Hadronic Reconstruction (with Machine Learning)

Pitt-PACC Workshop: LHC Physics for Run3

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TRIUMF

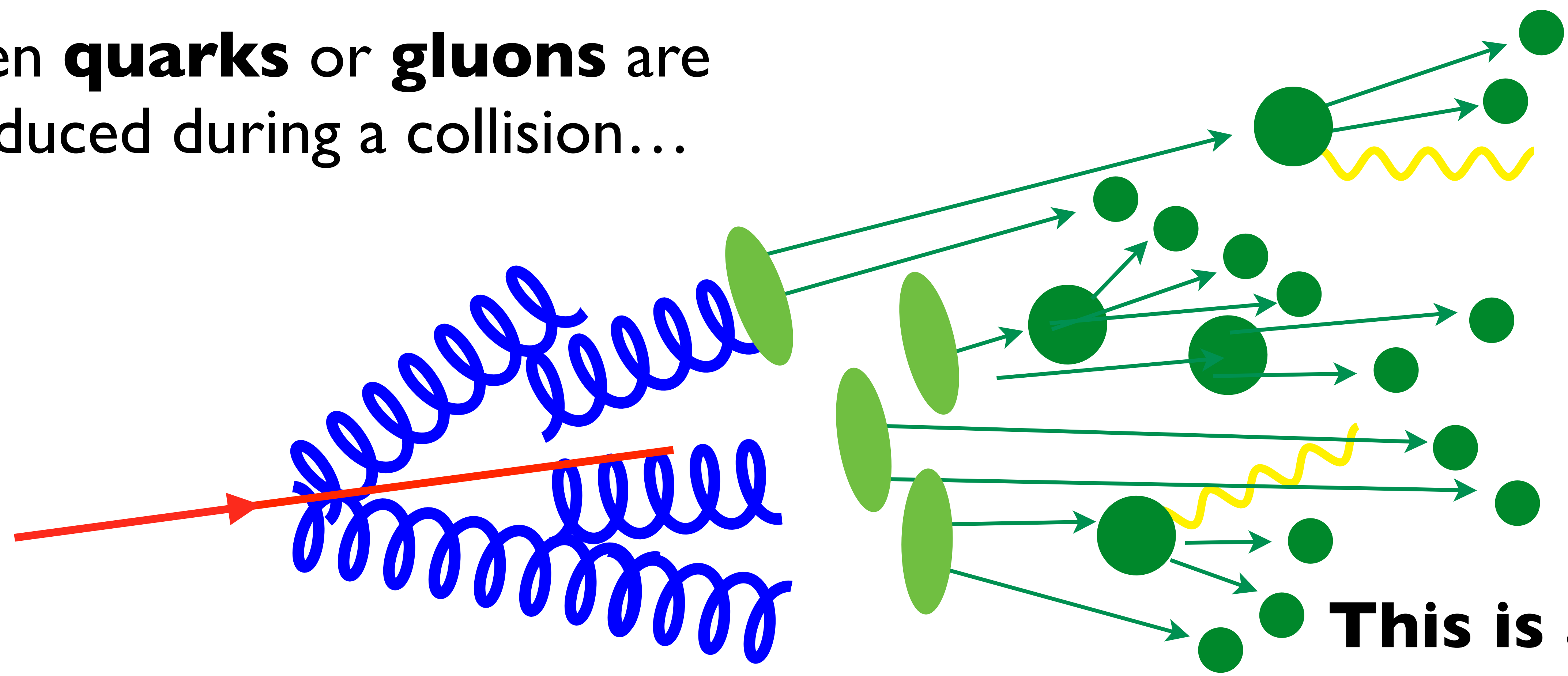
ATLAS EXPERIMENT

CMS

Jets at the LHC

Image credit: B. Nachman

When **quarks** or **gluons** are produced during a collision…



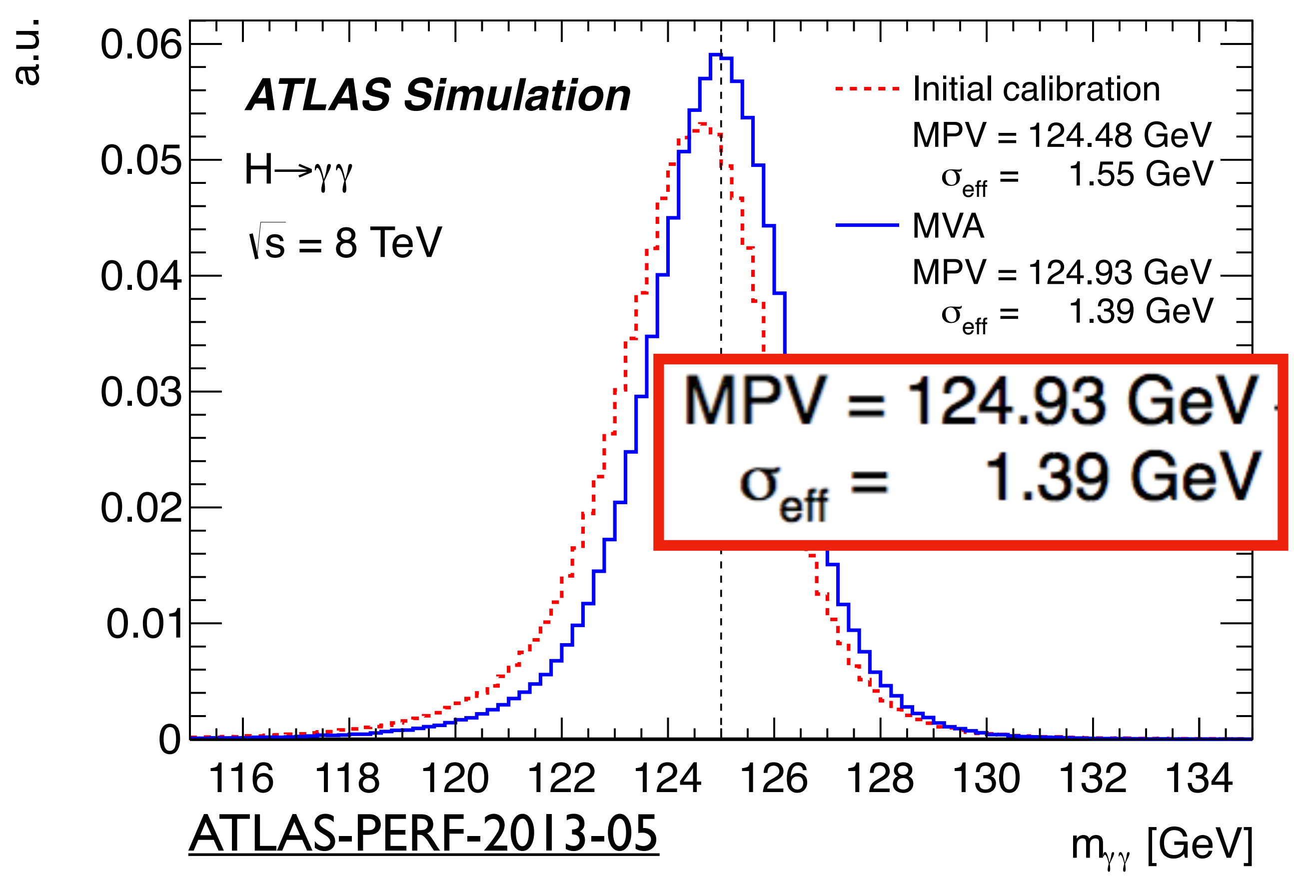
They "shower" into more gluons and quarks…

Which hadronize into stable (or unstable particles)

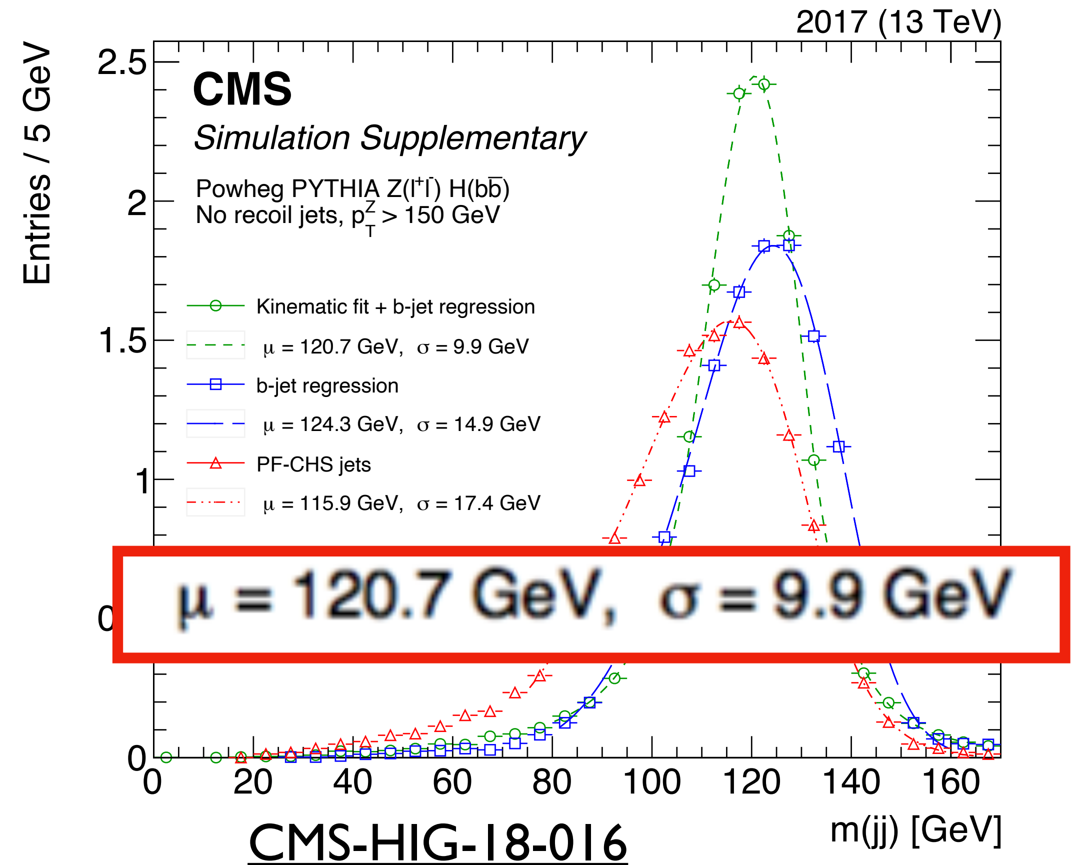
This is a jet!

Need to measure not just a single particle, but hundreds per event (mostly **pions,** 2/3 charged, 1/3 neutral)

The Hadronic Challenge



ATLAS-PERF-2013-05



CMS-HIG-18-016

Measuring jets is a huge challenge: resolution is clearly reduced compared to other types of final states!

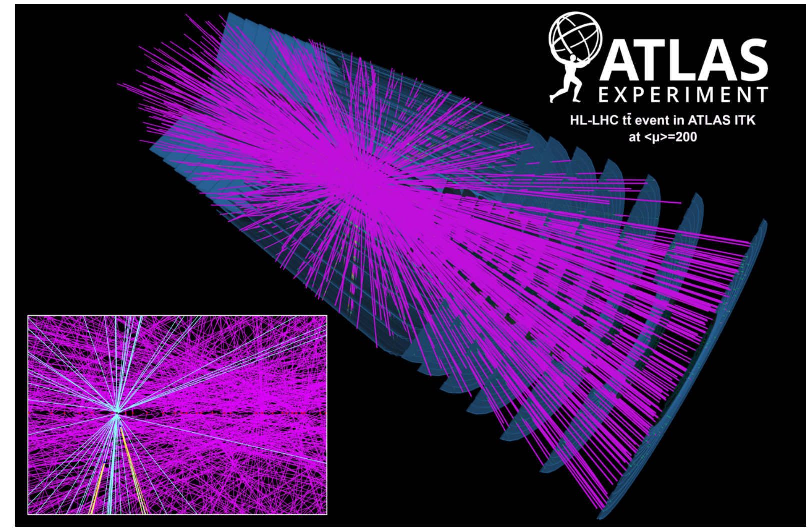
But the high branching ratio of the Higgs and possible new physics to jets still makes jets **critical** for searches and measurements

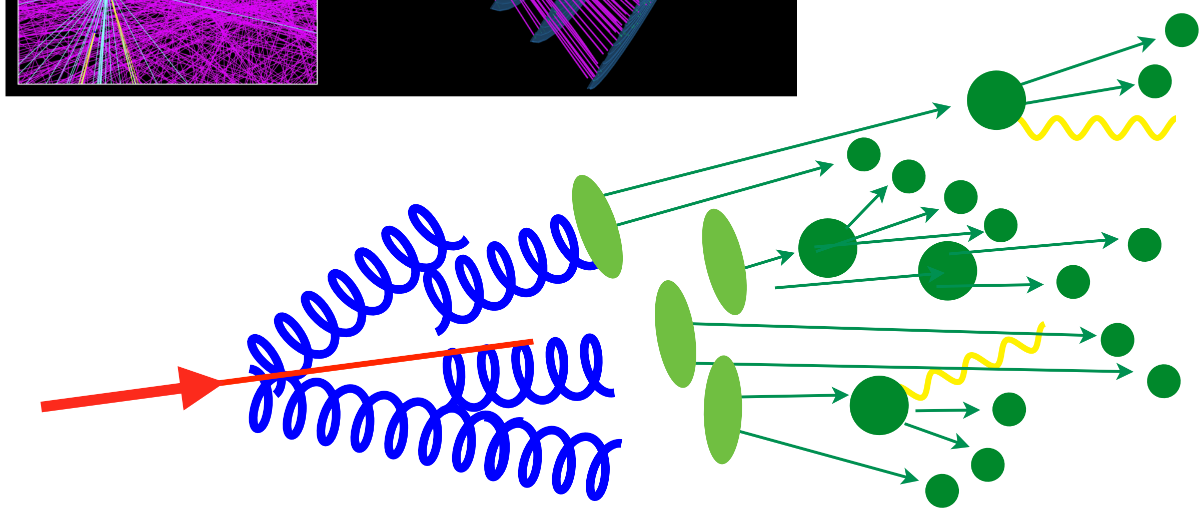
And new ideas can have a big impact!

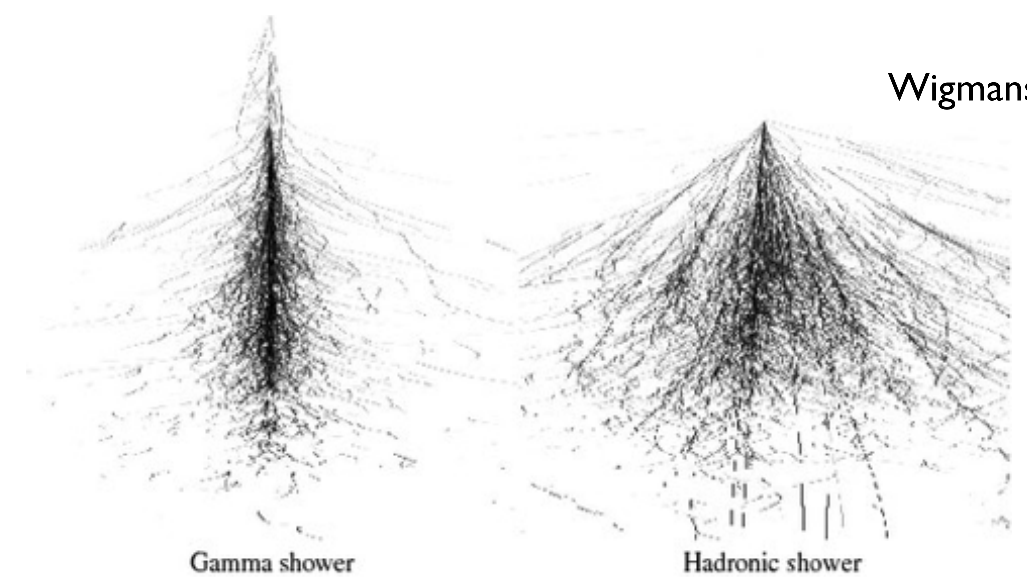
NB: not covering jet substructure (though there's a lot of ML there!)— see Petr's talk

Why is Jet Resolution So Bad?

