June 3, 2021, Jets and their substructure from LHC data, CERN

Deep learning jet modifications in heavy-ion collisions

JHEP03(2021)206 & arXiv:2106.11271

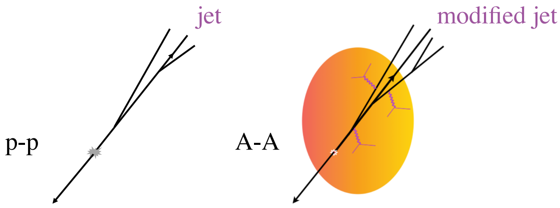
with Daniel Pablos and Konrad Tywoniuk

Yi-Lun Du

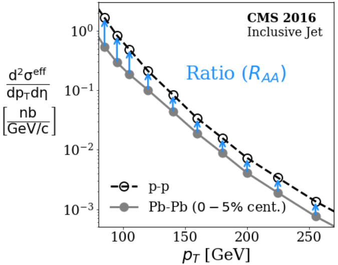
UNIVERSITY OF BERGEN

Outline

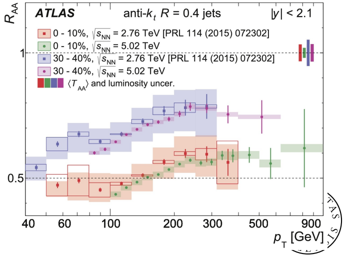
Jets in the medium



J. Brewer, HP'20



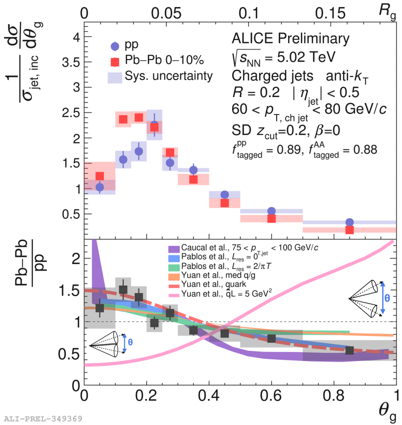
$$R_{AA} = \frac{\text{Spectrum in AA}}{\text{Spectrum in pp}}$$



ATLAS collaboration PLB 790 (2019) 108

- Quark-gluon plasma (QGP) created in heavy ion collision: deconfined phase, hot dense medium
- Jets serve as hard probe to the medium properties
- Jets are quenched in the medium via parton energy loss

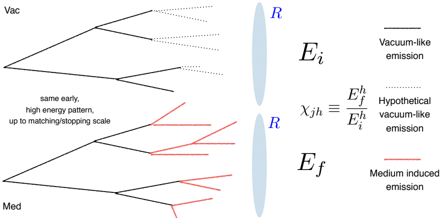
Jet modifications: ambiguous interpretations

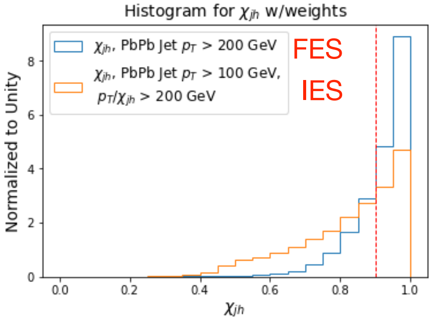


- Ratio of jet observables distr. between medium and vacuum, BOTH with $p_T^{jet} > p_T^{cut}$

- 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 doesn't pass the p_T cut in the selection, i.e., selection bias.
- Jets produce emissions with smaller R_g in medium than in vacuum: presumes medium scale dominates
- Jets with larger R_g in vacuum are more suppressed in medium: presumes vacuum scale dominates
- Can we disentangle these two effects with knowledge of the degree of quenching for each individual measured jets?

