QCD phenomenology at LIP

Guilherme Milhano [LIP & IST, Lisbon]
gmilhano@lip.pt

Phenomenology Group

- created in Jan 2018 as an aggregation of pheno activity within LIP [9.0 FTE]
  - Heavy Ion Pheno Group that had joined LIP from CENTRA@IST one year and half earlier
  - pheno activities [SM/BSM and quarkonia] by members of experimental collaborations [ATLAS and CMS]
  - cosmic-ray pheno activity by some Auger members
- stated aim: *LIP's Phenomenology group conducts research bridging theory and experiment in particle and astro-particle physics. Its research, while independent, is centred around areas in which LIP has active experimental activities and aims to identify areas in which LIP's broader programme may evolve in the future. Its purpose is to strengthen the impact of the overall LIP programme through the provision of excellent directed phenomenological research.*
- group very involved in creation of 'Big Data and Simulation Competence Centre' at LIP :: a pool of knowledge usable across LIP's activities
- by 2022 the group has approximately doubled its workforce (20.3 FTE Researchers and PhD/MSc students) across LIP's poles (Lisboa, Coimbra, Braga) with two main lines of work:
  - New Physics Searches [mostly in Braga]
  - QCD[mostly in Lisboa]

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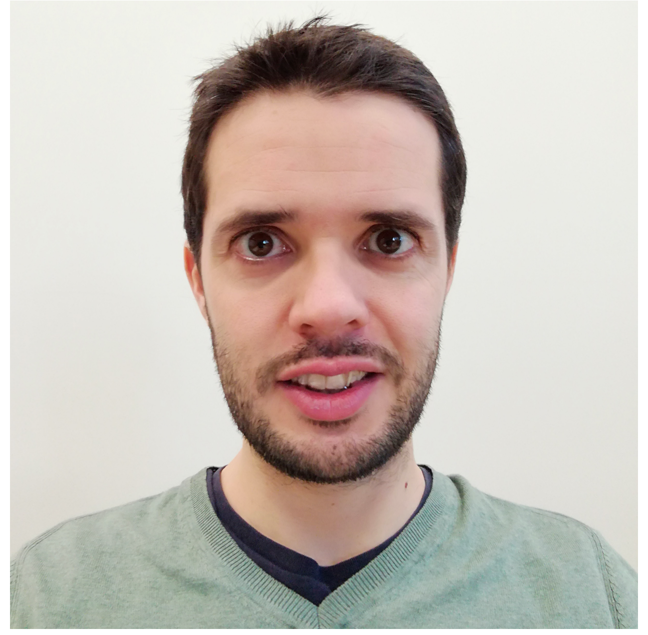
a disclaimer: non-perturbative QCD work is carried out in the NP-STRONG group

PEOPLE INVOLVED IN QCD ACTIVITIES :: RESEARCHERS

Guilherme Milhano [Lisboa],
current team leader
QCD [jet physics, QGP, CGC]

Liliana Apolinário [Lisboa],
QCD [jet physics, QGP]

Grigorios Chachamis [Lisboa],
QCD [forward physics, BFKL]



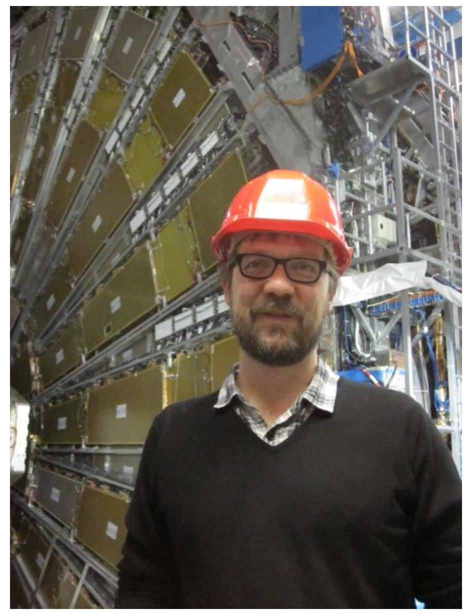
João Pires [Lisboa],
QCD [precision, jets, PDFs]

Pablo Guerrero [Lisboa],
QCD [CGC, jets]

Pietro Faccioli [Lisboa],
QCD [quarkonia]
:: also CMS and COMPASS/AMBER

Nuno Castro [Minho],
NP Searches [but also QCD ML activities]
:: also ATLAS

Miguel Romão [Minho],
NP Searches [but also QCD ML activities]
:: also Private Sector



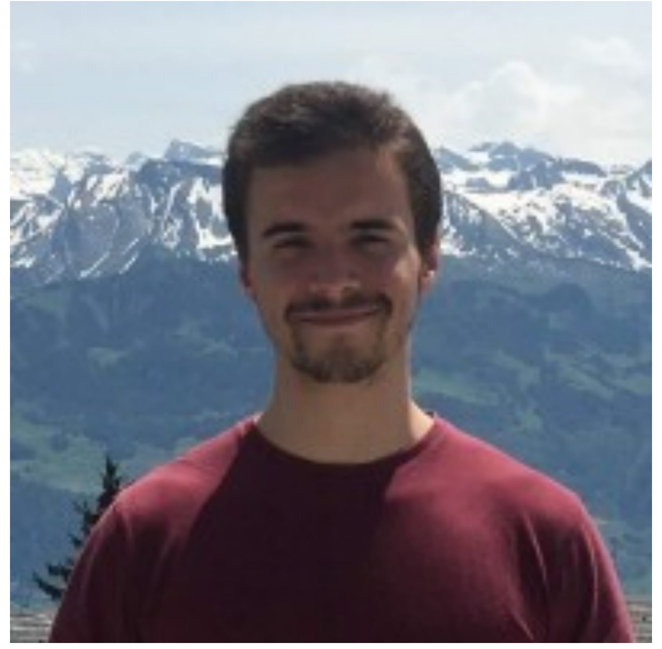
Ricardo Gonçalo [Coimbra],
NP Searches [but also QCD jet activities]
:: also ATLAS

Carlos Lourenço,
external collaborator
QCD [quarkonia]

People involved in QCD activities :: students

Mariana Araújo, PhD student [2019-]
Quarkonia
:: also CMS

João Gonçalves, PhD student [2021-]
Machine Learning for Jet Quenching



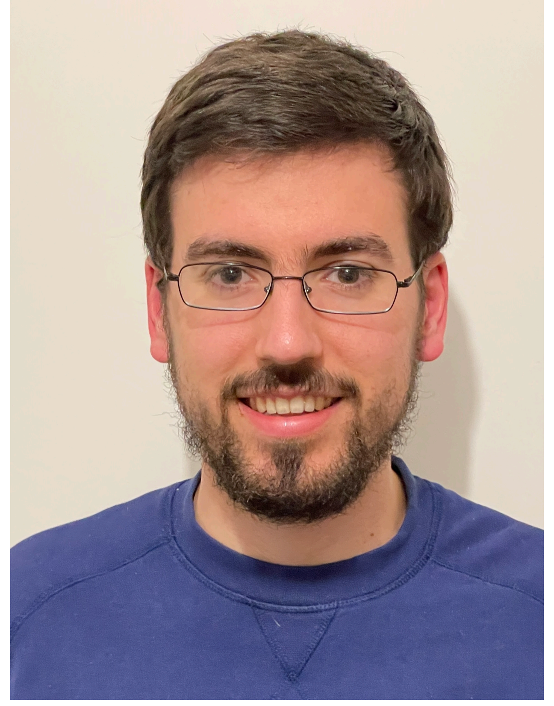
João Silva, PhD student [2021-]
Jet substructure
:: will spend 1 year at IGFAE

André Cordeiro, PhD student [2022-]
Space-time formulation of jet quenching
:: will spend 1 year at IGFAE

Dario Vaccaro, PhD student [straing Sep 2022]
BFKL Phyiscs

Tomás Cabrito, MSc student [2021-]
Generalized antennas

Francisco Barreiro, MSc student [2022-]
Quenching in small systems



Manuel Mariano, MSc student [2022-]
jet substructure in small systems

Lénea Luís, MSc student [2022-]
unbiased quenching observables

- 3 additional photoless MSc students
  - João Lopes :: coherence in QGP
  - Nuno Olavo :: hadronization time-scales
  - João Gomes :: Deep Learning for jets

COLLABORATIONS

- our QCD activities happen within a large network of collaborations
  - MIT, CERN-TH, Nikhef, Barcelona, Madrid, Lund, …

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- our QCD activities happen within a large network of collaborations
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- where the longest standing and most extensive collaboration is with IGFAE …

PHYSICAL REVIEW D **71,** 014003 (2005)

Numerical analysis of the Balitsky-Kovchegov equation with running coupling: Dependence of the saturation scale on nuclear size and rapidity

J. L. Albacete,[1,2] N. Armesto,[2] J. G. Milhano,[2,3] C. A. Salgado,[2] and U. A. Wiedemann[2]

[1]*Departamento de Física, Módulo C2, Planta baja, Campus de Rabanales, Universidad de Córdoba, 14071 Córdoba, Spain*

[2]*Department of Physics, CERN, Theory Division, CH-1211 Genève 23, Switzerland*

[3]*Instituto Superior Técnico (IST), CENTRA, Avenida Rovisco Pais, P-1049-001 Lisboa, Portugal*

(Received 20 August 2004; published 7 January 2005)

earliest joint paper of current IGFAE and Pheno@LIP members

2004 !

