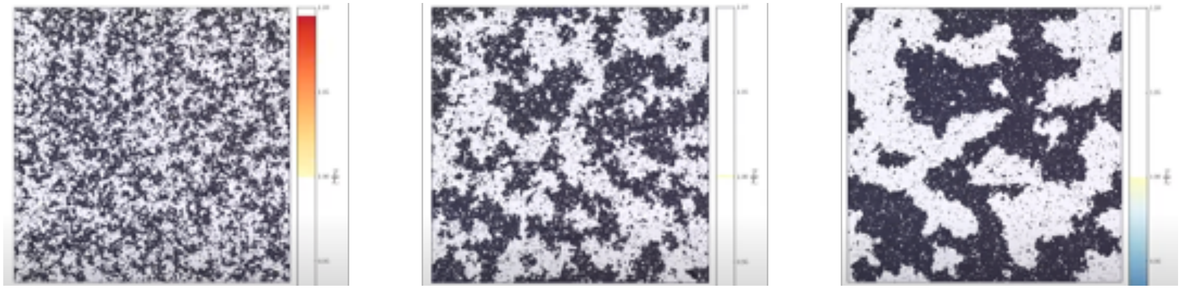
UNIVERSITY OF BERGEN

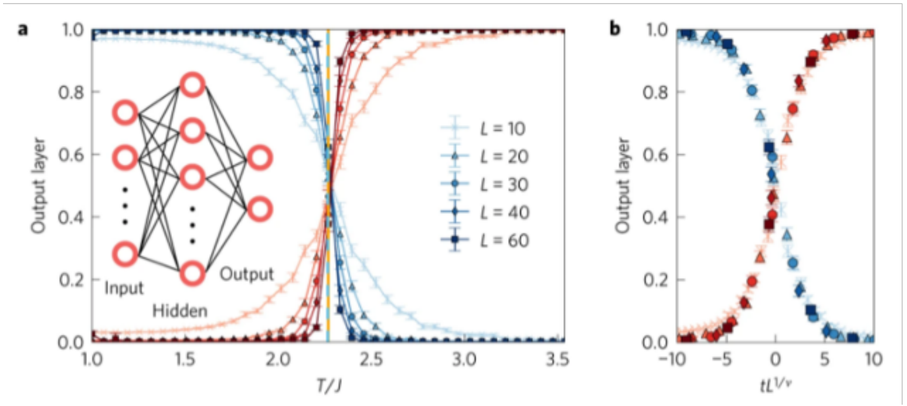
COMPUTING, ML & AI
THEORY PERSPECTIVE

Konrad Tywoniuk
konrad.tywoniuk@uib.no

NorCC workshop, Oslo/online, 14-15 September 2022

IMAGE RECOGNITION FOR PHASE TRANSITIONS



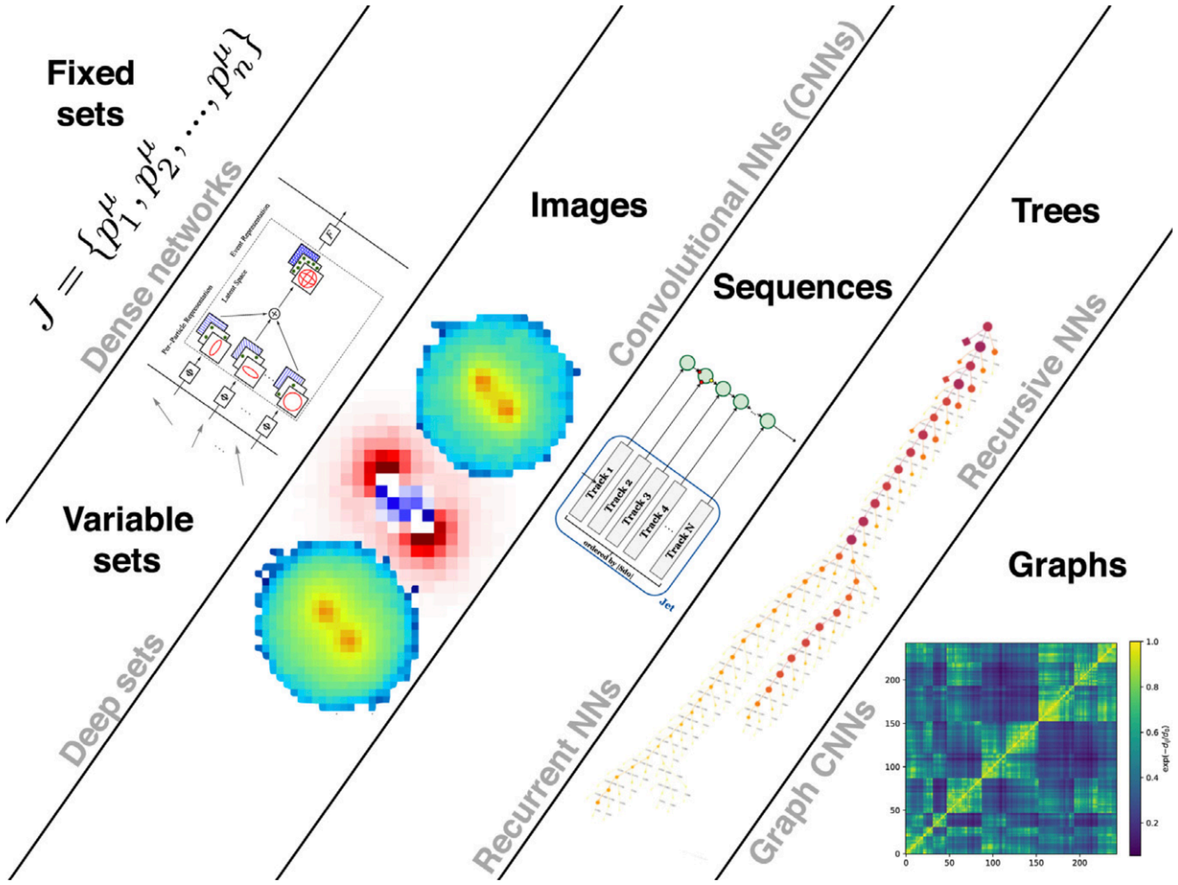


- new ML paradigm connected to large datasets
- canonical example: Ising model on the lattice
  - NN identifies phase transition temperature with high precision (supervised)
- later: unsupervised techniques, NN predicts new phases

Carrasquilla, Melko Nature (2017)
van Nieuwenburg, Liu, Huber Nature (2017)

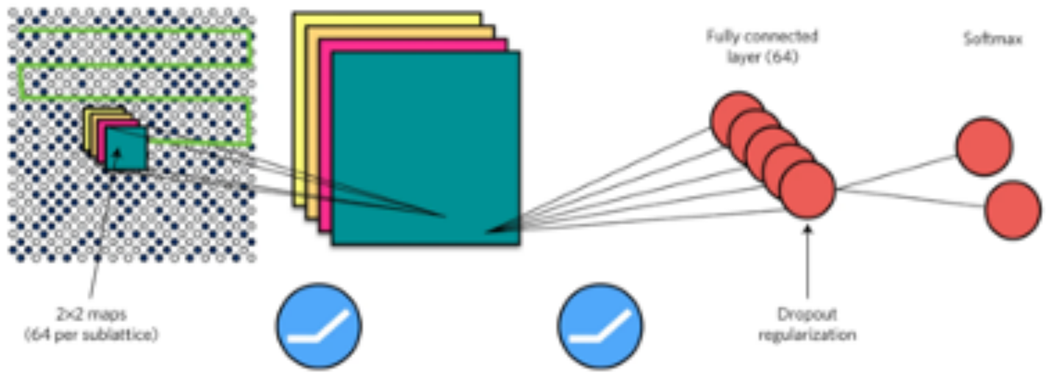
HIGH-ENERGY PHYSICS: APPLICATIONS

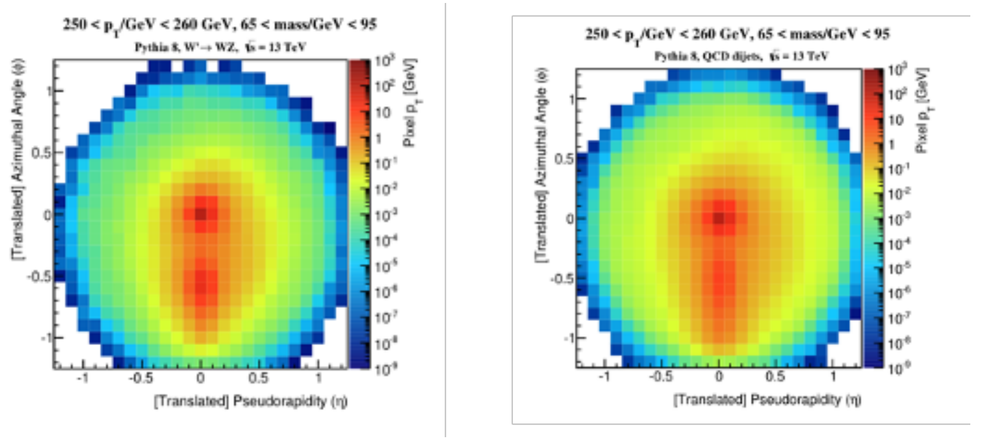
Larkoski, Moult, Nachmann 1709.04464



- rich data from collider physics (event level, jet level)
- various representations draw on various strengths
- main tasks: classification (tagging), regression, generation, anomaly detection…
- also: speed-up of parts of event generation,…

