Machine Learning for Pions

IML Forum, Particle Flow

Maximilian Swiatlowski

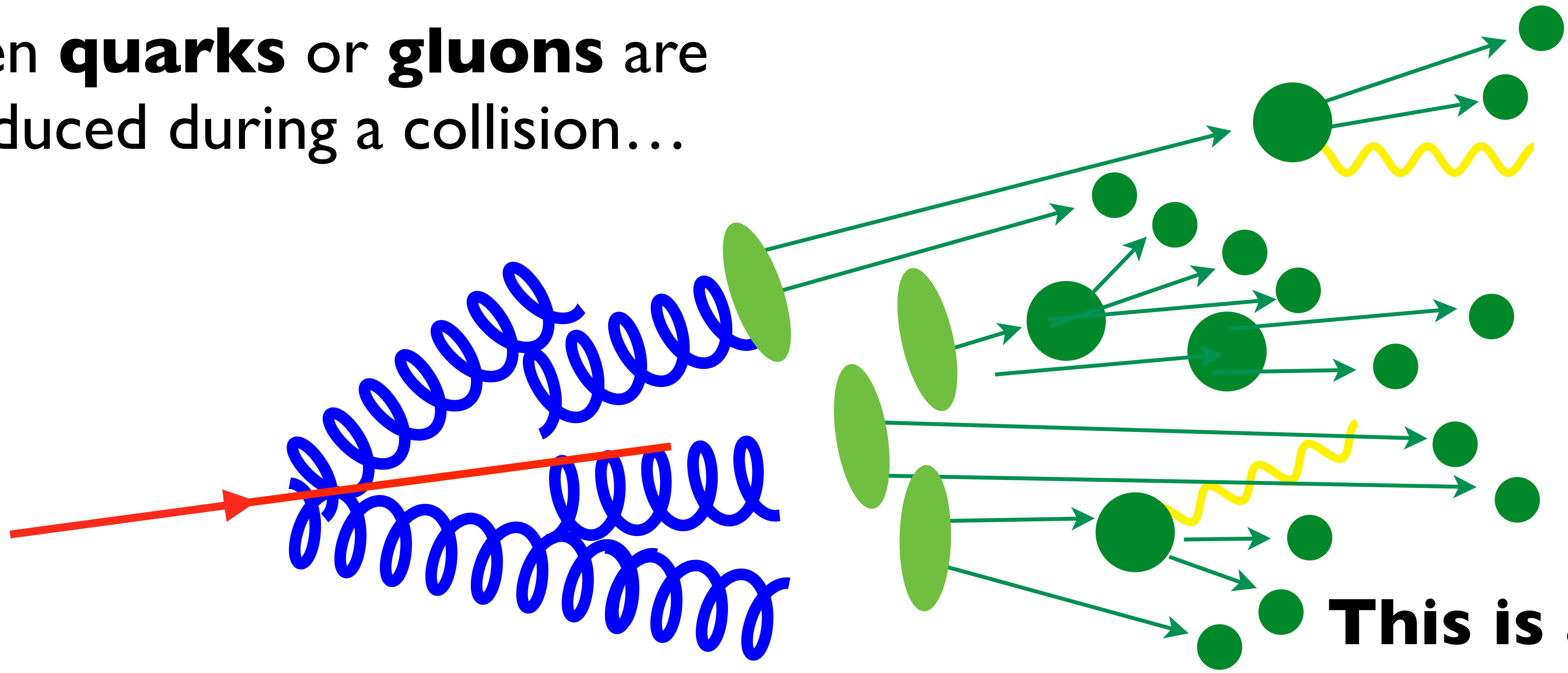
TRIUMF, obo of the ATLAS Collaboration

ATLAS
EXPERIMENT

Jets at the LHC

Image credit: B. Nachman

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



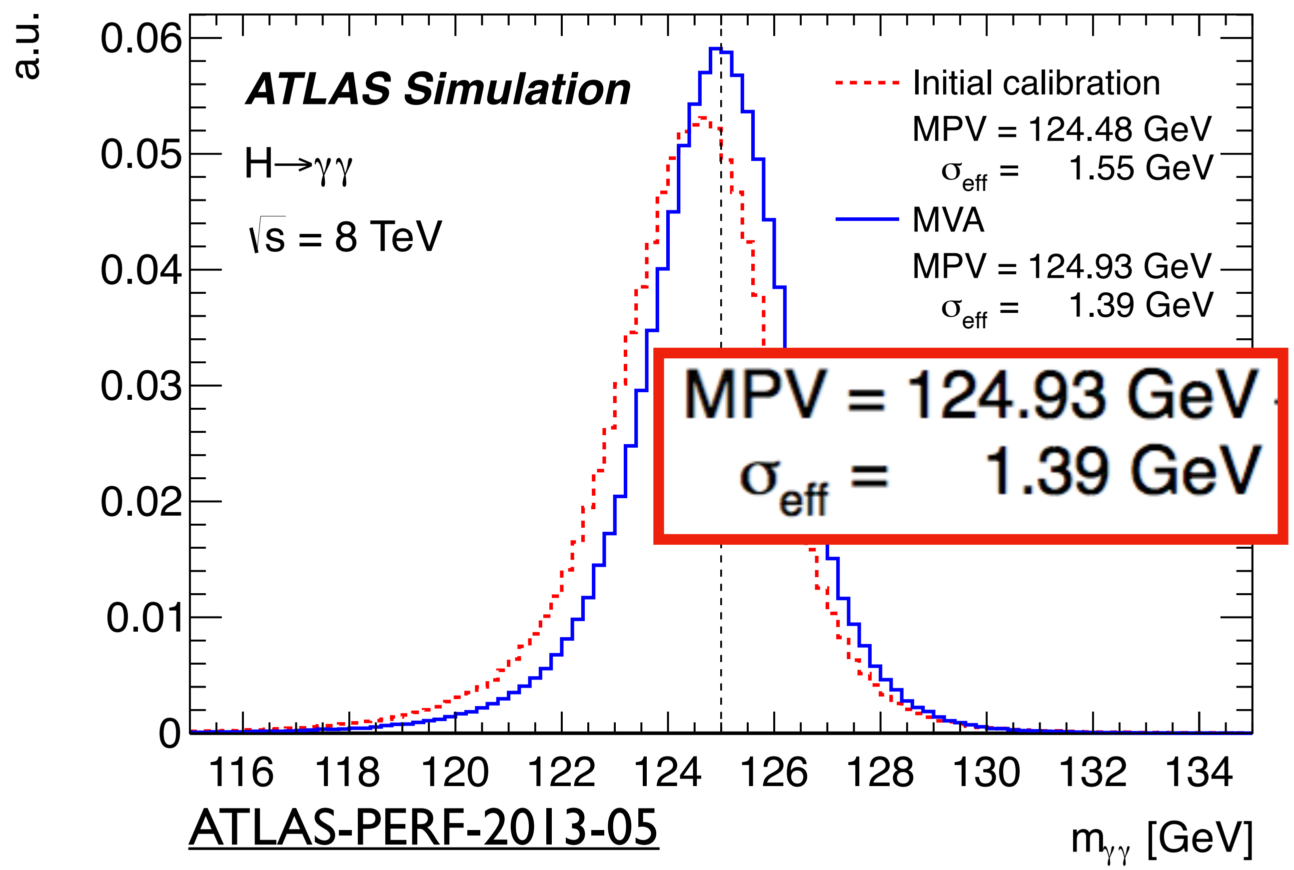
This is a jet!

