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[**Deep Learning** *for the* **Classification of Quenched Jets**]

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Deep Learning (DL)

Classification of Quenched Jets

arxiv:2106.08869 *Submitted to JHEP*

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QUENCHED JETS CLASSIFIER

Can DL distinguish between strongly modified jets from unmodified ones?

To obtain pure samples of modified jets from where the jet-QGP interaction may be studied

EXPLORING DIFFERENT DATA REPRESENTATIONS

DL is a powerful and versatile tool that allows to exploit data at various formats

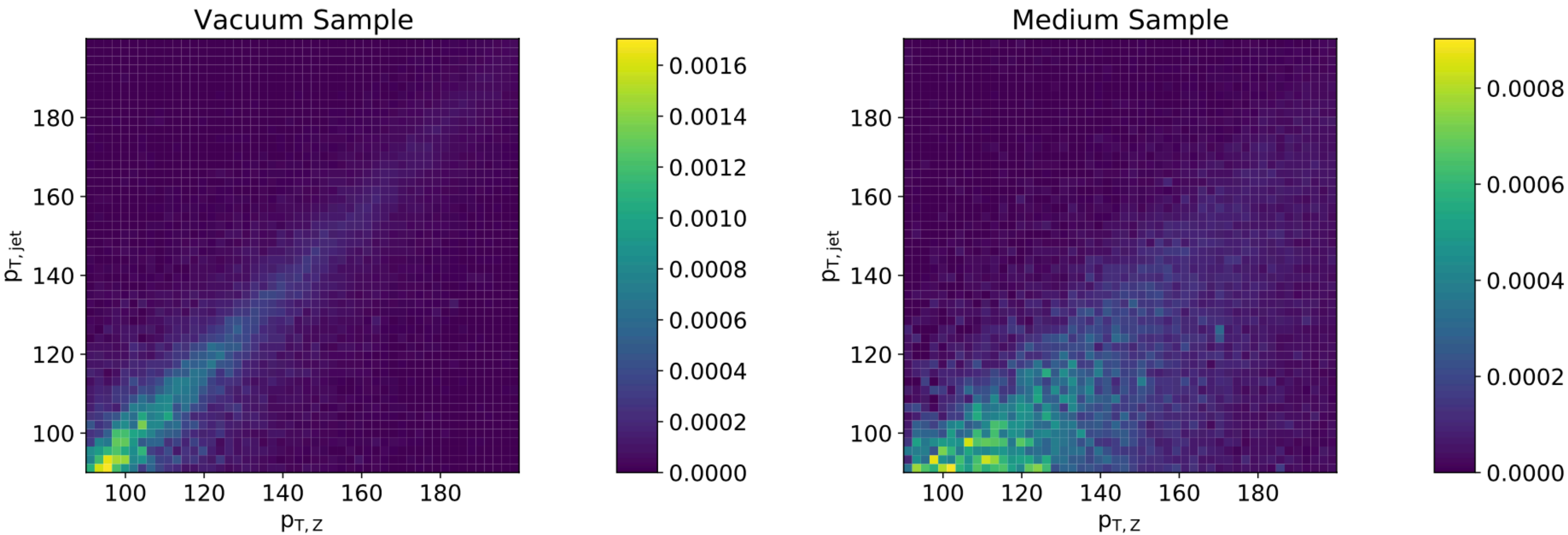
Allows to train intelligent systems in data that was not considered before

INTERPRETATION

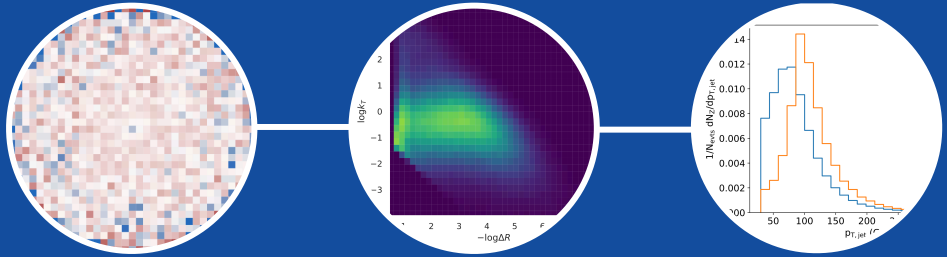
What have the DL models learnt as the difference between quenched and not quenched jets?

