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Deep learning jet modifications in heavy-ion collisions

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Outline

1 Motivation

2 Deep learning jet energy loss

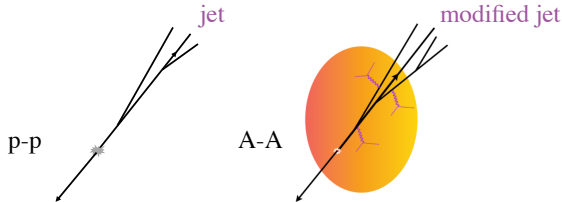
3 Application

- Sensitivity of jet observables to in-medium modification
- Jet tomography

4 Conclusion and outlook

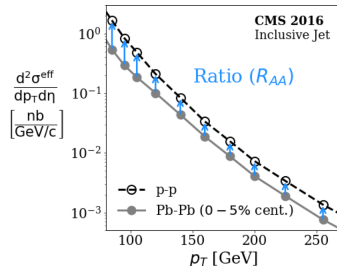


Jets in the medium

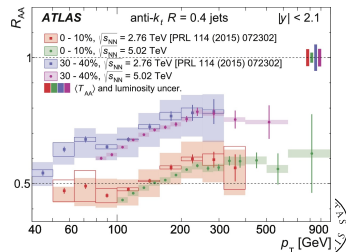


J. Brewer, HP'20

- Quark-gluon plasma (QGP) created in heavy ion collision:
deconfined phase, hot dense medium
- Jets, collimated sprays of energetic particles, serving as hard probe to **medium properties**
- Jets are **quenched** and **modified** in the medium via parton energy loss



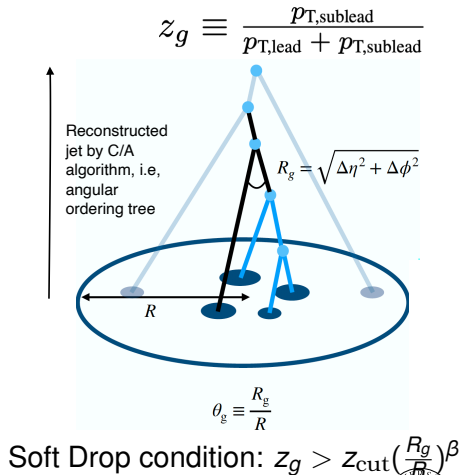
$$R_{AA} = \frac{\text{Spectrum in AA}}{\text{Spectrum in pp}}$$



ATLAS collaboration PLB 790 (2019) 108

Jet substructures

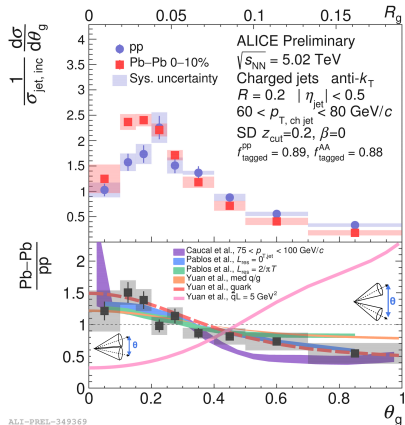
- Detector as camera: positions, energies of particles
- All jet constituents are **reclustered** in **angular ordering**.
- SoftDrop: find the **first hard** splitting between two subjects satisfying $z_g > z_{\text{cut}} \theta^\beta$ with **momentum sharing** z_g and **angle of branching** R_g .



J. Mulligan, HP'20



Jet modifications: ambiguous interpretations



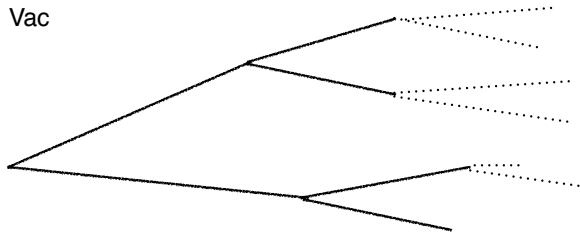
- Ratio of jet observables distr. between medium and vacuum, BOTH with $p_T^{jet} > p_T^{cut}$

- 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?