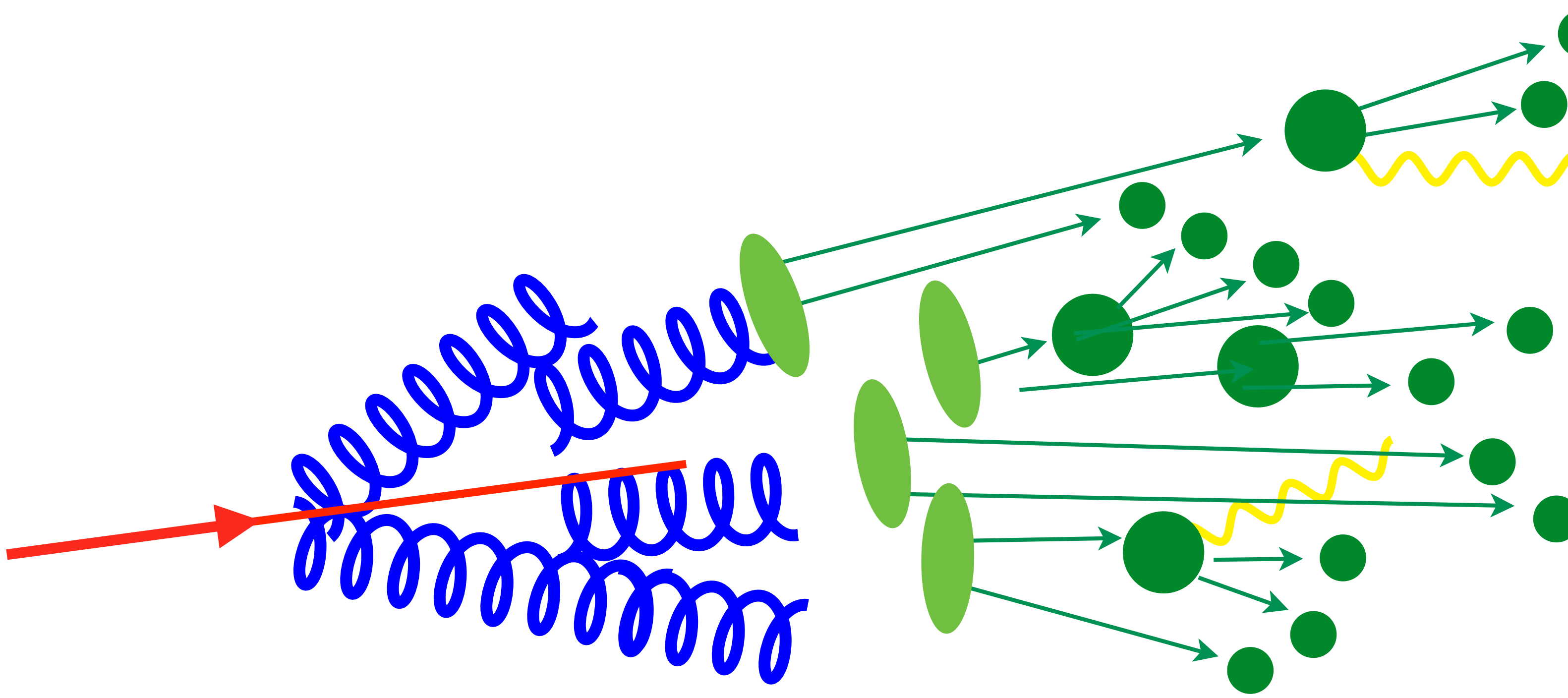
- Three main effects:
  1. Pileup (won't talk much about this today)
  2. Fluctuations in fragmentation/ hadronization/etc. (will mention briefly)
  3. Fluctuations in individual particle showers (focus of my talk)







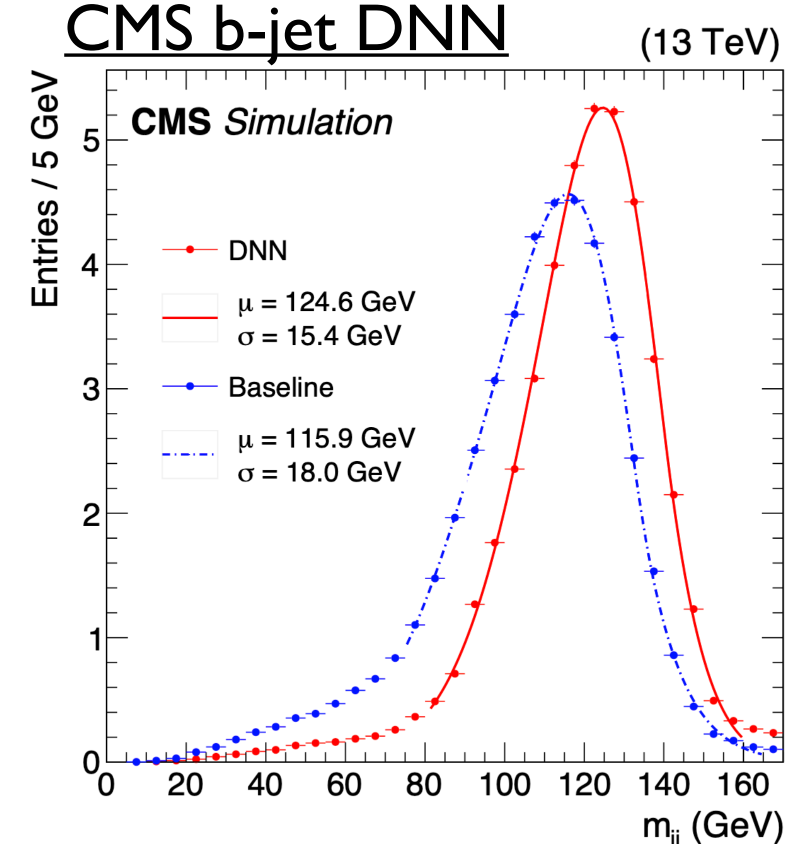
Differences in Fragmentation

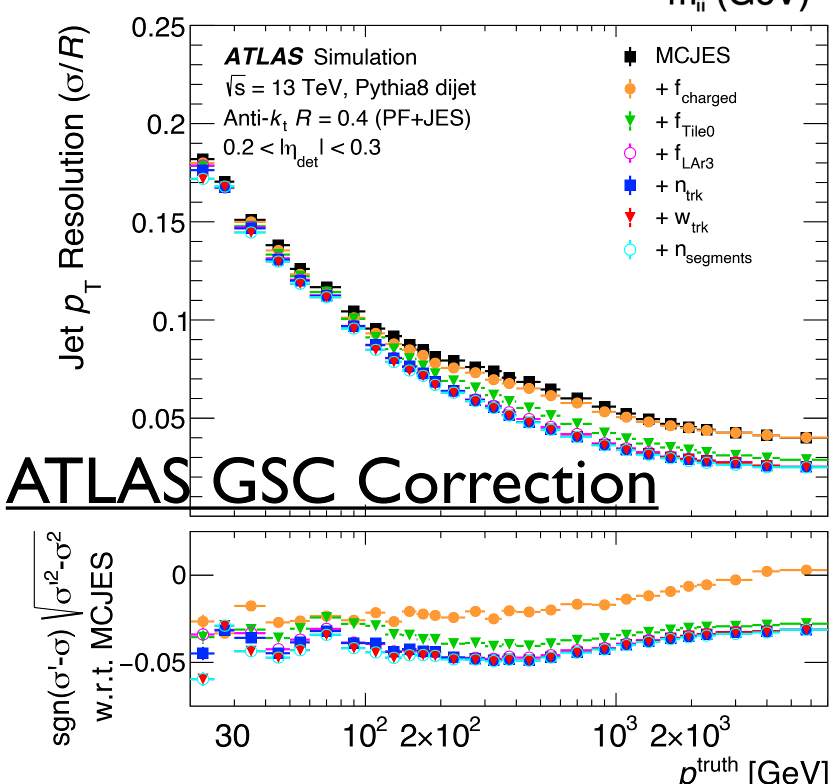


Individual particle showers fluctuate, but so do the jets themselves: the number of hadrons can vary, the types of hadrons, and so on…

Lots of techniques, both with and without machine learning, can correct for some of these fluctuations and improve resolution