Data Simulation

- Jet produced back-to-back with Z boson, $\sqrt{s_{NN}} = 5.02$ TeV
- JEWEL 2.2.0 MC with medium induced effects at parton-shower level (excluding medium recoils)
- $Z \rightarrow \mu\mu,\ p_{T,Z} > 90$ GeV, $m_Z \in [75,105]$ GeV
- Anti-kt jet with R=0.5, $p_{T,jet} > 30$ GeV, $|\eta_{jet}| < 1.0,\ \Delta\phi_{Z,jet} > 7\pi/8$



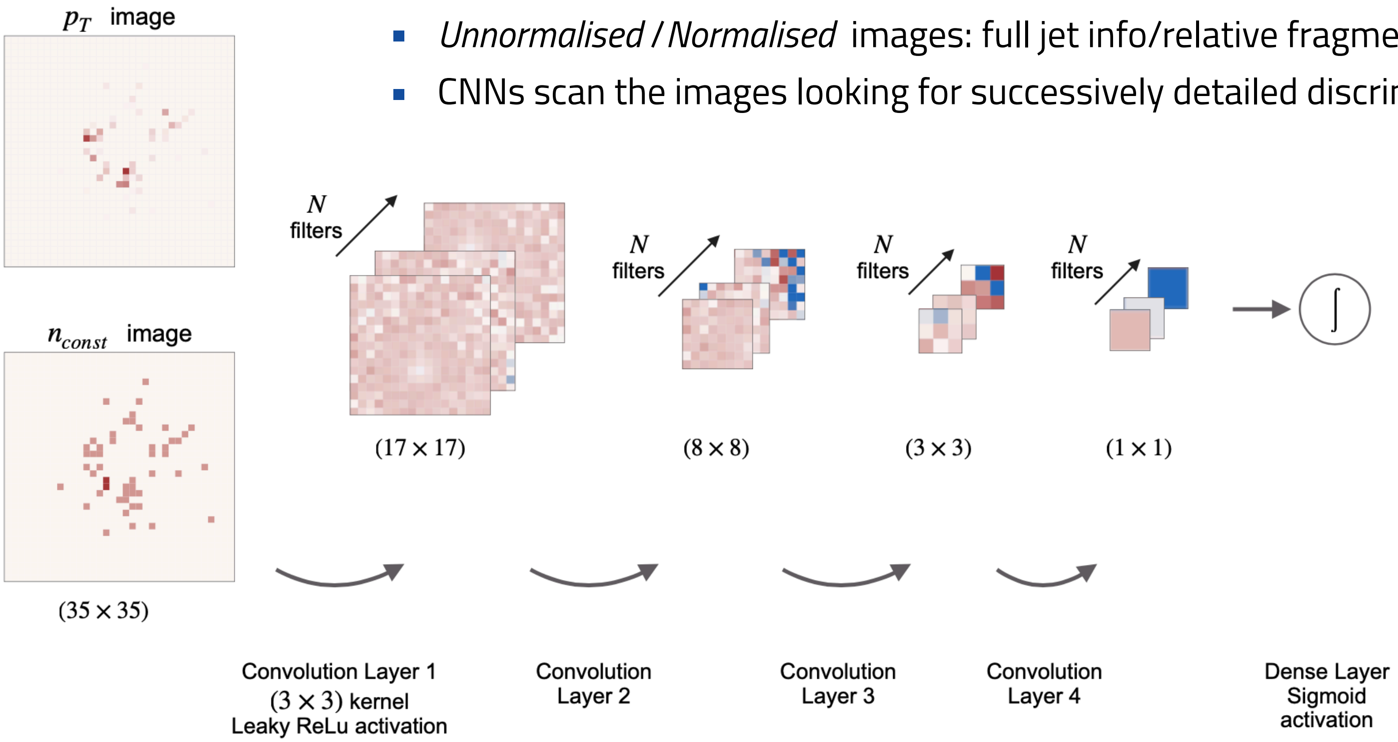
Data Representations



- Calorimeter images, Lund plane coordinates and Tabular jet pT and number of constituents
- Each carrying different implicit features of the substructure of quenched jets

