig<20 GeV/c
1.2 GeV/c< p_T^assoc<p_T^trig
STAR 2016
I_AA(π0+h±)