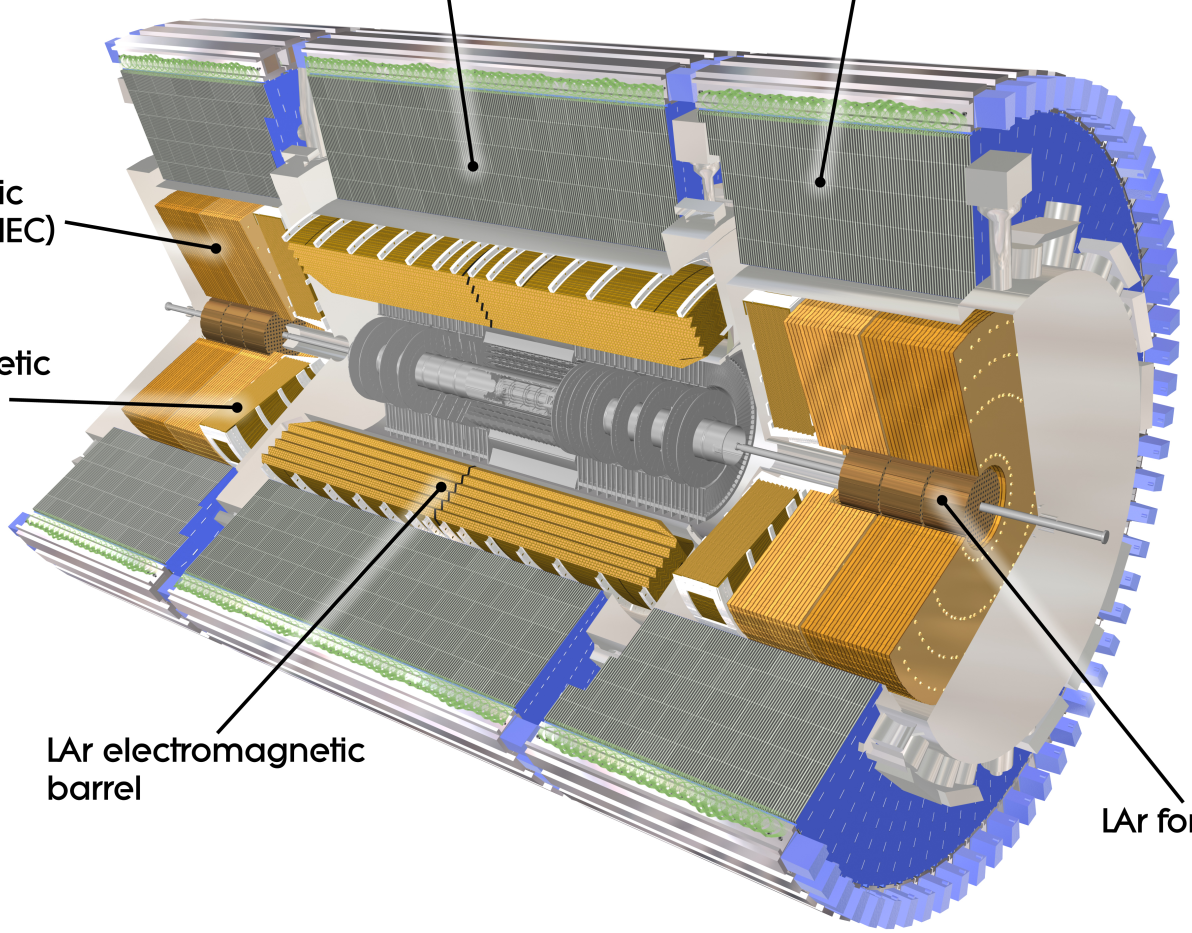
CMS b-jet DNN





ATLAS GSC Correction

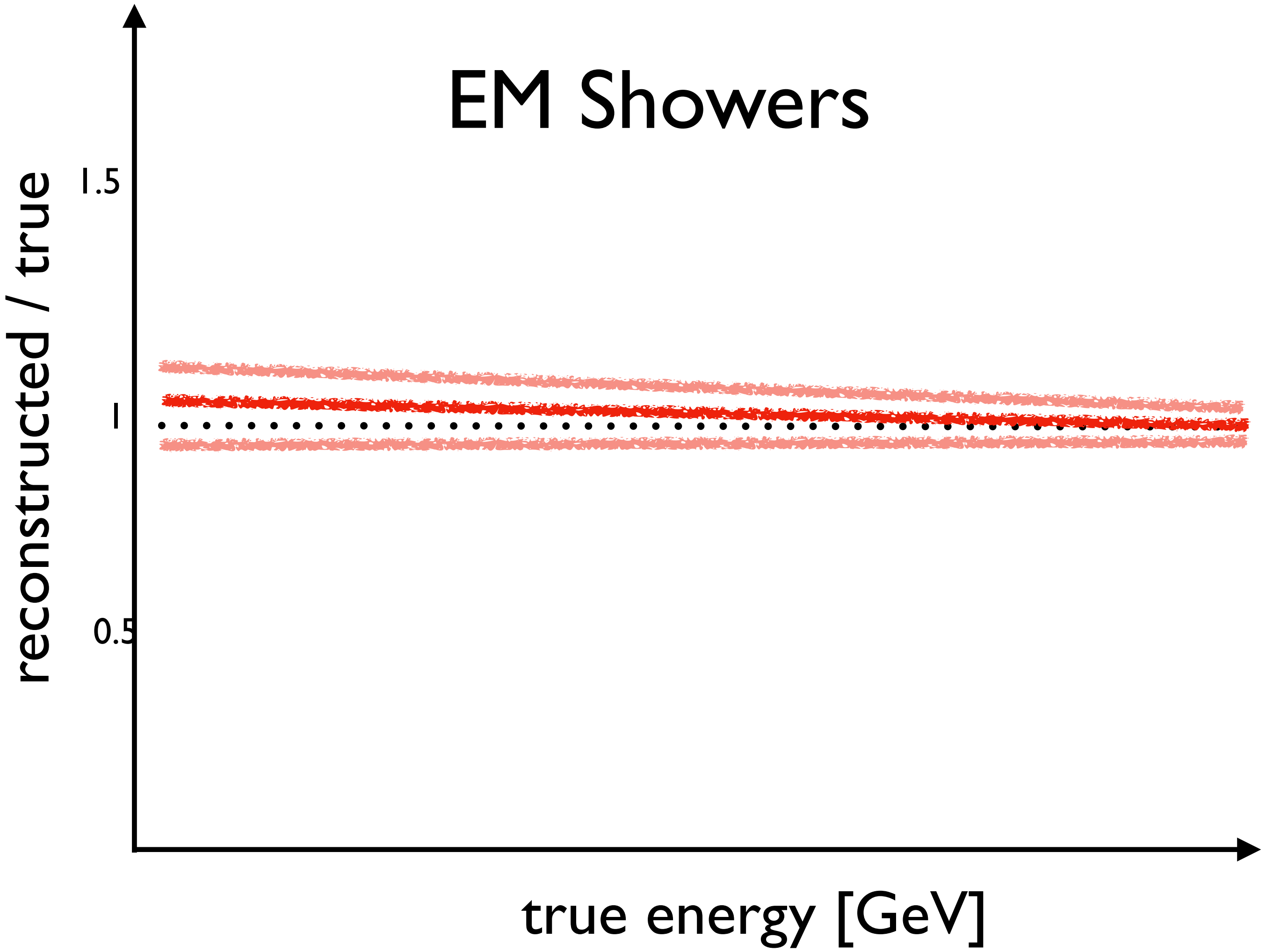
Calorimetry at the LHC

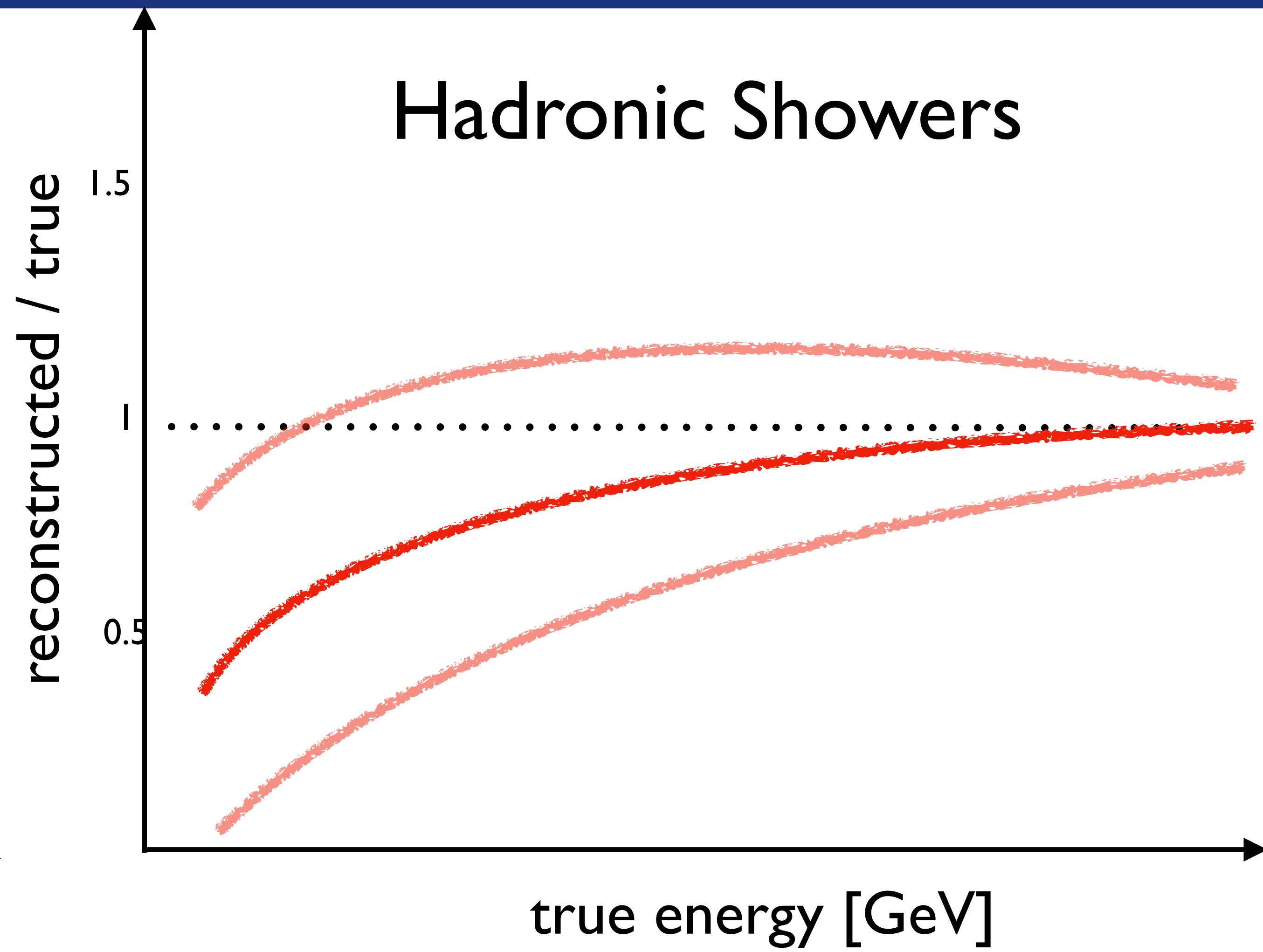


ATLAS's and CMS's calorimeters built to measure particles within jets: record energy and location of interactions/depositions

However, different particles interact with the calorimeter differently: π^0 decay to $\gamma\gamma$, while $\pi^{\pm}$ are stable and interact directly

Calorimeters and Showers





Our calorimeters are calibrated to the EM scale: EM showers (from e, γ, π^0) are measured 'correctly'

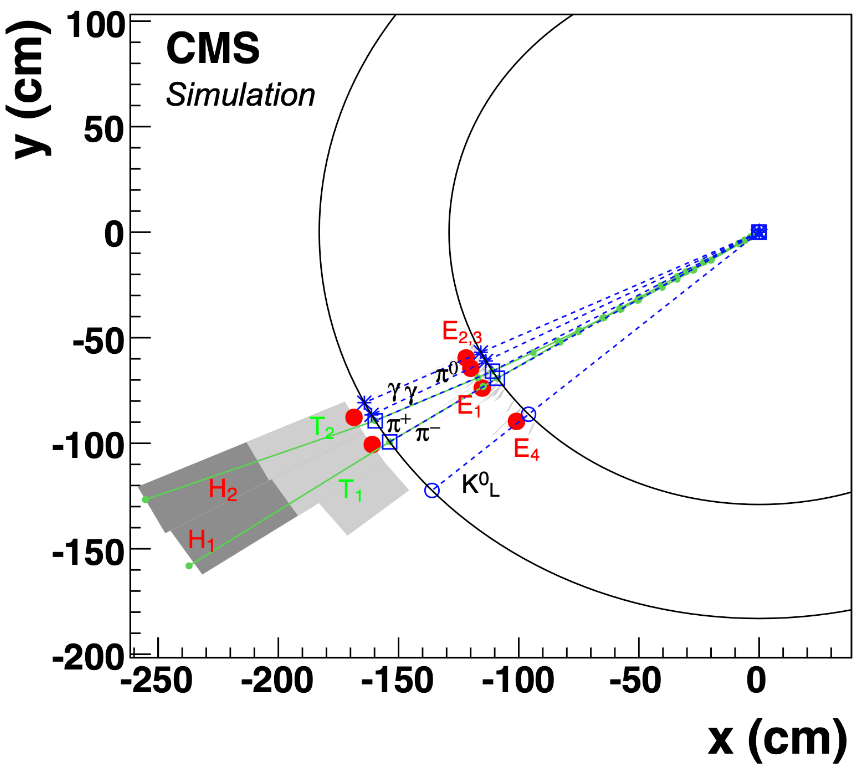
Resolution is good: all showers are 'similar'

Hadrons can also interact with nuclei: no way to measure this energy in ATLAS/CMS!

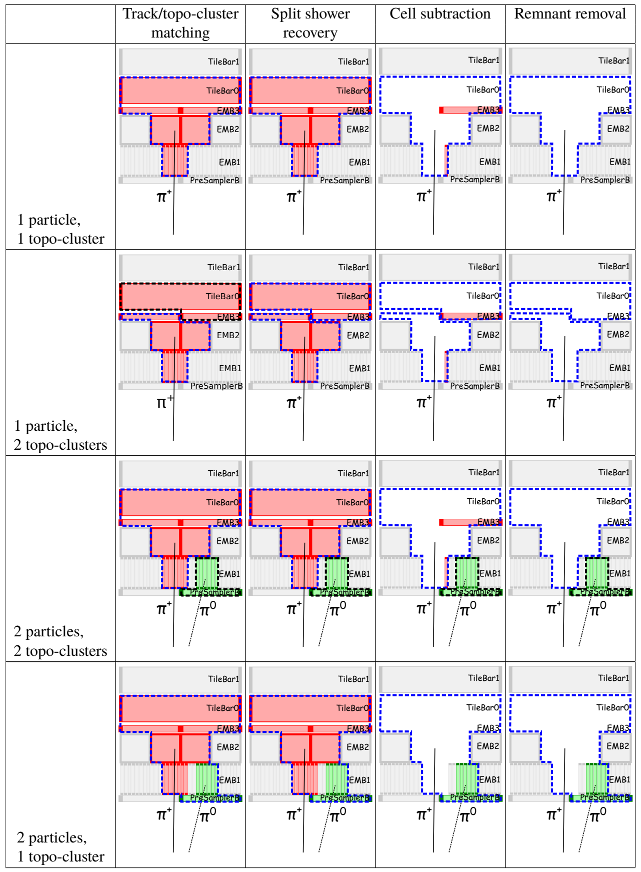
Every shower is unique: huge resolution penalty from variations

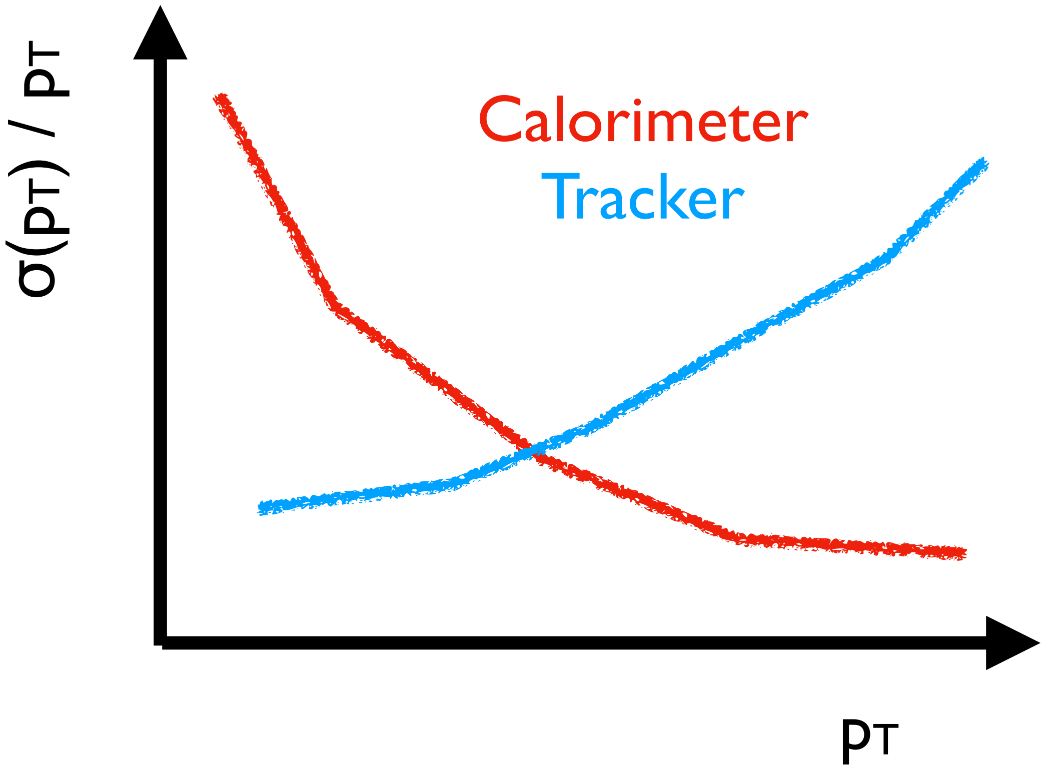
Hadronic Reconstruction, Today

CMS PFlow



ATLAS PFlow

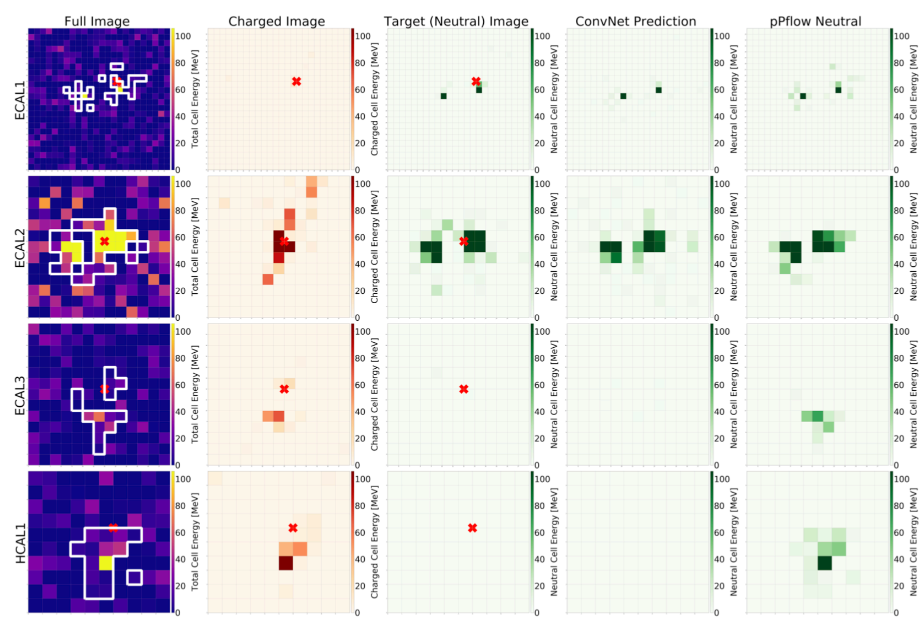




One way to improve: use inner-detector tracks to measure hadrons whenever possible: significantly improved resolution in many cases!

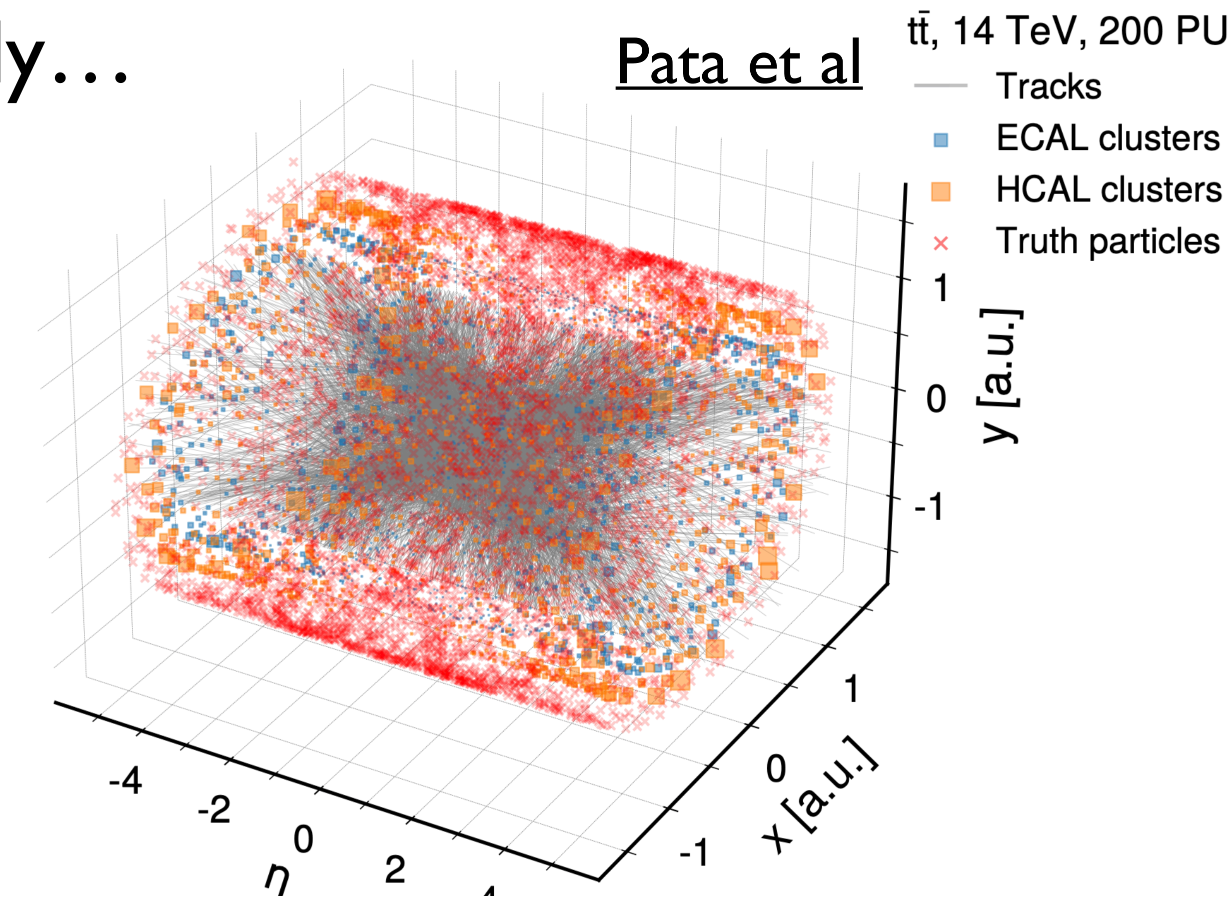
Hadronic Reconstruction, Tomorrow

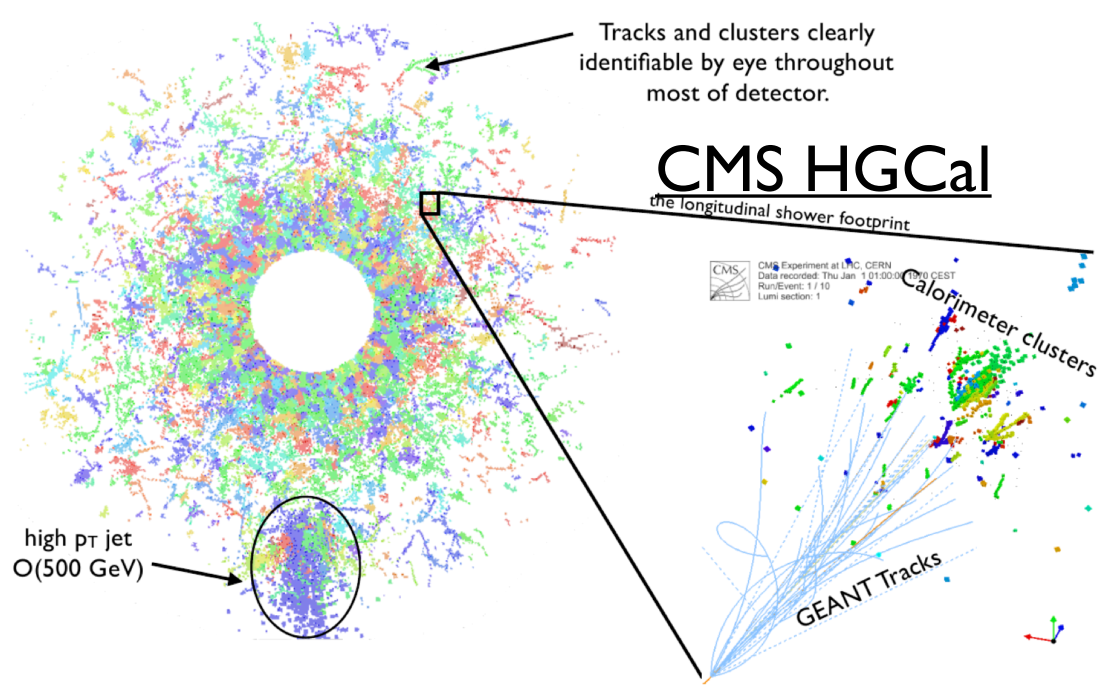
ML has improved jet calibration already…