HIGH-ENERGY PHYSICS: JET IMAGES

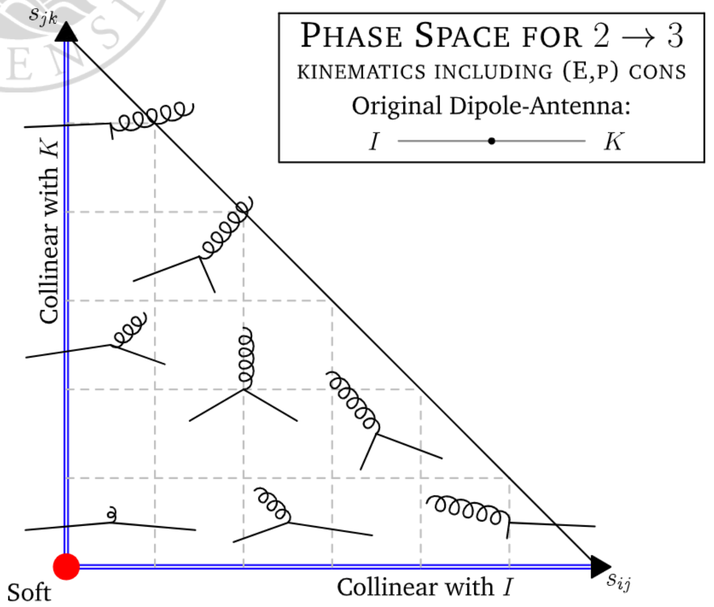




de Oliveira, Kagan, Mackey, Nachman, Schwartzman JHEP (2015)

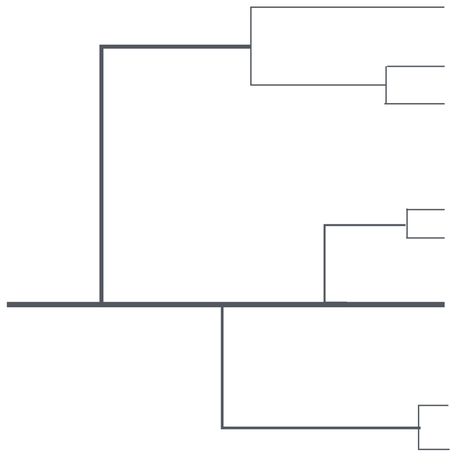
- average image of W decay (left) and quark/gluon jets (right)
- preprocessing involves rotation, scaling of pixels etc.
- achieves good performance, some level of interpretability

QUARK/GLUON DISCRIMINATION ON THE LUND PLANE

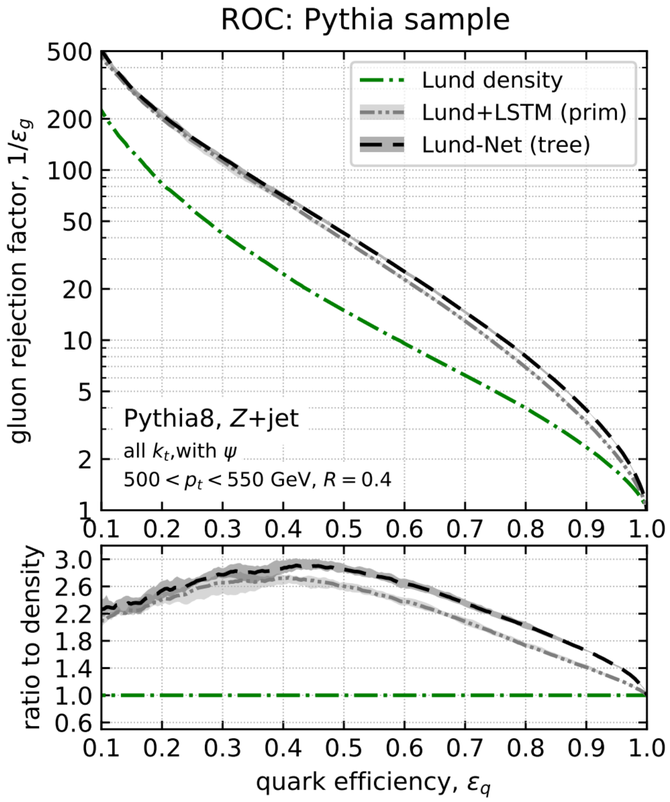


PHASE SPACE FOR $2 \to 3$
KINEMATICS INCLUDING (E,P) CONS
Original Dipole-Antenna:
I —•— K

splitting kinematics



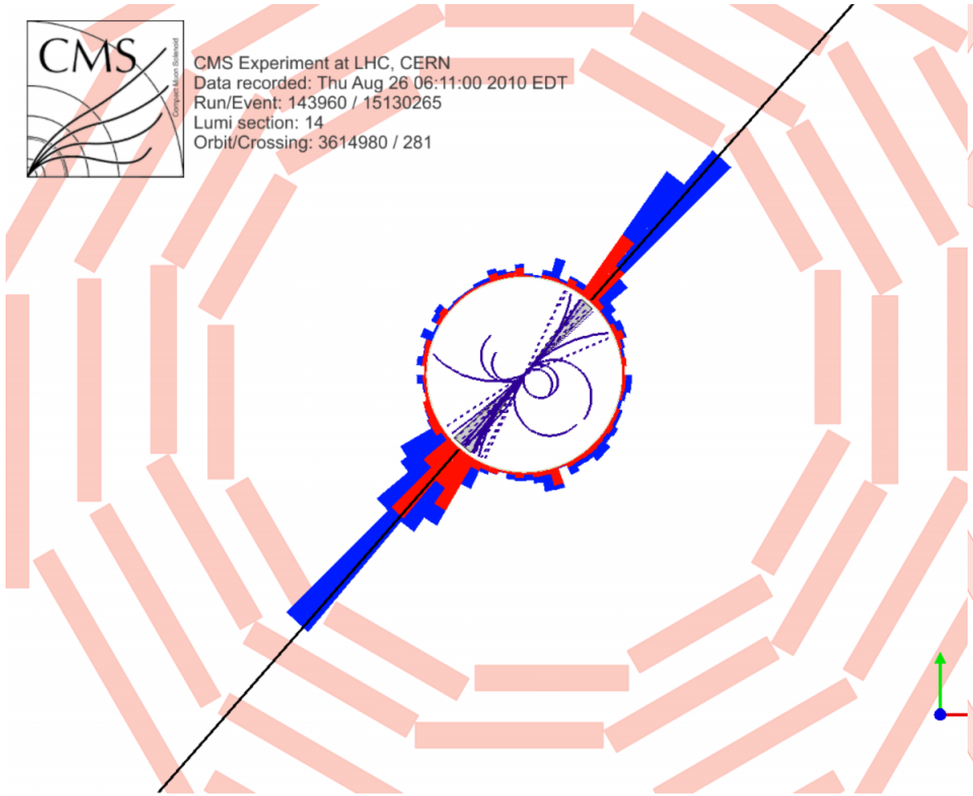
sequence of splittings = tree structure



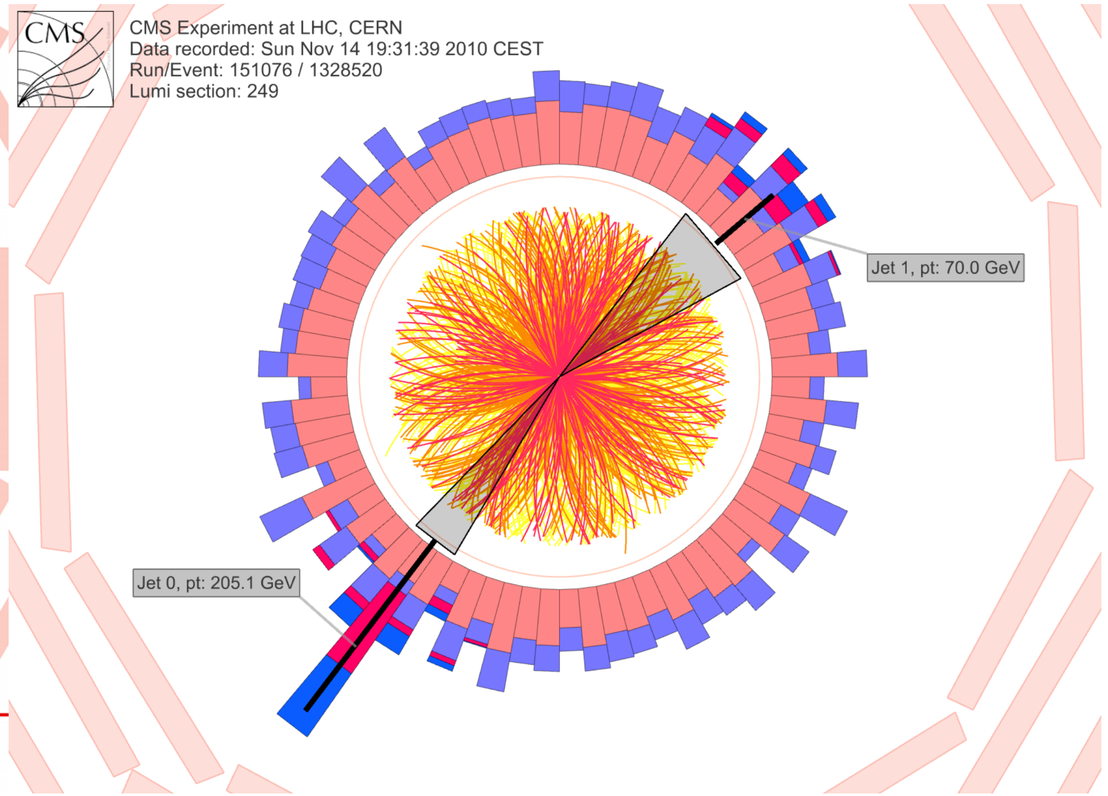
Dreyer, Soyez, Takacs 2112.09140

- leveraging more information about the sequence of splittings
  - most are governed by perturbative QCD
- resilient to many non-perturbative processes that come on top