They "shower"
into more gluons and quarks…

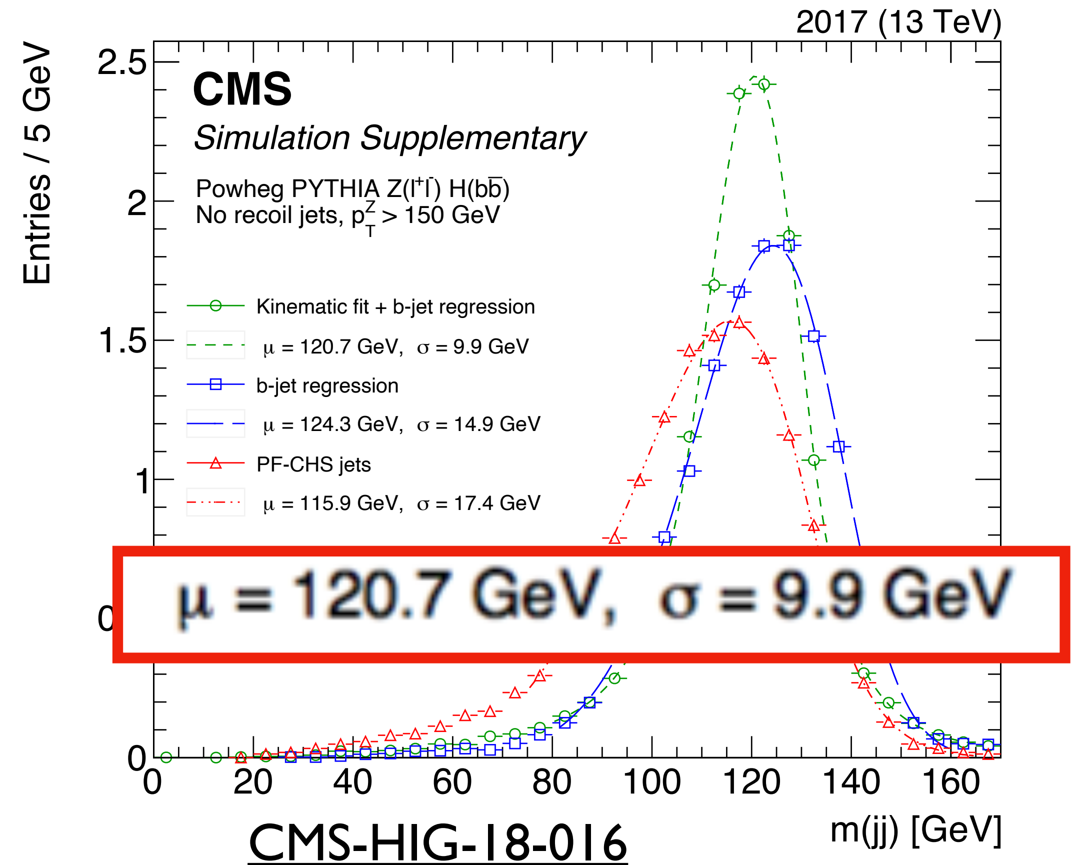
Which hadronize into
stable (or unstable particles)

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



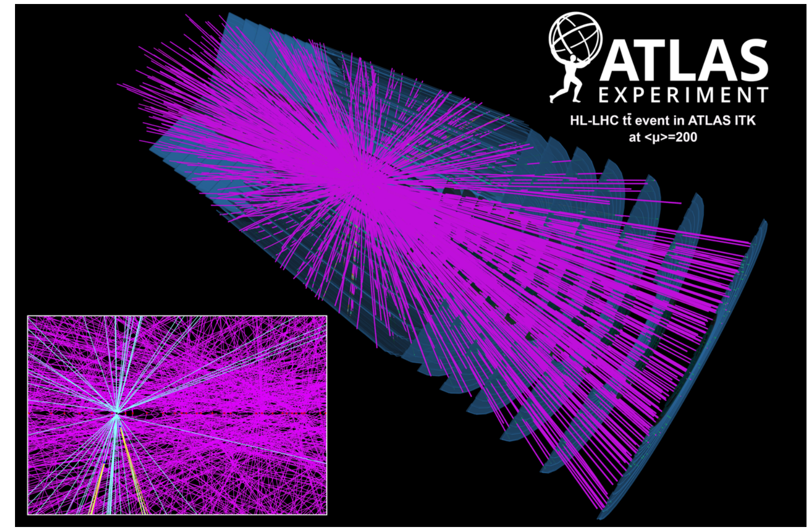
CMS-HIG-18-016

Measuring jets is a huge challenge: resolution is clearly worse 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!

Why is Jet Resolution So Bad?

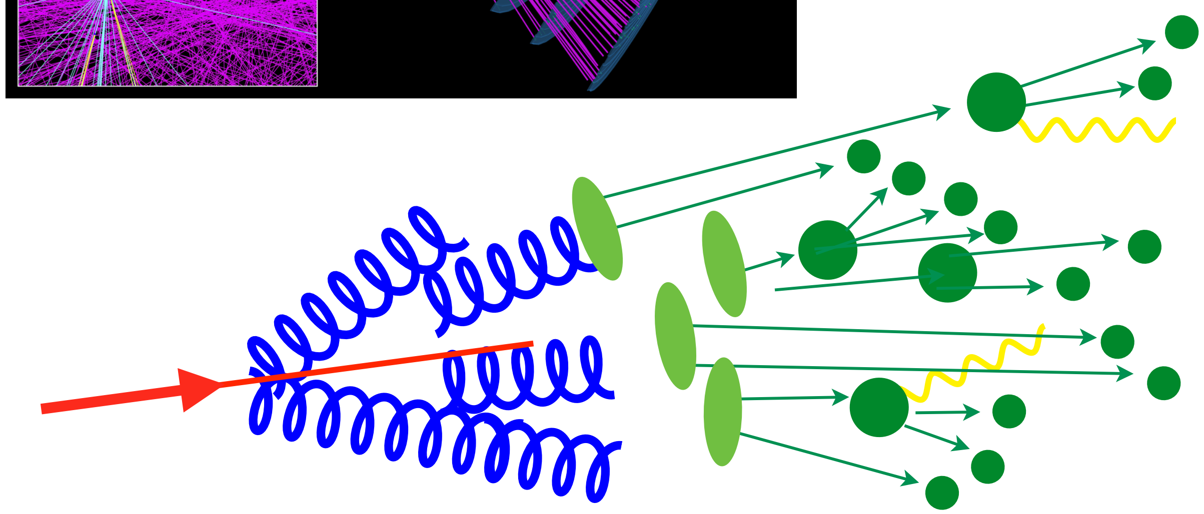


- Three main effects:

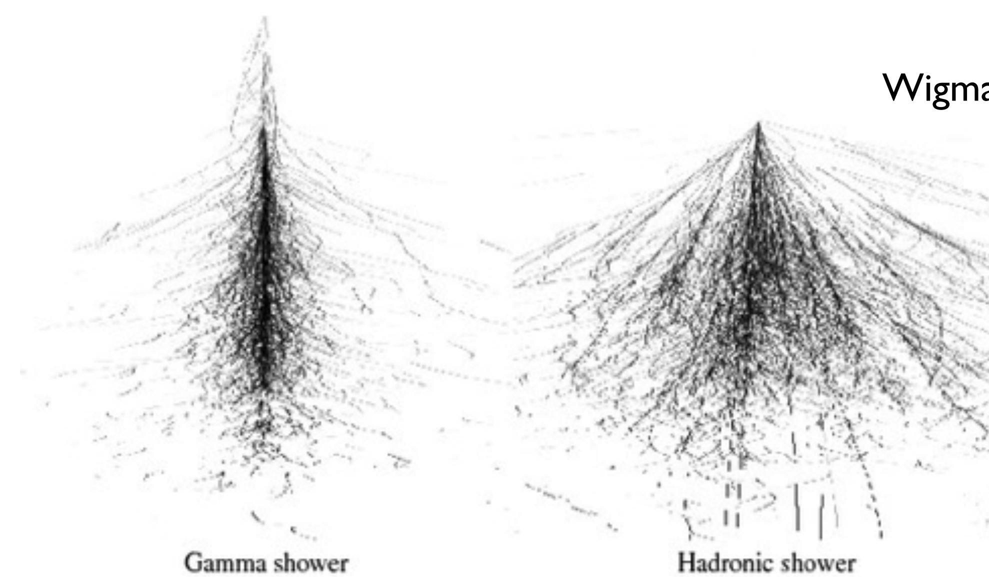
    1. Fluctuations due to pileup (won't talk much about this today)