a few examples of recent work

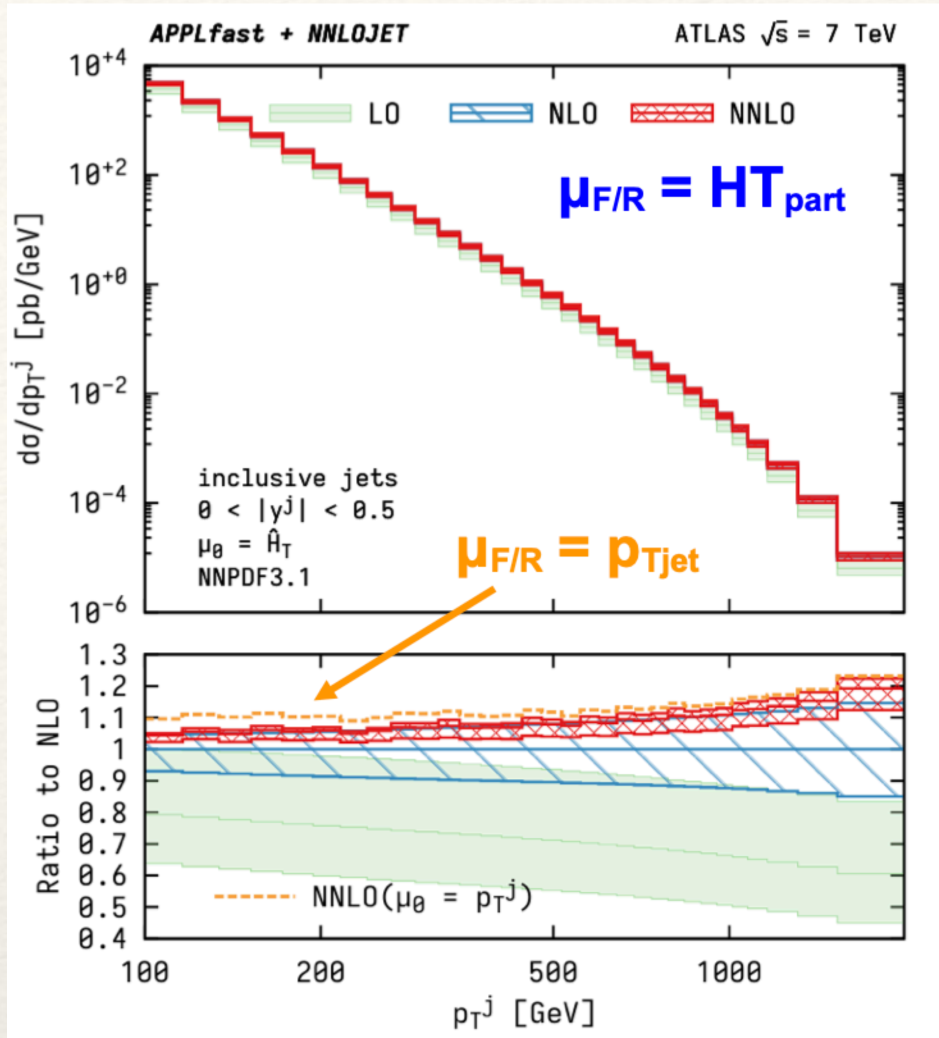
[with focus on non-joint Pheno@LIP/IGFAE work]

NNLO grids for jet production at the LHC

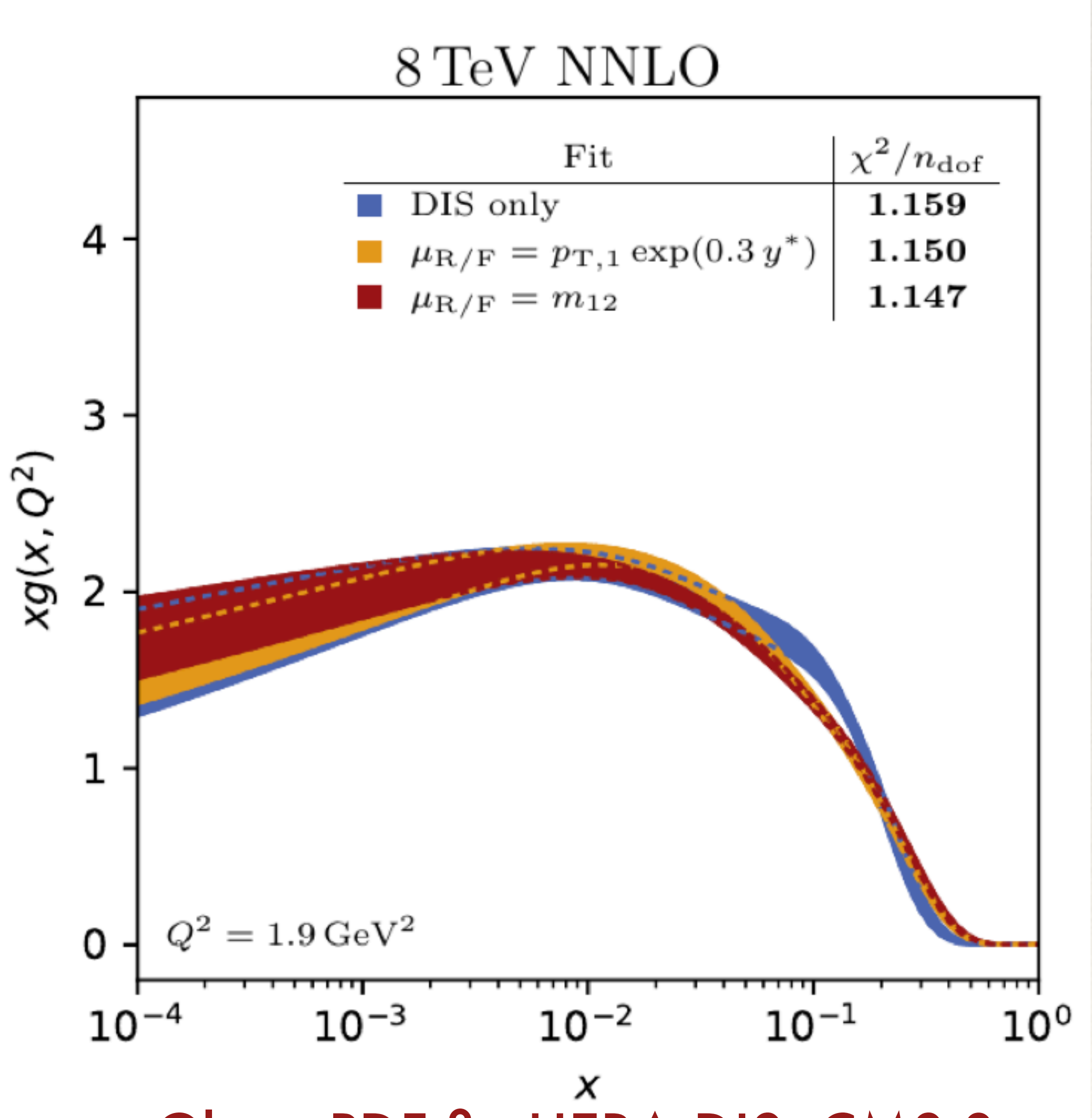
- New interpolation grids for numerous jet datasets at the LHC computed for ATLAS&CMS
- ingredients: → theory predictions from MC NNLOJET
- output → pQCD cross sections projected on grids in FASTnlo and APPLGRID formats
- Interpolation of the MC cross section on a (x_1,x_2,Q^2) grid allow fast recalculations of the cross section for several PDF and α_s values. Ex: CMS 8 TeV 3D dijet cross section:

```
$fnlo-tk-cppread 2jet.NNLO.fnl3832_yb0_ys0_ptavgj12.tab.gz NNPDF31_nnlo_as_0118 _ LHAPDF
```

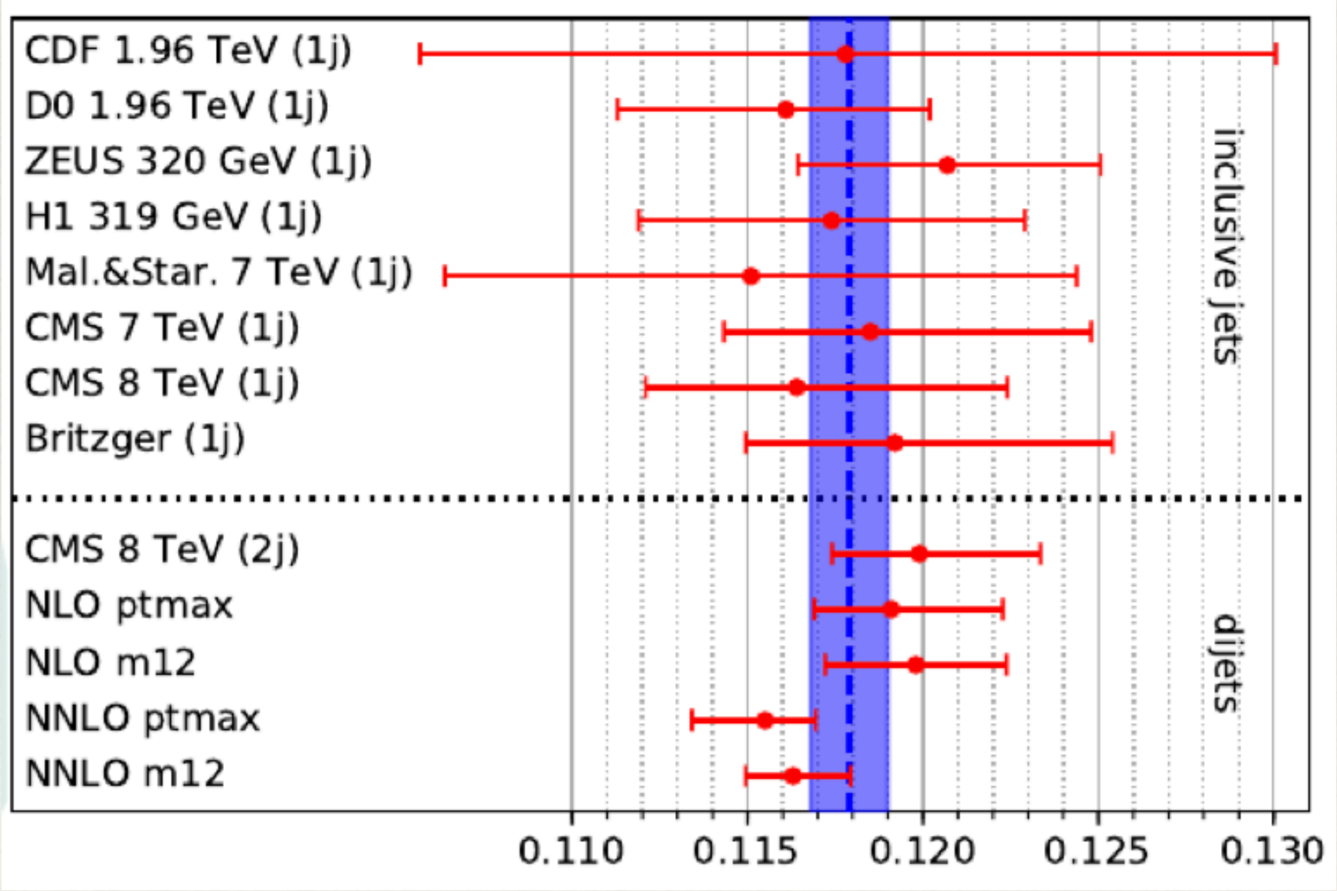
- Grid size: few GB ; NNLO cross section evaluation time: few minutes
- Proofs of principle: → gluon PDF fit with HERA DIS+CMS 8 TeV dijet data with xfitter → gluon PDF+α_s fit at NNLO (for two renormalisation and factorization scale choices)