JET QUENCHING IN HEAVY-ION COLLISIONS



proton-proton
two-jet event

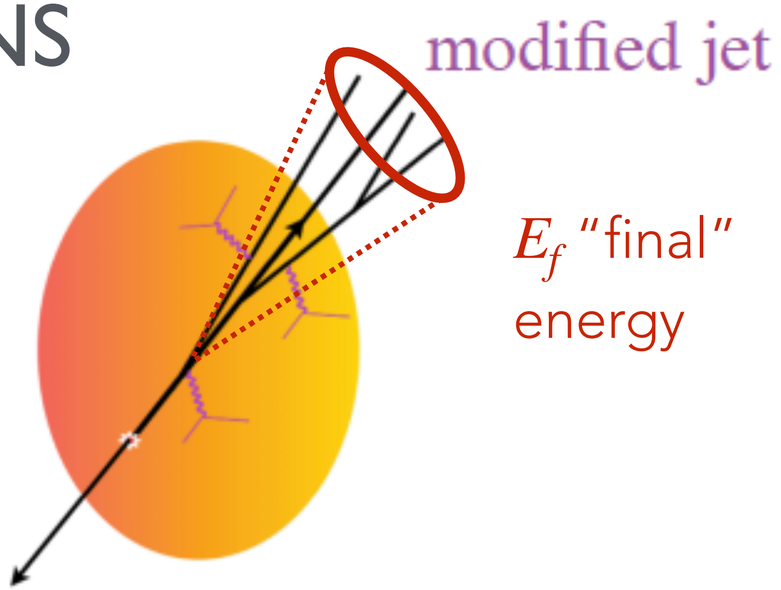


heavy-ion
two-jet event

JET QUENCHING IN HEAVY-IONS

Du, Pablos, KT 2012.07797 , 2106.11271

- **Main idea:** on a jet-by-jet basis, can we estimate the original jet energy, had it not interacted with the medium?



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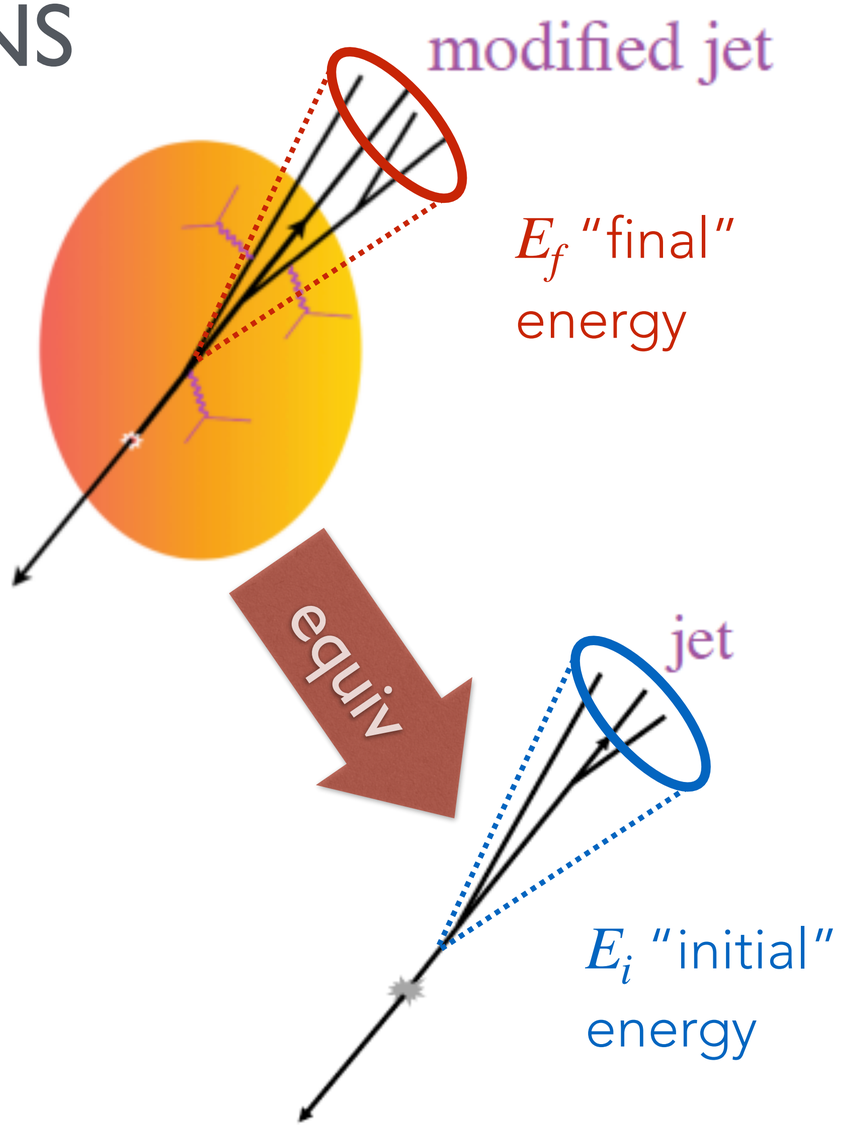

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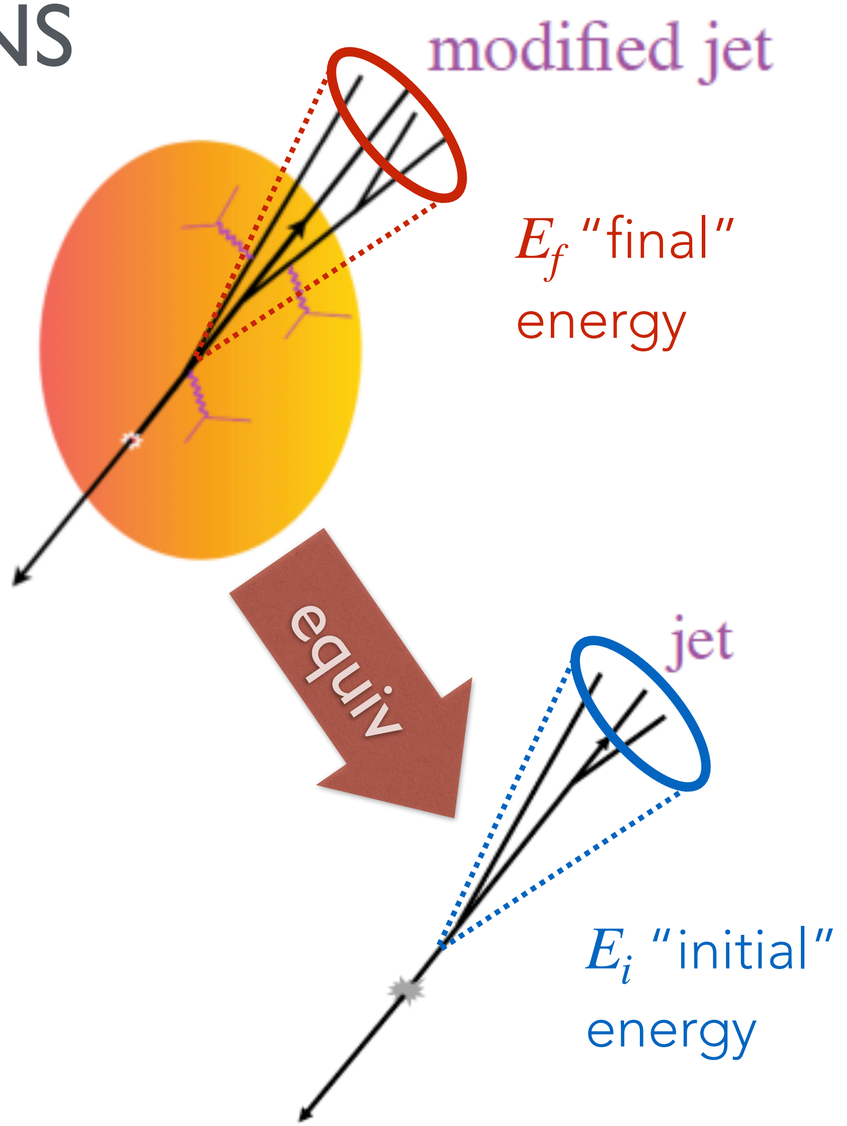

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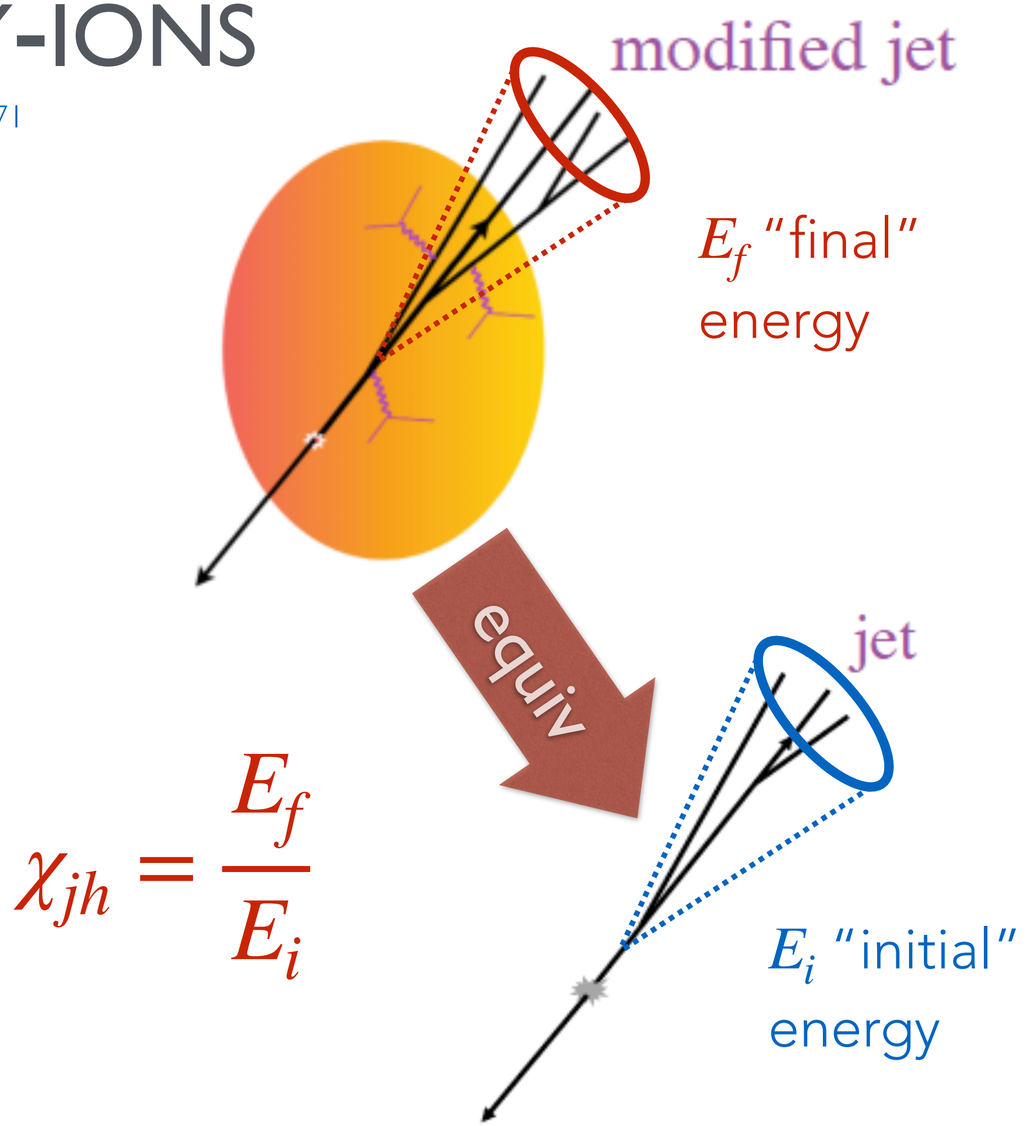