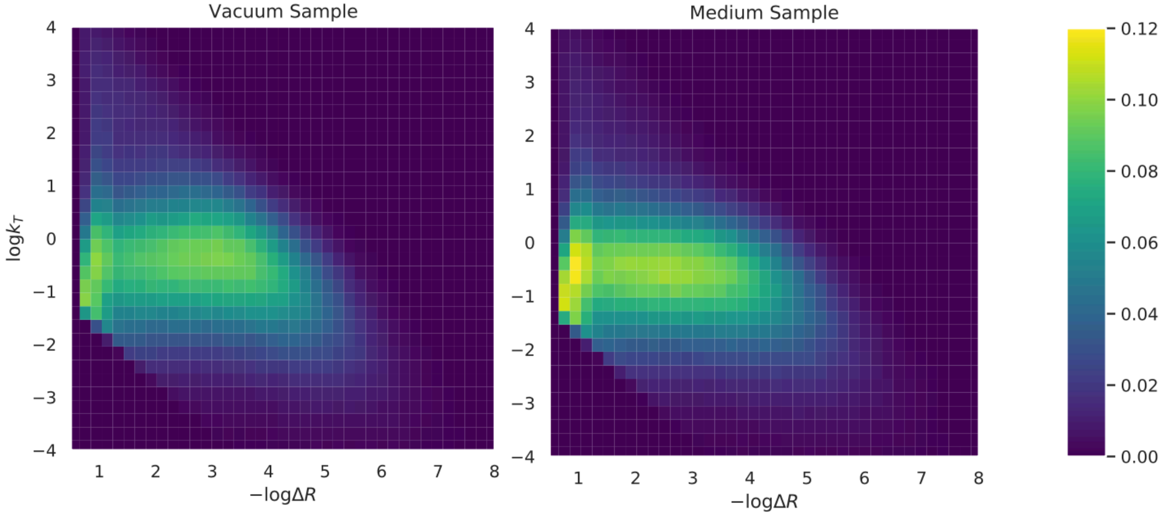
Jet images **Convolutional Neural Networks (CNN)**

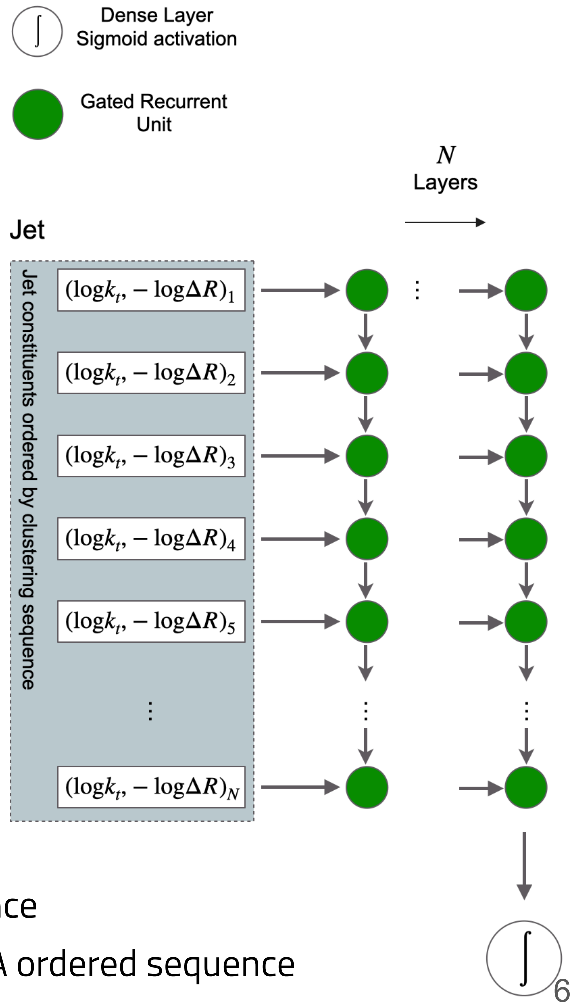
- 2 $\Delta\eta, \Delta\phi$ grids centred in the jet axis with jet pT and *n* constituents
- *Unnormalised / Normalised* images: full jet info/relative fragmentation pattern
- CNNs scan the images looking for successively detailed discriminant patterns



Lund planes

Recurrent Neural Networks (RNN)