Scale uncertainty bands: LO, NLO, NNLO



Gluon PDF fit: HERA DIS+CMS 8 TeV 3D dijet data



Fitted α_s values obtained with the CMS dijet data and other jet cross sections

Fitted $\alpha_S(M_Z)$ values

NLO	$\mu = p_{T,1}e^{0.3y^*}$	$0.1191 \pm 0.0015(\text{exp})^{+0.0028}_{-0.0016}(\text{scale})$
	$\mu = m_{12}$	$0.1198 \pm 0.0015(\text{exp})^{+0.0021}_{-0.0021}(\text{scale})$
NNLO	$\mu = p_{T,1}e^{0.3y^*}$	$0.1155 \pm 0.0012(\text{exp})^{+0.0008}_{-0.0017}(\text{scale})$
	$\mu = m_{12}$	$0.1163 \pm 0.0013(\text{exp})^{+0.0010}_{-0.0004}(\text{scale})$

α_s scale uncertainties smaller at NNLO and smaller α_s values (CMS 3D dijet data)

J.Pires et al., NNLO interpolation grids for jet production at the LHC arXiv:2207.XXXX

Jet time reclustering

[Apolinário, Cordeiro, Zapp :: EPJC 81, 561 (2021)]

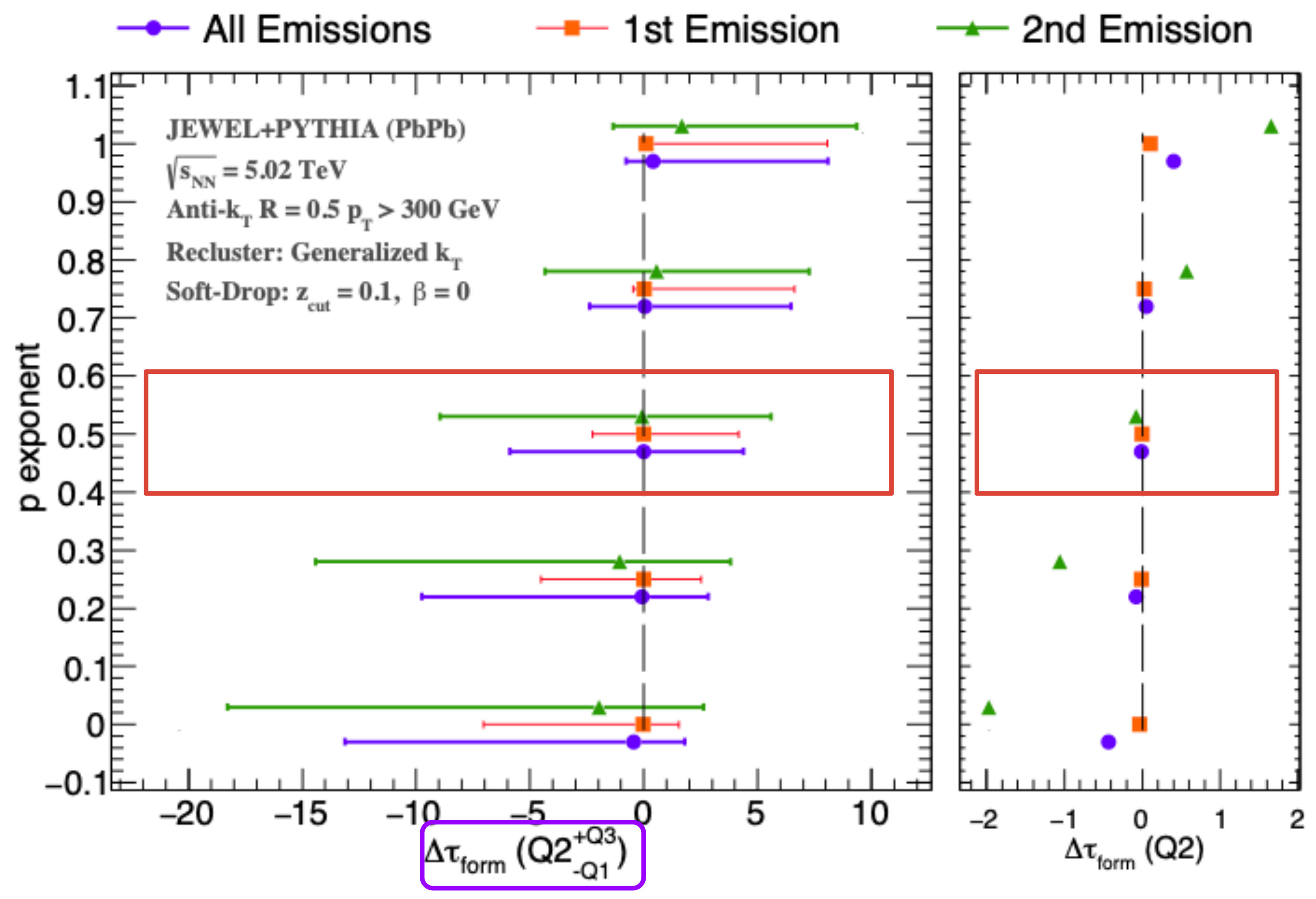
- Recluster jets using the generalised-k_T measure:

$$d_{ij} = \min(p_{t,i}^{2p}, p_{t,j}^{2p}) \frac{\Delta R_{ij}^2}{R^2} \qquad d_{iB} = p_{t,j}^{2p}$$

- Setting p = 0.5 (τ algorithm) clusters jets in formation time:

$$d_{ij} \sim p_{t,i} \frac{\Delta R_{ij}^2}{R^2} \sim p_{t,i}\theta^2 \sim \frac{1}{\tau_{\rm form}}$$

This choice maximises correlation between parton shower and jet reclustering information

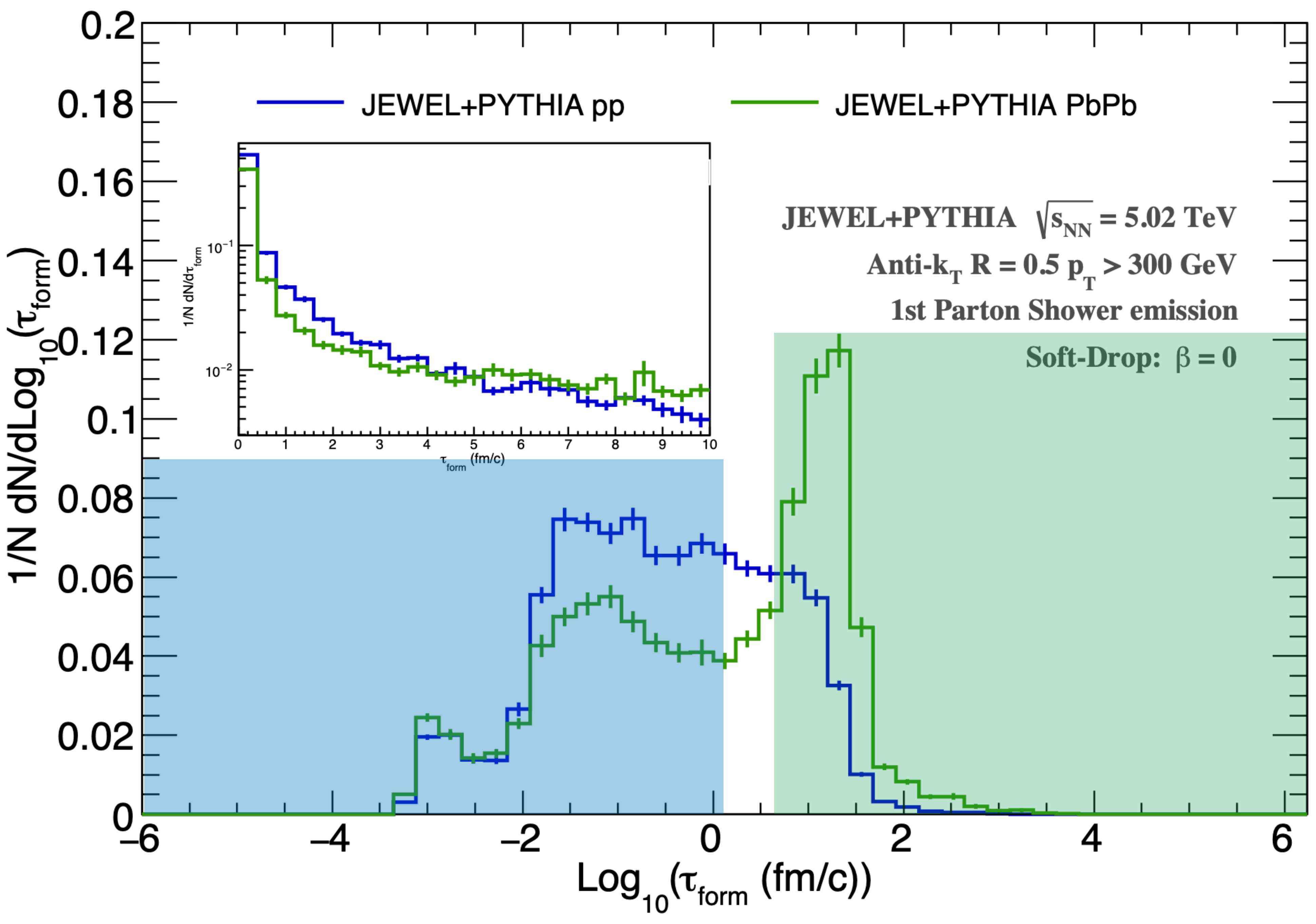


$$\Delta\tau_{\rm form} = \tau_{\rm form}^{\rm Parton\ Shower} - \tau_{\rm form}^{\rm Unclustering}$$

Setting p = 0.5 minimises the width and asymmetry of the Δτ distribution

- Allows selection of two populations
  - "Early" jets: τ < 1 fm/c (strongly modified)
  - "Late" jets: τ > 3 fm/c (weakly modified)

A *jet quenching classifier*: Important step towards a tomographic analysis of the QGP!



