

QPT 2023, Dec 17, Zhuhai

# Deep learning jet modifications in heavy-ion collisions

JHEP03(2021)206 & PRL 128, 012301 (2022)

with Daniel Pablos and Konrad Tywoniuk

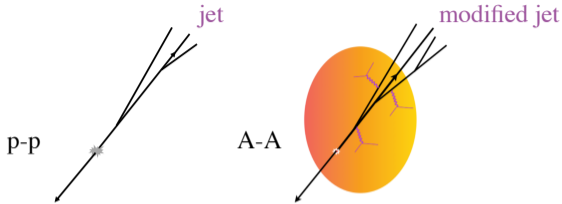
**Yi-Lun Du**



# Outline

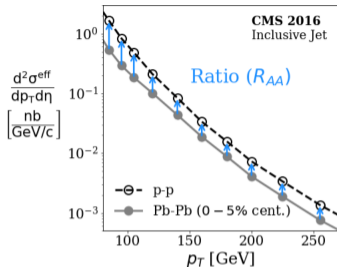
- 1 Motivation: Deep learning jet energy loss**
- 2 General Setup & Performance**
- 3 Applications**
  - Sensitivity of jet observables to in-medium modification
  - Towards jet tomography
- 4 Conclusion and outlook**

# Jets in the medium

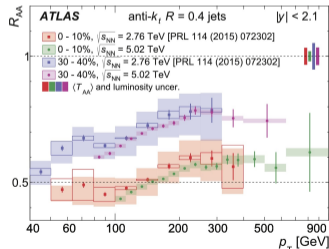


J. Brewer, HP'20

- Quark-gluon plasma (QGP) in heavy-ion collisions:  
deconfined quarks & gluons, strongly-coupled medium
- Jets, collimated sprays of energetic particles, serving as hard probe to medium properties
- Jets are quenched in the medium via parton energy loss
- Jet modifications: ratio of jet observables distr. between medium and vacuum, with  $p_T^{\text{jet}} > p_T^{\text{cut}}$

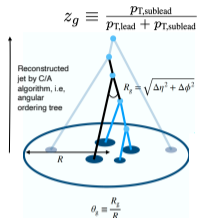
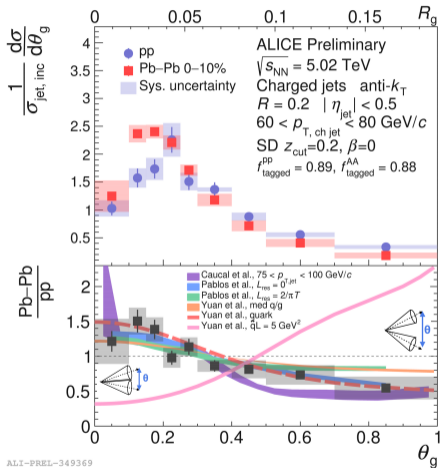


$$R_{AA} = \frac{\text{Spectrum in AA}}{\text{Spectrum in pp}}$$



ATLAS collaboration PLB 790 (2019) 108

# Jet modifications: ambiguous interpretations

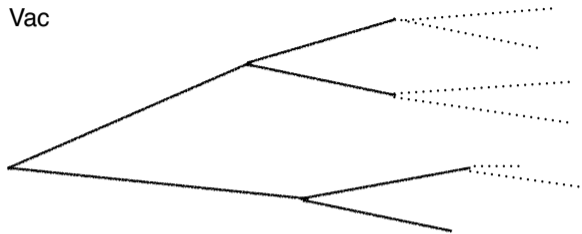


- **Interplay:** jet substructures, e.g.,  $R_g$ , could
  - be **modified** during the passage through the medium and/or
  - affect the **amount of jet energy loss** and then this jet don't pass the  $p_T$  cut of the distribution, i.e., **selection bias**.
- Can we disentangle these two effects with knowledge of **the degree of quenching** for each individual measured jets?