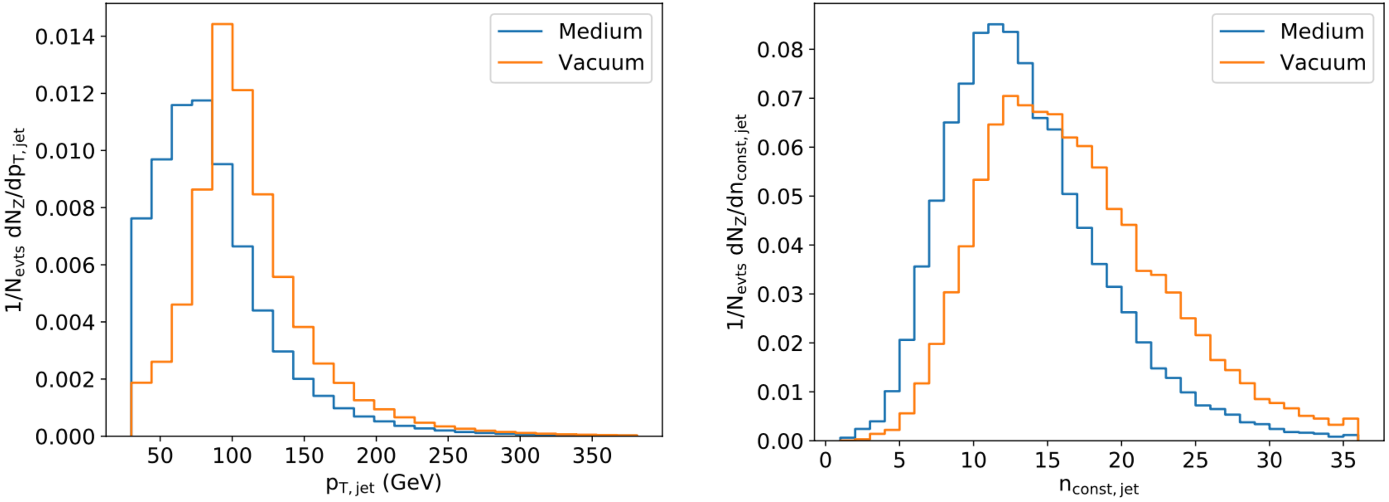




- $(\log k_T, \log\Delta R)$ coordinates of the Cambridge/Aachen clustering sequence
- RNNs are sensitive to causal ordering (eg. speech) and may exploit the C/A ordered sequence

Tabular data

Dense Neural Networks (DNN)



- Baseline for the discriminant power of jet pT and *n* of constituents
- To assess the gain with the jet substructure information implicit on Images and Lund planes

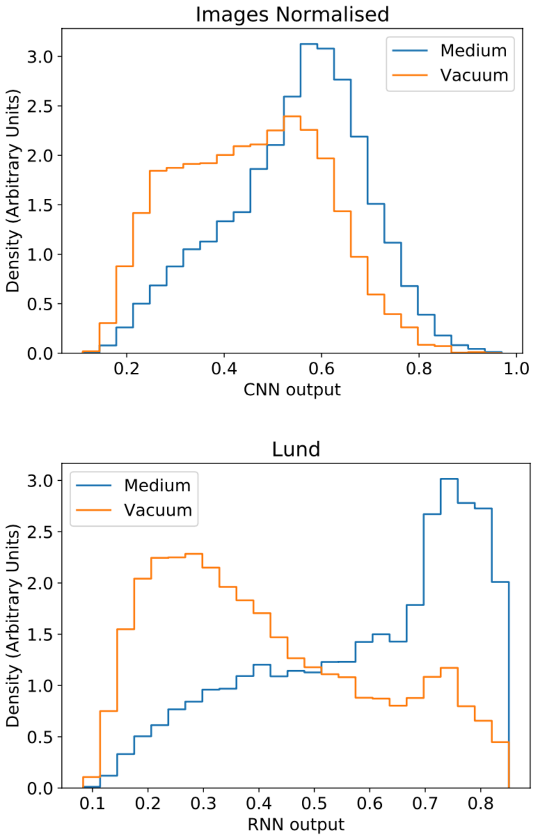
DL Training

Hyperparameter optimization

- Data set split in train/validation/test in 1:1:1 proportion
- Vacuum VS Medium samples
- DL models implemented in *Keras*
- Bayesian loop to optimise networks' hyper parameter using *Optuna*