$$\chi_{jh} = \frac{E_f}{E_i}$$

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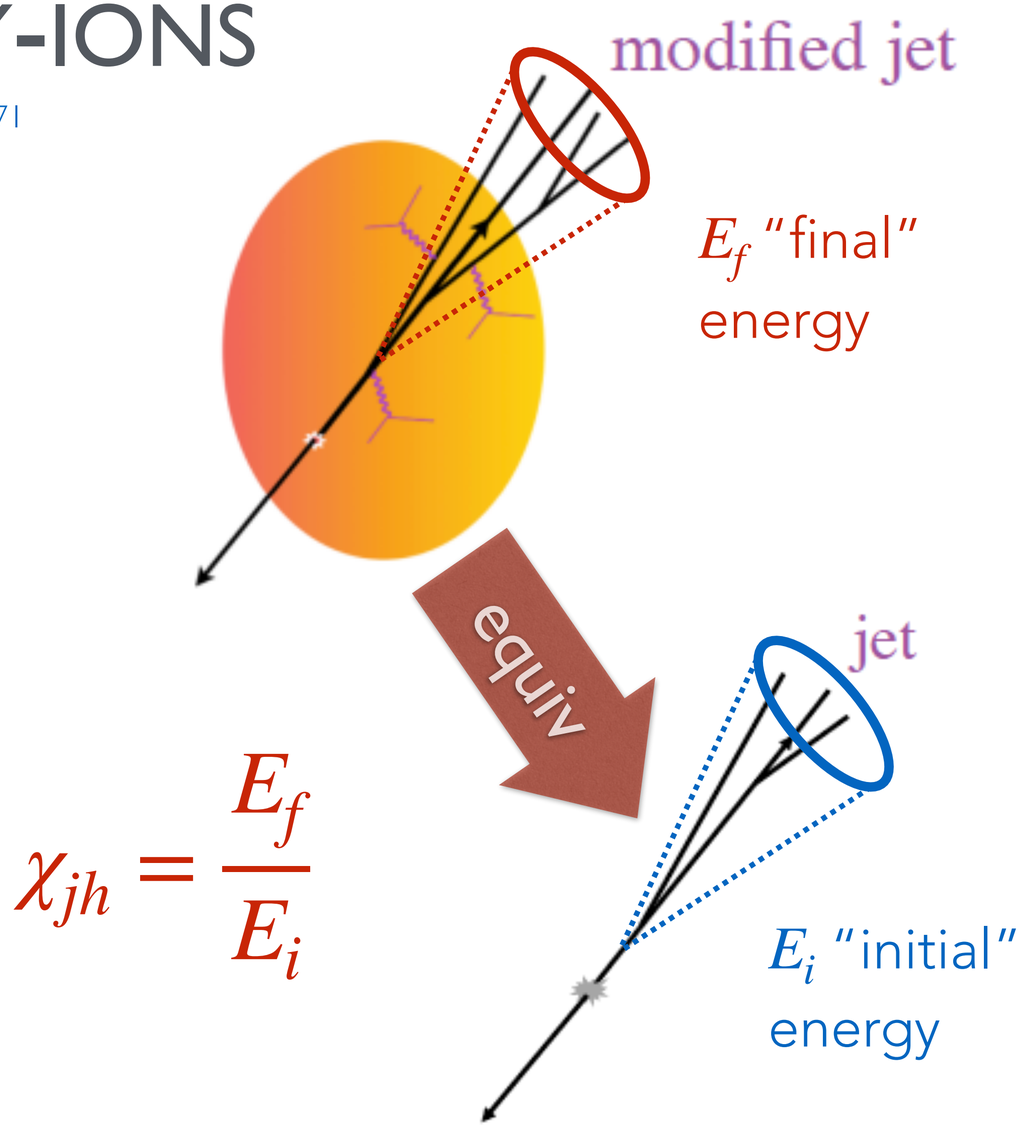

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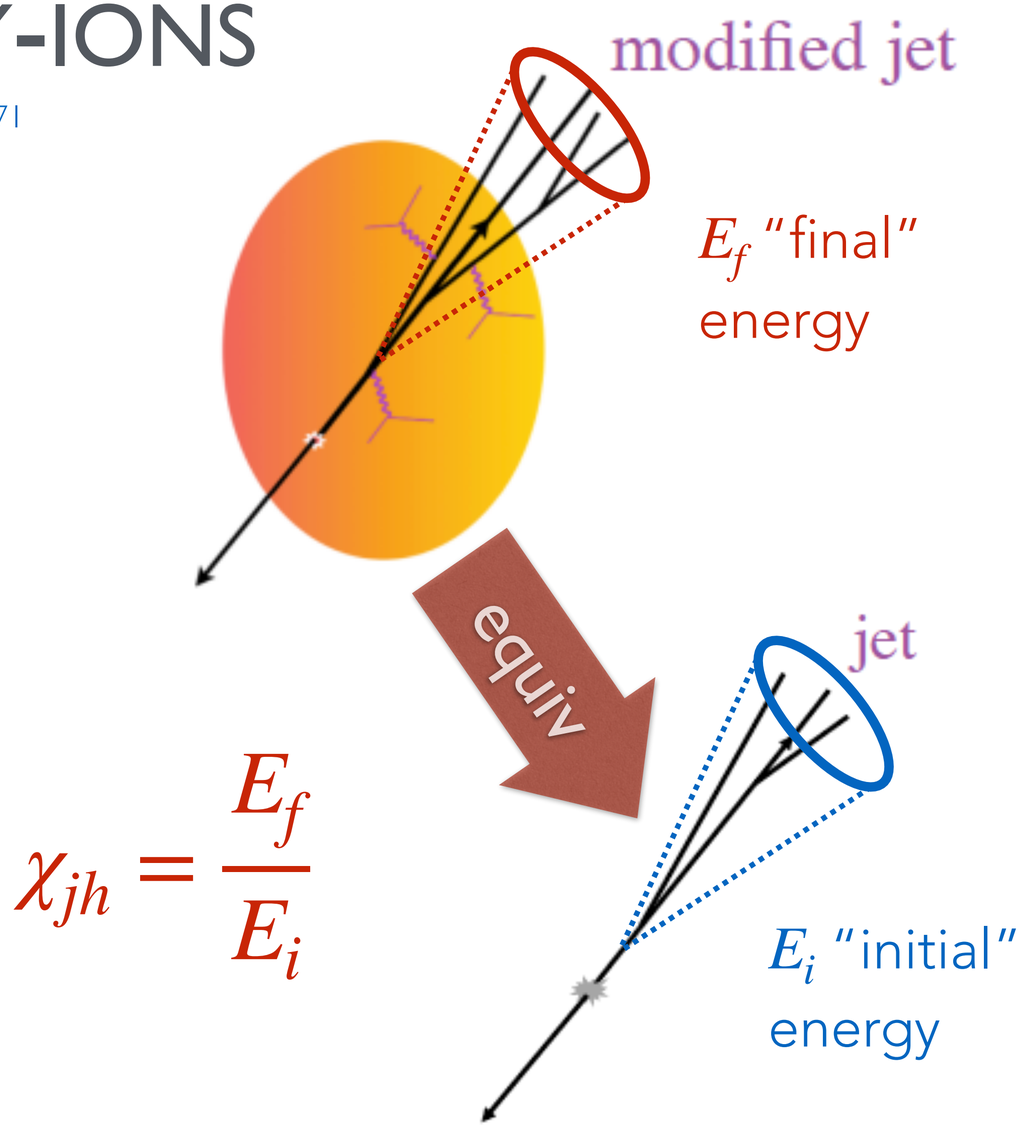