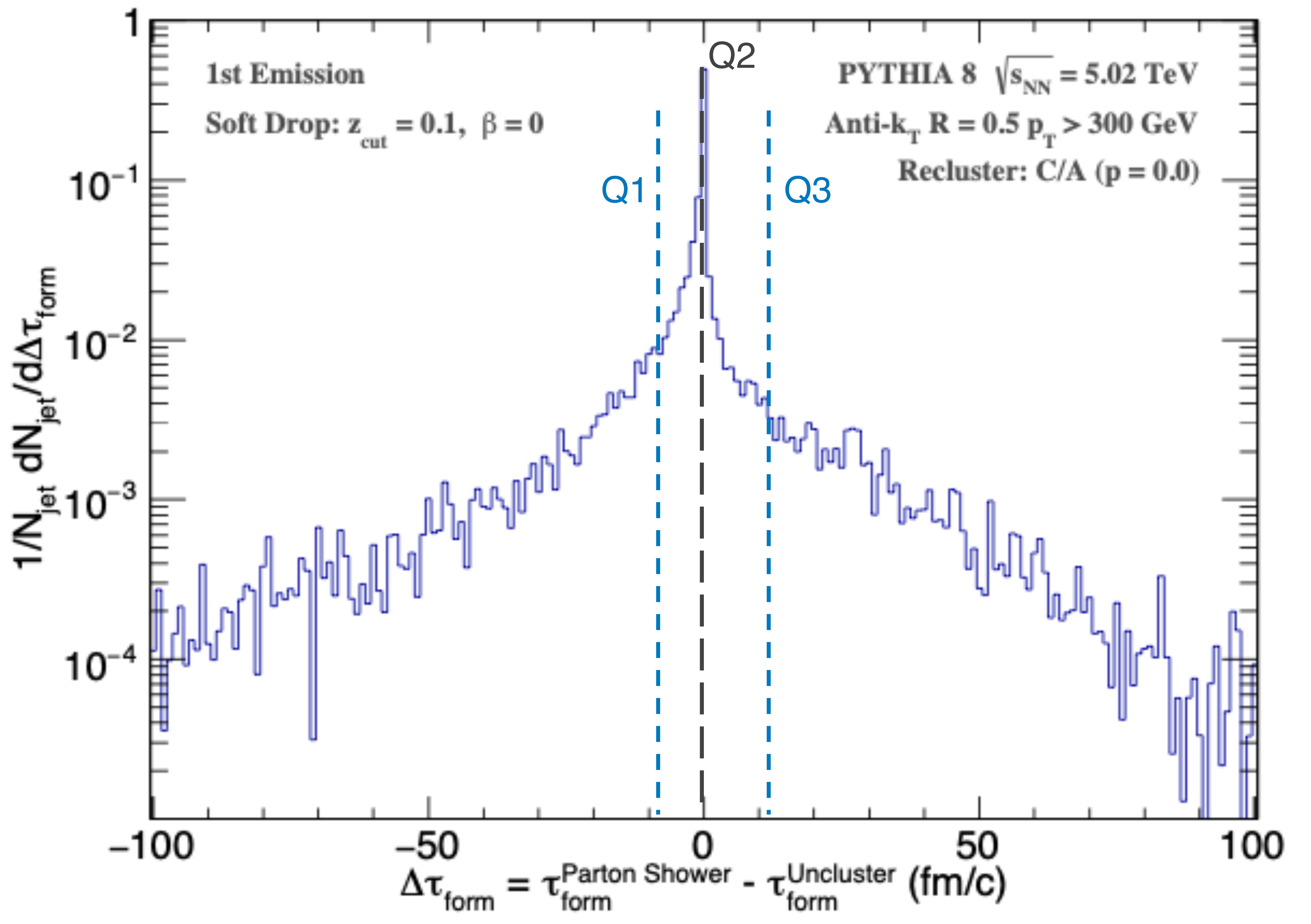
Estimating jet formation times

[Apolinário, Cordeiro, Zapp :: EPJC 81, 561 (2021)]

- Quantify the jet – parton shower correlation with the difference between formation times,

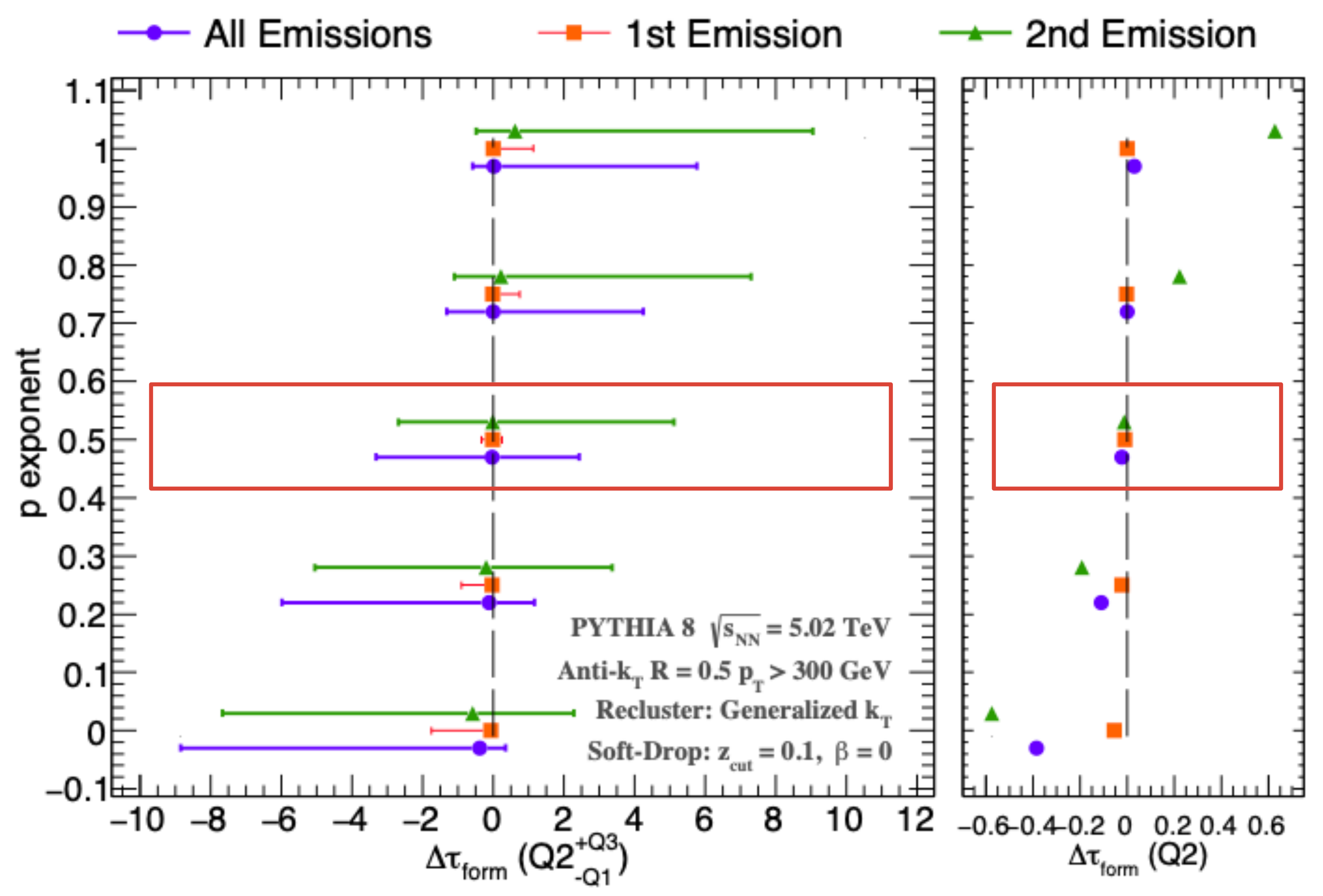
$$\Delta\tau_{\text{form}} = \tau_{\text{form}}^{\text{Parton Shower}} - \tau_{\text{form}}^{\text{Unclustering}}$$

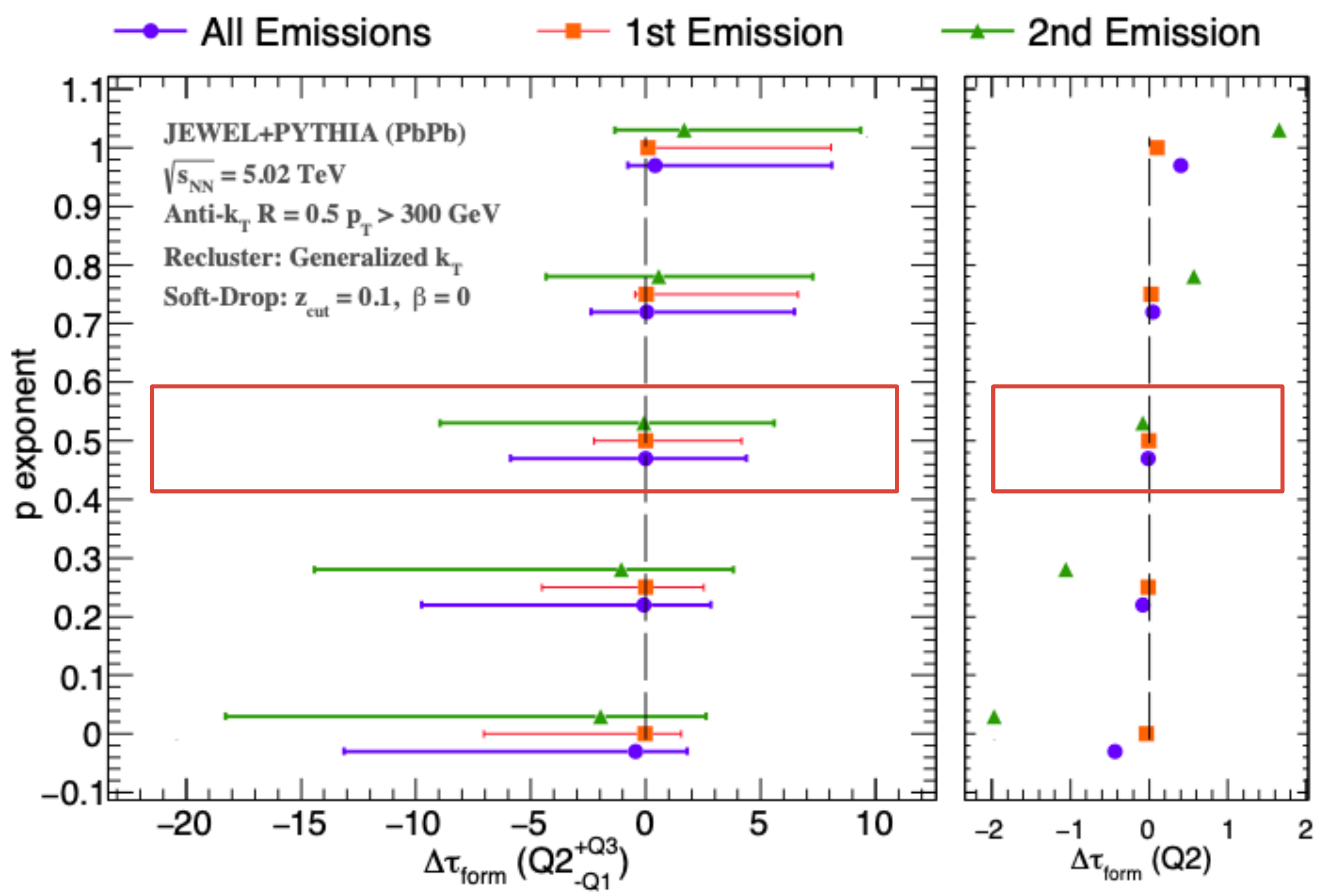
This distribution is quantified by its quartiles – to capture its asymmetry



The τ algorithm: most centred and symmetric distributions for both vacuum and medium samples