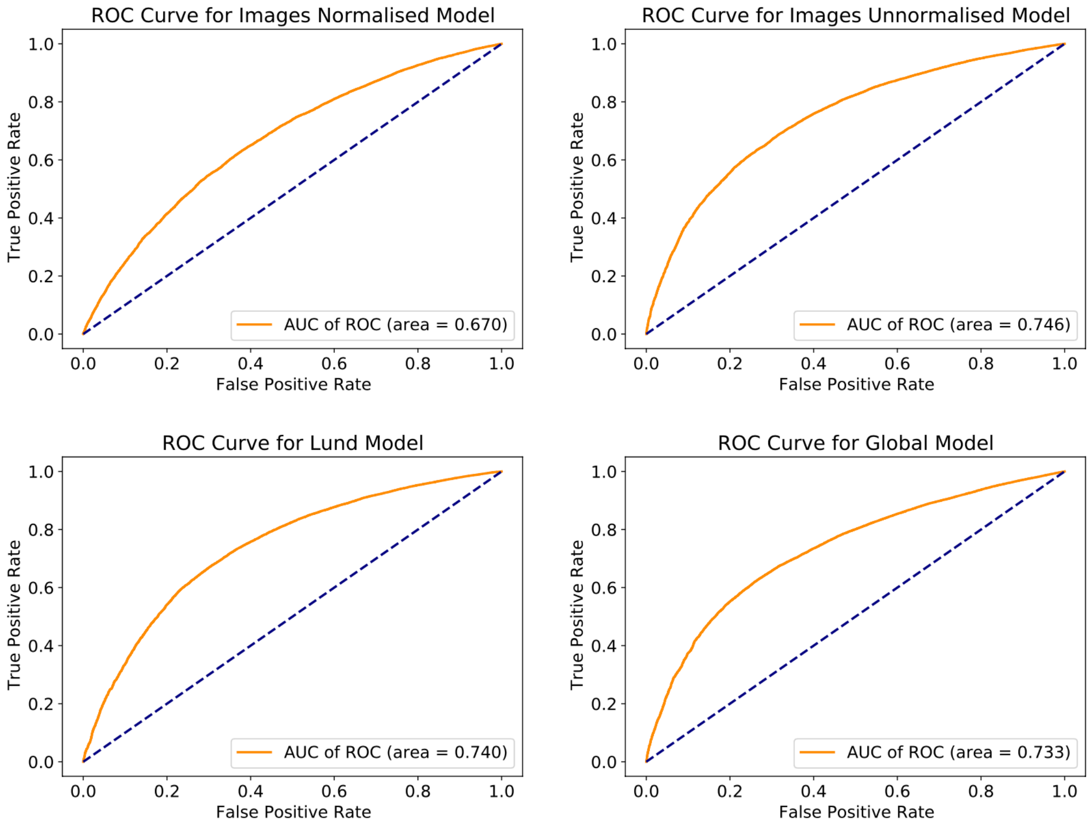
Model Type		Hyperparameter	Value
CNN (Images)	Normalised	Number of Filters	104
		Spatial Dropout Rate	0.3
		Gamma	0.925
	Unnormalised	Number of Filters	88
		Spatial Dropout Rate	0.0
		Gamma	0.970
RNN (Lund)		Number of Layers	2
		Number of Units	15
		Gamma	0.935
DNN (Global)		Number of Layers	6
		Number of Units	116
		Dropout Rate	0.1
		Gamma	0.93

DL models discriminants



- Identification of strongly quenched jets with examples from a Medium sample which is not pure
- Part of the network will learn the effects of jet quenching
- Jet pT and *n* of constituents are important to the task