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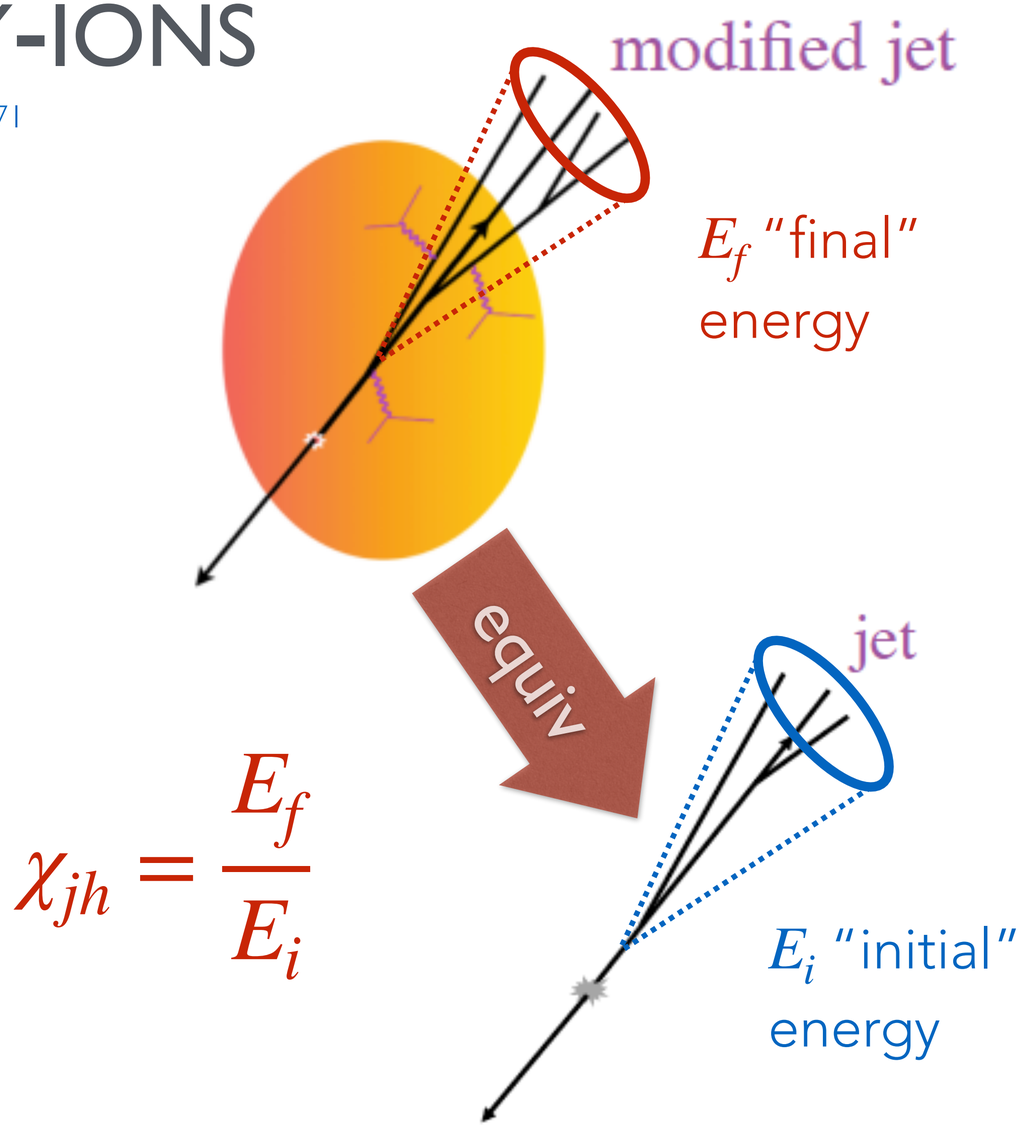

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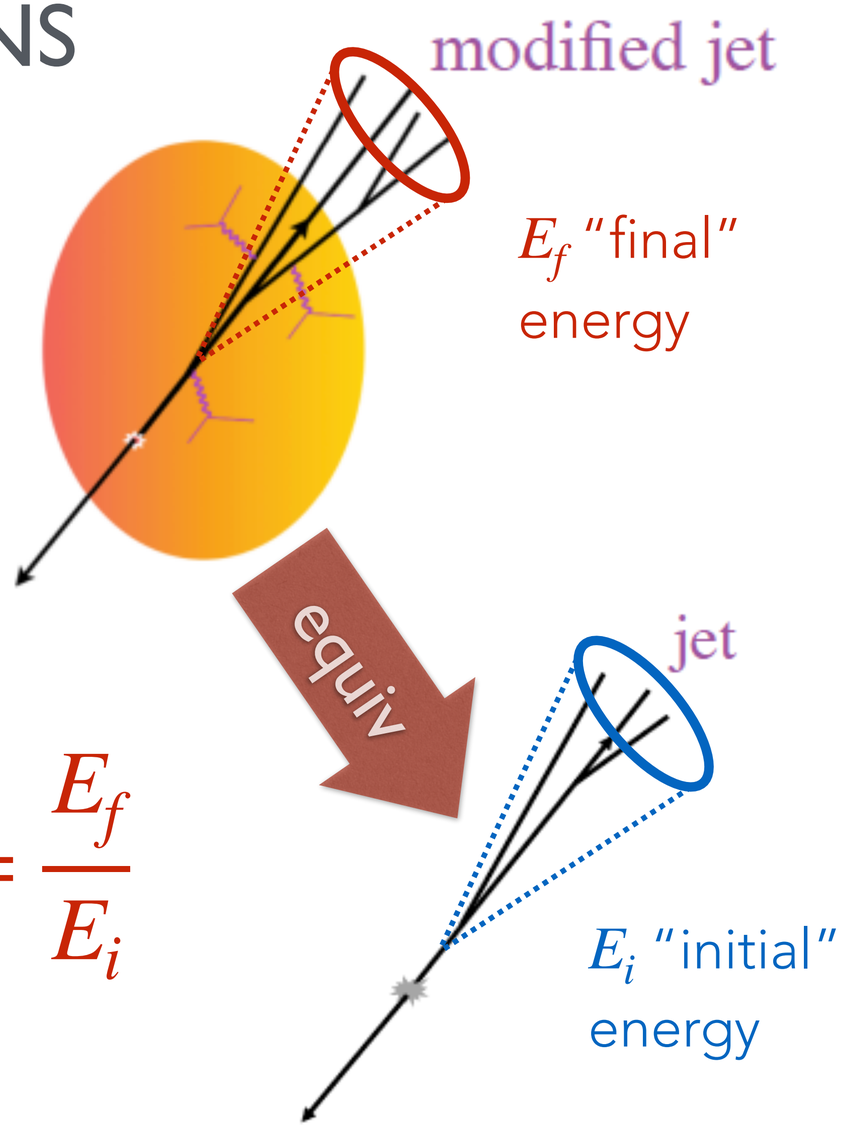

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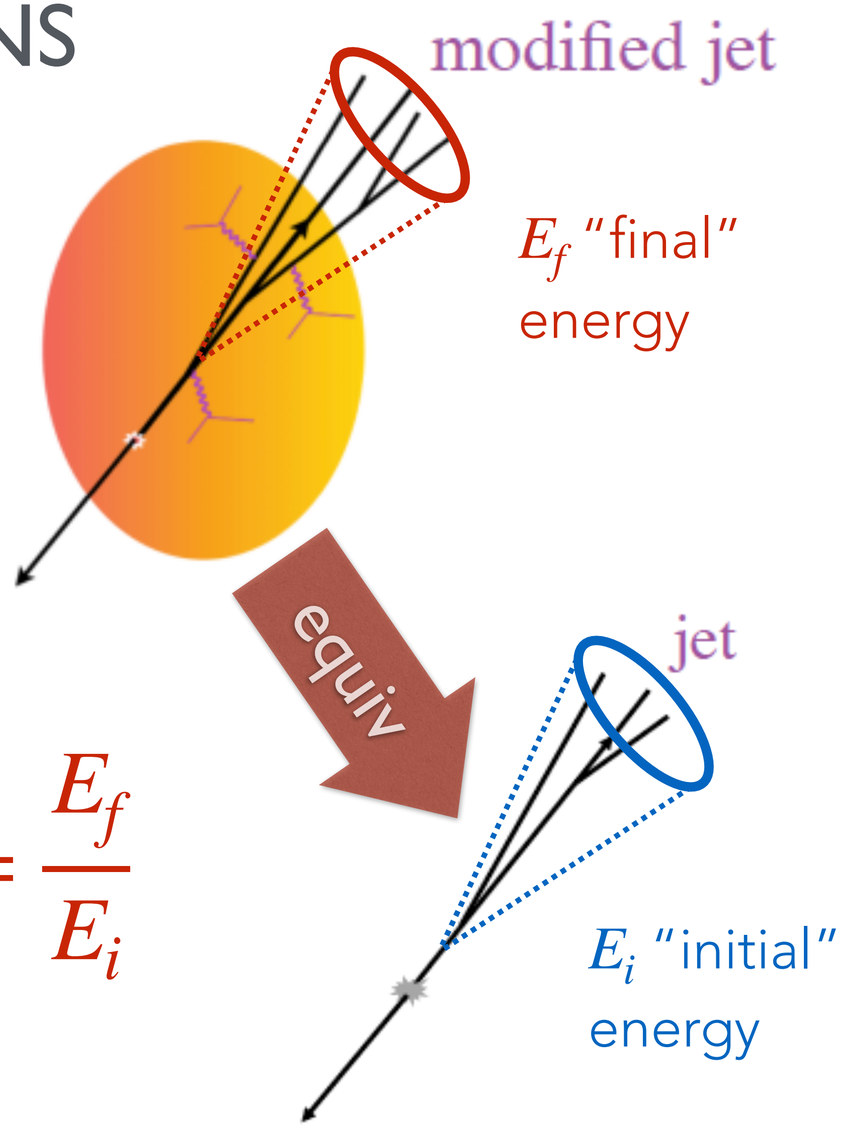
  - generalizable to other models
- two ML architectures: CNN for jet images and FCNN for set of observables