An unbiased estimator of jet formation time



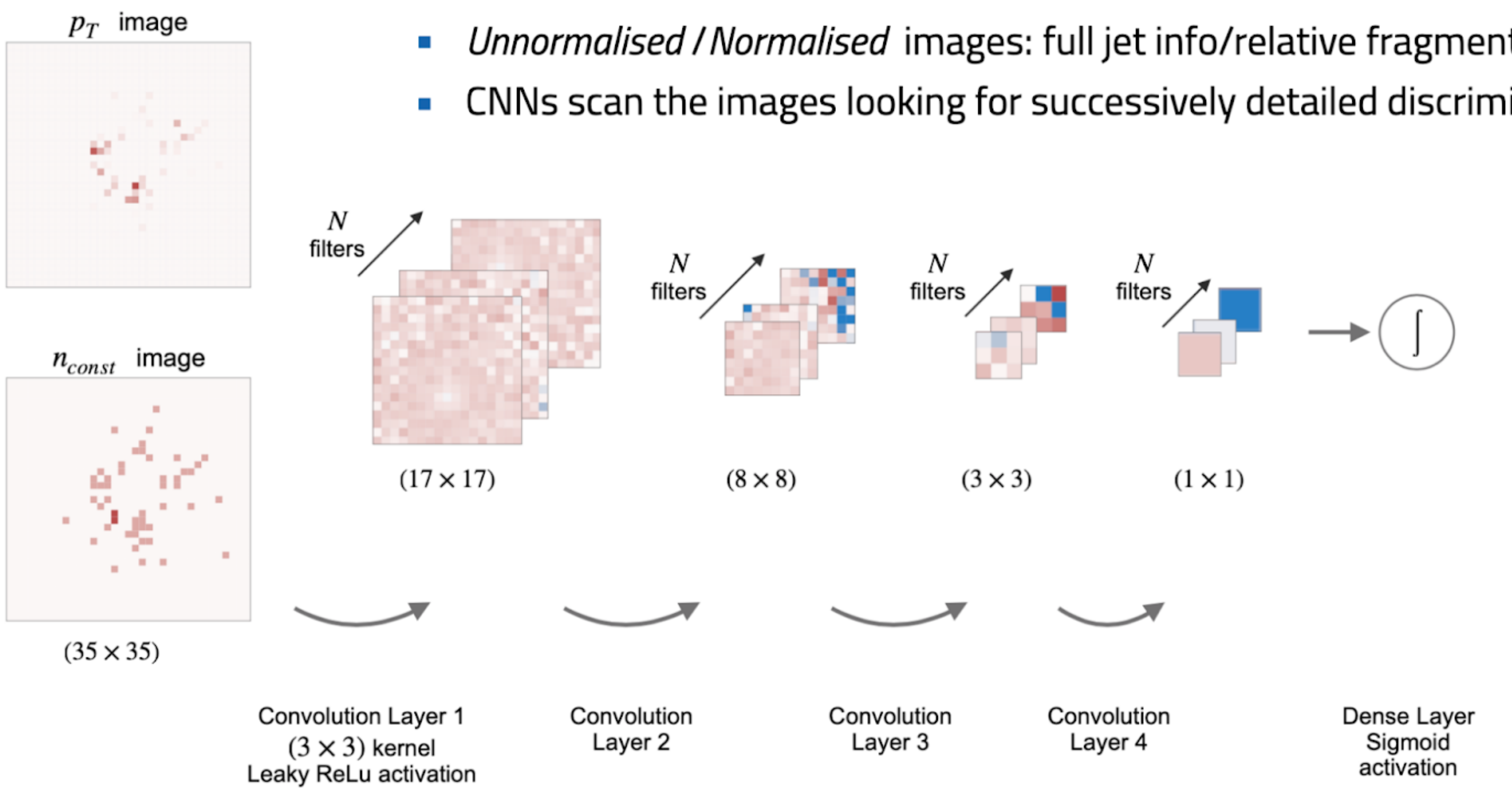


CLASSIFICATION OF QUENCHED JETS

Apolinário, Castro, Crispim Romão, Milhano, Pedro, Peres, :: *JHEP* 11 (2021) 219

- jet representations with varying theoretical input for different ML/DL architectures
  - jet images :: Convolutional Neural Network (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



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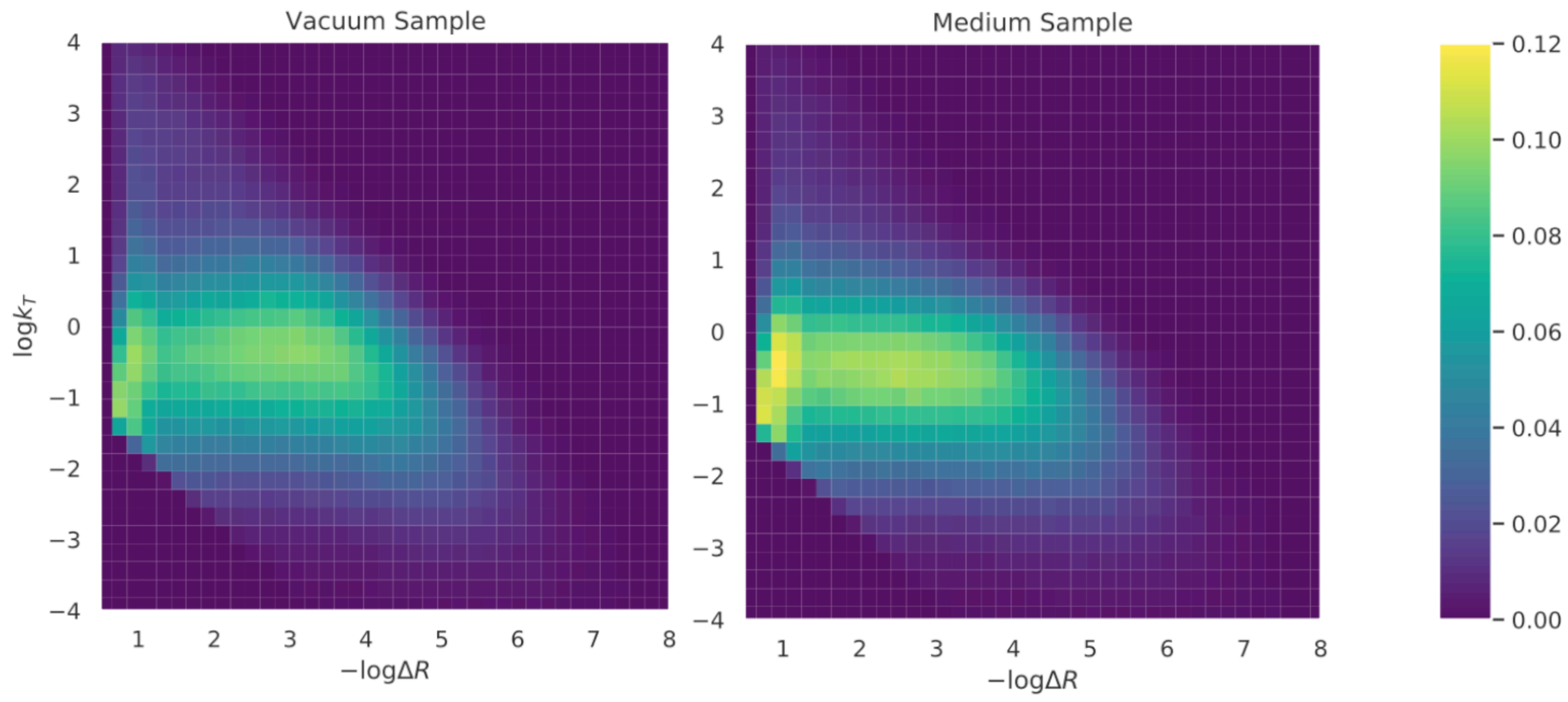
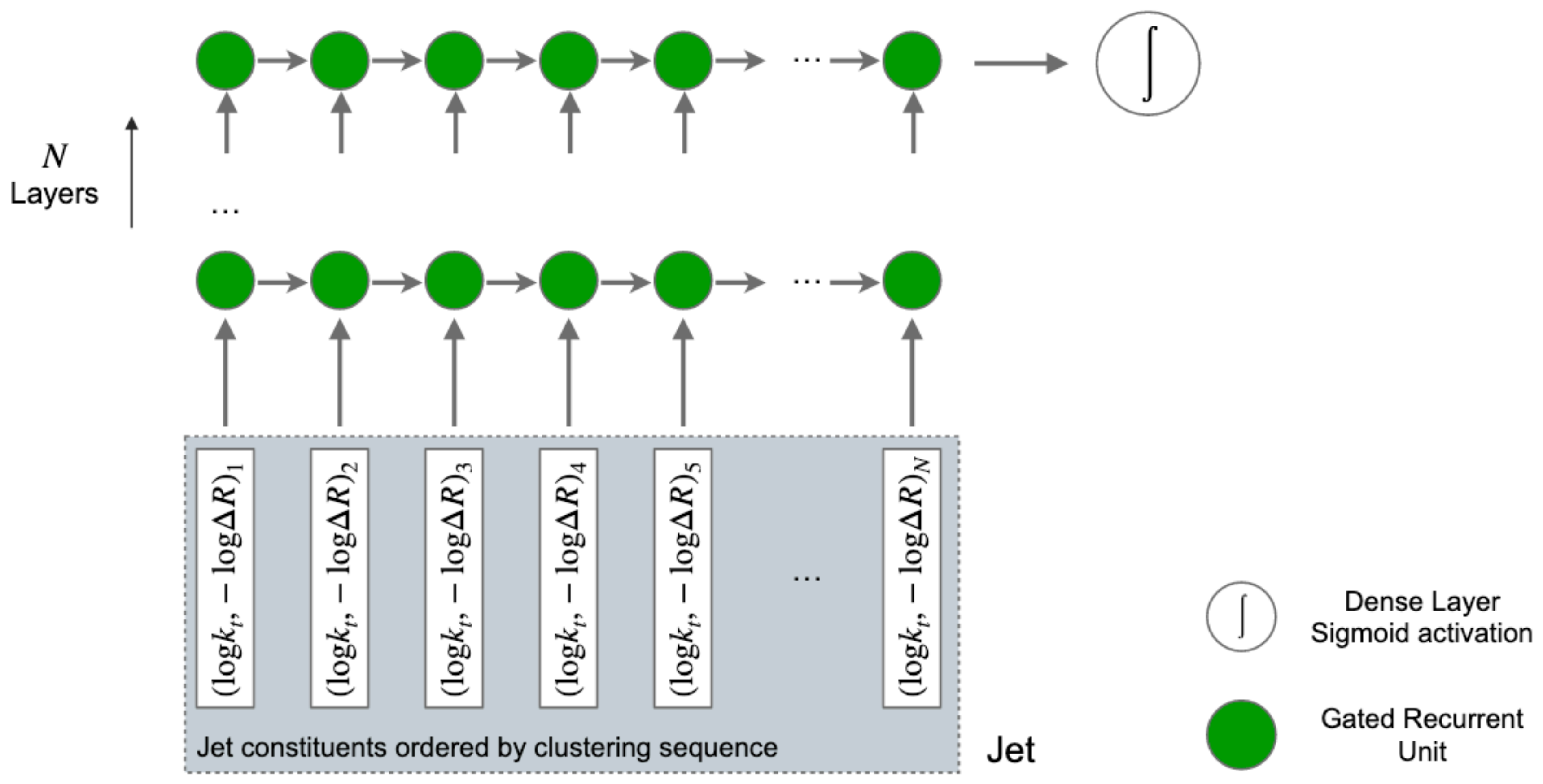
- jet representations with varying theoretical input for different ML/DL architectures
  - jet images :: 2-channel [p_T and multiplicity] calorimetric images in a grid centred on jet axis :: Convolutional Neural Network (CNN) :: channels both normalized and unnormalized
  - Lund plance coordinates :: Recurrent Neural Network (RNN)





CLASSIFICATION OF QUENCHED JETS

Apolinário, Castro, Crispim Romão, Milhano, Pedro, Peres, :: *JHEP* 11 (2021) 219

- jets in pp and AA are mostly alike [they are QCD jets] but differences [modifications] are measurable [at an ensemble level]
    - are differences enough to allow for discriminations on a jet-by-jet physics ?
    - is there enough information for a machine to learn to tell them apart ?