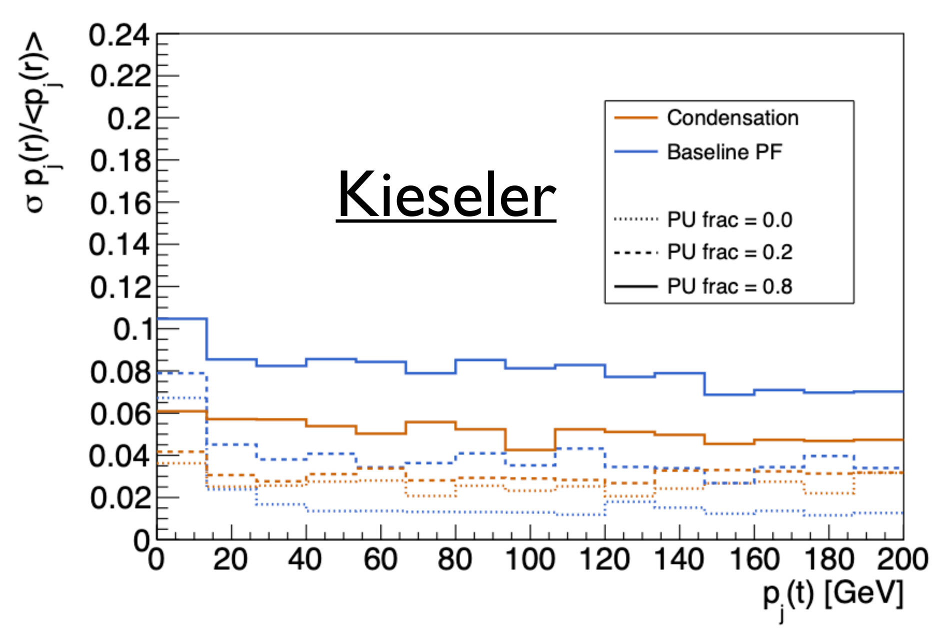
Di Bello et al

Pata et al





CMS HGCal



Kieseler

Can we also improve jet inputs with ML?

Calorimeter-Only Pion Reconstruction With Deep Learning

ATLAS-PHYS-PUB-2020-018

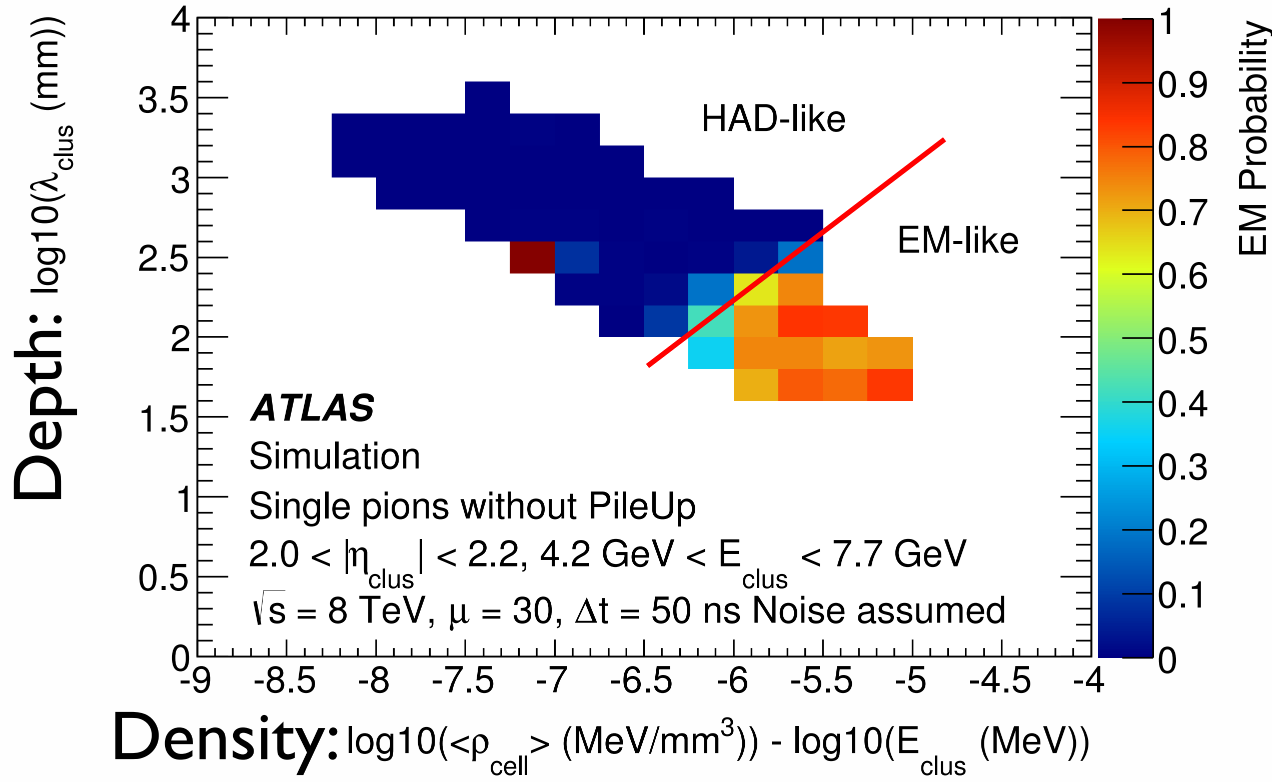
Apologies for focusing on a single, biased example!

Calorimeter-Only Calibrations

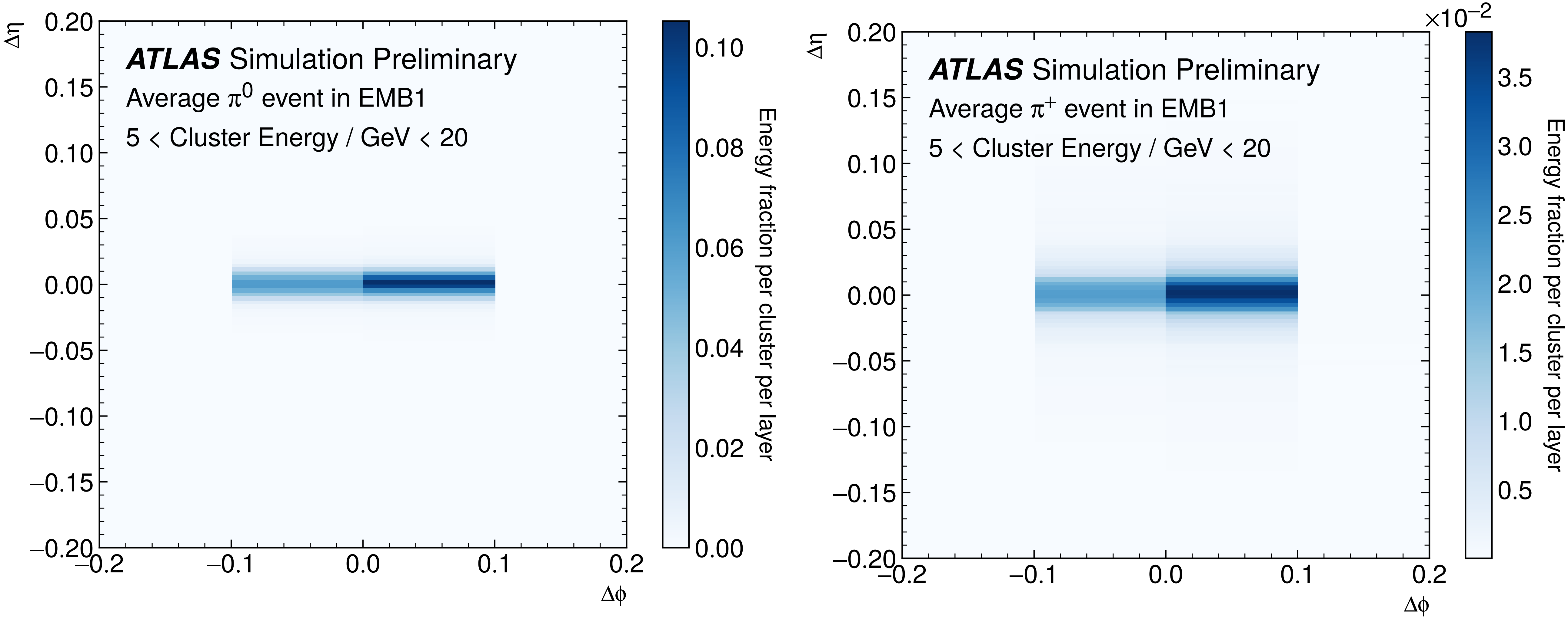
Traditionally, ATLAS has used the "Local Cell Weighting" technique for calorimeter-only jet reconstruction

1. Classify topo-clusters as "EM-like" or "Hadronic-like"
2. Apply a calibration appropriate for EM or Hadronic pions

Features used are quite simple: depth and density.
Can we do more with the high granularity calorimeter information?



Average Pions

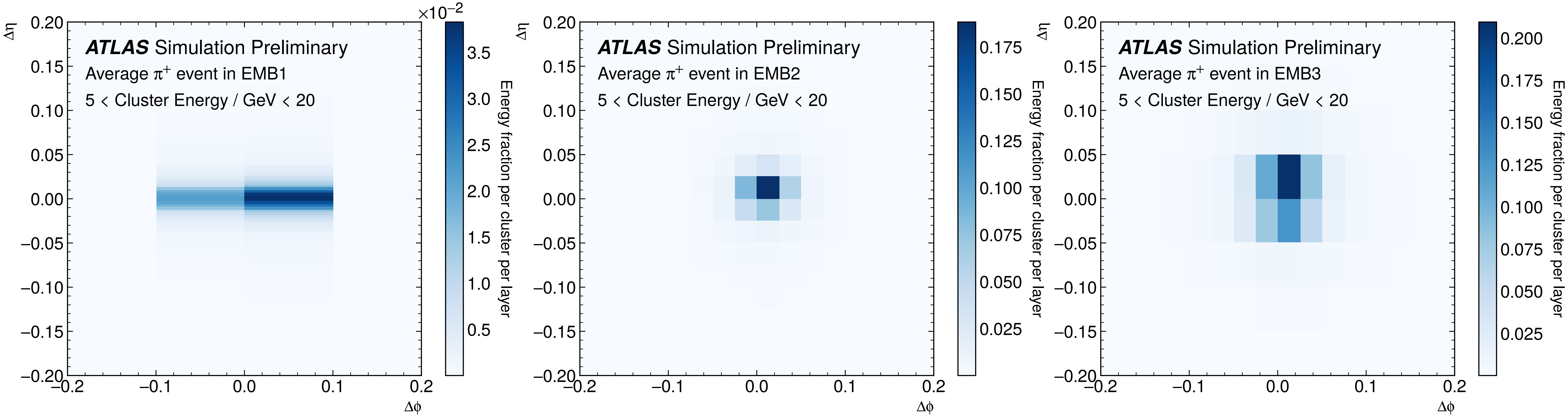


Treat energy in each 'cell' of topocluster as pixel intensity

Here, compare π^0 and $\pi^{\pm}$ in the first layer of the calorimeter: use simulated samples of pure π's

See expected differences: $\pi^{\pm}$ are 'broader'

Calorimeter Layers



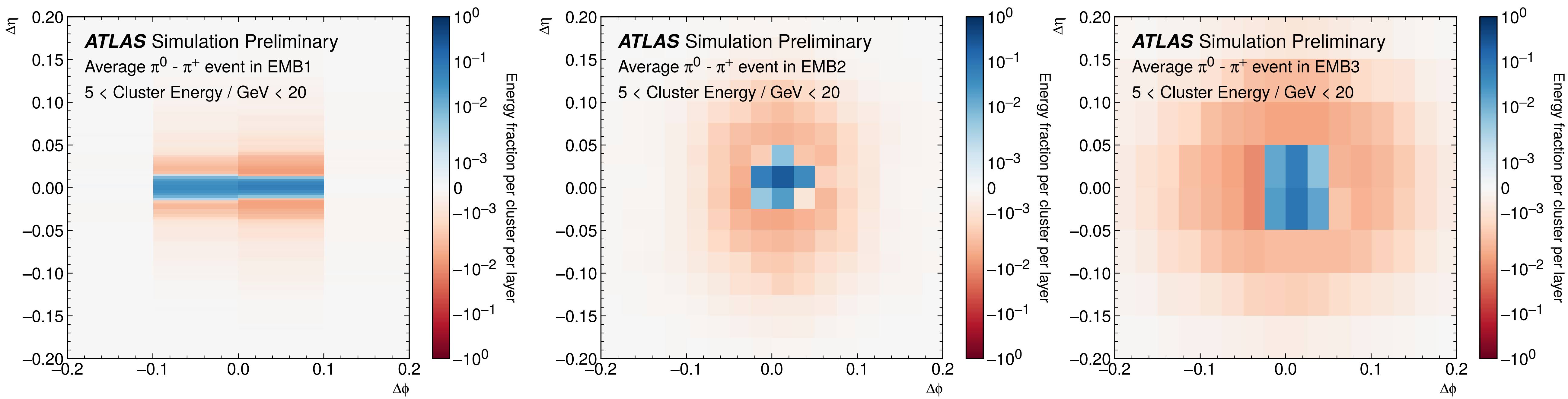
Different calorimeter layers have different granularity

Here, show π^+ in first three calorimeter layers

Three additional layers also available

Can consider these as 'RGB channels' in NNs

Differences Between Pions



By just subtracting π^+ from π^0 images, can already visualize differences between EM and hadronic showers

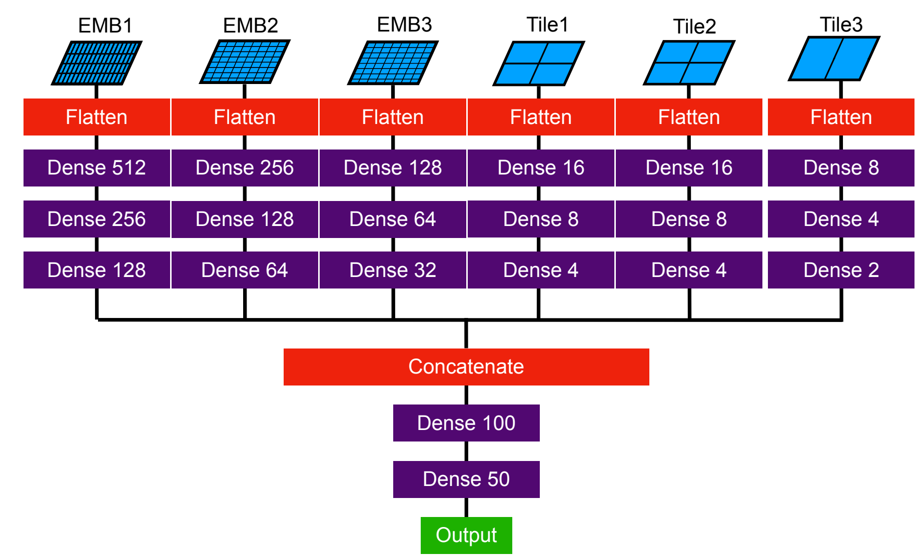
Can deep learning classifiers use this information?