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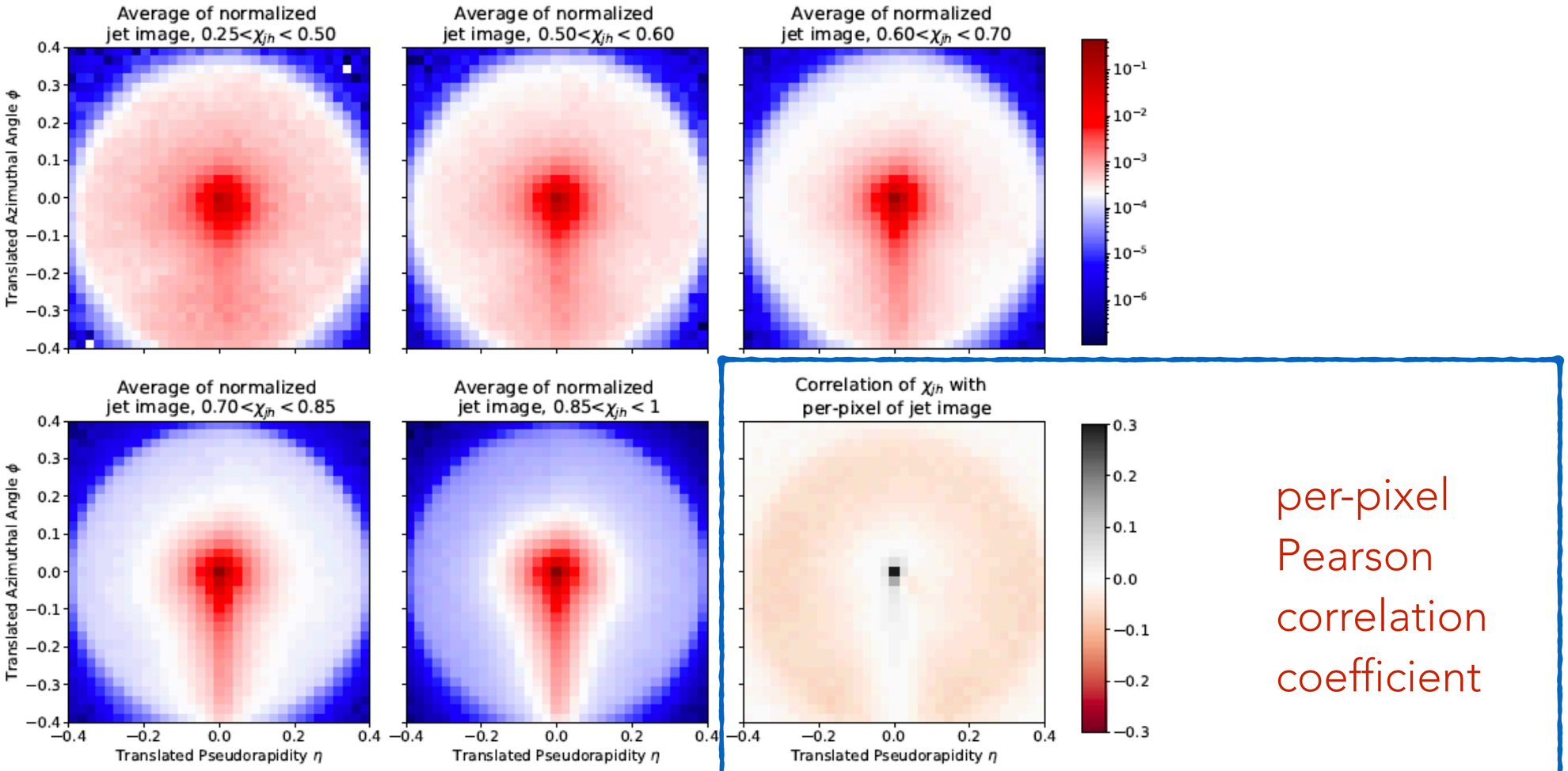
JET IMAGES OF QUENCHED JETS

Du, Pablos, KT 2012.07797



per-pixel Pearson correlation coefficient

APPLICATIONS: ONE EXAMPLE

Du, Pablos, KT 2012.07797
see also Apolinario, Castro, Romao, Milhano, Pedro 2106.08869

- consider two classes:
  - unquenched $\chi_{jh} > 0.9$
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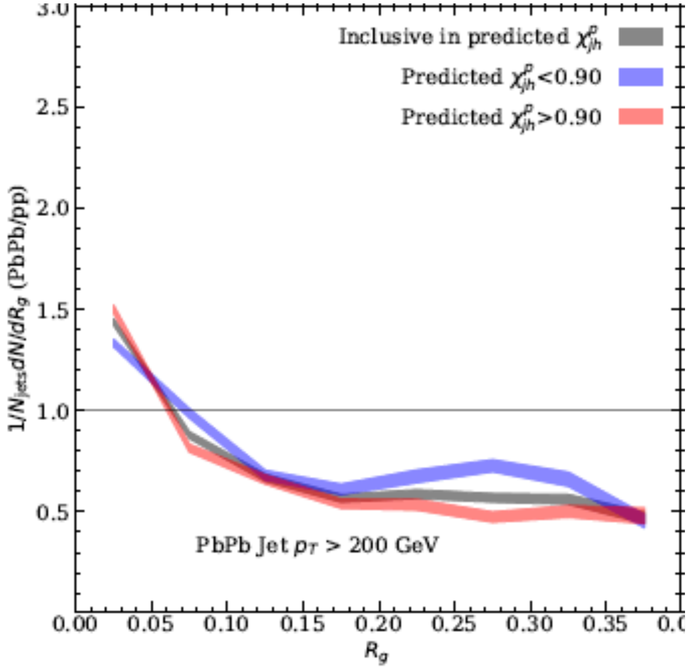
  - impose cut on final energy $p_T > 200$ GeV

Jet shape



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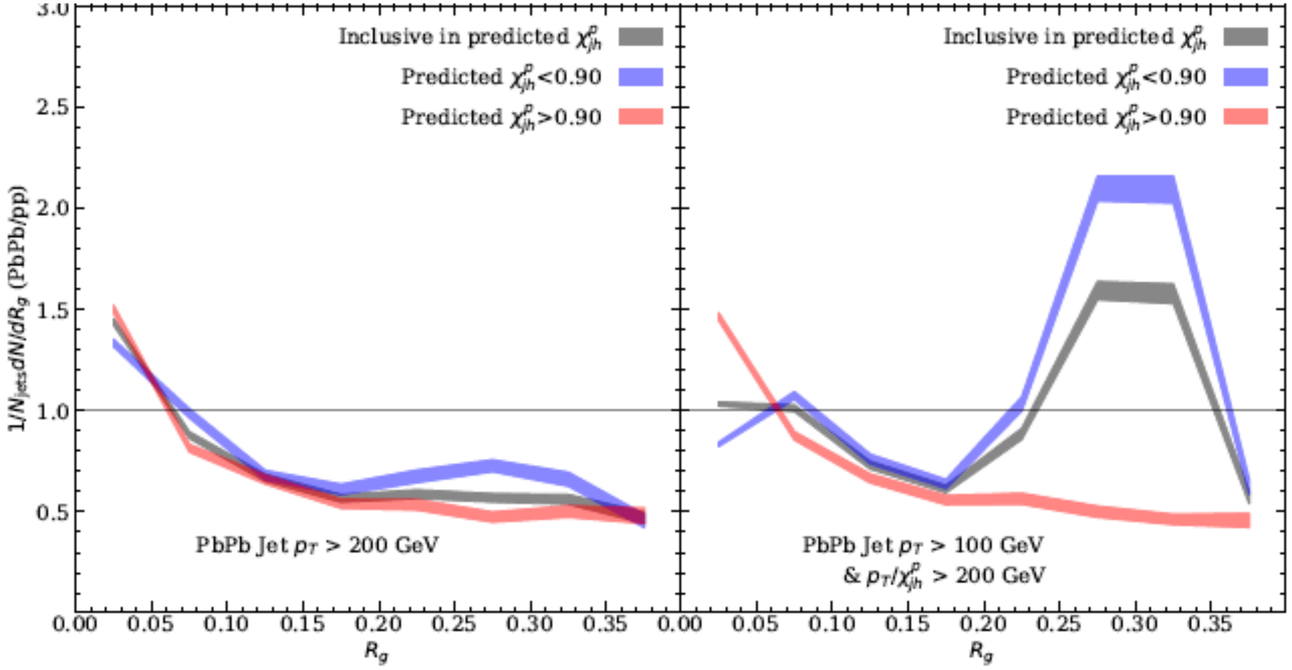