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  - Lund plance coordinates :: (kT, ΔR) for primary branch of C/A [angular ordered] declustering of jet :: Recurrent Neural Network (RNN)
  - Tabular data :: global (pT and multiplicity) for each jet :: Dense Neural Network (DNN)
    - benchmark case with minimal information

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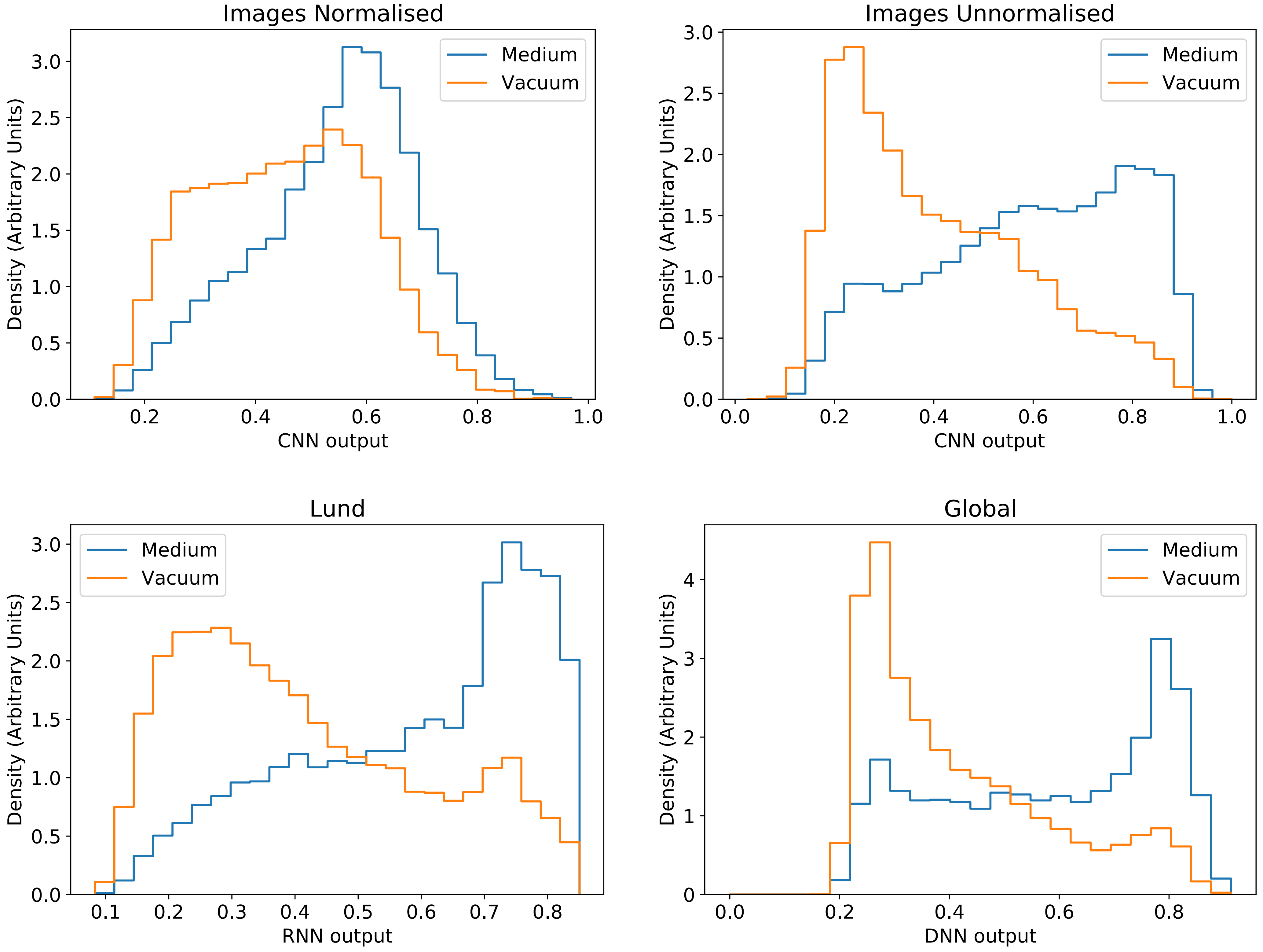
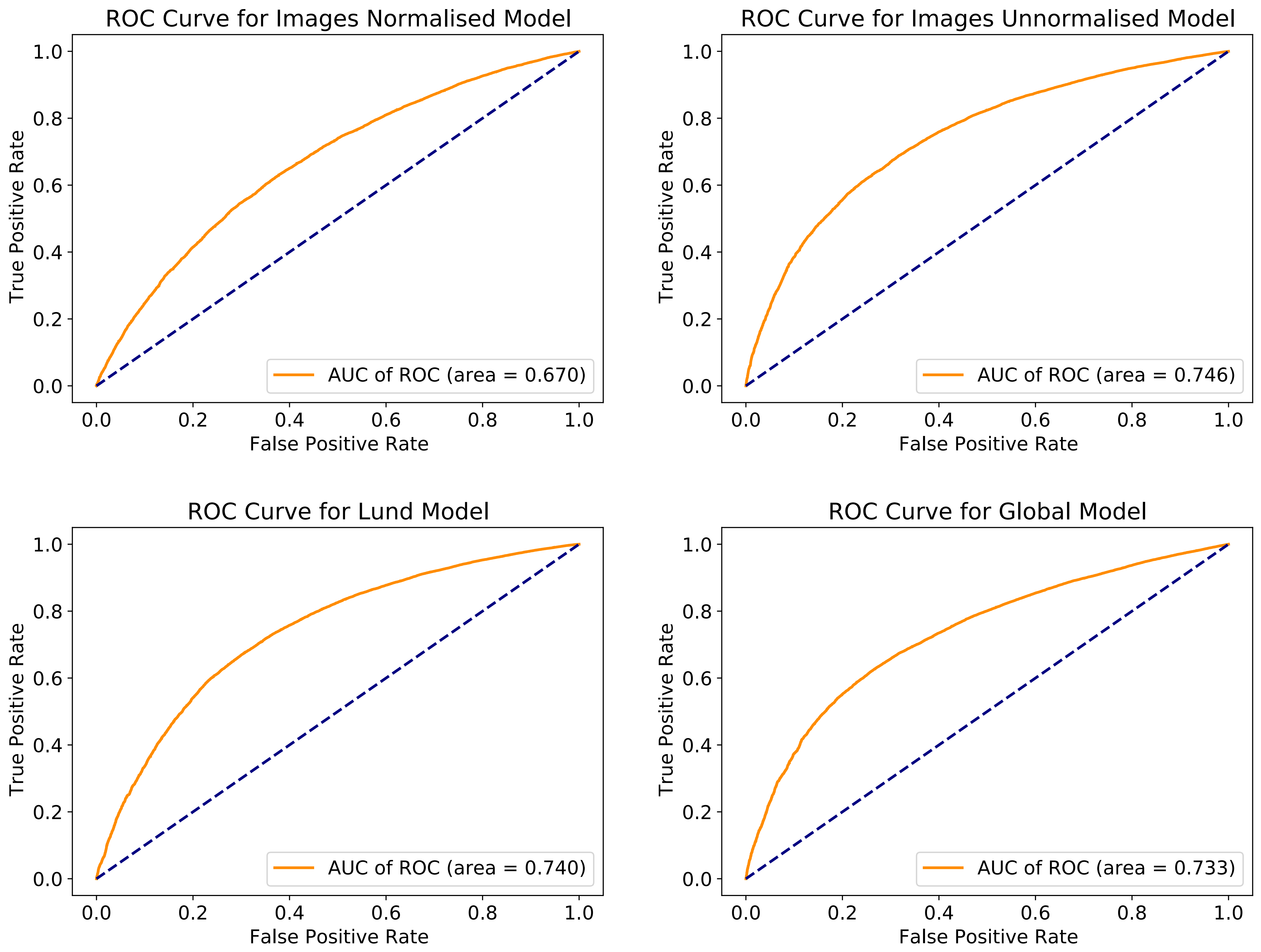


network outputs [discriminant]