    2. Fluctuations in fragmentation/hadronization/ etc. (see backup)

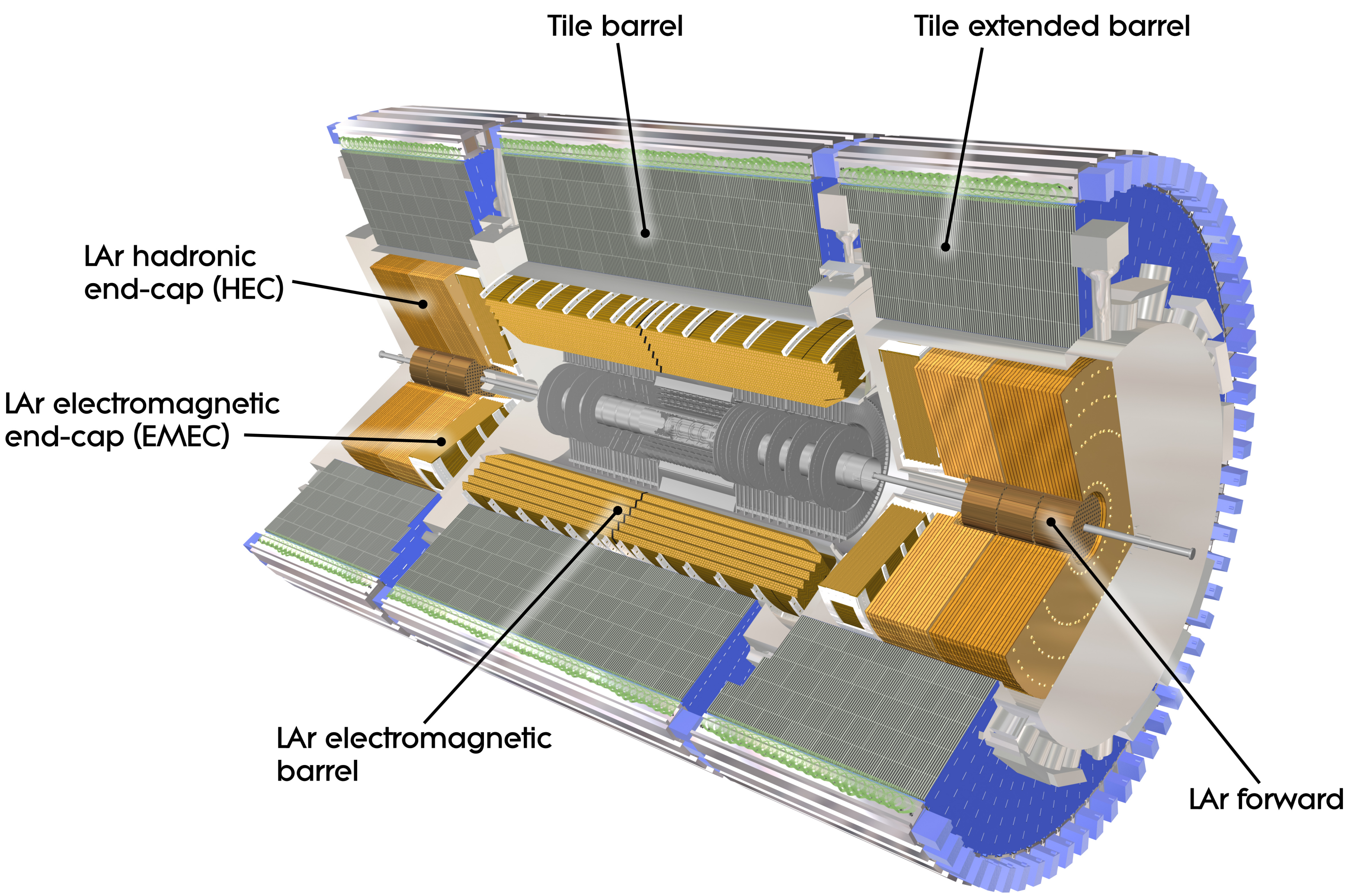
    3. **Fluctuations in individual particle showers** (focus of this talk)