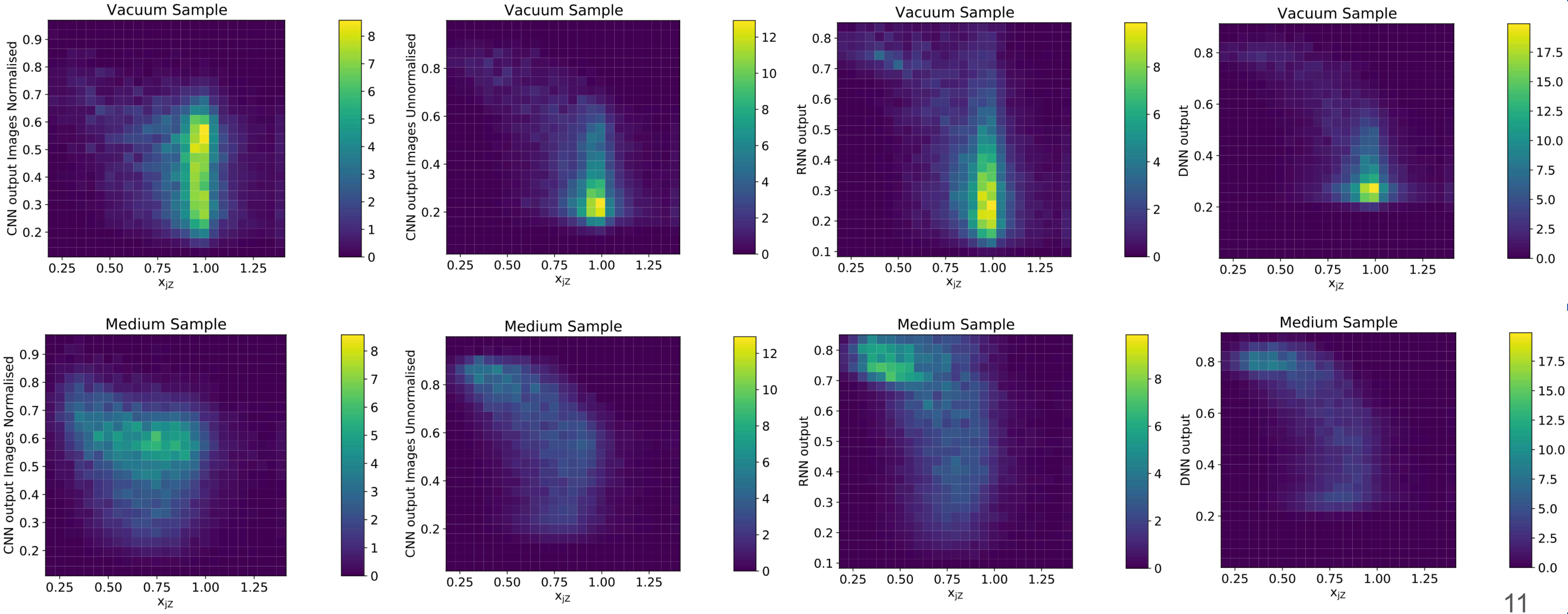
DL models discriminants



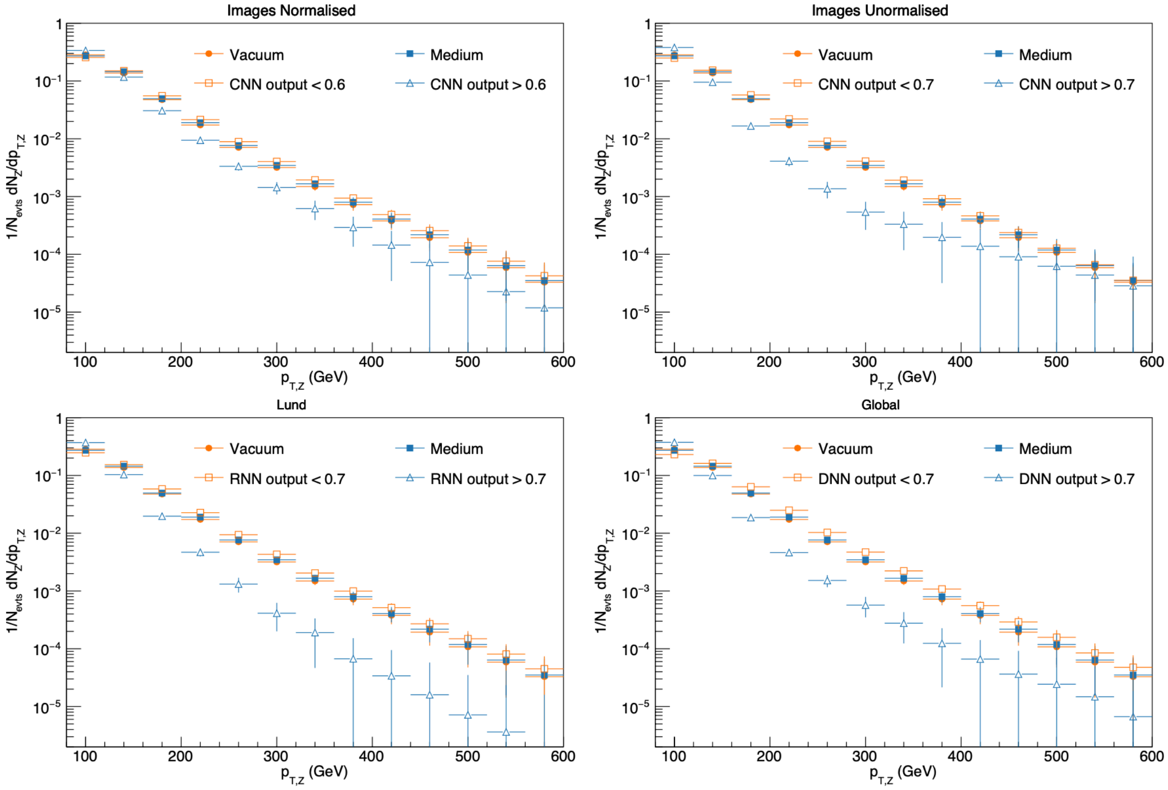
- RNNs and CNNs on unnormalised images outperform the DNN trained on jet pT and *n* constituents