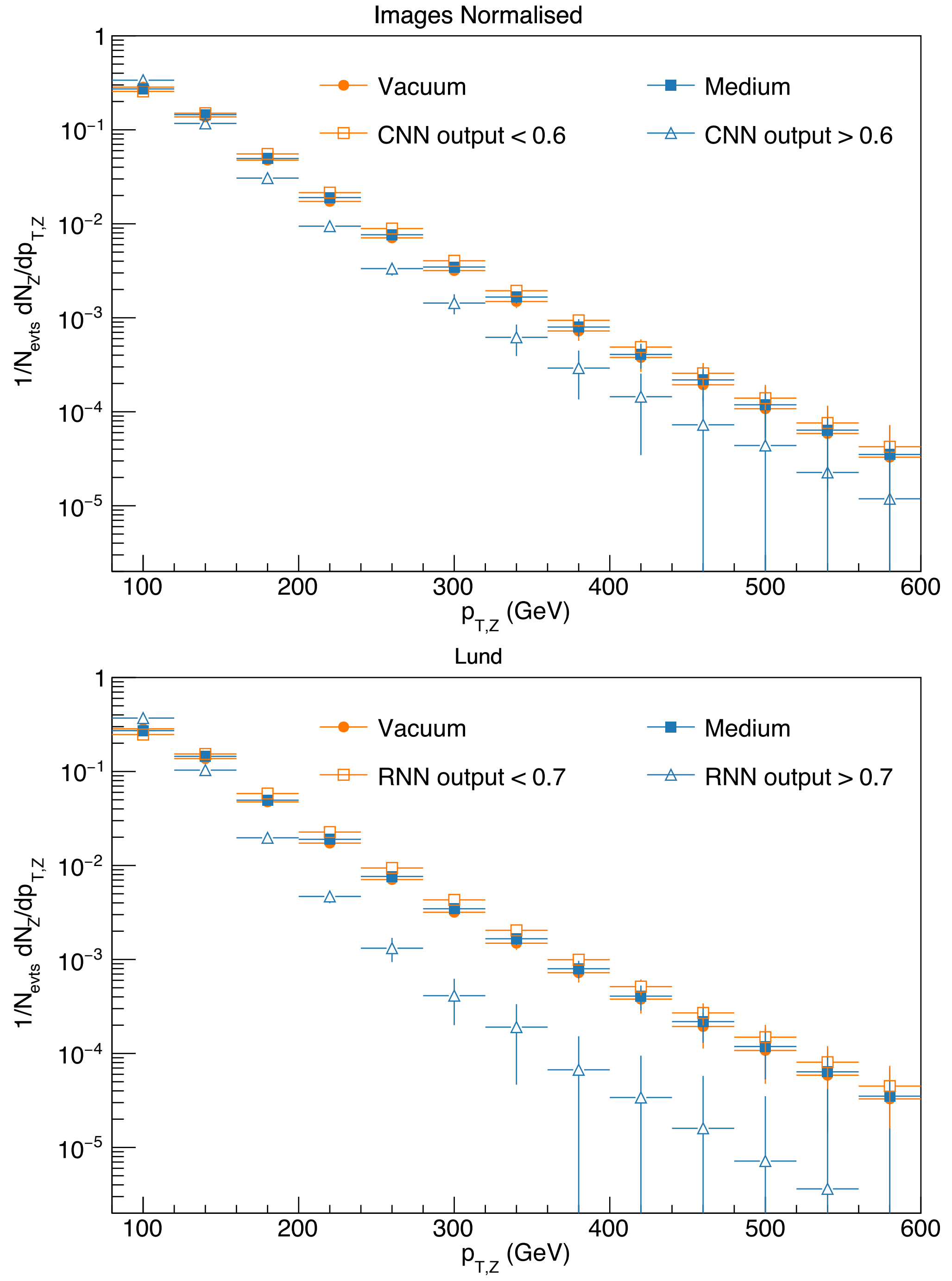


Model	$p_{T,jet}$ >30 GeV	$p_{T,jet}$ >125 GeV
Normalised jet images CNN	0.67	0.65
Unnormalised jet images CNN	0.75	0.68
Lund sequences RNN	0.74	0.69
Global DNN	0.73	0.64

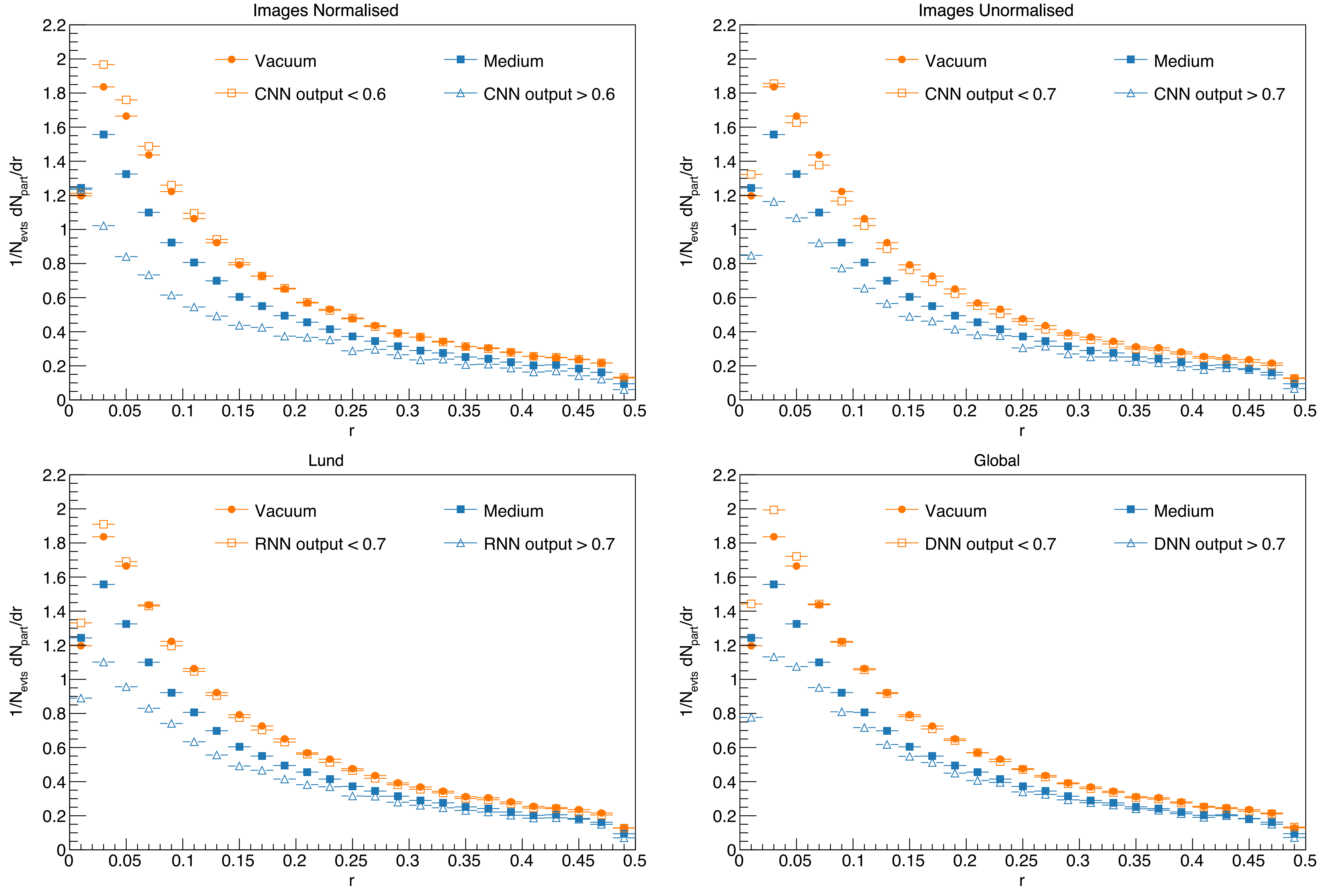
performance

CLASSIFICATION OF QUENCHED JETS :: RECONSTRUCTED

Apolinário, Castro, Crispim Romão, Milhano, Pedro, Peres, :: *JHEP* 11 (2021) 219



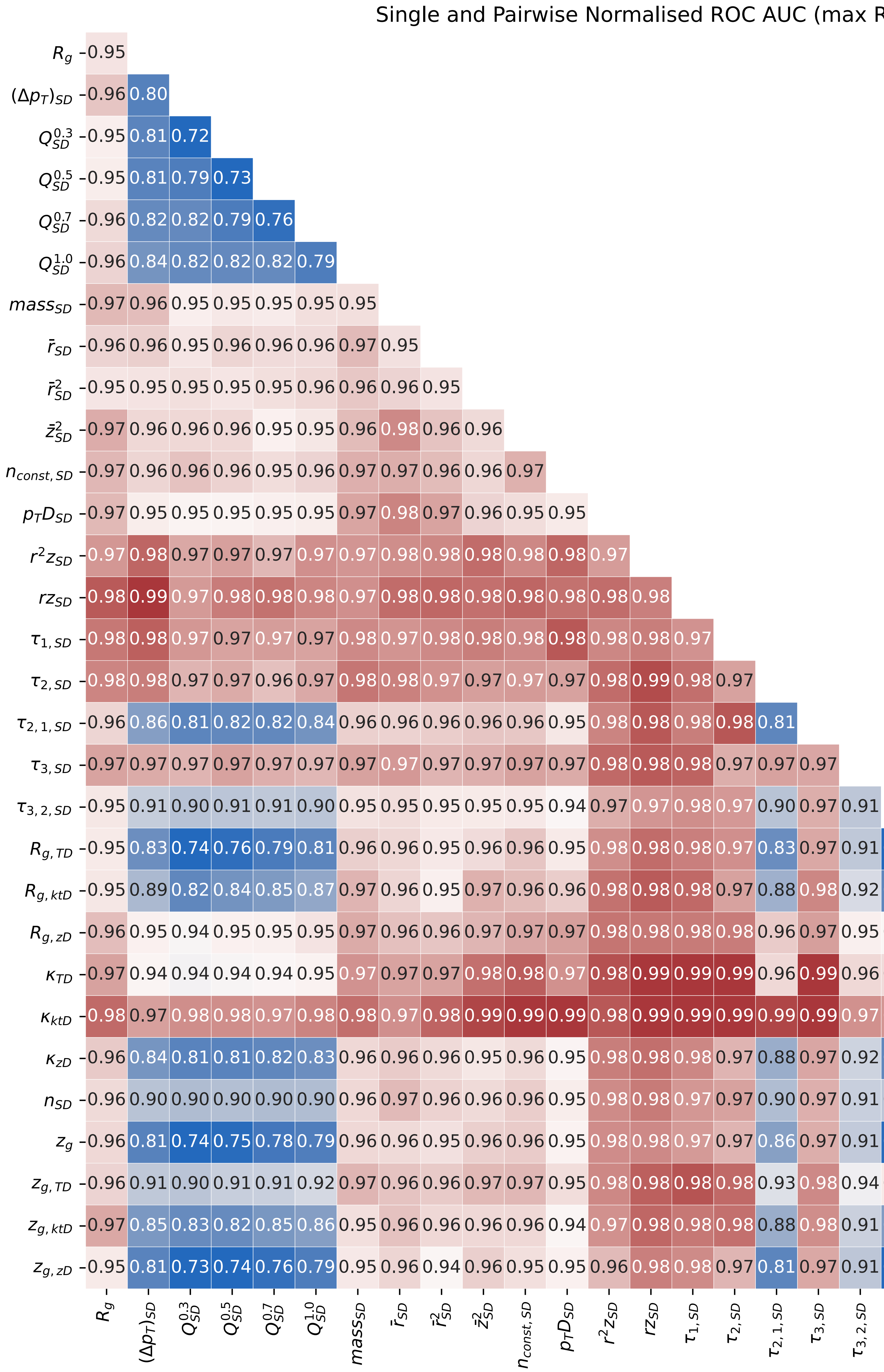
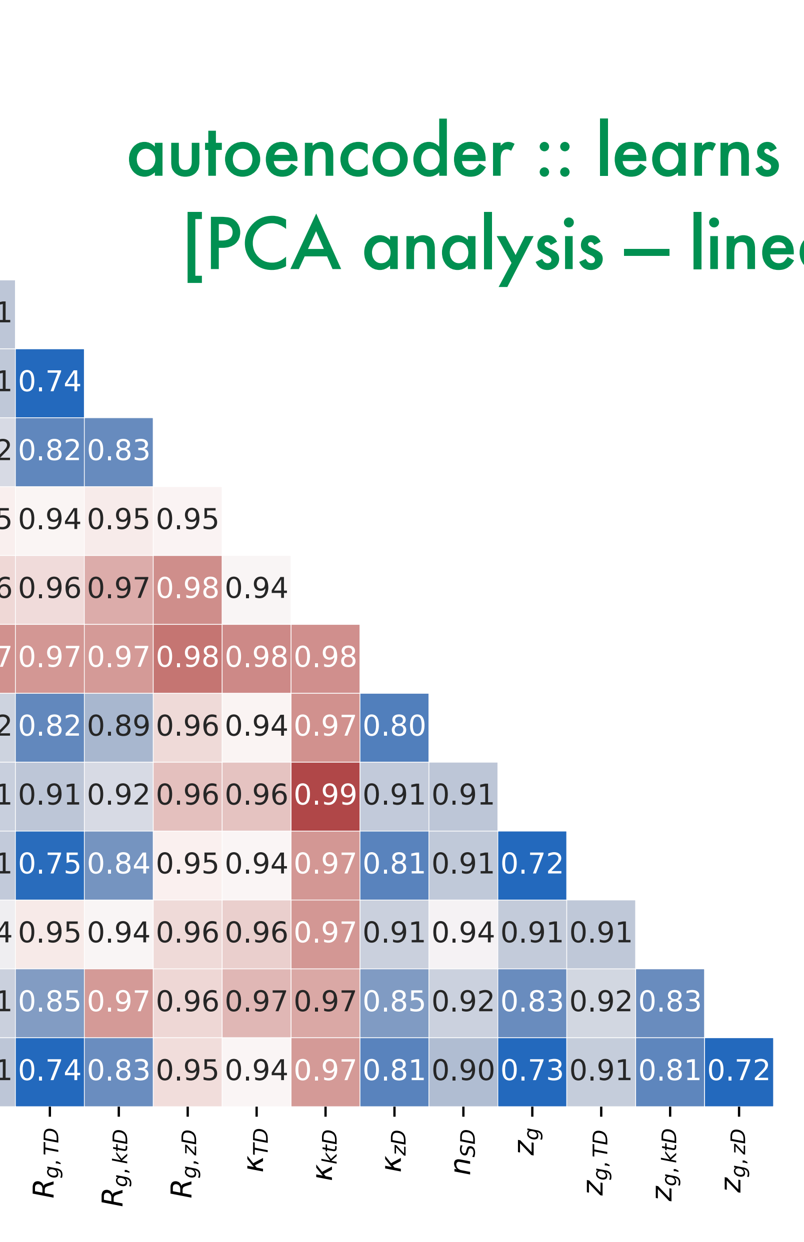
transverse momentum spectrum