Wigmans



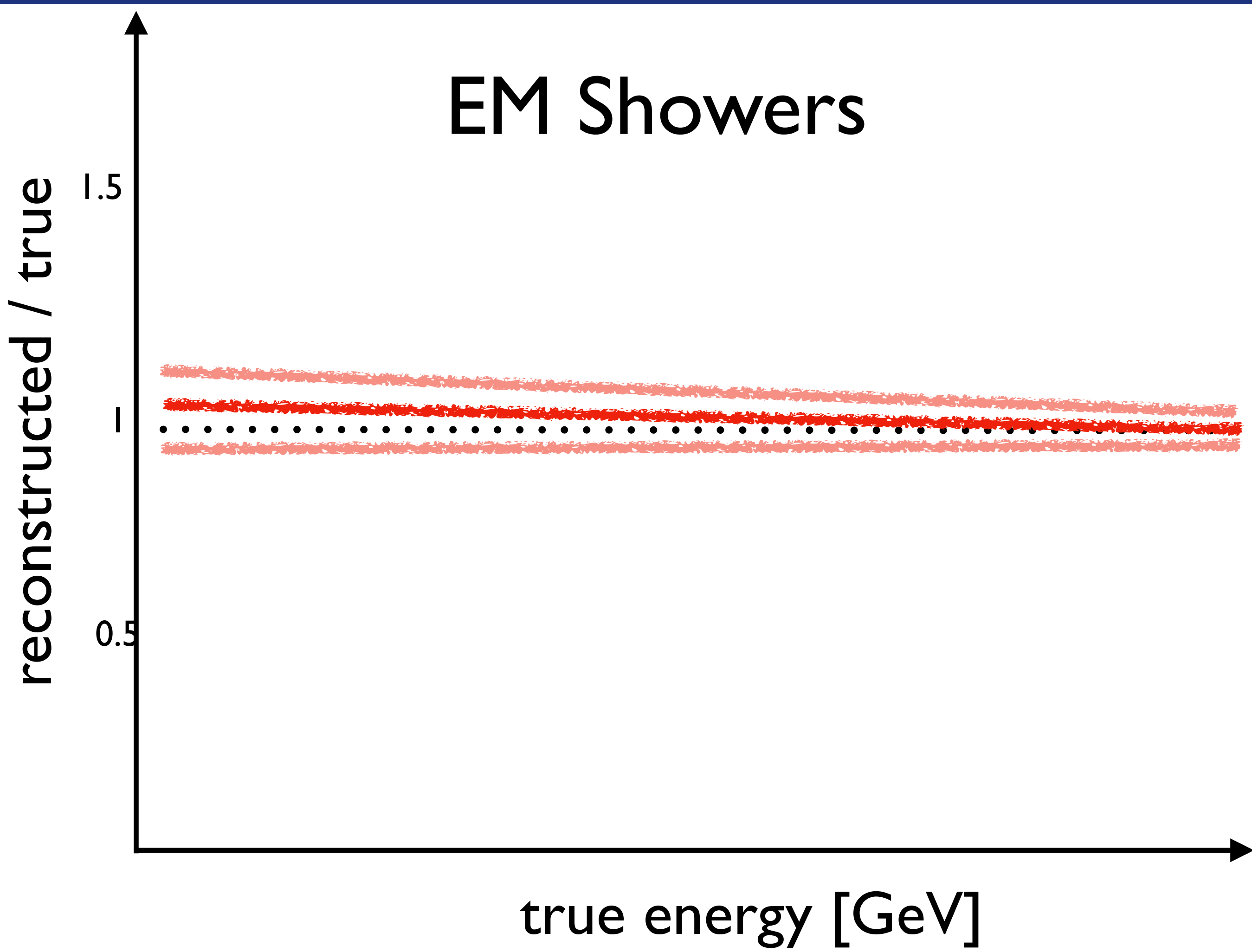
Calorimetry at the LHC

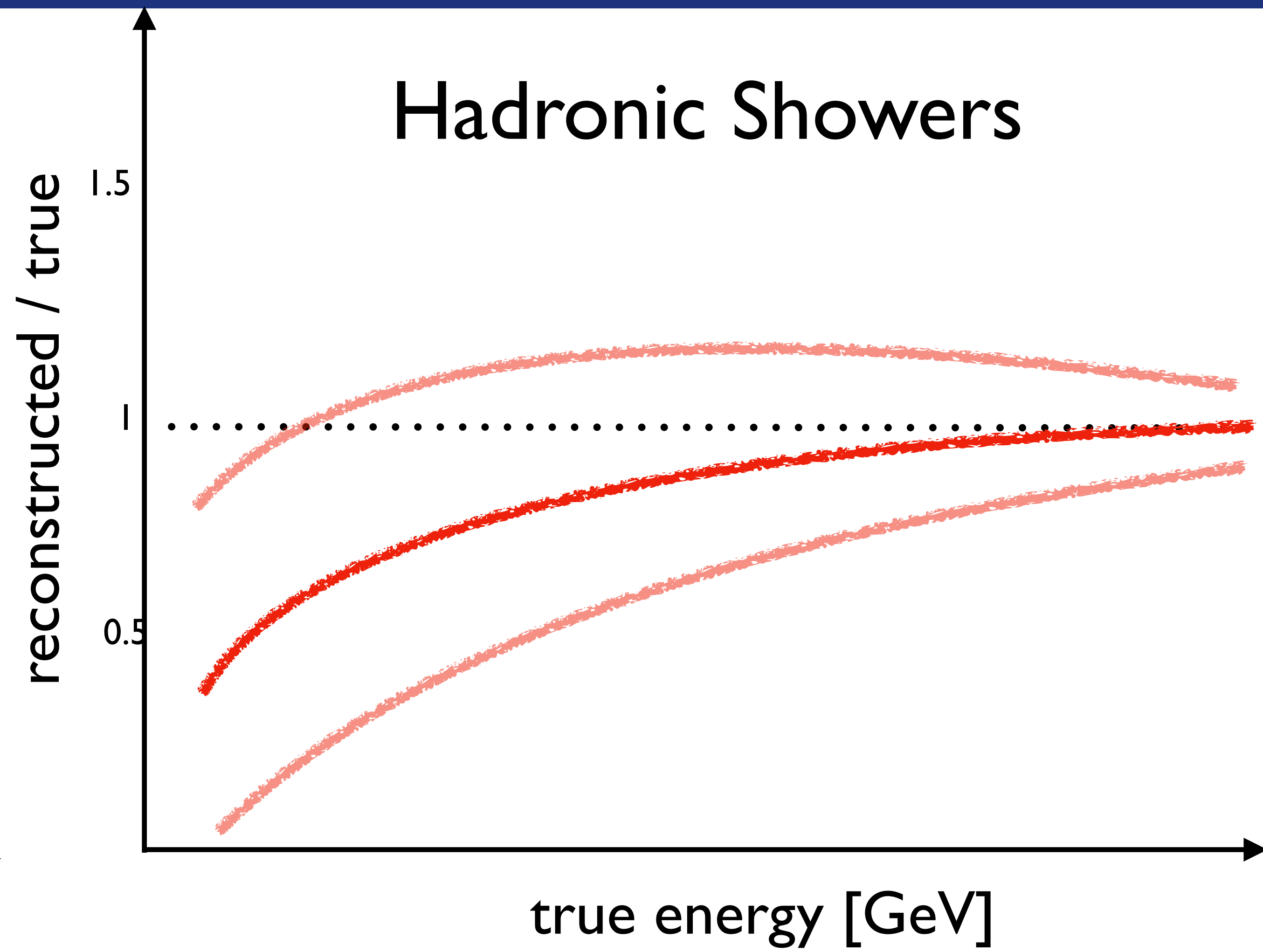


ATLAS's and CMS's calorimeters built to measure particles within jets: record energy and location of interactions/depositions

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'

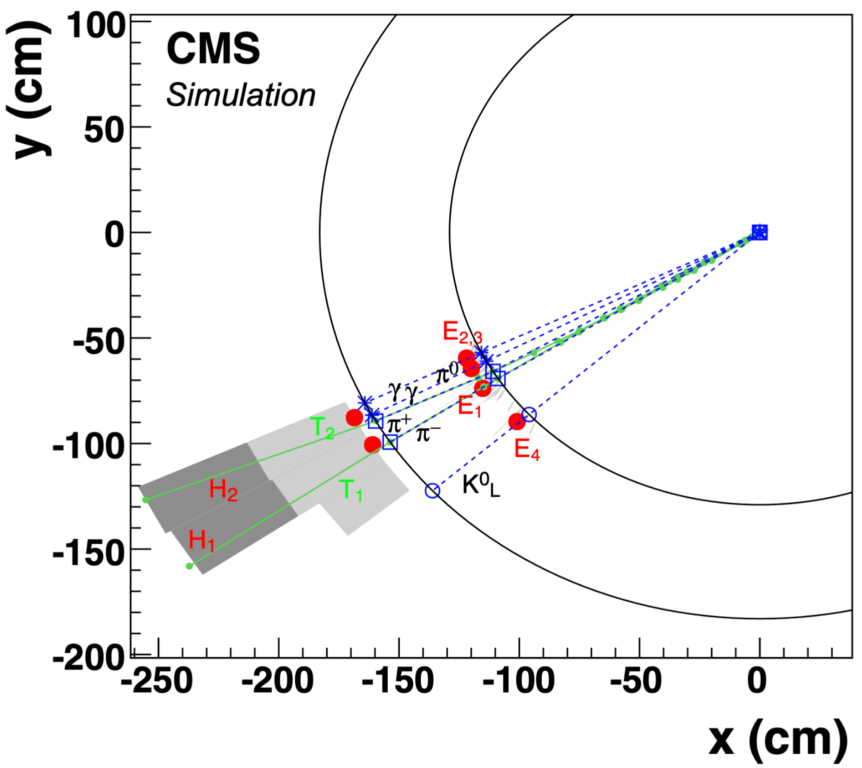
Resolution is good: all showers are 'similar'

Hadrons can also interact with nuclei, produce low energy neutrons, etc.: undetectable energy

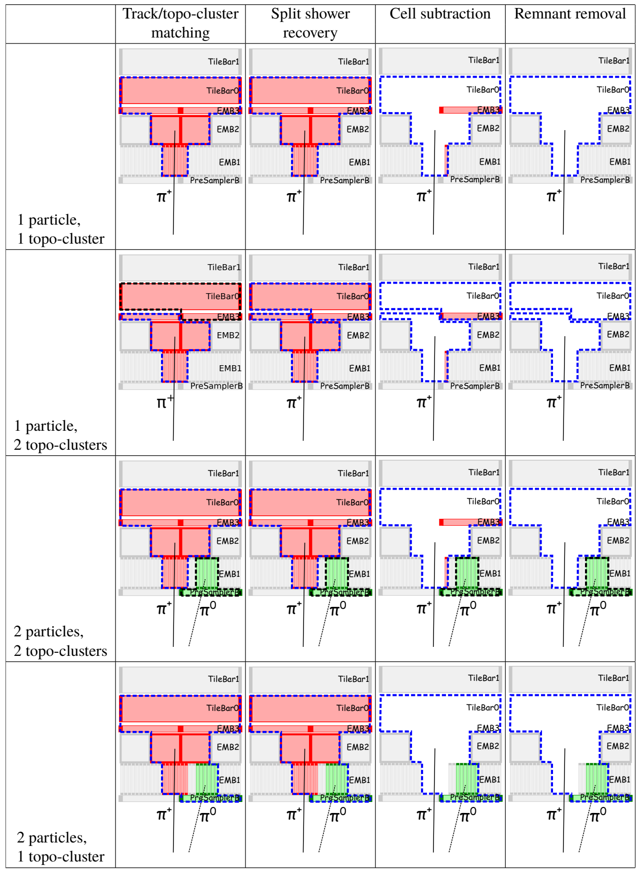
Every shower is unique: huge resolution penalty from variations