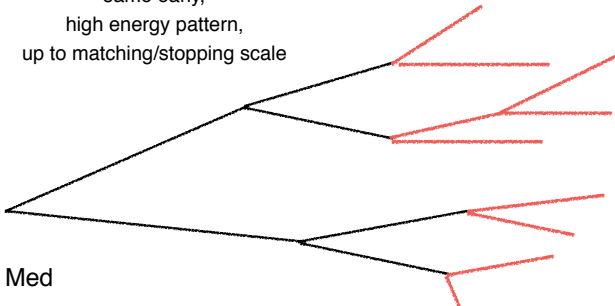


Energy loss ratio

Vac



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



Med



$$E_i$$

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

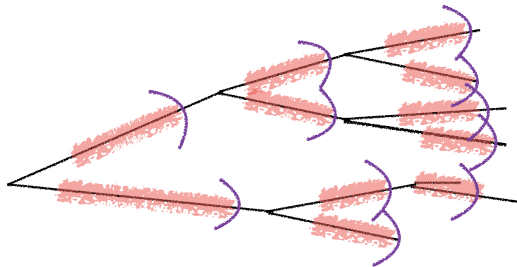
$$E_f$$

—————
Vacuum-like
emission

.....
Hypothetical
vacuum-like
emission

—————
Medium induced
emission

Hybrid model



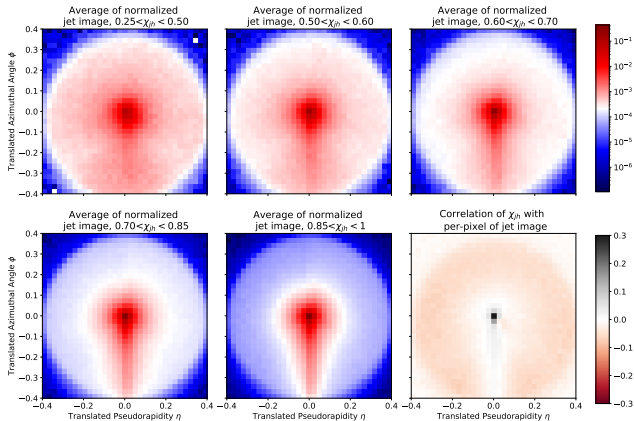
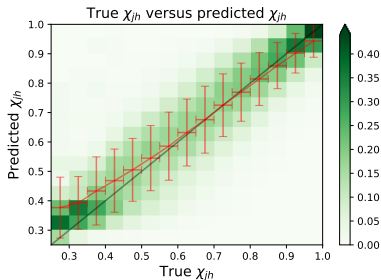
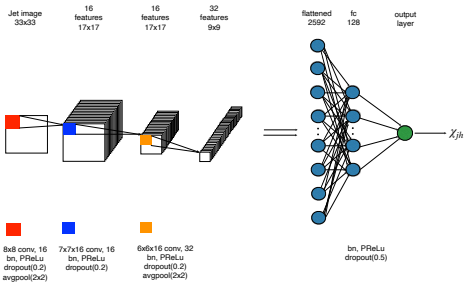
- PYTHIA8 down to hadronization scale
- Strongly coupled energy loss at every stage
- Hadrons from the hydro. wake (medium response)

- 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



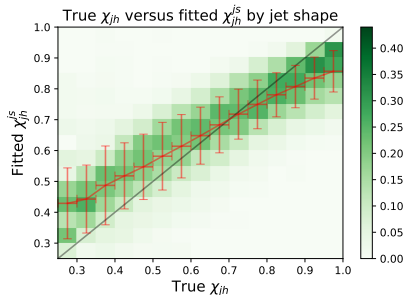
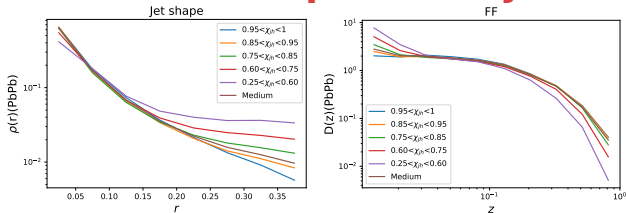
- Jet quenching increases the number of **soft particles at large angles**
- Jet shape can capture the main feature



Prediction with jet observables & Interpretability

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!**



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



Jet selections

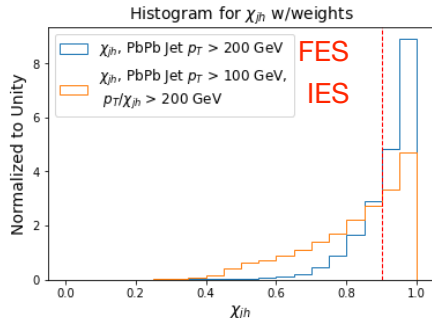
Study jet observables for jets that belong to 2 different quenching classes:

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

■ pp jets: $p_T > 200$ GeV

■ PbPb jets:

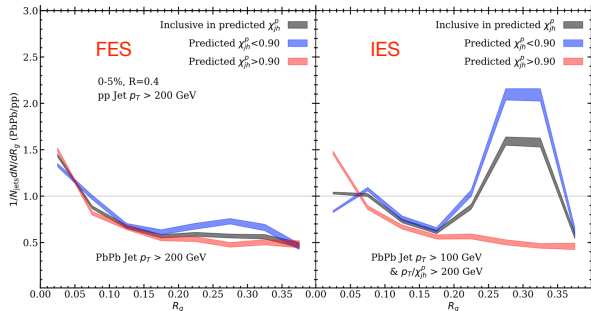
- Final Energy Selection (**FES**): impose p_T cut on final energy $p_T > 200$ GeV → Steeply falling energy loss dist. **Biased by little quenched samples!**
- Initial Energy Selection (**IES**): impose p_T cut on **initial energy** via χ_{jh} , $p_T/\chi_{jh} > 200$ GeV & $p_T > 100$ GeV → More support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



Jet radius, R_g

R_g ratio between PbPb and pp jets

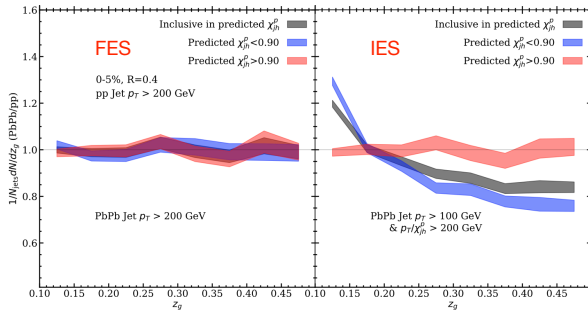
- **FES**: Selection bias towards jets with smaller R_g , originated by p_T cut.
- **IES**:
 - **Unquenched class**: still biased due to χ_{jh} cut: to belong to this class, a jet had better to be with smaller R_g , compared with all pp jets.
 - **Quenched class** presents features related to energy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



Groomed momentum sharing fraction, z_g

z_g ratio between PbPb and pp jets

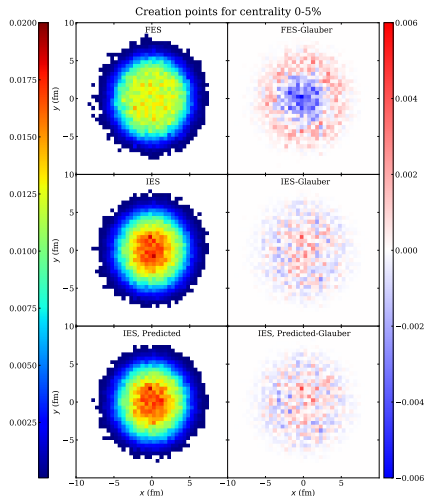
- **FES**: No selection bias observed. Scale of emission isn't strongly dependent on splitting fraction z_g .
- **IES**:
 - **Quenched class** presents features related to energy loss, **compared with unquenched class**: jet quenching leads to enhancement of smaller z_g subjets.



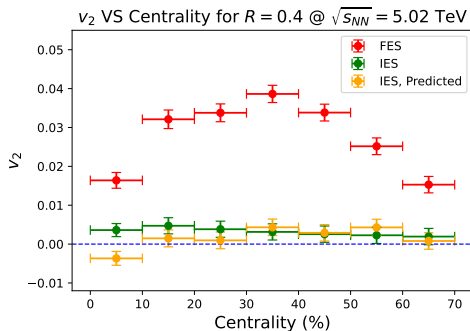
Y.-L. Du, D. Pablos, K. Tywoniuk, JHEP03(2021)206



Applications: creation points & orientation



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

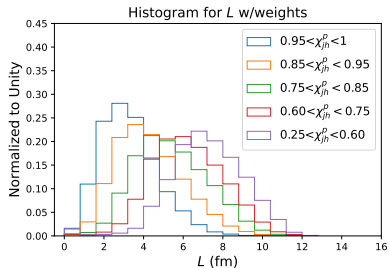


- IES “removes” final state interactions (selection bias), since we record “all” jets.
- IES provides access to the genuine jet creation point (path length) distribution and possible initial-state jet anisotropy.