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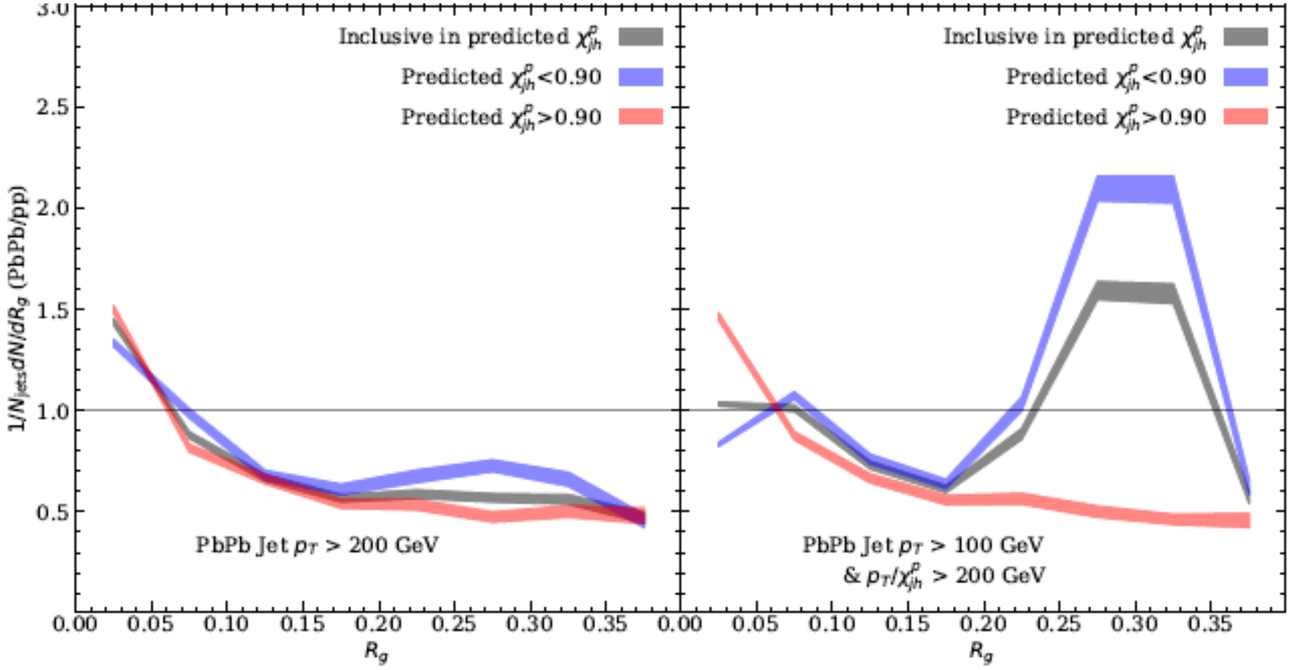
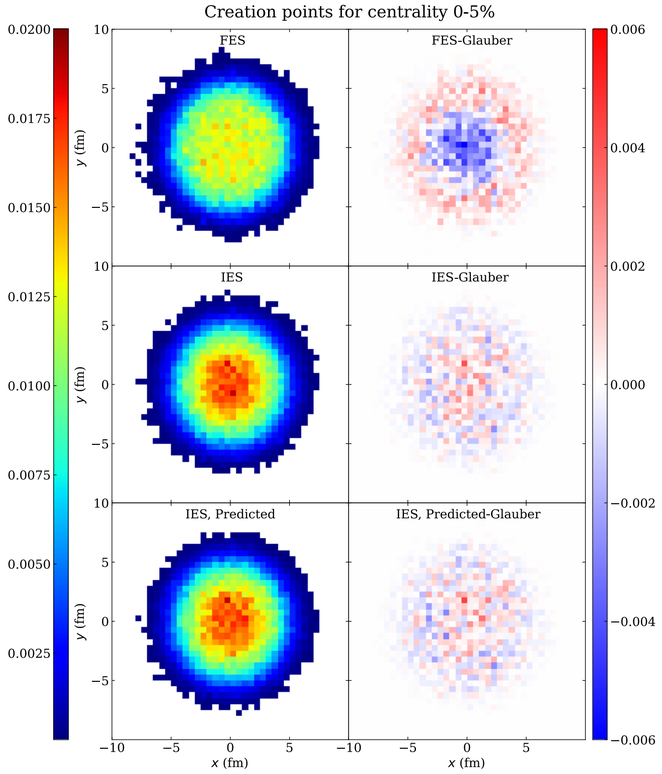
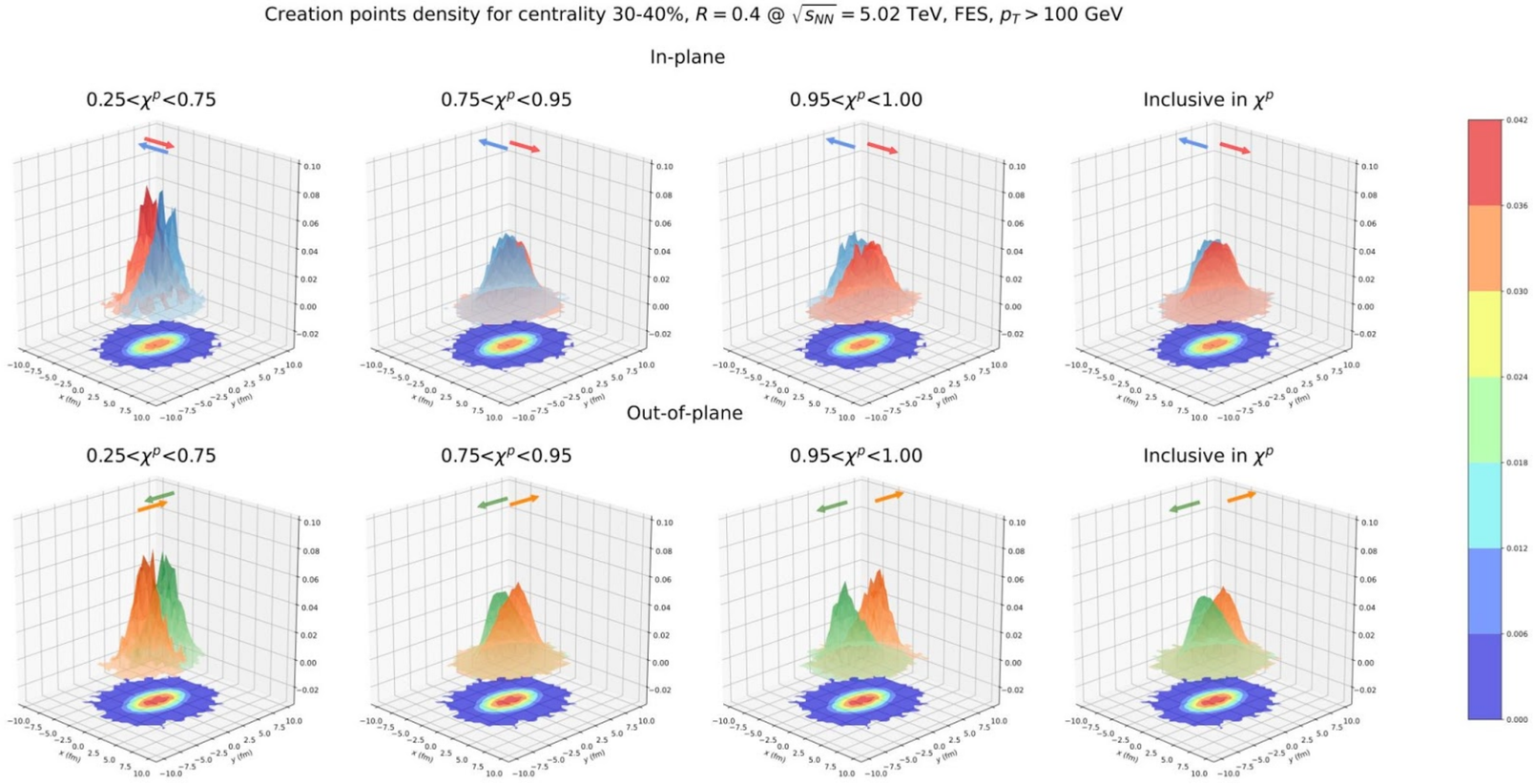


IES reduces the bias induced by the steeply falling jet spectrum, reveals stronger jet modifications!