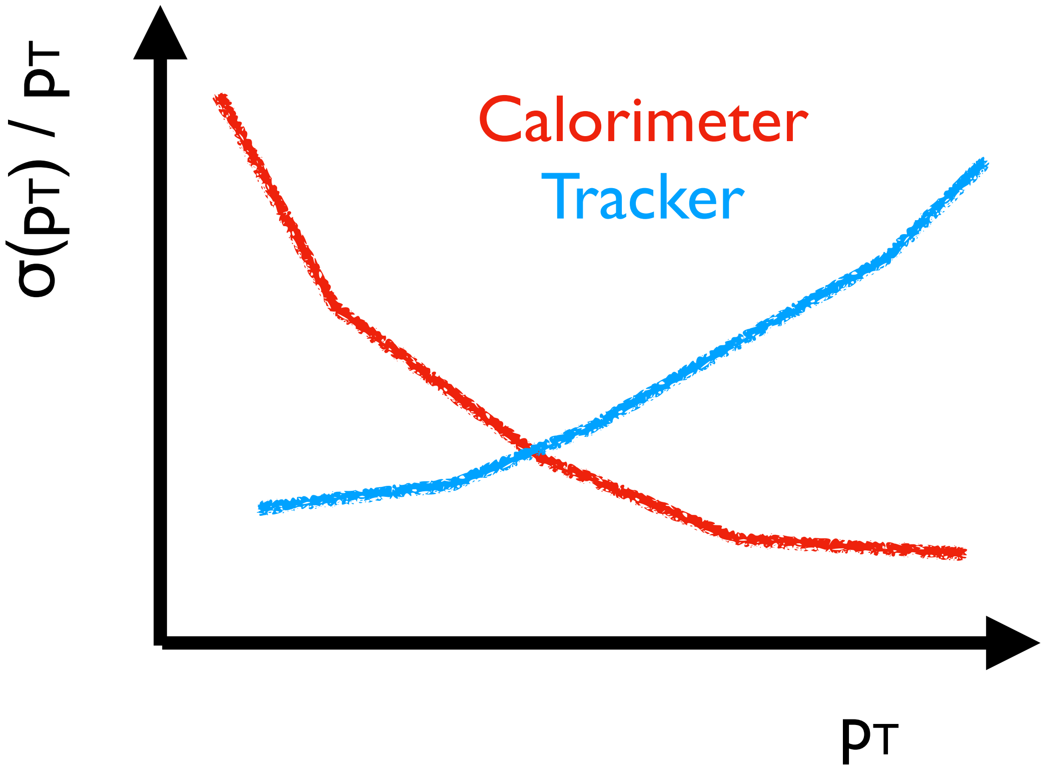
Hadronic Reconstruction, Today

CMS PFlow



ATLAS PFlow

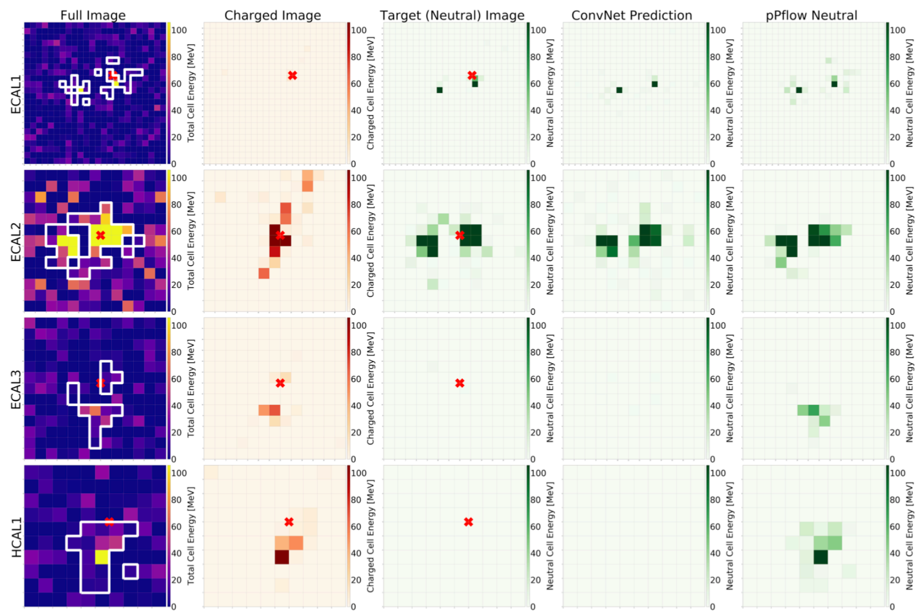




One way to improve: use inner-detector tracks to measure hadrons whenever possible: significantly improved resolution in many cases!

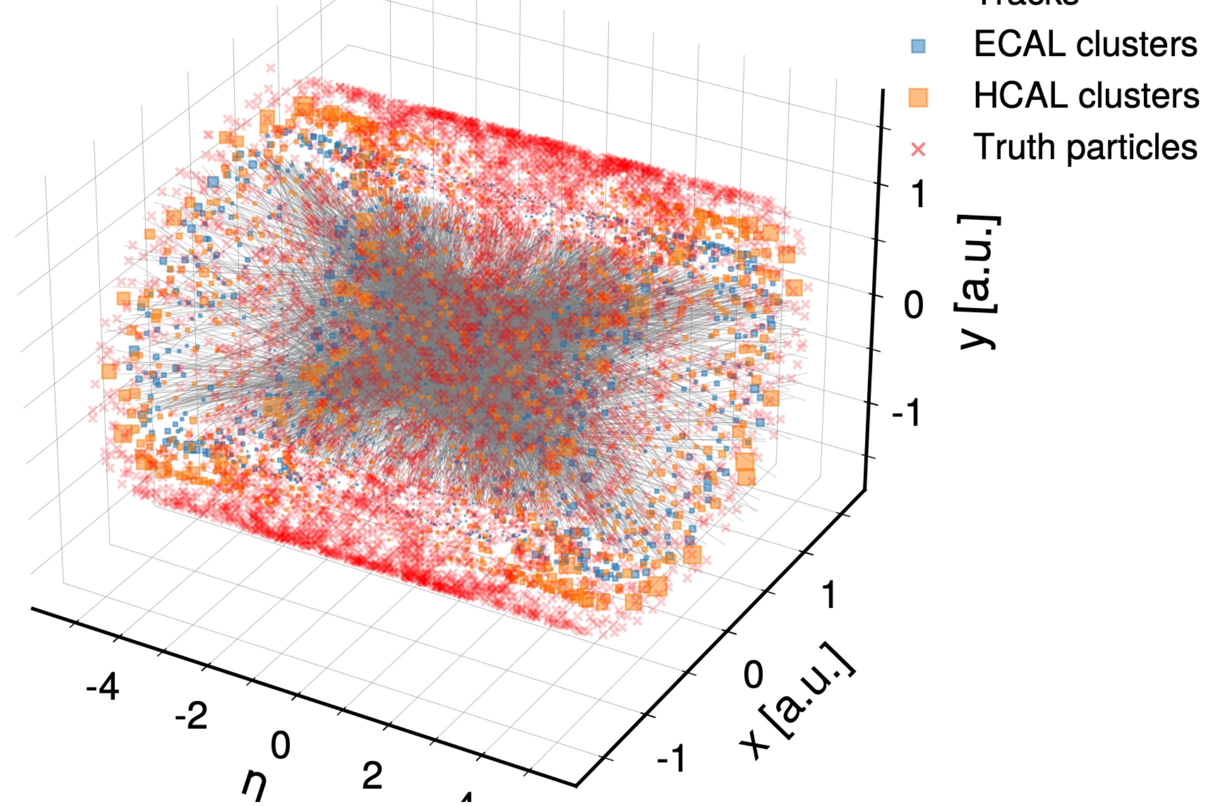
Hadronic Reconstruction, Tomorrow

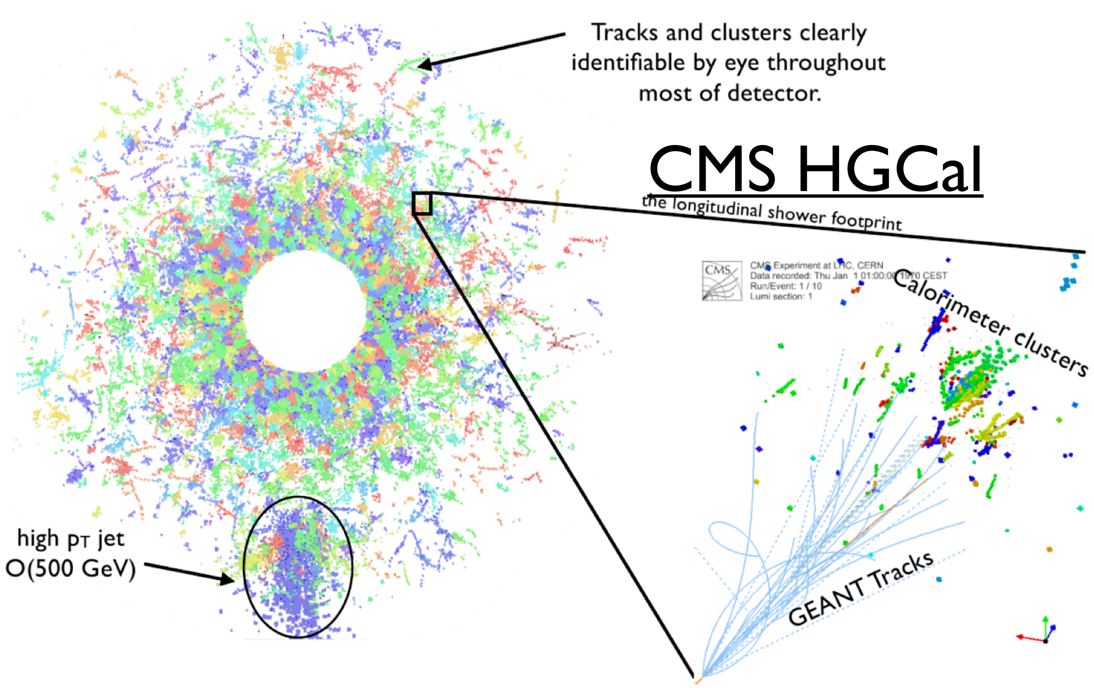
Huge number of studies in the literature!