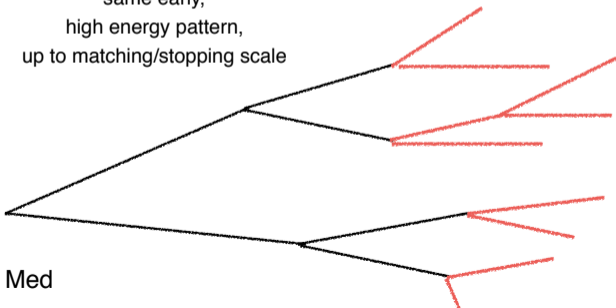


# Define the generalizable energy loss ratio

Vac



same early,  
high energy pattern,  
up to matching/stopping scale



Med

$R$

$E_i$

$$\chi_{jh} \equiv \frac{E_f^h}{E_i^h}$$

$R$

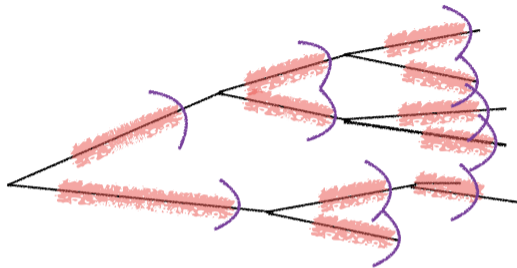
$E_f$

—————  
Vacuum-like  
emission

.....  
Hypothetical  
vacuum-like  
emission

—————  
Medium induced  
emission

# Strong/weak hybrid model

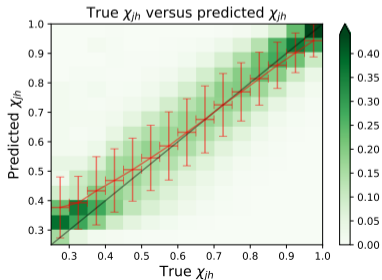
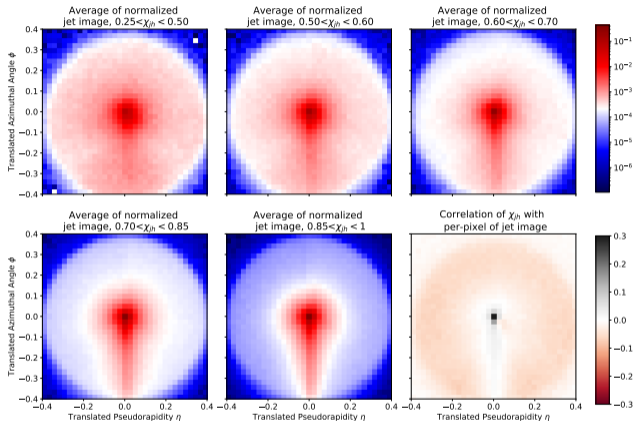
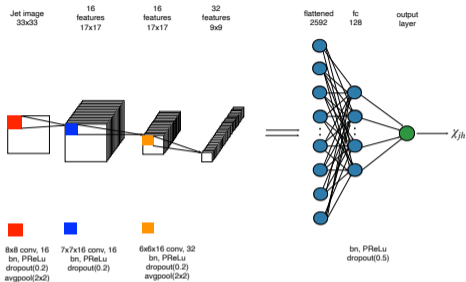


- PYTHIA8 down to hadronization scale
- Strongly coupled energy loss at every stage
- Hadrons from the hydro. wake (medium response)

- Vacuum jets using  $\hat{p}_{T,\min} = 50$  GeV, with oversampling power  $p_T^4$ .
- PbPb collisions in 0-5% centrality at  $\sqrt{s} = 5.02$  ATeV.
- Reconstructed jets with anti- $k_T$ ,  $R = 0.4$ , required to be  $|\eta| < 2$  and  $p_T^{\text{jet}} > 100$  GeV.
- $\sim 250,000$  jets. 80% for training and 20% for validation.

Casalderrey-Solana, Gulhan, Milhano, Daniel Pablos, Rajagopal JHEP '15,'16,'17

# CNN Prediction & Interpretability



- Jet quenching increases the number of **soft particles at large angles**
- Jet shape can capture the main feature

# Jet selections

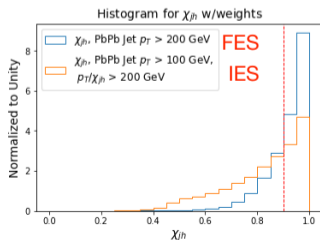
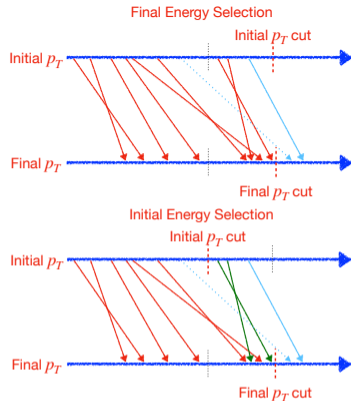
Study jet observables for jets that belong to 2 different quenching classes:

- **Unquenched class:**  $\chi_{jh} > 0.9$ .
- **Quenched class:**  $\chi_{jh} < 0.9$ .