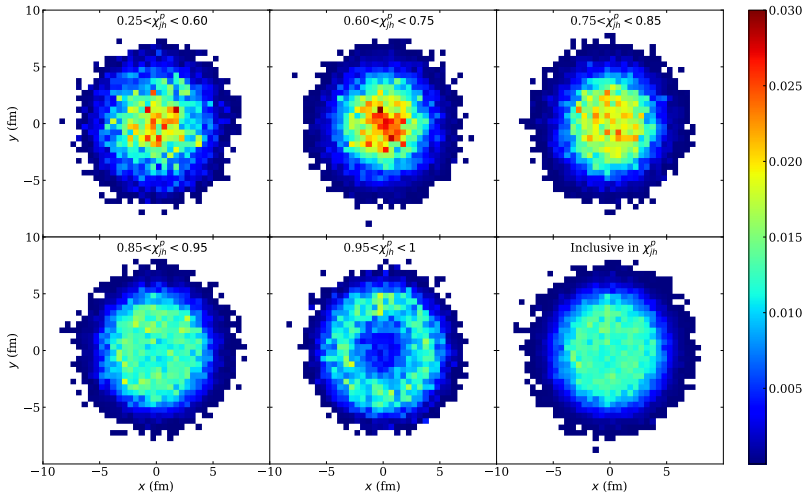
Y.-L. Du, D. Pablos, K. Tywoniuk, arXiv: 2106.11271



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 .
→ Great potential to make tomographic application!



Conclusion and outlook

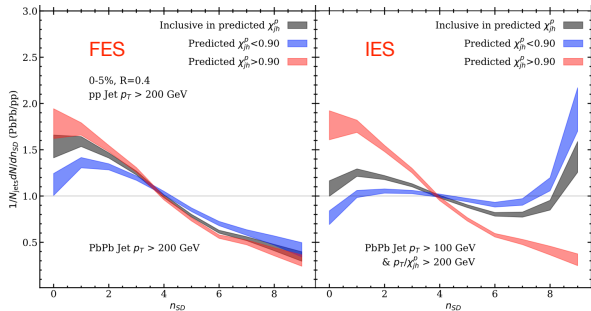
- CNN can extract energy loss jet-by-jet from jet image with **good performance**
 - **Procedure generalisable** to many jet quenching models
 - Jet shape contains significant predictive power: **angular distribution of soft particles**
 - **Mitigate selection bias** and **reveal medium effects** on 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?



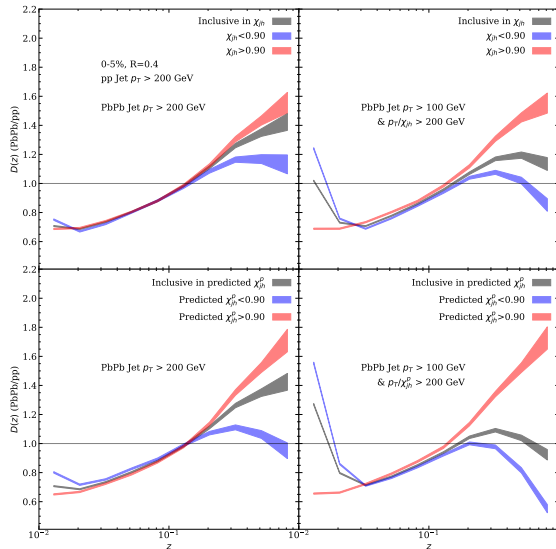
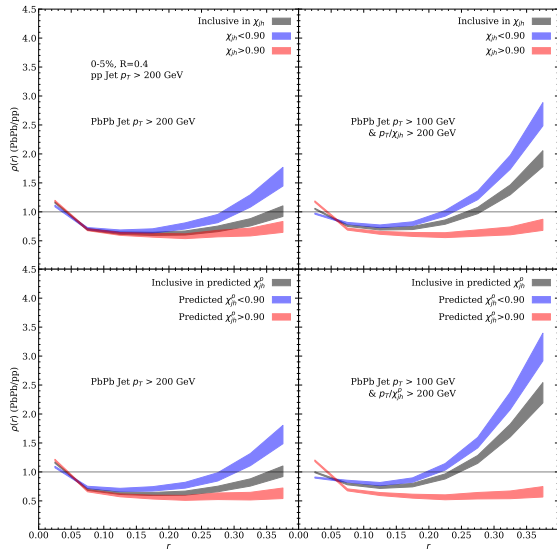
Backup: Soft Drop multiplicity, n_{SD}

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} .



Backup: Jet shape & FF with FES & IES



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.

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