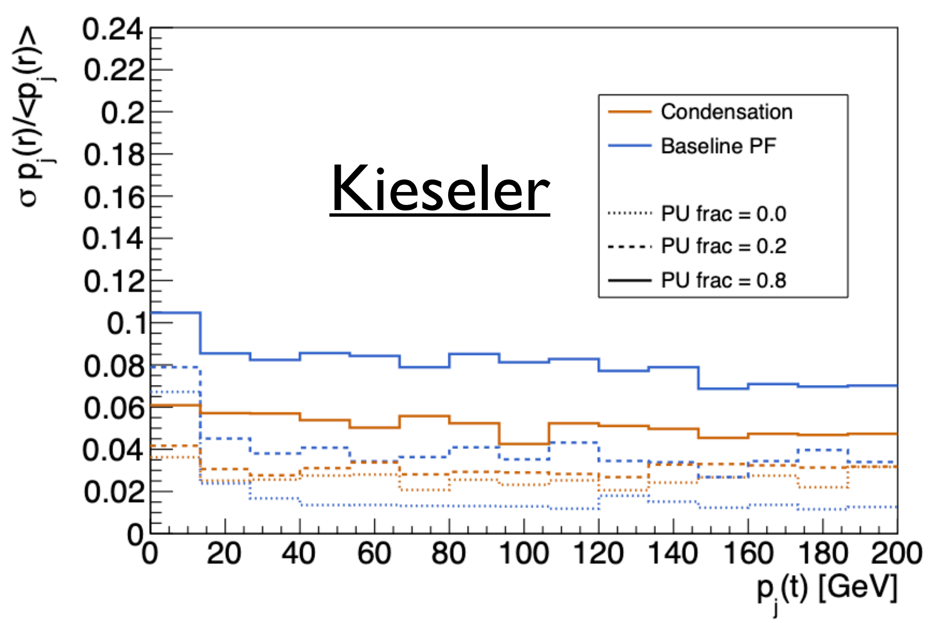
Di Bello et al

Pata et al





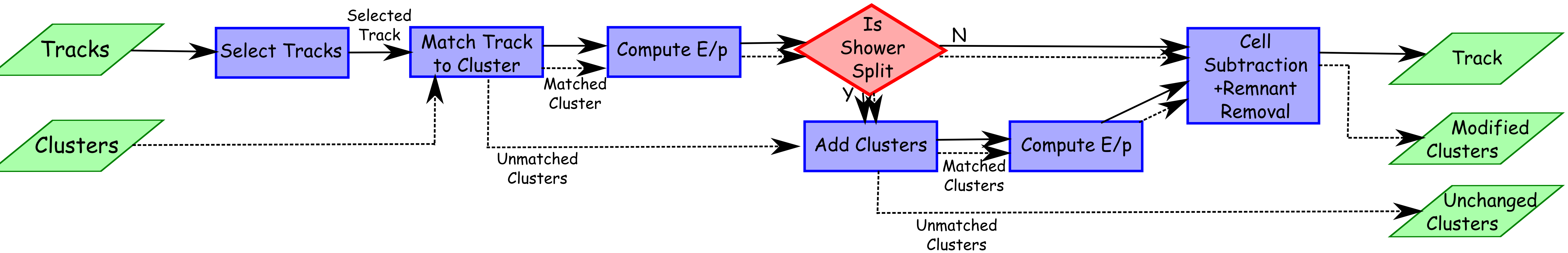
CMS HGCal

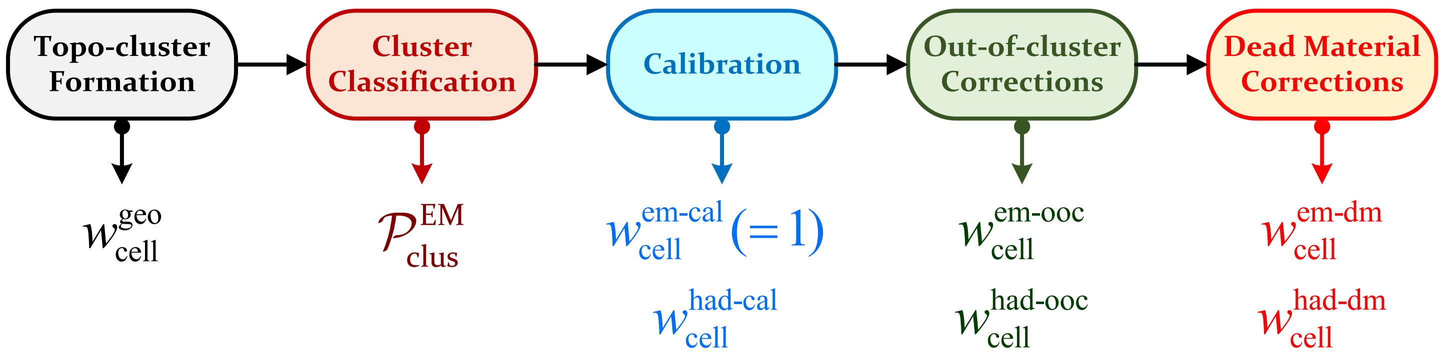


Kieseler

Can we also improve jet inputs with ML?

A Step-By-Step Approach



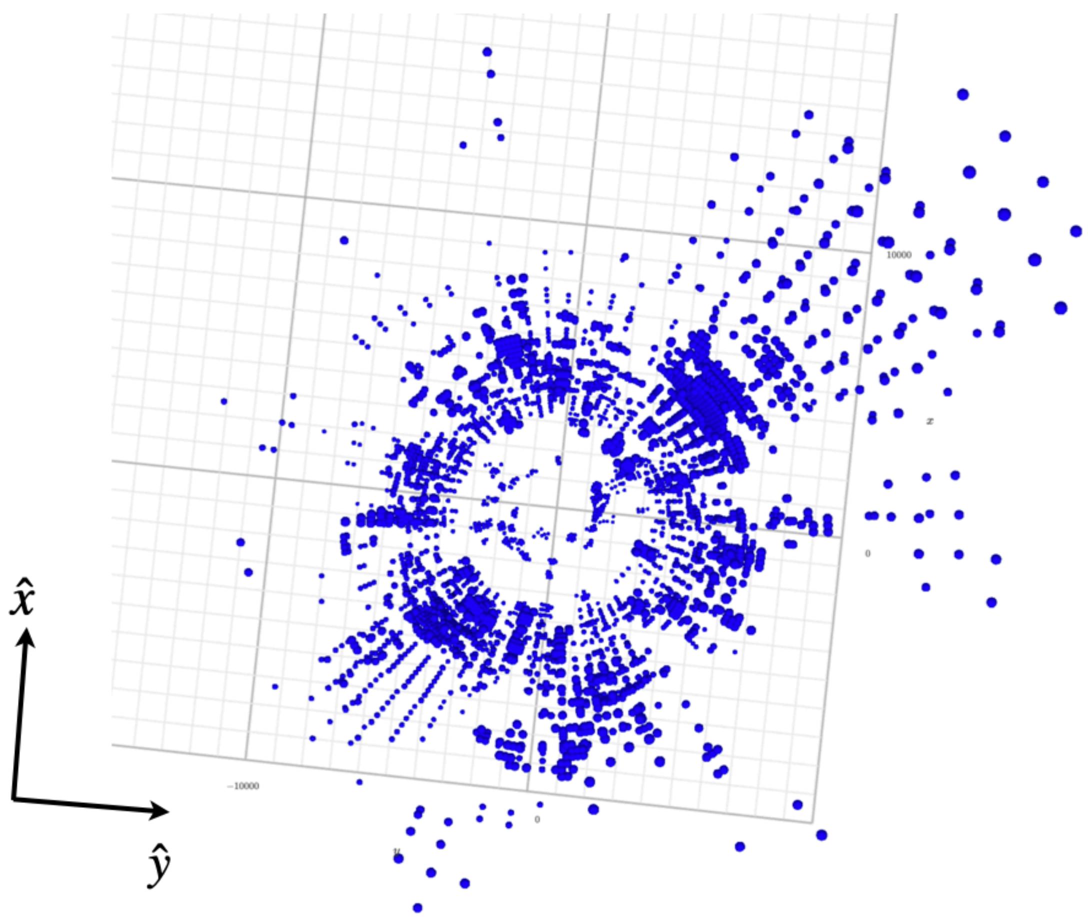


- Existing expert-tuned algorithms in ATLAS for PFlow and calorimeter calibration follow a step-by-step approach
  - Follow a similar strategy for ML: break the problem into pieces and solve independently
  - Today: focus on hadronic/EM shower separation, and full detector energy regression