Energy loss ratio & Jet selections



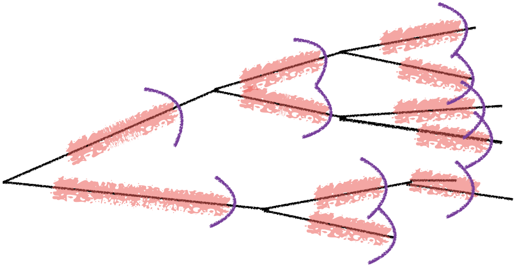


Study jet observables for jets that belong to 2 different quenching classes:

- 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 χ_{jh}, $p_T/\chi_{jh} > 200$ GeV & $p_T > 100$ GeV $\rightarrow$ More support of fairly quenched jets in the quenched class. More distinguishable!

Hybrid model

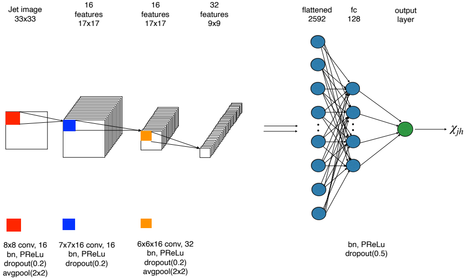


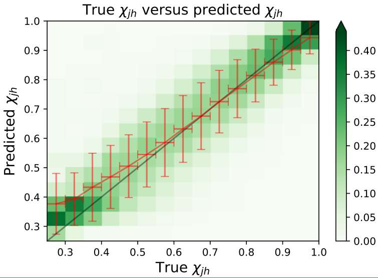
- PYTHIA8 down to hadronization scale
- Strongly coupled energy loss at every stage
- Hadrons from the hydro. wake (medium response)

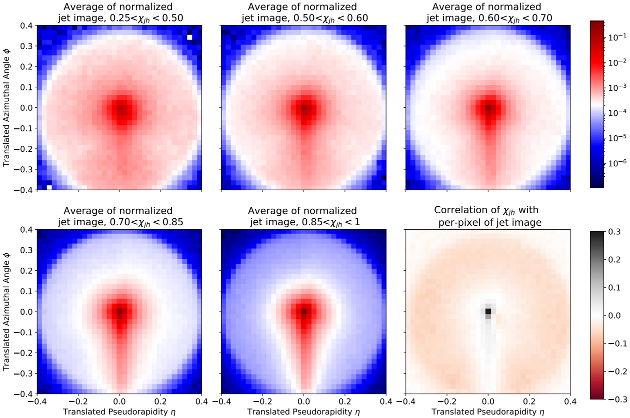
Casalderrey-Solana, Gulhan, Milhano, Daniel Pablos, Rajagopal JHEP '15,'16,'17

- 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 $p_T^{\rm jet} > 100\,\mathrm{GeV}$.
- $\sim$ 250,000 jets. 80% for training and 20% for validation.

CNN Prediction & Interpretability





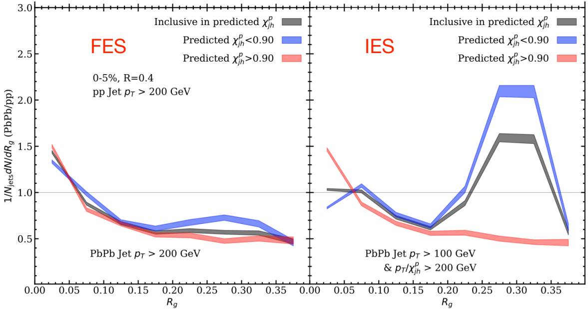


- Jet quenching increases the number of soft particles at large angles
- Jet shape can capture the main feature