Classification

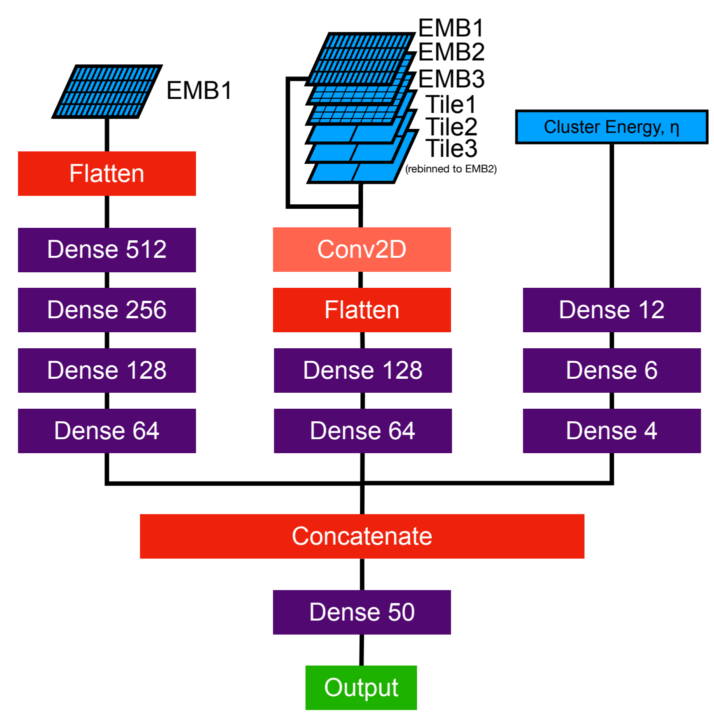
Architectures

Three general classes
of NN architecture studied

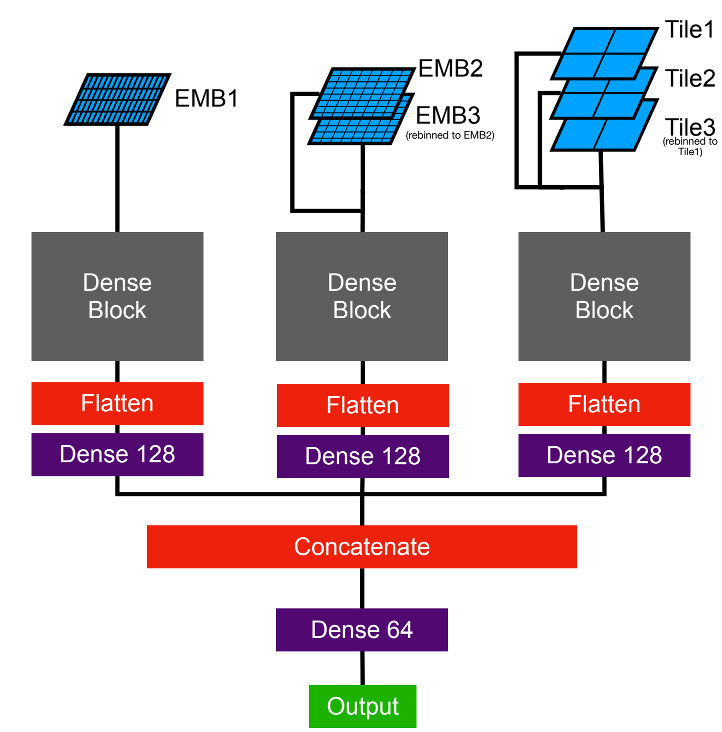
DNN: Large, deep networks
with cells as direct inputs



CNN: use convolutions to
extract useful features from
different portions of the image



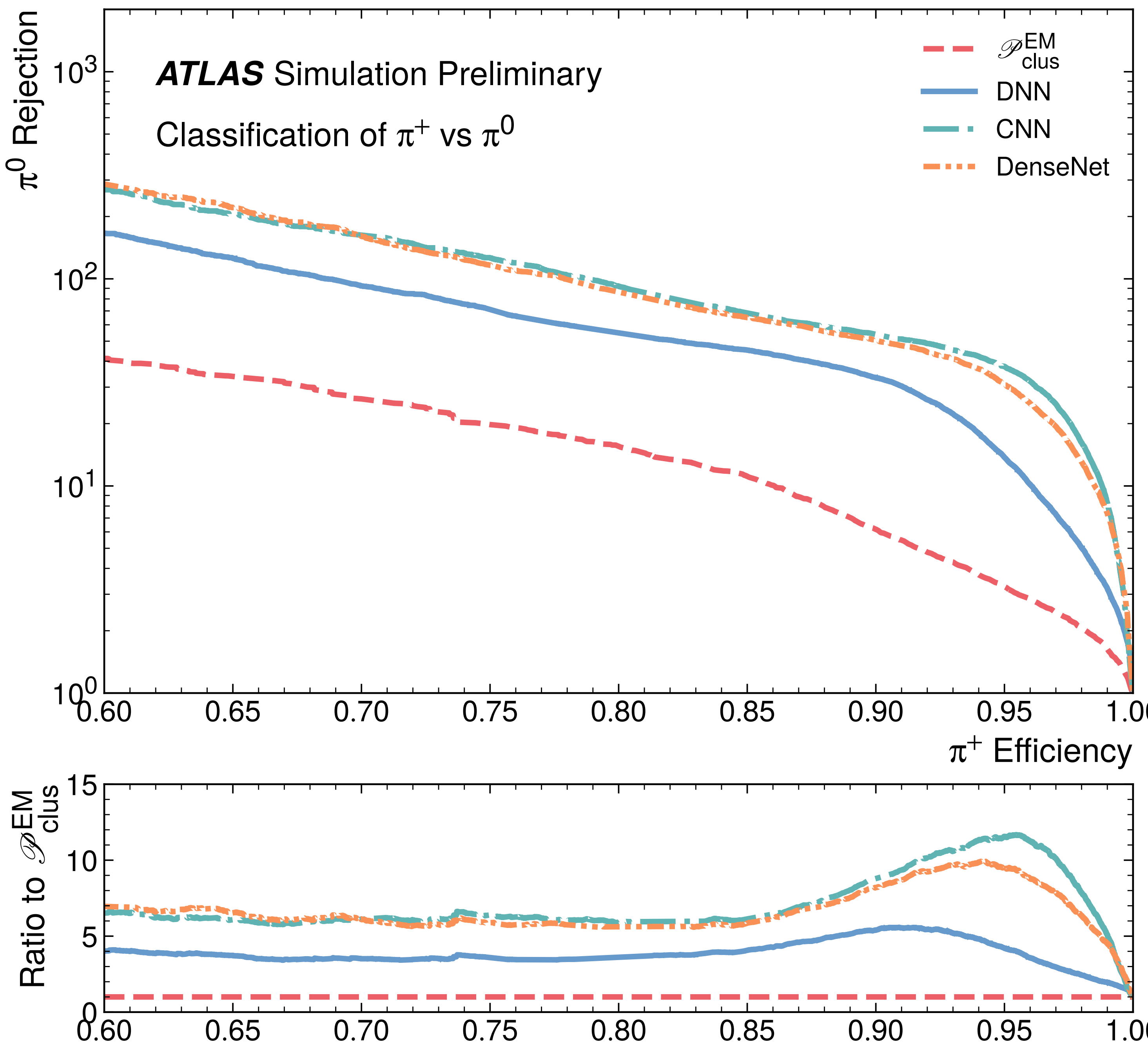
DenseNet:
Industry-designed,
sophisticated CNN
with information
propagation



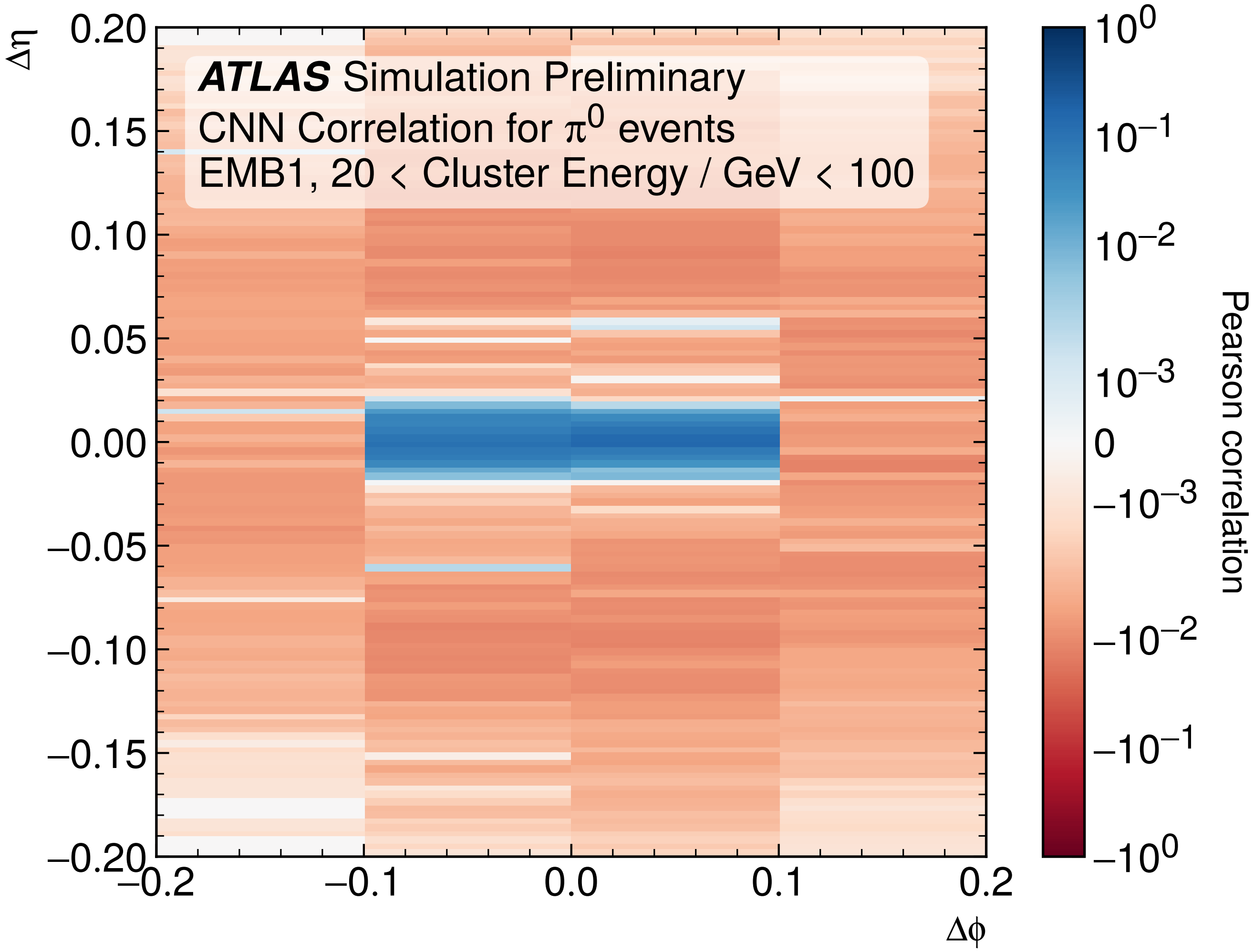
Classification ROC

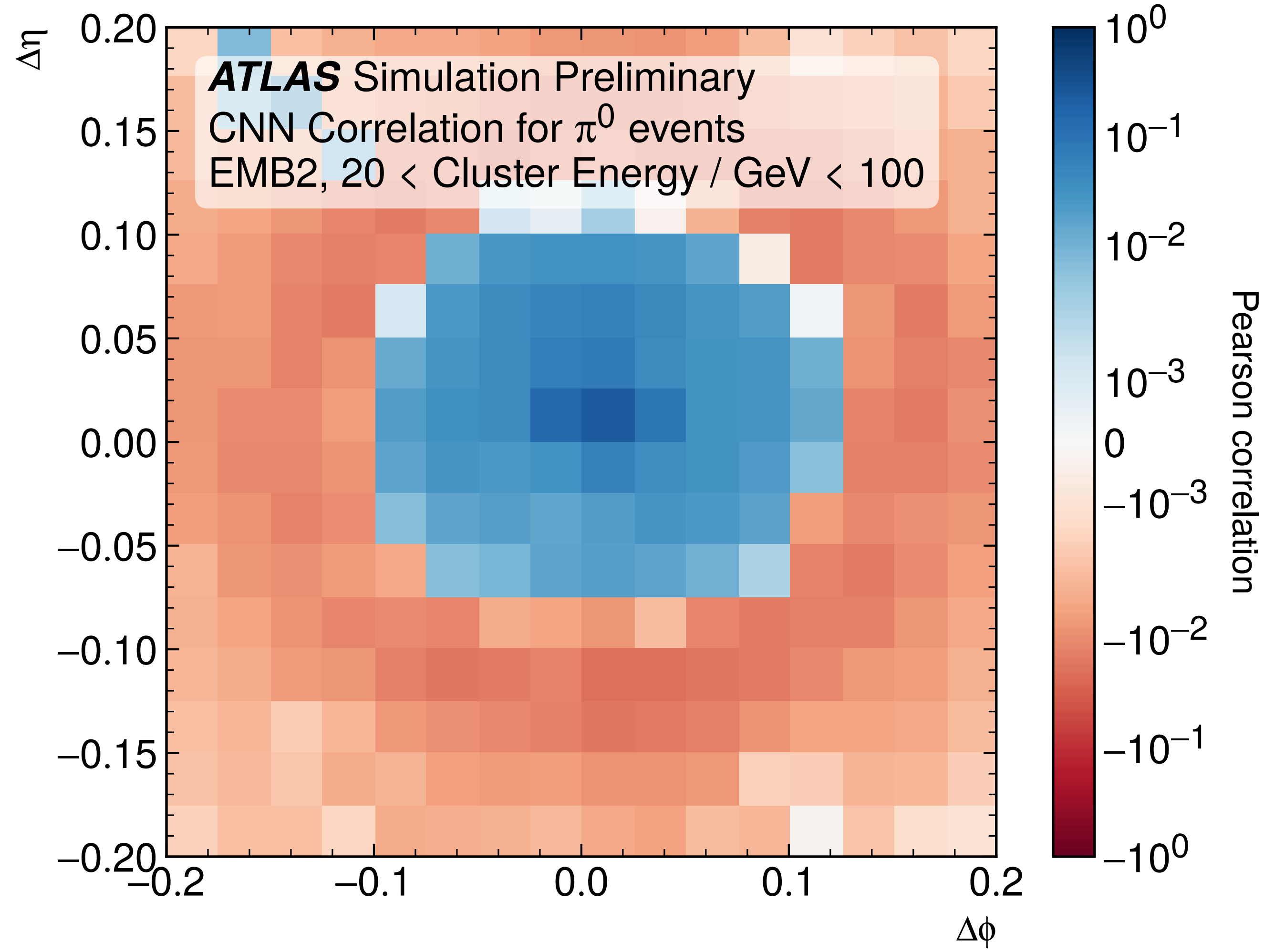
Compare π^+ efficiency vs π^0 rejection (1/efficiency) for different algorithm

Compared to baseline, see huge performance Improvement: factor of 12x!