Point Cloud Deep Learning Methods for Pion Reconstruction in the ATLAS Experiment

ATL-PHYS-PUB-2022-040

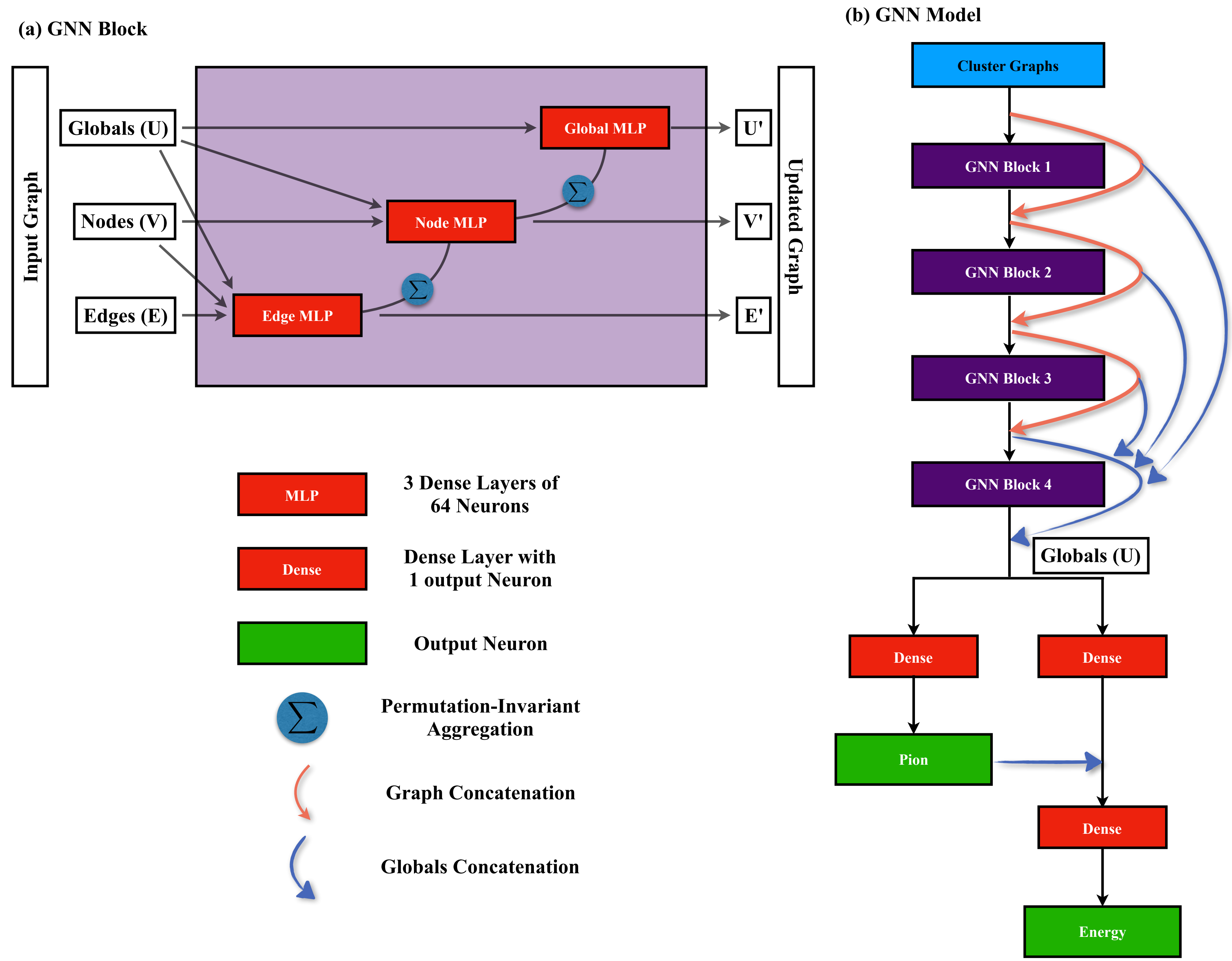
Data and Representation



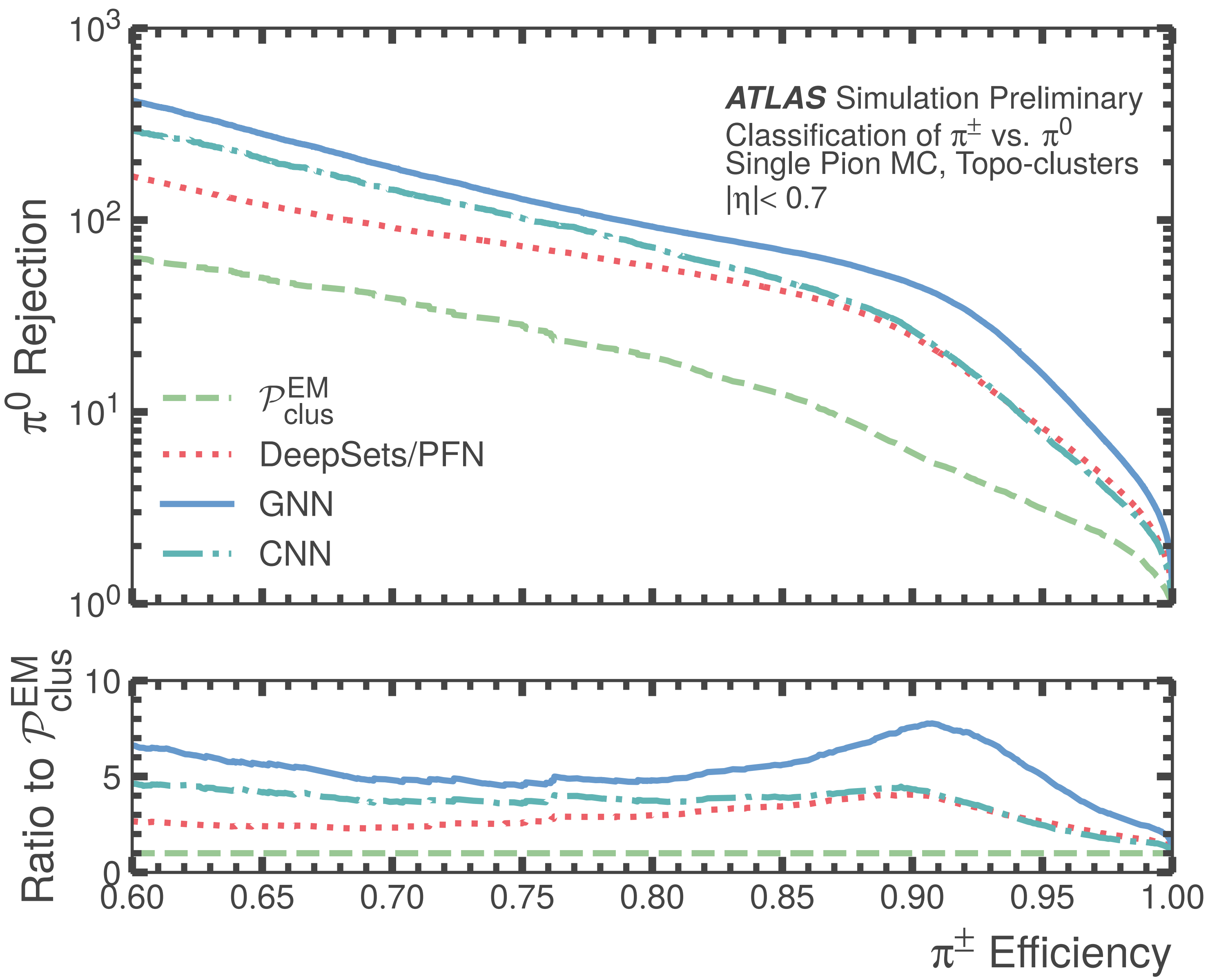
- Study single $\pi^{\pm}, \pi^{0}$ datasets from simulation
  - Solve single particles before going onto multi-particle "confusion" problem
- Primary calorimeter objects are "topological clusters"
  - Formed from ~188k calorimeter cells in the detector
  - Represent topoclusters as "point clouds" formed from calorimeter cells
  - Previously studied CNNs and image-recognition techniques: point clouds more adaptable to calorimeter geometry