- We gain from the jet substructure patterns enclosed in the Lund plane and jet image representation

DL discriminant, correlation with $x_{jZ} = \frac{p_{Tj}}{p_{TZ}}$

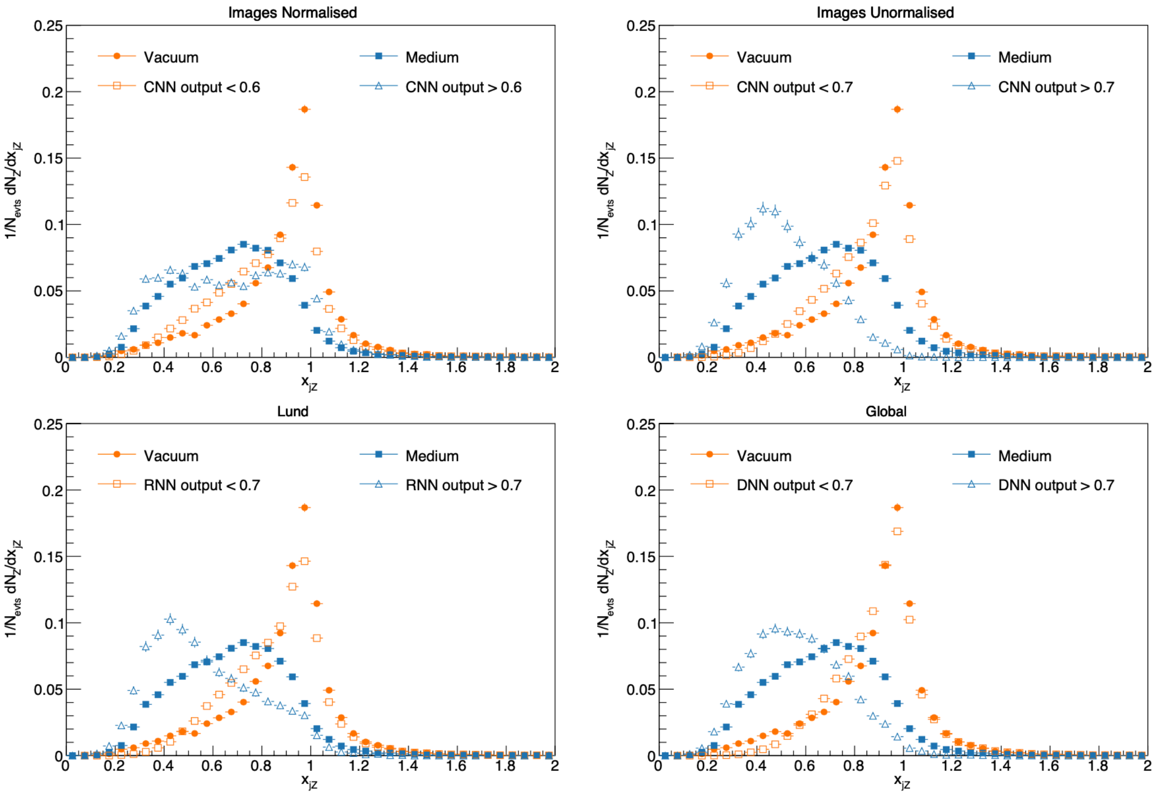


DL interpretation



- Selected *vaccum-like* sample follows Vaccum MC truth, i.e. models are able to identify vacuum jets
- Selected *medium-like* spectra is suppressed wrt Medium MC truth, decision boundary does not follow Medium VS Vacuum simulation