Classifier Correlation: π^0





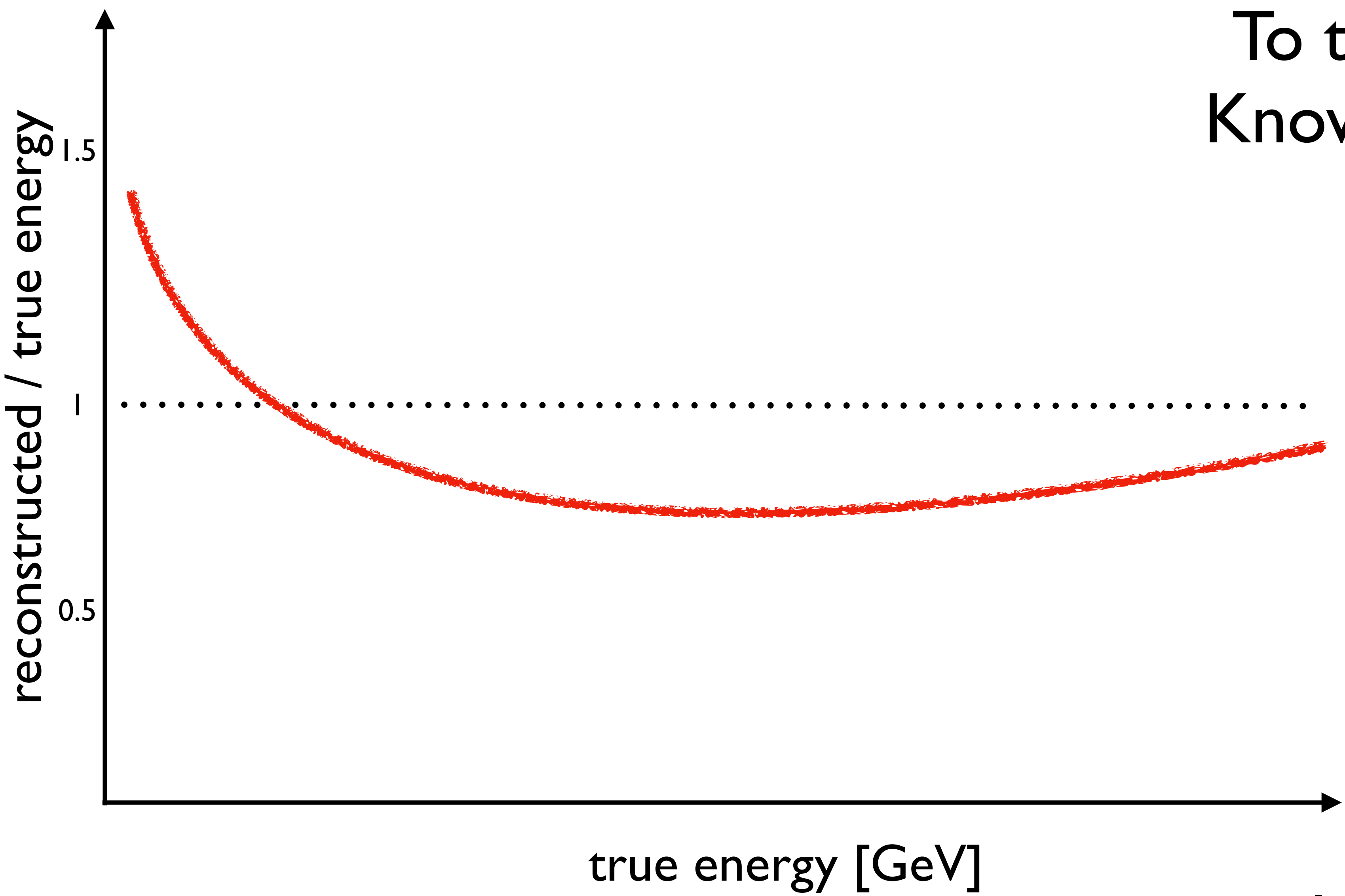
Here, calculate the correlation coefficient between each pixel and the classifier

Can visualize (very roughly) what the CNN is learning

Can see the physics we expected from the images!

Energy Regressions

Understanding Calibrations

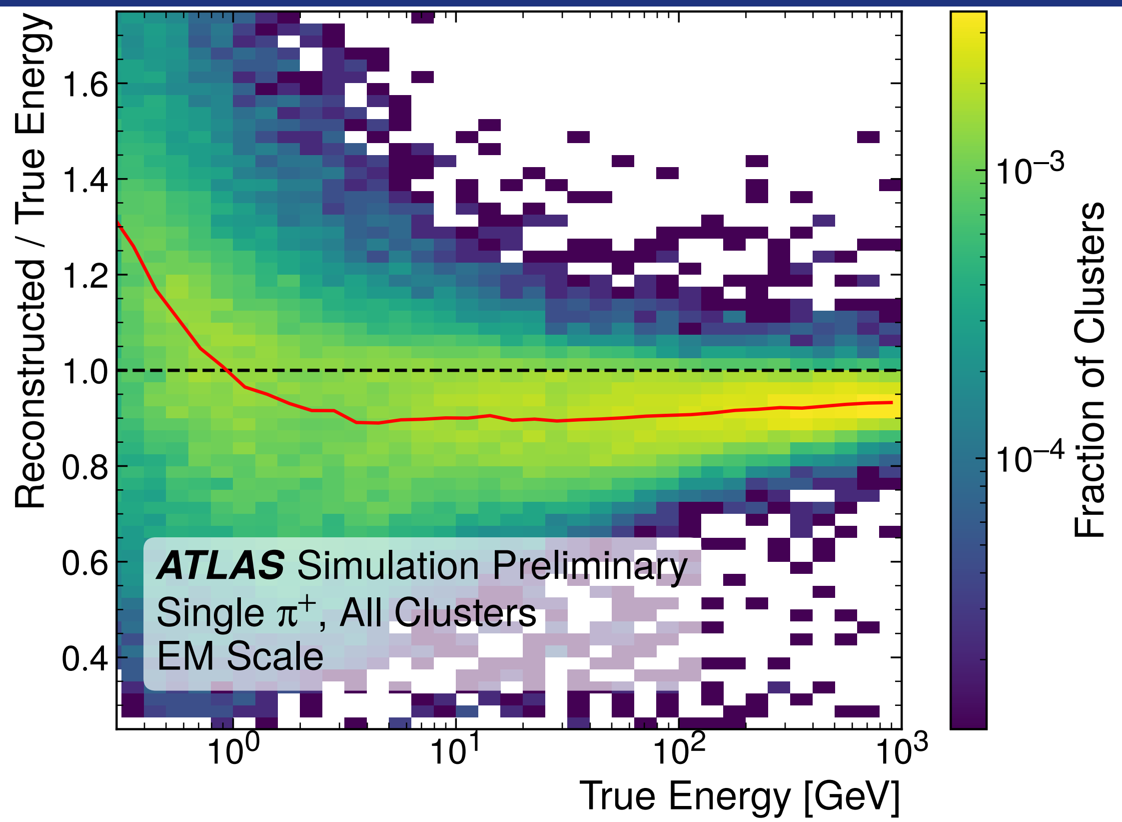


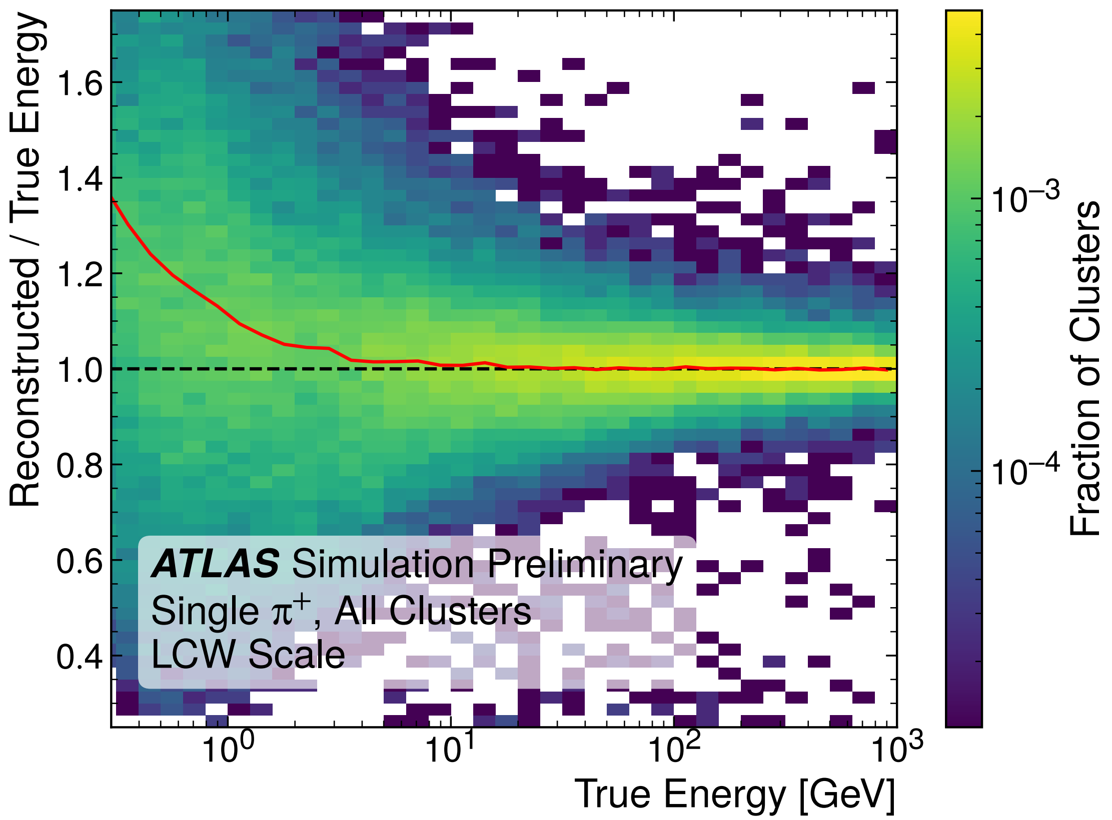
Use simulated data
To test energy calibrations:
Know 'truth' from simulation

Compare reconstructed energy to true energy, as a function of True energy

Ideally: close to 1, and narrow distributions

Correcting π^+





At 'EM' scale, can see energy reconstruction issues for hadronic particles, like π^+

Energy is *missed* due to non-measured nuclear interactions

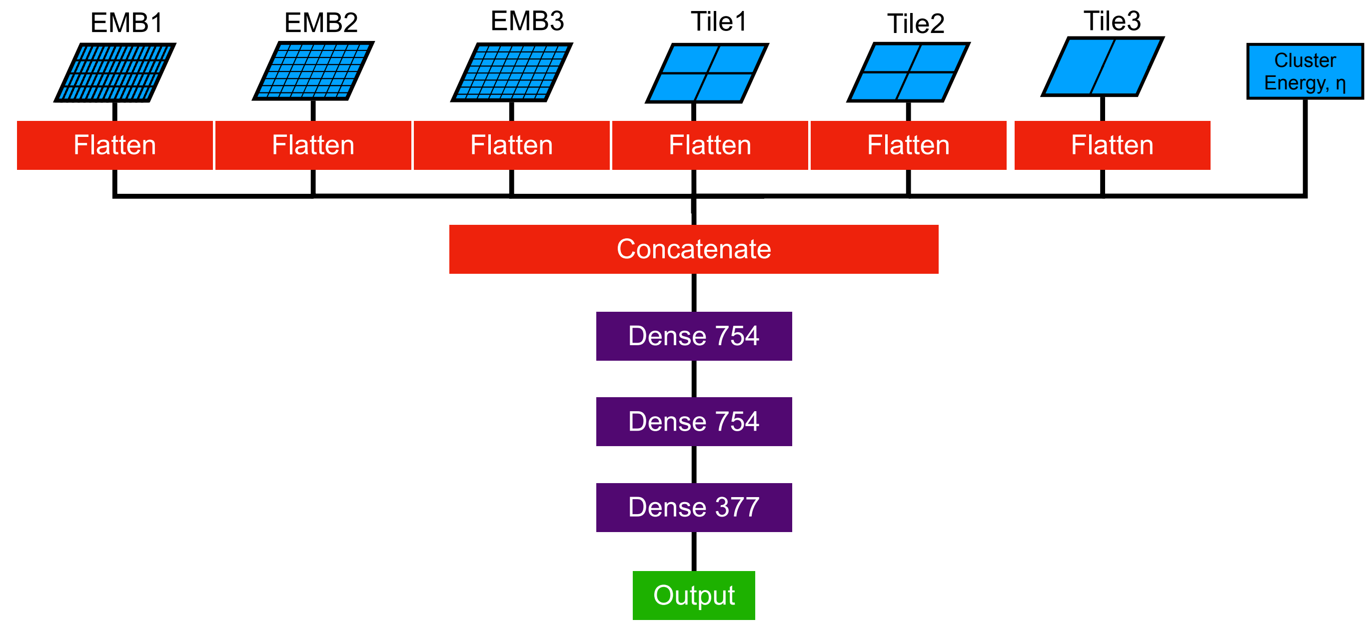
Feature-based method corrects for this: see 'correct' energy scale for wide range of true energy, but over-compensation at low energy