■ pp jets:  $p_T > 200$  GeV

■ PbPb jets:

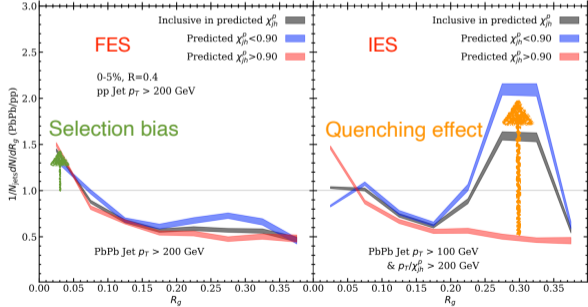
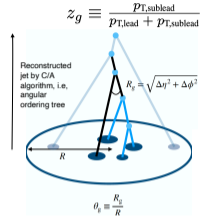
- **Final Energy Selection (FES):** impose  $p_T$  cut on final energy  $p_T > 200$  GeV  $\rightarrow$  Steeply falling energy loss dist. **Biased by little quenched samples!**
- **Initial Energy Selection (IES):** impose  $p_T$  cut on *initial energy* via  $\chi_{jh}$ ,  $p_T/\chi_{jh} > 200$  GeV &  $p_T > 100$  GeV  $\rightarrow$  More support of fairly quenched jets in the quenched class. **More distinguishable!**



# Jet groomed angle, $R_g$

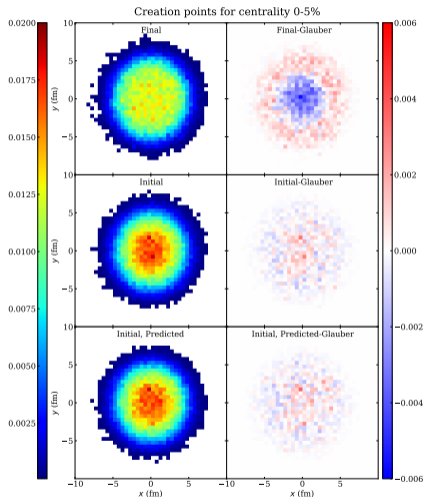
$R_g$  ratio between PbPb jets and **all** pp jets

- **FES**: Selection bias towards jets with smaller  $R_g$ , **originated by  $p_T$  cut.**
- **IES**:
  - **Unquenched class**: still biased due to  $\chi_{jh}$  cut: to belong to this class, a jet had better to be with smaller  $R_g$ , **compared with all pp jets.**
  - **Quenched class** presents features related to energy loss, **compared with unquenched class**: jet quenching leads to enhancement of large  $R_g$  - **creation of a new, semi-hard branch at large angle from medium response.**

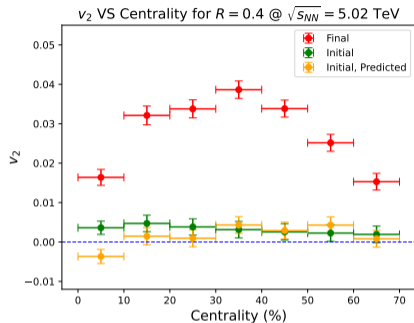


Y.-L. Du, D. Pablos, K. Tywoniuk, JHEP03(2021)206

# Applications: creation points & orientation



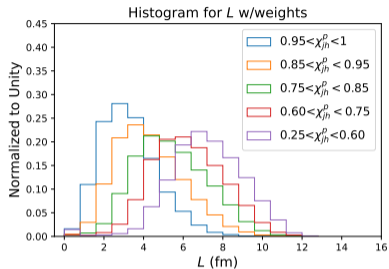
$$v_2 = \left\langle \frac{p_x^2 - p_y^2}{p_x^2 + p_y^2} \right\rangle$$