Jet radius, R_g

R_g ratio between PbPb and pp jets

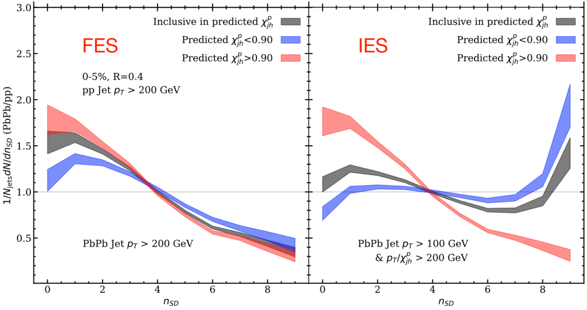
- FES: Selection bias towards jets with smaller R_g, originated by p_T cut.
- IES:
  - Unquenched class: still biased due to χ_{jh} cut: to belong to this class, a jet had better to be with smaller R_g, compared with all pp jets.
  - Quenched class presents features related to energy loss, compared with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



Soft Drop multiplicity, n_{SD}

n_{SD} ratio between PbPb and pp jets

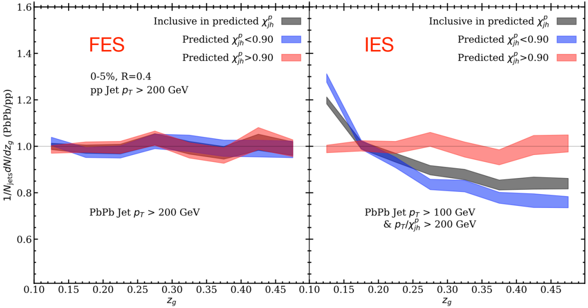
- FES: Selection bias towards jets with fewer n_{SD}, originated by p_T cut.
- IES:
  - Unquenched class: still biased due to χ_{jh} cut: to belong to this class, a jet had better to be with fewer n_{SD}, compared with all pp jets.
  - Quenched class presents features related to energy loss, compared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



Groomed momentum sharing fraction, z_g

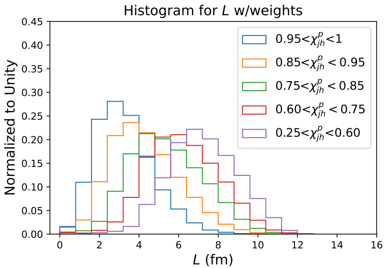
z_g ratio between PbPb and pp jets

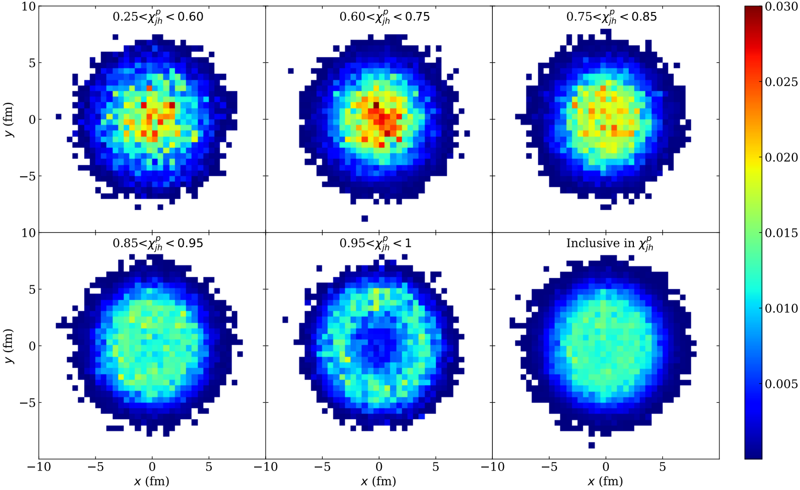
- FES: No selection bias observed. Scale of emission isn't strongly dependent on splitting fraction z_g.
- IES:
  - Quenched class presents features related to energy loss, compared with unquenched class: jet quenching leads to enhancement of smaller z_g subjets.