ML ASSISTED TOMOGRAPHY



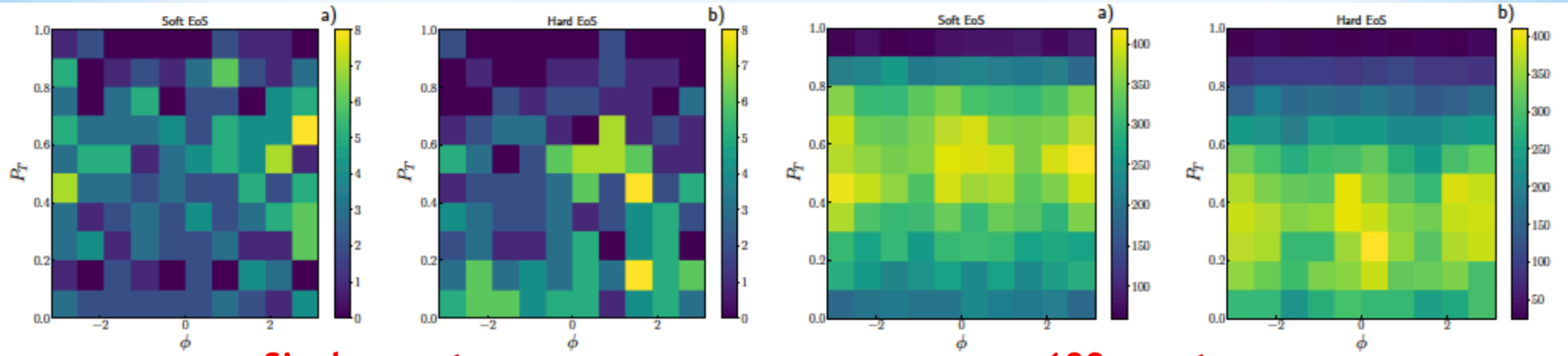


Recovery of full jet population

Location of jet origin

Classification of EoS in relativistic heavy-ion collisions using Deep Learning

Kvasiuk, Zabrodin, Bravina et al., JHEP07 (2020) 133

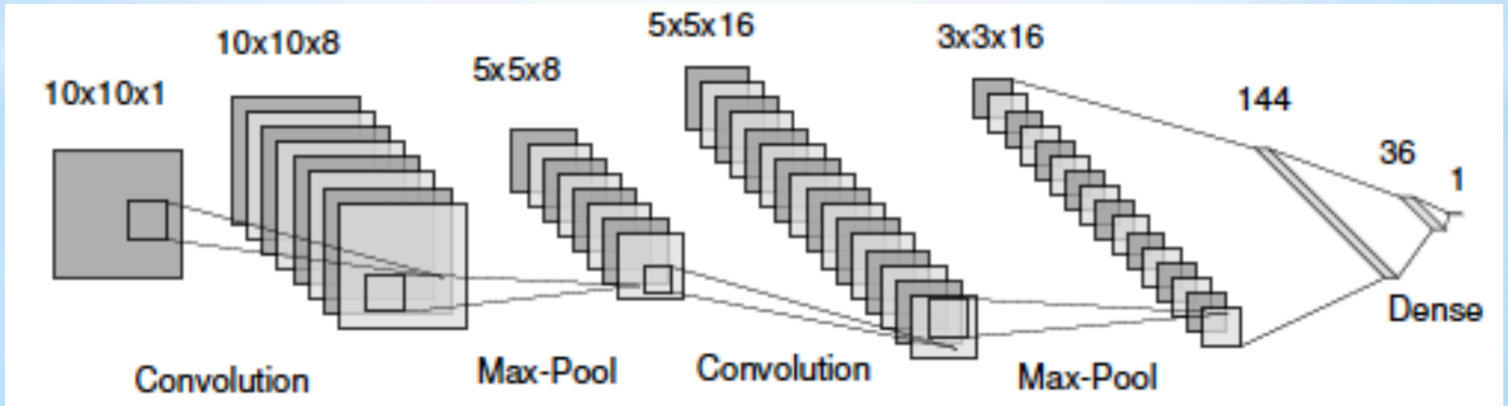


Single event

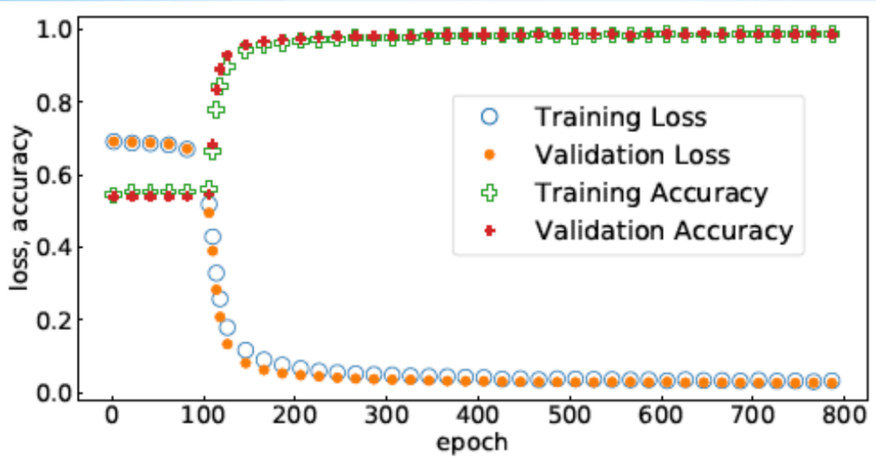
100 events

Proton densities in UrQMD generated events with (a) soft and (b) stiff Equation of State (EoS).

Deep Convolutional Neural Network



TRAINING AND CLASSIFICATION ACCURACY

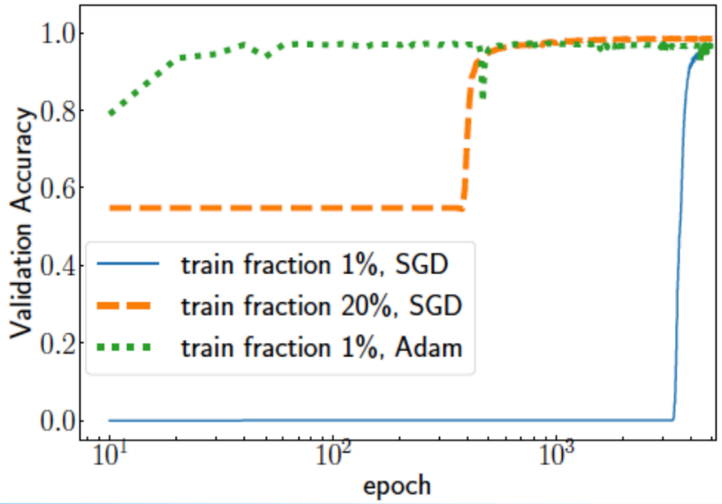


Training energies $\sqrt{s}$ (GeV)	Efficiency (%) 7	11	14
7	94	55	50
11	77	98	90
14	74	96	98

Model trained on one particular energy can be useful at neighbor energies

Stochastic Gradient Descent (SGD) method vs Adam algorithm

Au+Au @ $\sqrt{s} = 11$ GeV

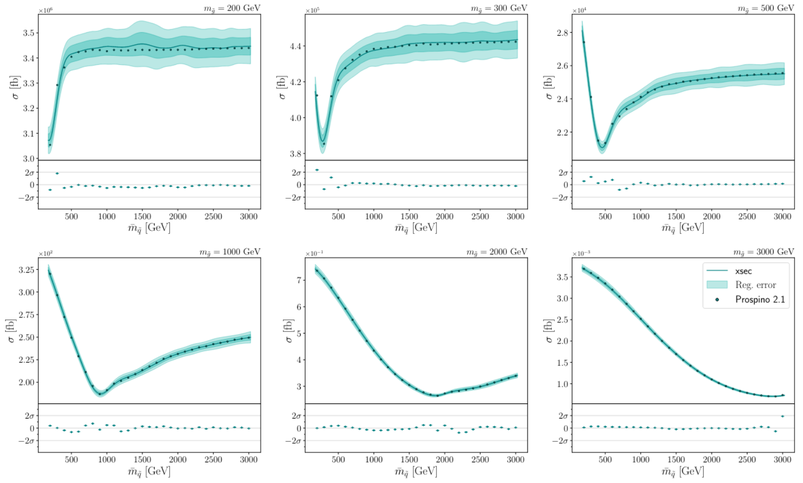


Training CNN classifier with the Adam algorithm permits one to reach hight accuracy during very short training time with little amount of the training data.

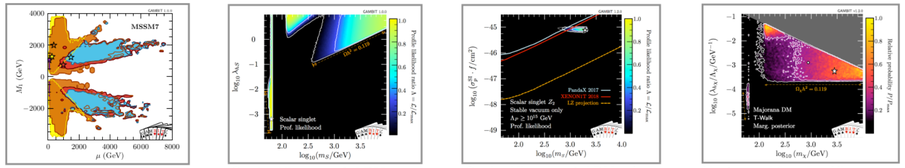
Next step: classification with a combined EoS, containing both soft and stiff EoS

ML FOR THEORY, ACTIVITIES IN OSLO

- *Main focus:* Fast regression-based emulators for slow computations/simulations
- Main methods: Variations of **Gaussian processes** and **Bayesian neural nets**. Both **offline** and **online** learning.
- Main motivation: The computational cost of investigating experiment impact on realistic, many-parameter BSM theories
- (global fits, model comparisons, goodness-of-fit estimation, …)
- *Main projects:*
  - **PLUMBIN':** Develop techniques and codes for fast regression for expensive physics computations
  - **GAMBIT:** Use such fast emulators in large-scale GAMBIT global fits, and use GAMBIT to train new emulators
- *Codes:*
  - **`xsec`:** Gaussian processes for fast NLO cross-sections
  - **`GAMBIT`:** Global fits, high-dim dimensional parameter space exploration
  - **`GPTree`** (in development): Continual regression w/ tree of GPs
  - More to come out of the new **PLUMBIN'** project…



`xsec`

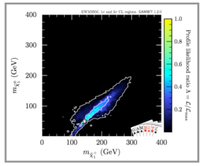


MSSM7: 1705.07917
GUT-scale SUSY: 1705.07935

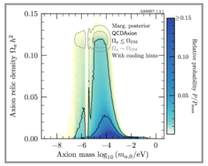
Scalar Higgs portal DM: 1705.07931

Scalar Higgs portal DM w/ vac. stability: 1806.11281

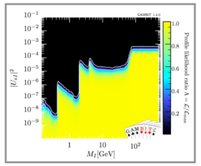
Vector and fermion Higgs portal DM: 1808.10465



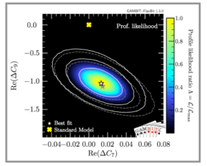
EWMSSM: 1809.02097



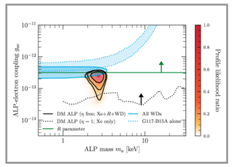
Axion-like particles: 1810.07192



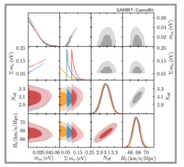
Right-handed neutrinos: 1908.02302



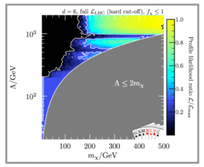
Flavour EFT: 2006.03489



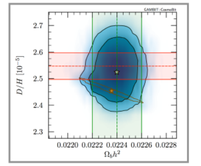
More axion-like particles: 2006.03489



Neutrinos and cosmo: 2009.03287



Dark matter EFTs: 2106.02056



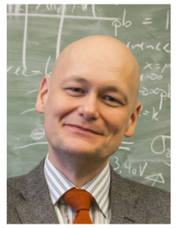
Cosmo ALPs: 2205.13549

GAMBIT

ML FOR THEORY, ACTIVITIES IN OSLO: PLUMBIN'

- *PLUMBIN' — Developing solvents for unclogging the calculational bottleneck in high-energy physics*
- RCN+UiO FRIPRO "Fellesløft", funded for 2022–2028
- Collaboration between Dept. of Physics and Dept. of Mathematics, UiO
- *Current team:* 2 permanent, 1 postdoc, 3 PhD students, 3 master students
- *Upcoming positions:*
  - PhD, 2024–2027 (Mathematics)
  - PhD, 2025–2028 (Physics)
  - Postdoc, 2023–2025 (Mathematics)
  - Postdoc, 2024–2026 (Physics)
- *Some ML-related project goals:*
  - Create ML-based regression tool for fast evaluation of expensive QFT calculations (e.g. high-order cross-sections).
  - Create framework for continual (online) regression. Use it to speed up global fits and extract trained emulators directly from such fits.
  - Use these tools to perform larger and more detailed studies of how LHC results + other experiments impact BSM physics

The PLUMBIN' Team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SUMMARY

- lots of activities in ML applications to high-energy physics
  - promising for the future
  - many further ideas to pursue
- traditional techniques combined with data analysis
  - important to maintain interpretability