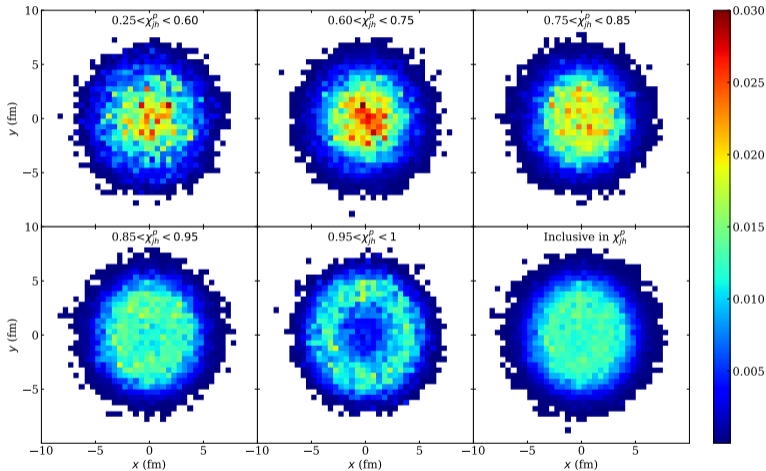
- IES “removes” final state interactions (selection bias), since we record “all” jets.
- IES provides access to the genuine jet creation point (path length) distribution and possible initial-state jet anisotropy.

Y.-L. Du, D. Pablos, K. Tywoniuk, *Phys. Rev. Lett.* **128**, 012301 (2022)

# Applications: Jet tomography, length VS $\chi_{jh}$



Due to the **strong correlation** between  $L$  and  $\chi_{jh}$ , selecting jets with different  $\chi_{jh}$  will naturally select jets that traversed different  $L$ .  
→ Great potential to make tomographic application!



also see Zhong Yang, et al., EPJC 83, 652 (2023)

# Conclusion and outlook

- CNN can extract energy loss jet-by-jet from jet image with **good performance**
  - **Procedure generalisable** to many jet quenching models
  - Jet shape contains significant predictive power: **angular distribution of soft particles**
  - **Mitigate selection bias** and **reveal medium effects** on various jet observables
  - Open opportunity to make **tomographic** study
- 
- **Generalizability** to other MC quenching models?
  - Applicability to more **realistic environment**: fluctuating background?
  - **Better performance** from other state-of-the-art neural networks?
  - **Extract traversed length** with better precision?
  - Unfold jet **initial properties** apart from jet energy?

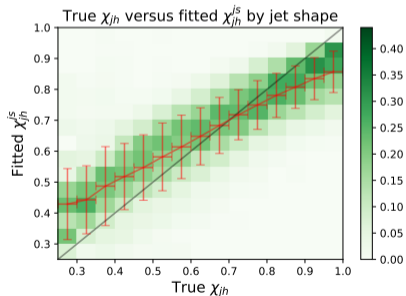
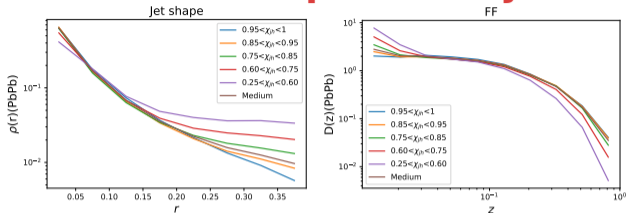


Thanks for your attention!

# Prediction with jet observables & Interpretability

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

- Jet shape outperforms jet FF.
- Motivates construction from jet shape by 17-parameter fitting:
  - Still a bit worse than CNN
- Jet observables recover the performance by jet image with **equivalent** predictive power: **interpretability!**

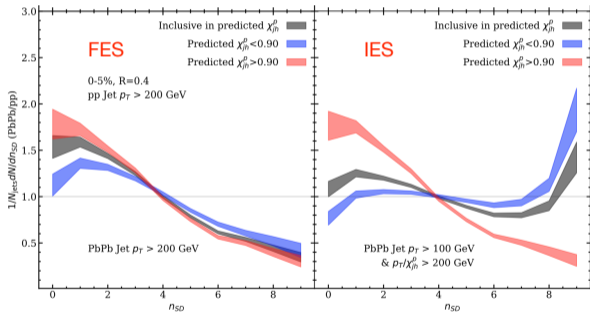


$$\chi_{jh}^{js} = \sum_i \left( \frac{\rho_{Ti}}{\rho_T} \right)^{\alpha_i} r_i^{\beta_i} + \gamma$$