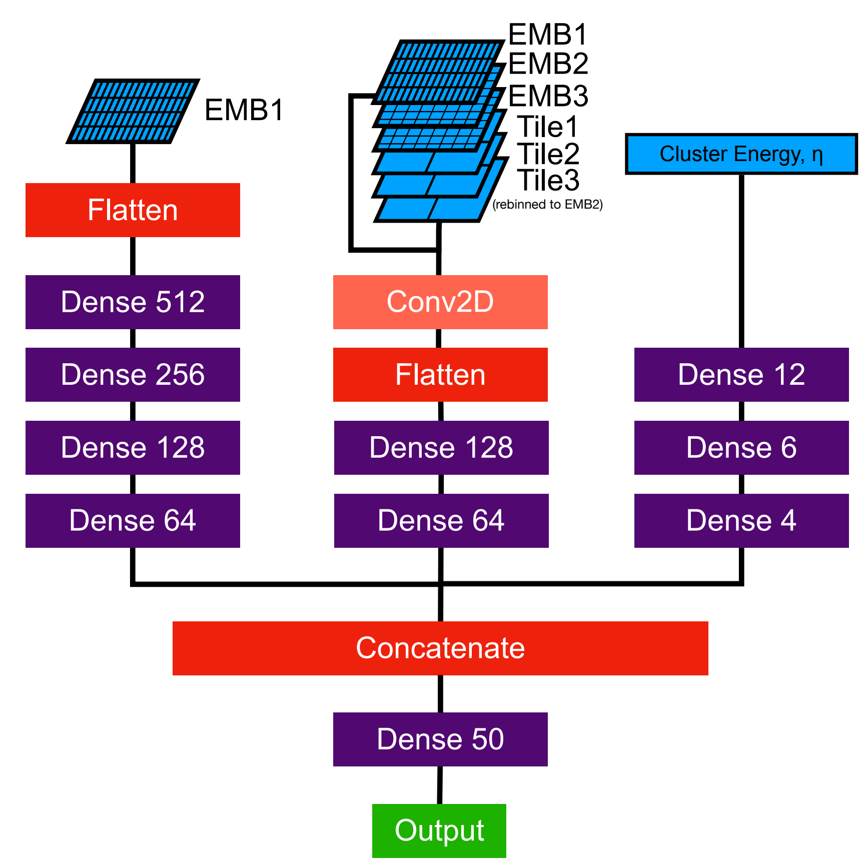
Regression Architectures

Train regressions on pure π^0 and π^+ samples

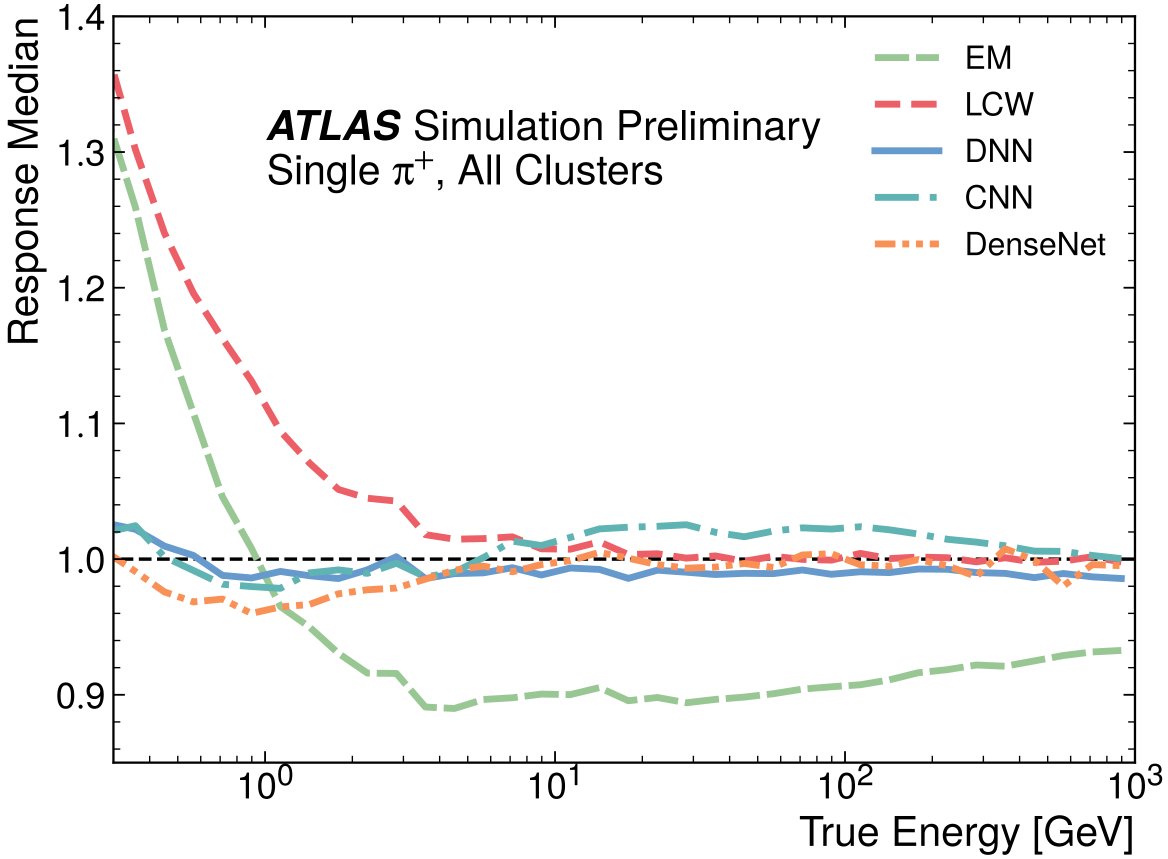
Target: ‘true’ energy from simulation

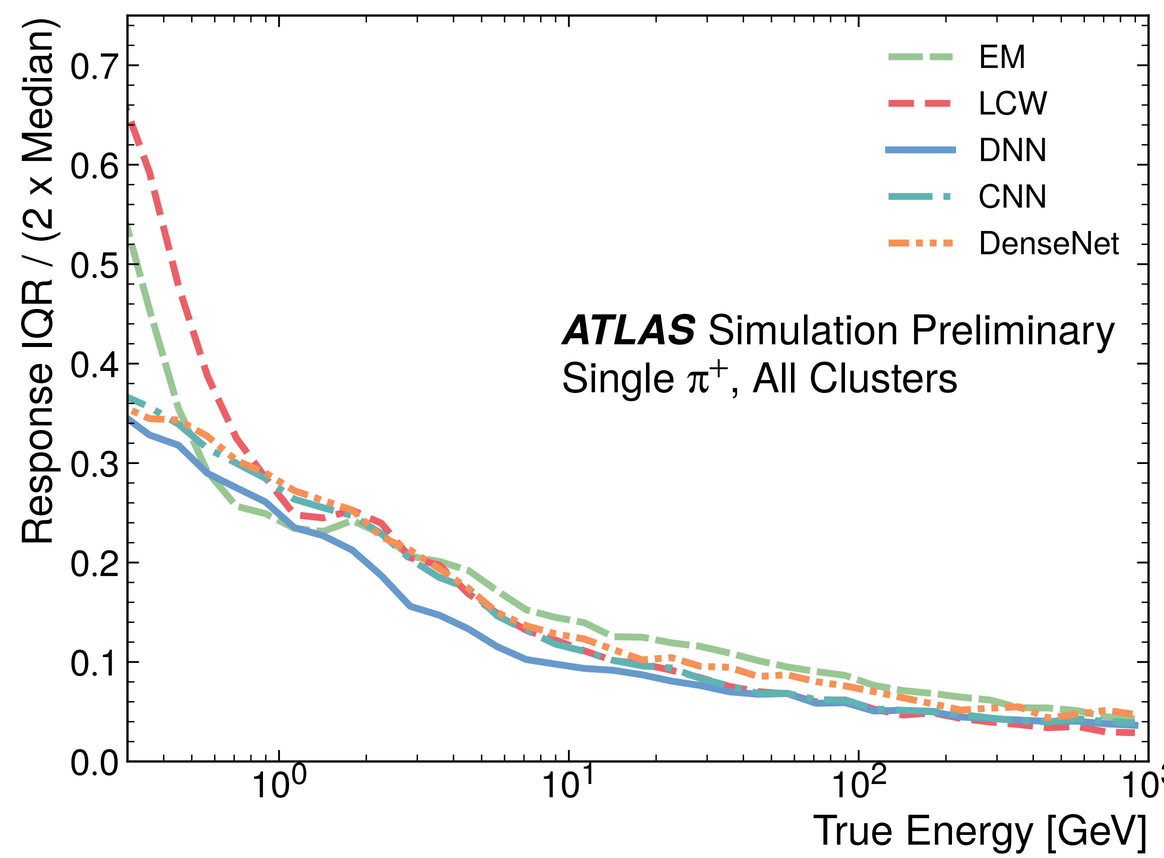
Use similar NN architectures as for the classifier, but also include ‘raw’ energy





Comparing Results





Scale goal: get close to 1

DNN outperforms default, and 'feature-based' correction!

Resolution goal: get close to 0

DNN again outperforms other methods

Conclusions

Conclusions

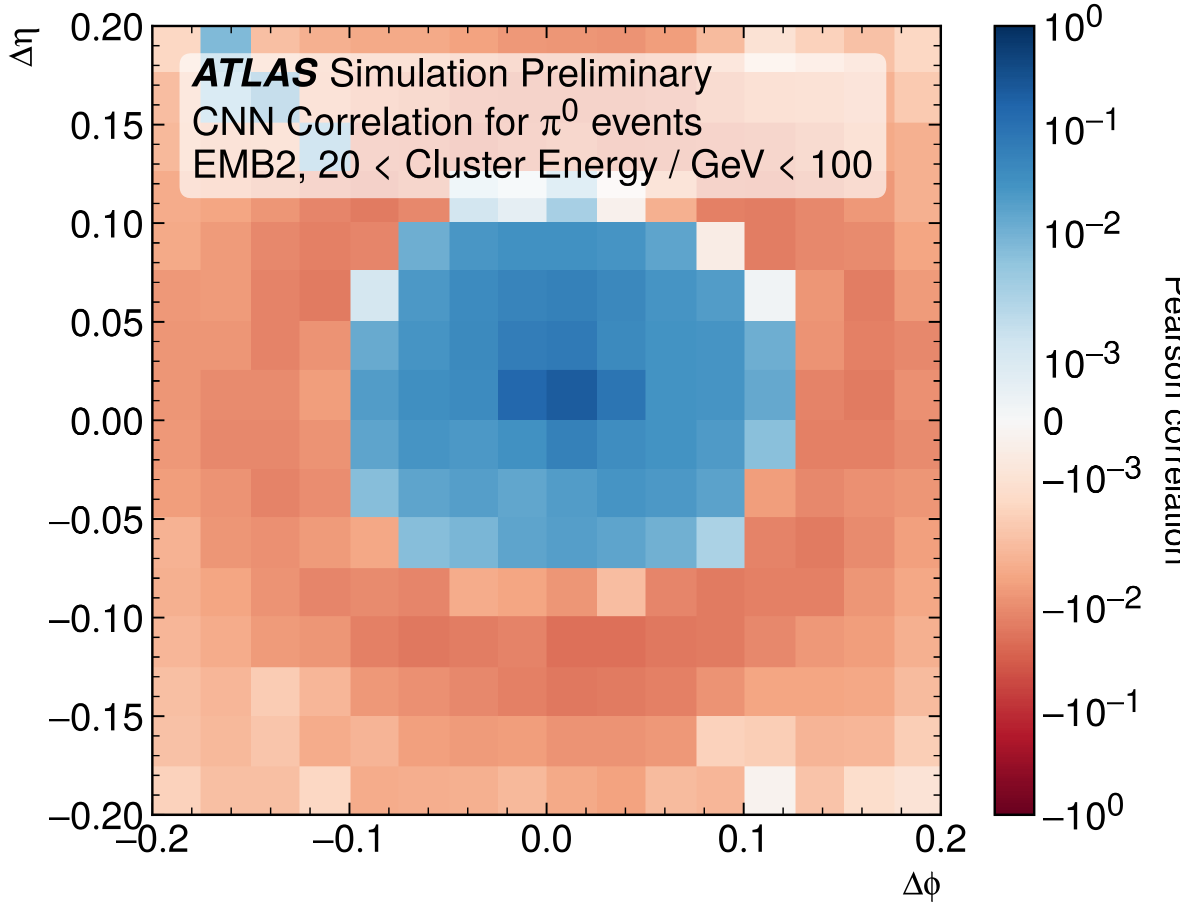
Better resolution can enable better physics at the LHC

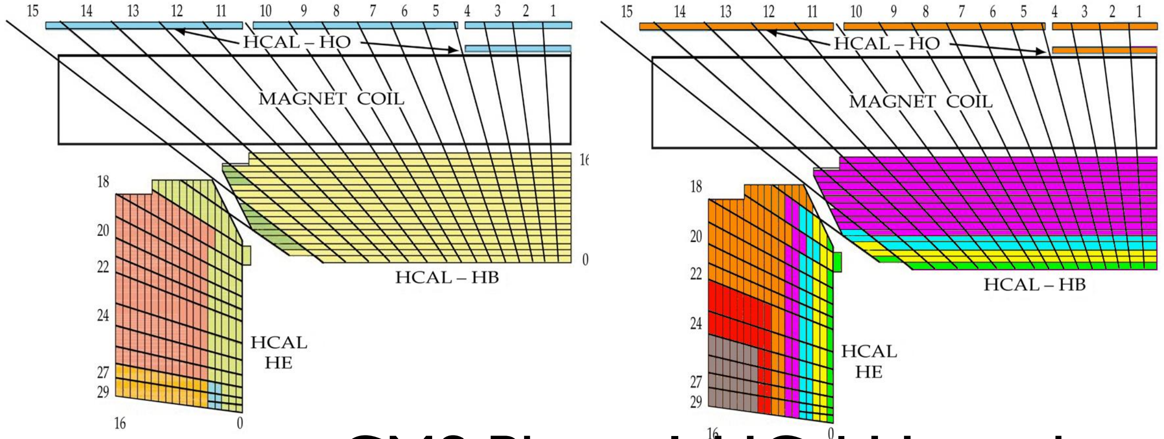
Machine learning has already had a huge impact on jet calibrations and jet tagging

The next frontier is *low-level inputs to jets*: can we use our exquisite detector granularity to help jets catch up to other final states?

Can this be a big upgrade for Run 3? When can this go into the trigger?

Particularly exciting given upgrades (Phase 1 and Phase 2) for both exp.!