DL interpretation



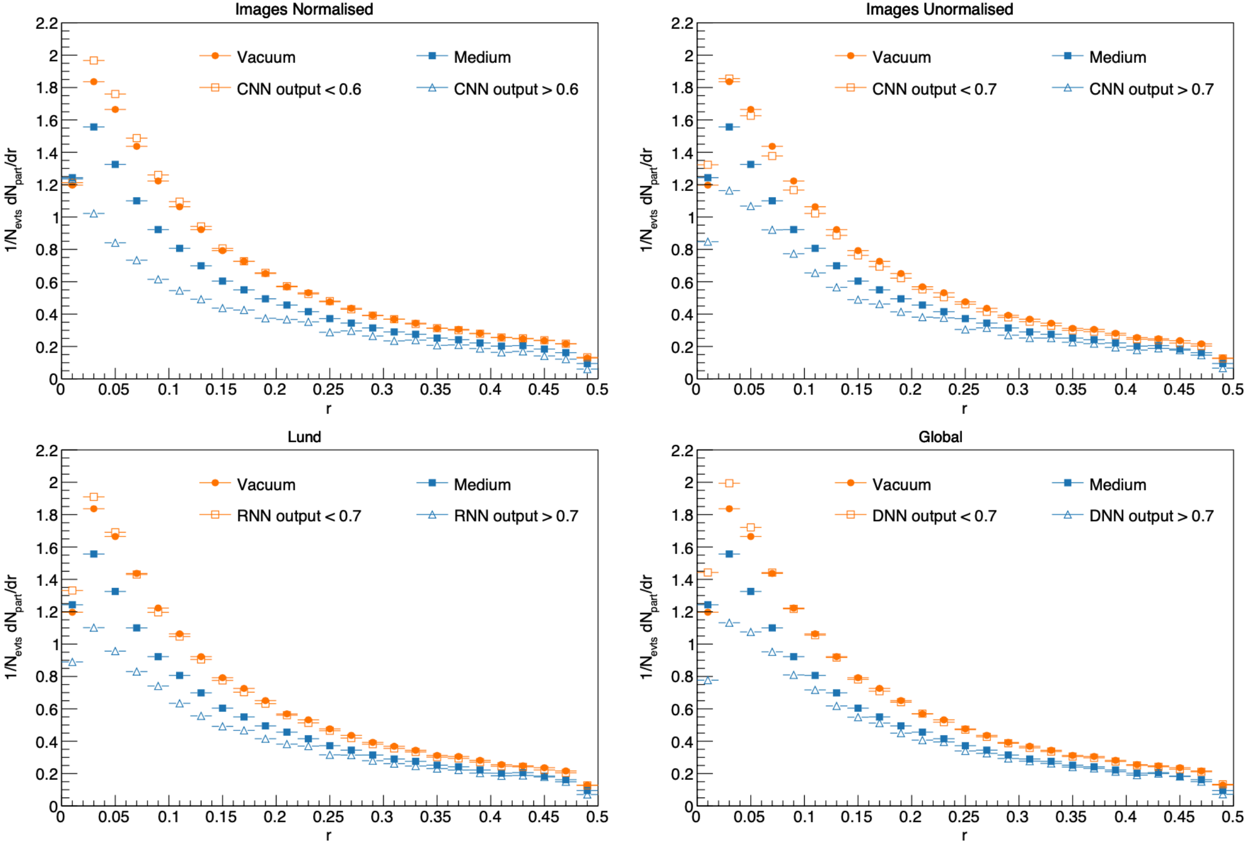
- Selected *vaccum-like* sample slightly displaced from Vaccum MC truth, i.e. models may identify jets from the Medium sample which didn't interact strongly with QGP
- Selected *medium-like* spectra enhances medium-like features displacing x_{jZ} towards smaller values

Conclusions

- Used DL flexibility to explore different representations of jets for building a classifier of quenched jets
- Investigated the distribution of jet observables in *vacuum-* and *medium-like* samples selected with the DL quenching classifiers
- Classifiers based on Lund plane coordinates and Jet images outperform discriminants from tabular data
  - These data formats encode additional information about jet fragmentation
  - RNNs and CNNs are able to capture it

BACKUP

DL interpretation



DL interpretation