# Backup: Soft Drop multiplicity, $n_{SD}$

$n_{SD}$  ratio between PbPb and pp jets

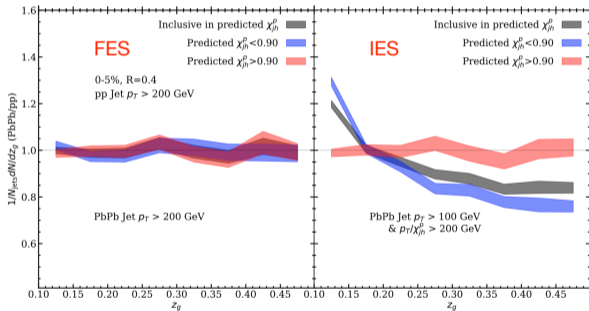
- **FES:** Selection bias towards jets with fewer  $n_{SD}$ , originated by  $p_T$  cut.
- **IES:**
  - **Unquenched class:** still biased due to  $\chi_{jh}$  cut: to belong to this class, a jet had better to be with fewer  $n_{SD}$ , compared with all pp jets.
  - **Quenched class** presents features related to energy loss, compared with unquenched class: jet quenching leads to enhancement of large  $n_{SD}$ .



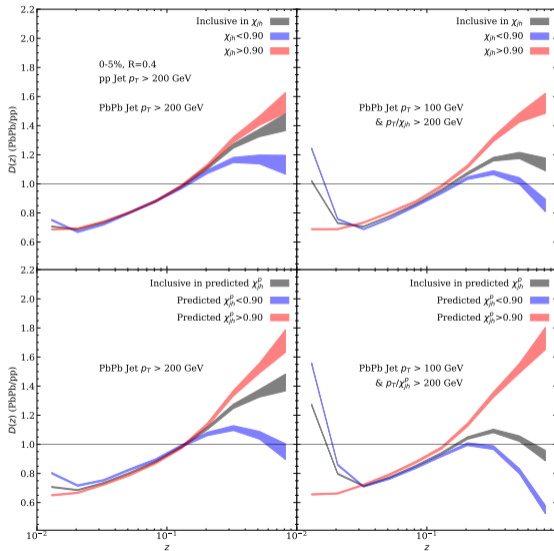
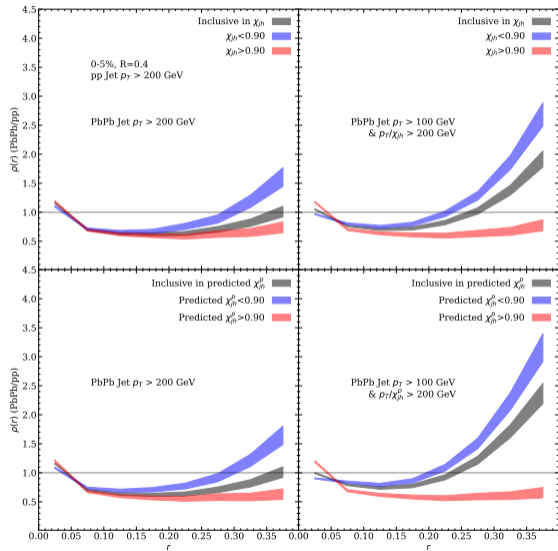
# Backup: Groomed momentum sharing fraction, $z_g$

$z_g$  ratio between PbPb and pp jets

- **FES**: No selection bias observed. Scale of emission isn't strongly dependent on splitting fraction  $z_g$ .
- **IES**:
  - **Quenched class** presents features related to energy loss, **compared with unquenched class**: jet quenching leads to enhancement of smaller  $z_g$  subjets.



# Backup: Jet shape & FF with FES & IES



# Backup: Jet tomography with $\chi_{jh}$ & $v_2$

$$\blacksquare v_2 = \frac{p_x^2 - p_y^2}{p_x^2 + p_y^2}$$

- **Top row:** In-plane jets ( $v_2 > 0$ ) going **left** ( $p_x < 0$ ) and **right** ( $p_x > 0$ )
- **Bottom row:** Out-of-plane jets ( $v_2 < 0$ ) going **up** ( $p_y > 0$ ) and **down** ( $p_y < 0$ )
- **To get very quenched**, jets have to travel longer in medium. So  $v_2$  &  $p_{x,y}$  are helpful for jet tomography.

Creation points density for centrality 30-40%,  $R = 0.4$  @  $\sqrt{s_{NN}} = 5.02$  TeV, FES,  $p_T > 100$  GeV