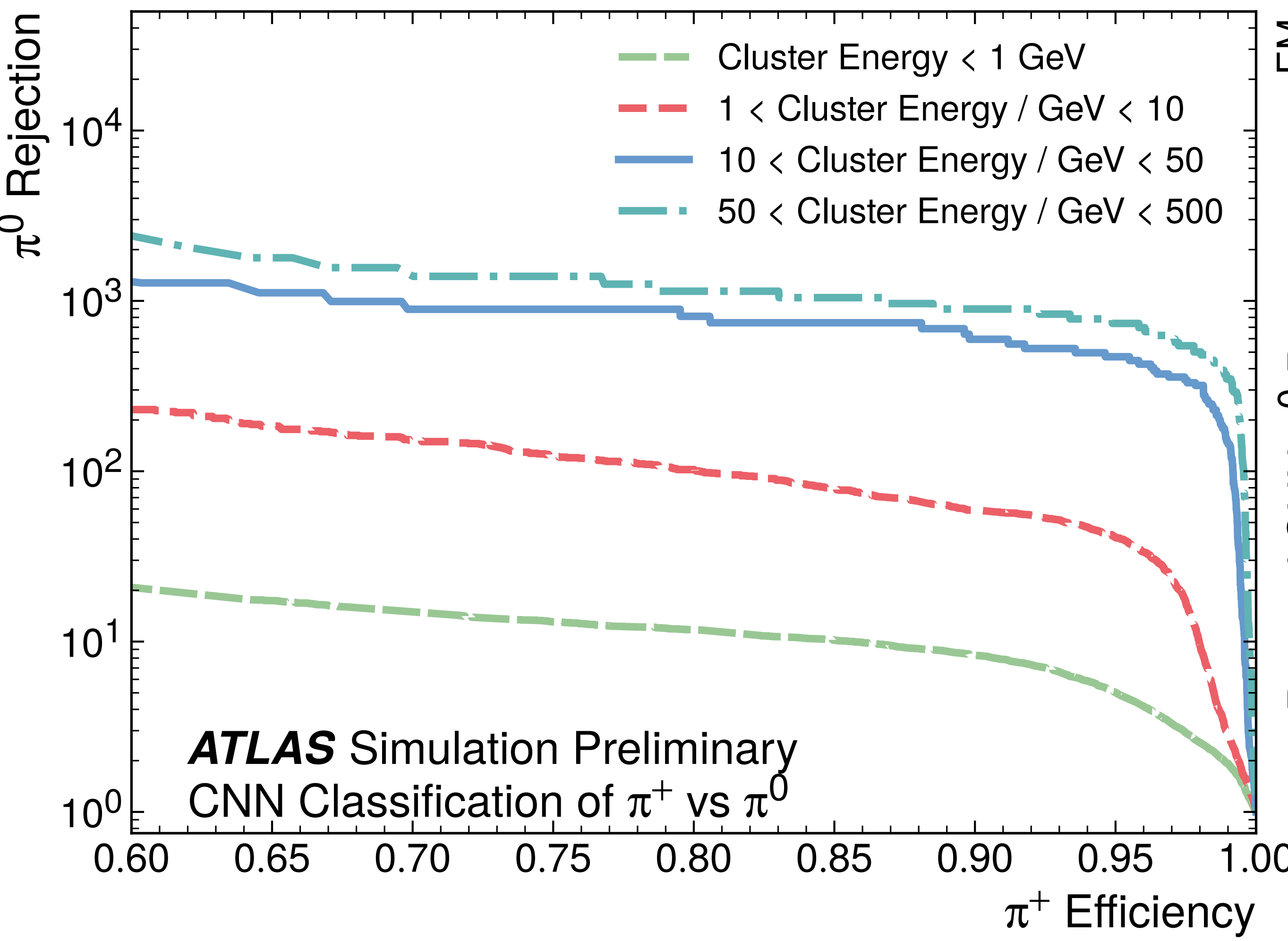


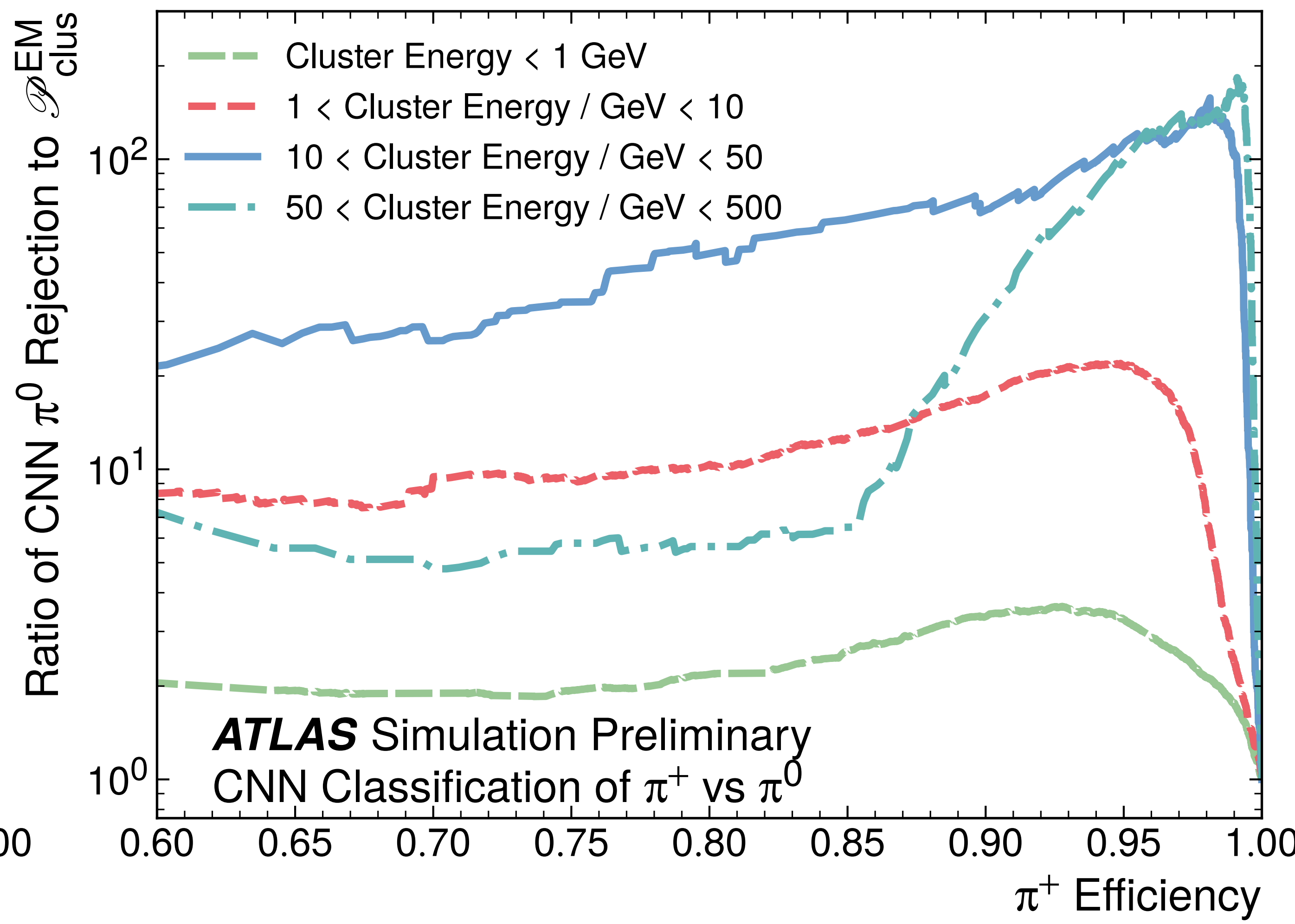


CMS Phase 1 HCal Upgrade

Thank you!

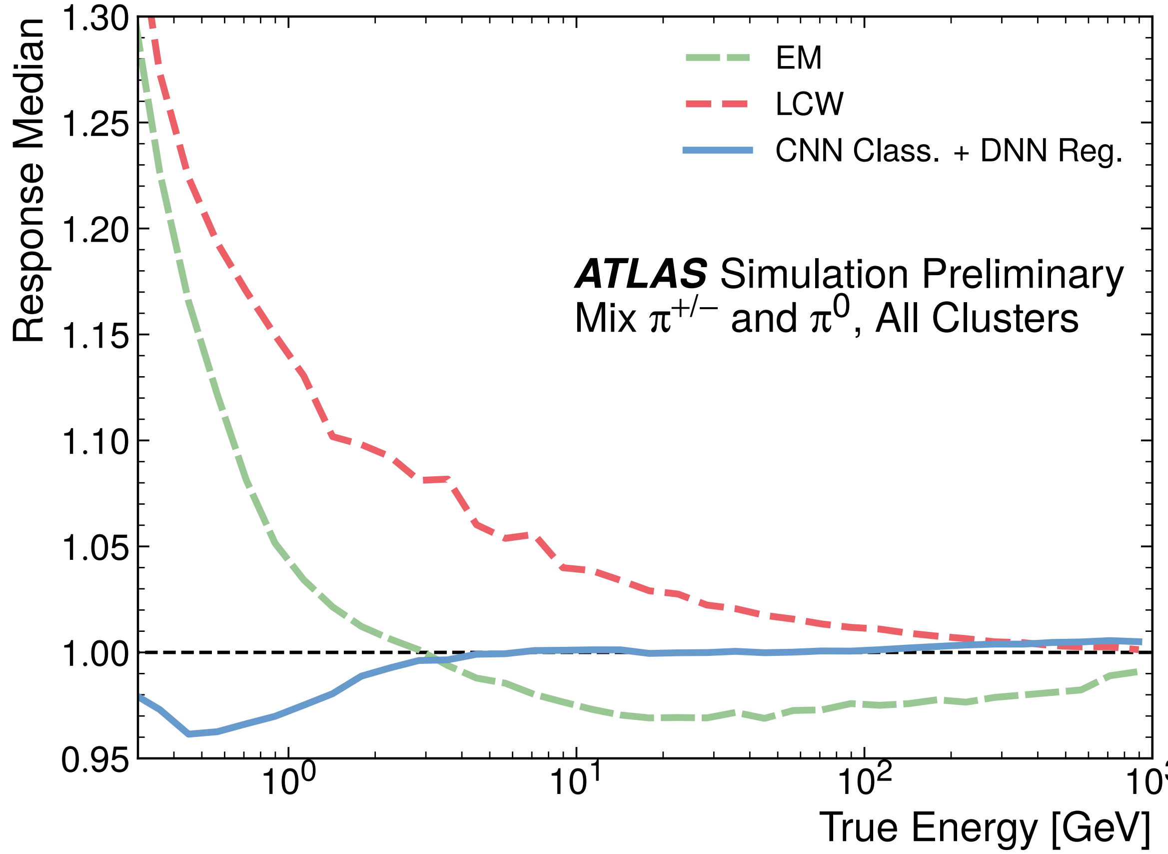
Binned Performance

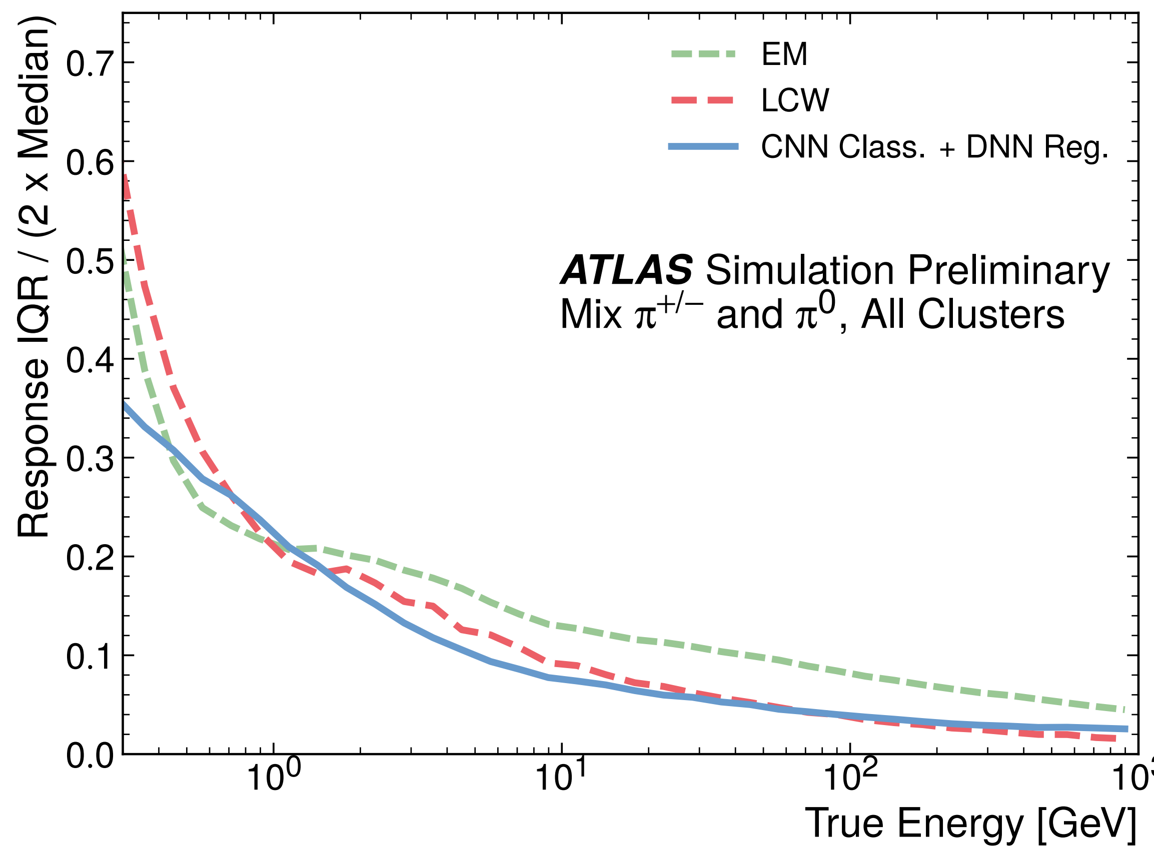




- Also show the CNN (best architecture) performance in bins of energy
    - And compare to LC in bins of energy
- Results are encouraging: good performance over all energies!
    - Factor of 100x improvement for 10-50 GeV π^0 rejection!

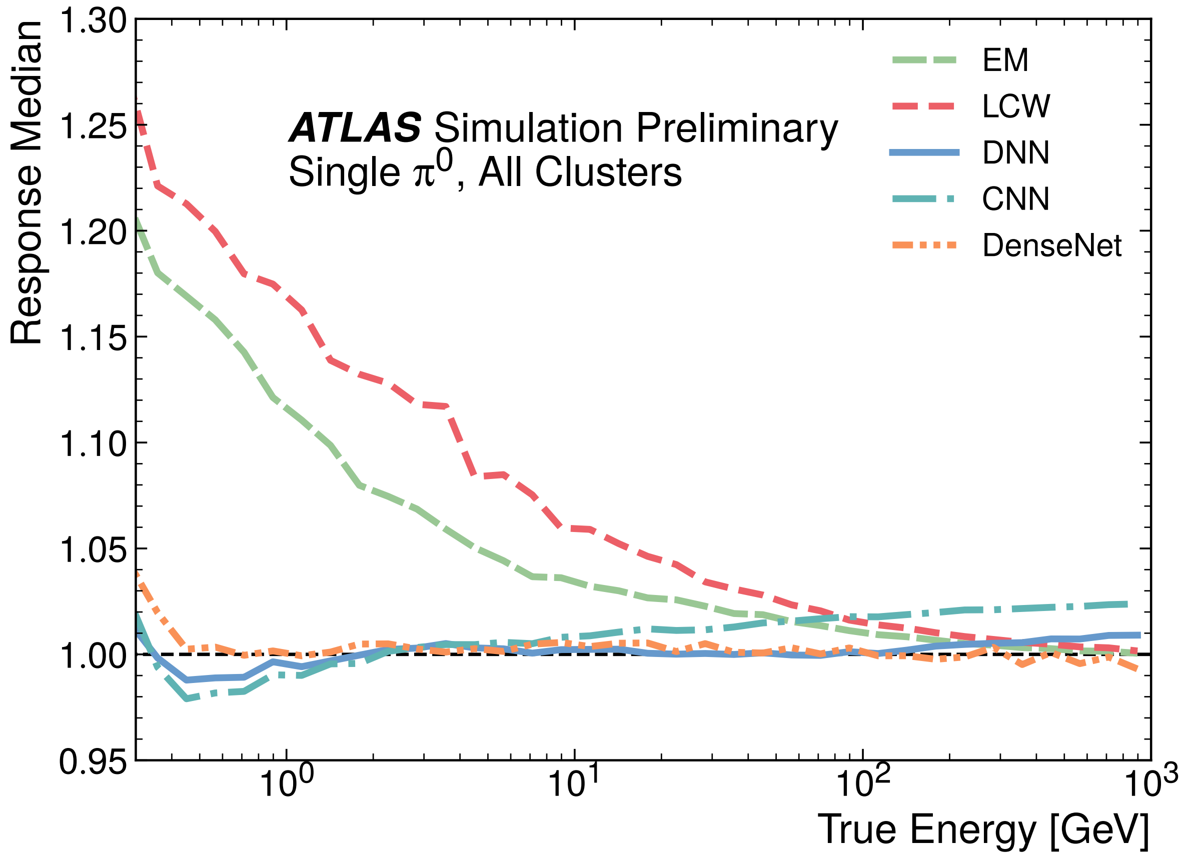
Combining in a Mixed Sample

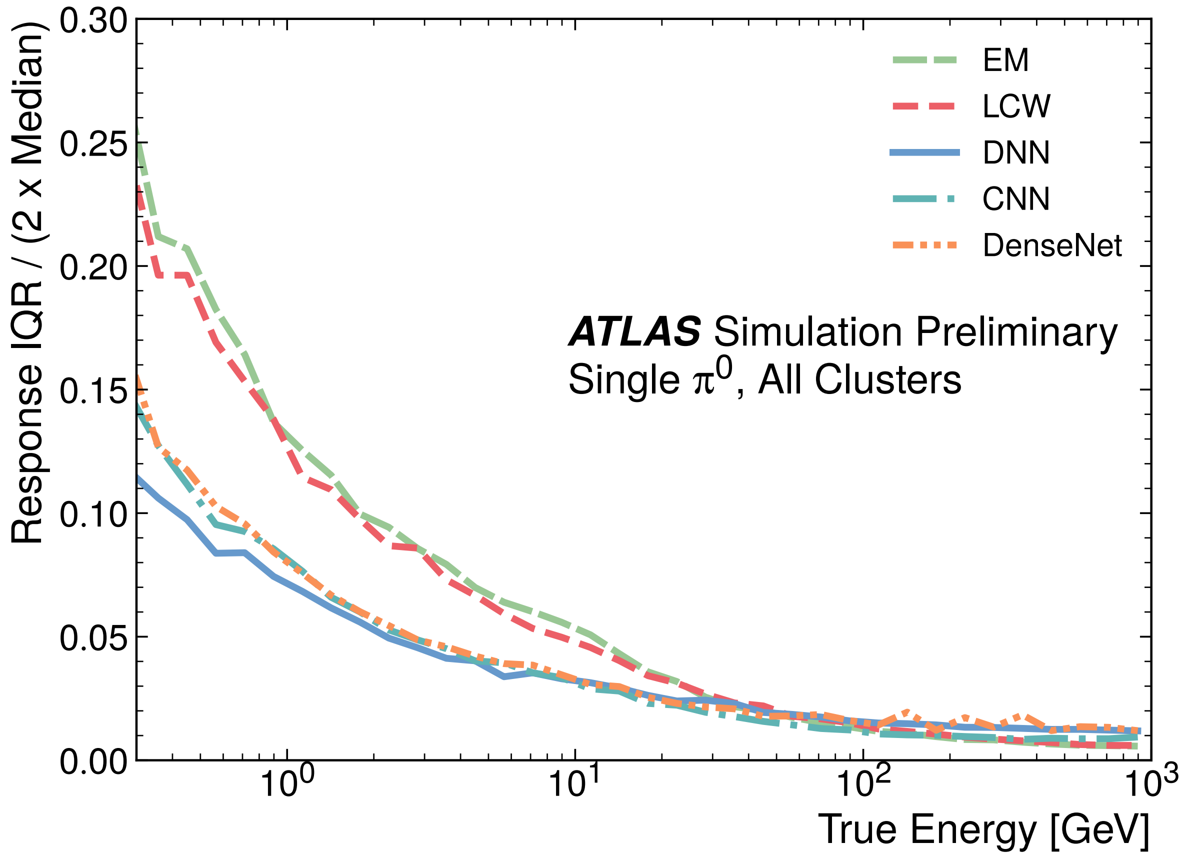




- So far, evaluated only in pure samples
- Can also mix charged and neutral pions in 2:1 ratio to mimic jets
- Apply classifier at ~95% π^+ efficiency, and then apply chosen regression
- Good performance! Better median and resolution than defaults

Comparing Results





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