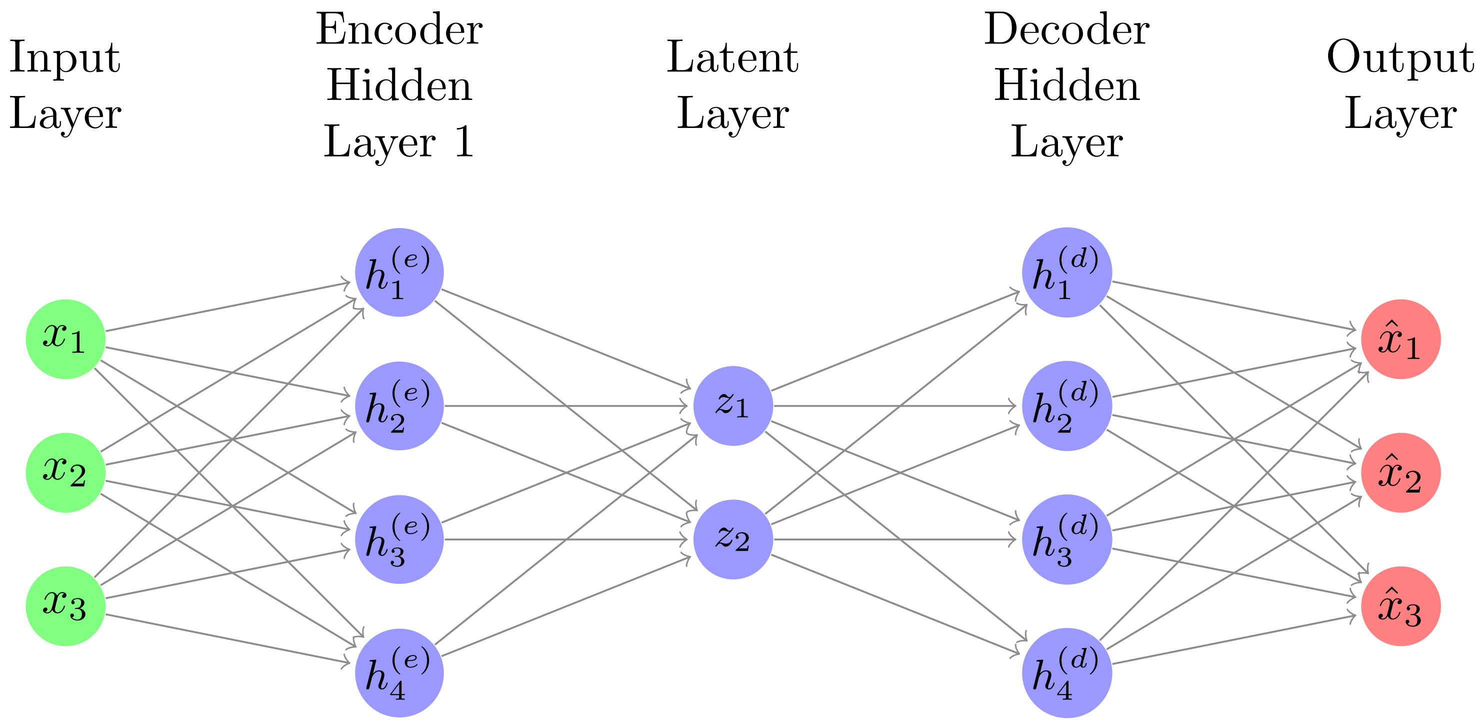


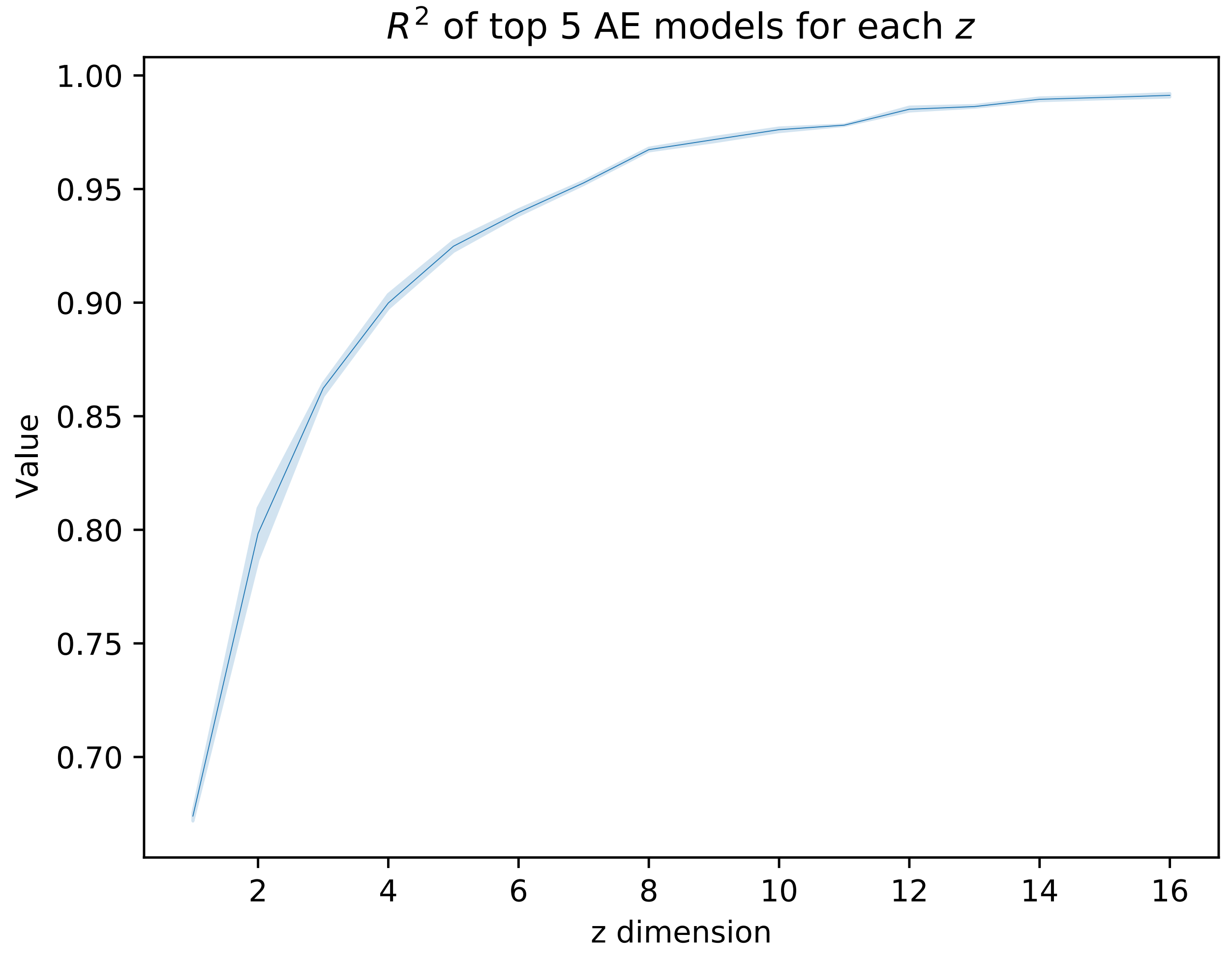
jet profile

HOW MANY OBSERVABLES IS ENOUGH?

Crispim Romão, Milhano, van Leeuwen, :: *in preparation*





autoencoder :: learns non-linear relations amongst inputs
[PCA analysis – linear correlations only – also done]

correlations between observables encode a wealth of information

loss of predictive power signals sensitivity to QGP effects