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

Applications: Jet tomography, length VS χ_{jh}

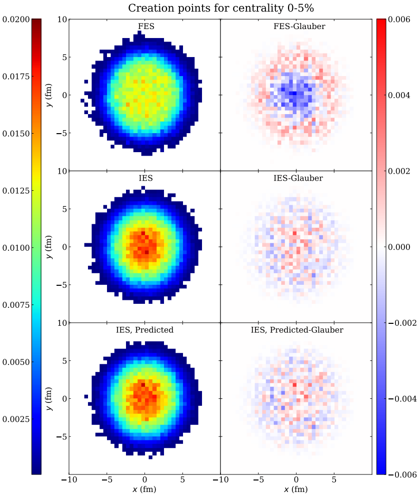




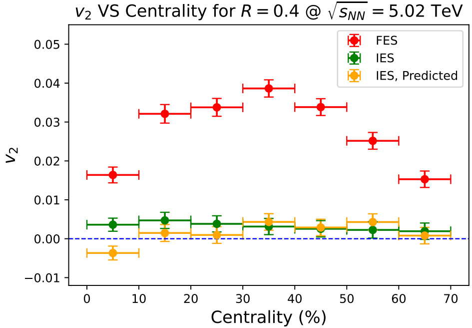
Due to the strong correlation between L and χ_{jh}, selecting jets with different χ_{jh} will naturally select jets that traversed different L.

$\rightarrow$ Great potential to make tomographic application!

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 distribution and initial orientation.

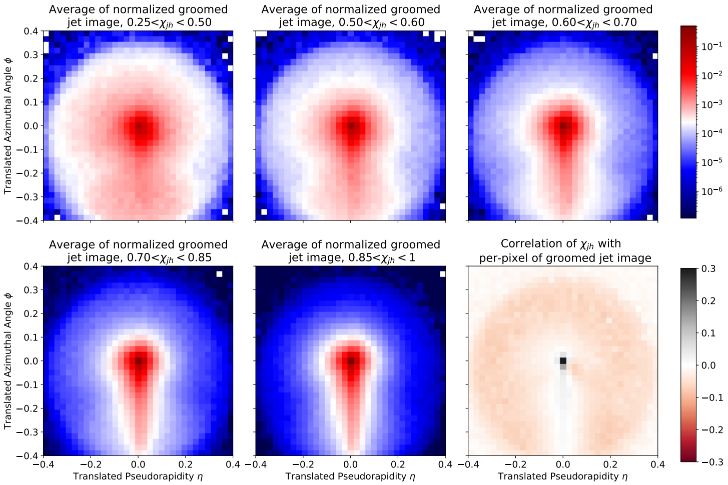
Y.-L. Du, D. Pablos, K. Tywoniuk, arXiv: 2106.11271

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?

Backup: Groomed jet image VS χ_{jh}



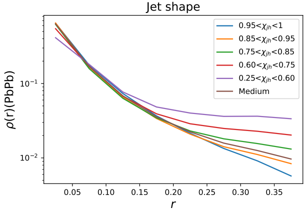
Input	Output	Network	Loss
Groomed jet image	χ_{jh}	CNN	0.0065
Jet image above 1 GeV	χ_{jh}	CNN	0.0042
Jet image above 2 GeV	χ_{jh}	CNN	0.0066

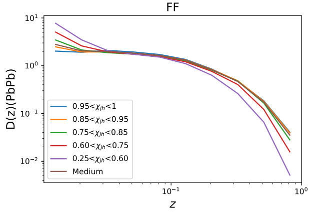
- Removing soft particles (at large angles) reduces performance
- Generalizability challenges:
  - Large fluctuating background
  - Hardonization modelling
  - Other quenching models

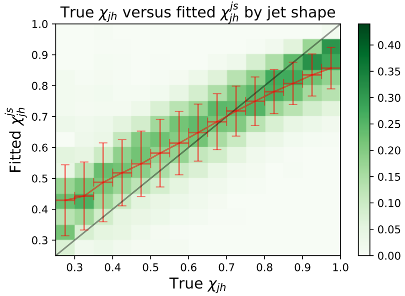
Backup: Prediction performance with FCNN

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

- 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!







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

Backup: Jet tomography with χ_{jh} & v_2

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