GNN Architecture

- GNN is a natural architecture for a point cloud dataset
- Simultaneously train GNN to classify pion class (π^0: EM shower; $\pi^{\pm}$: hadronic shower) and calibrate energies
  - Also consider simple “Deep Sets” point cloud model: no edge information

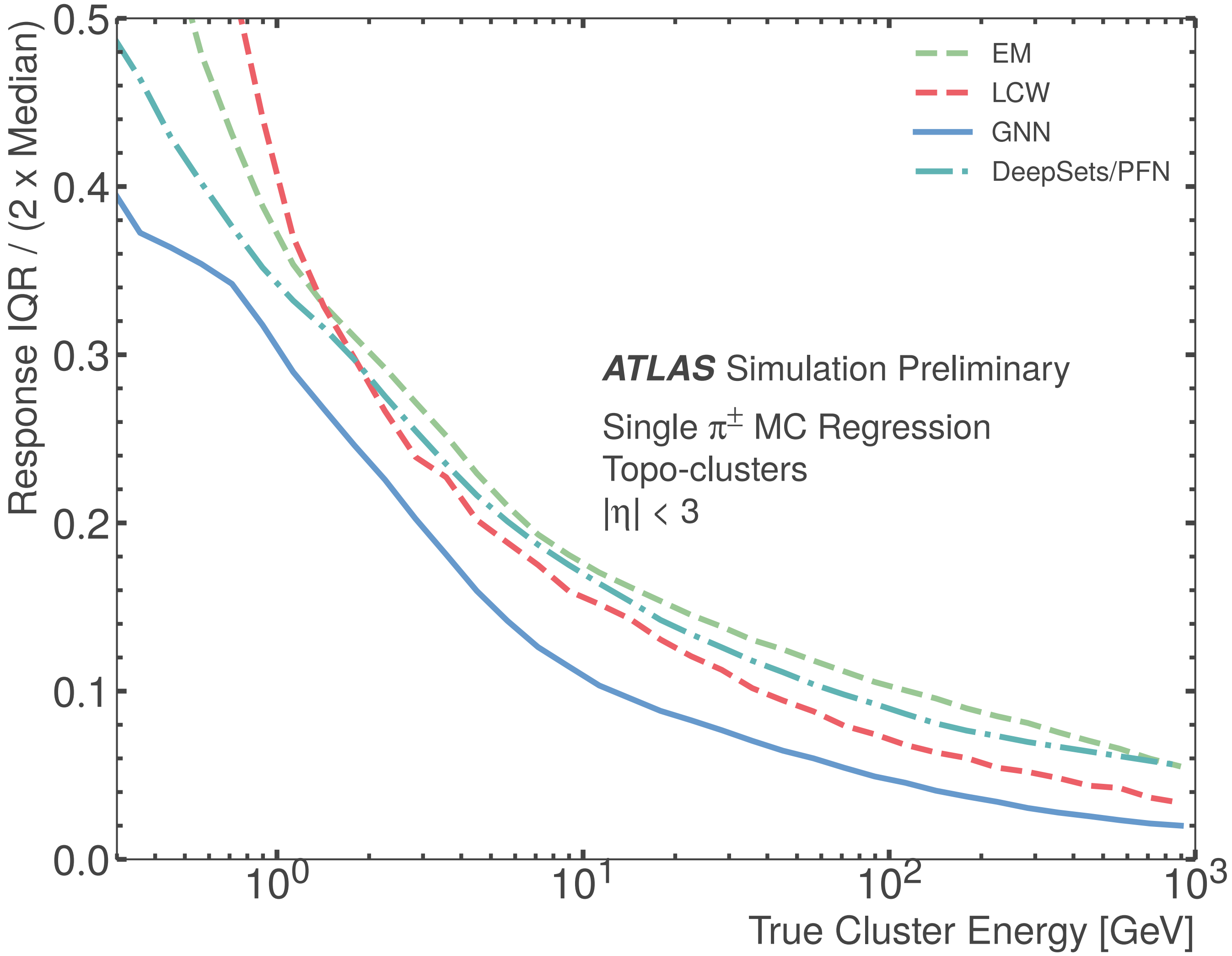


Classification Results



- All ML methods significantly outperform baseline $\mathscr{P}^{\mathrm{EM}}$ method!
- GNN and DeepSets also robust out to forward η regions: no special tuning for geometry required
- **ML can be used to identify shower types in the calorimeter**

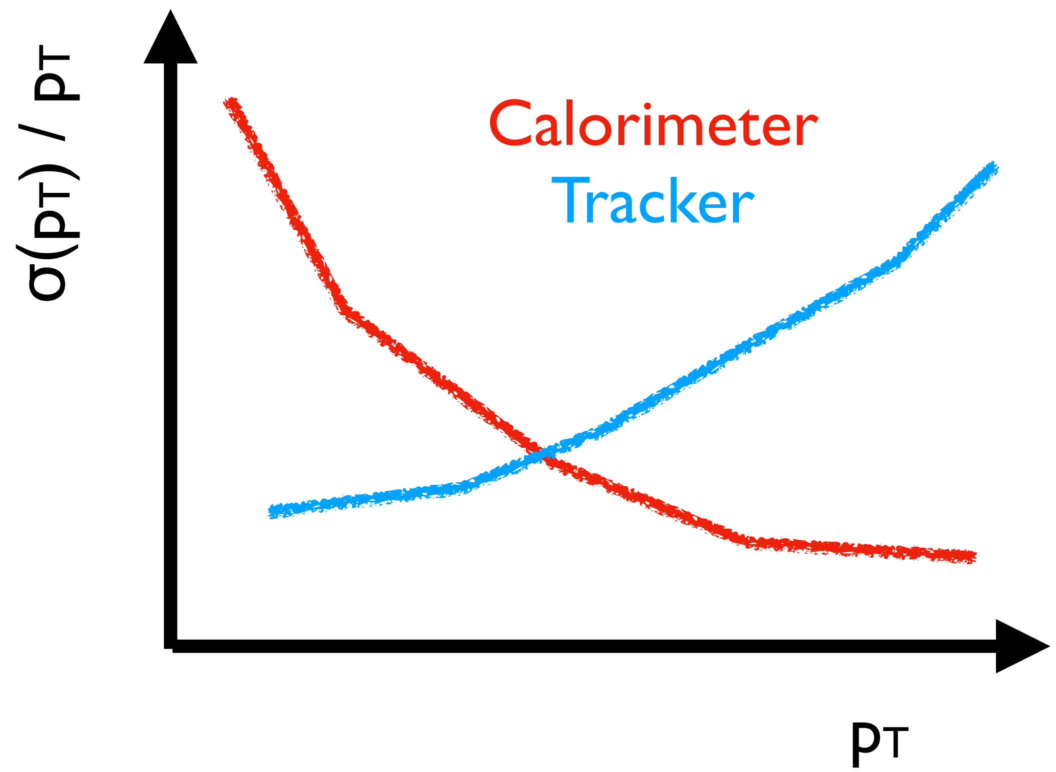
Calorimeter Calibration



- Can also compare pure calorimeter energy calibration with GNN compared to baseline EM and LCW techniques
  - GNN significantly improves calorimeter-only energy resolution!
  - DeepSets improves over very basic EM calibration, worse than expert-tuned LCW
    - Model was not thoroughly optimized: could potentially be improved

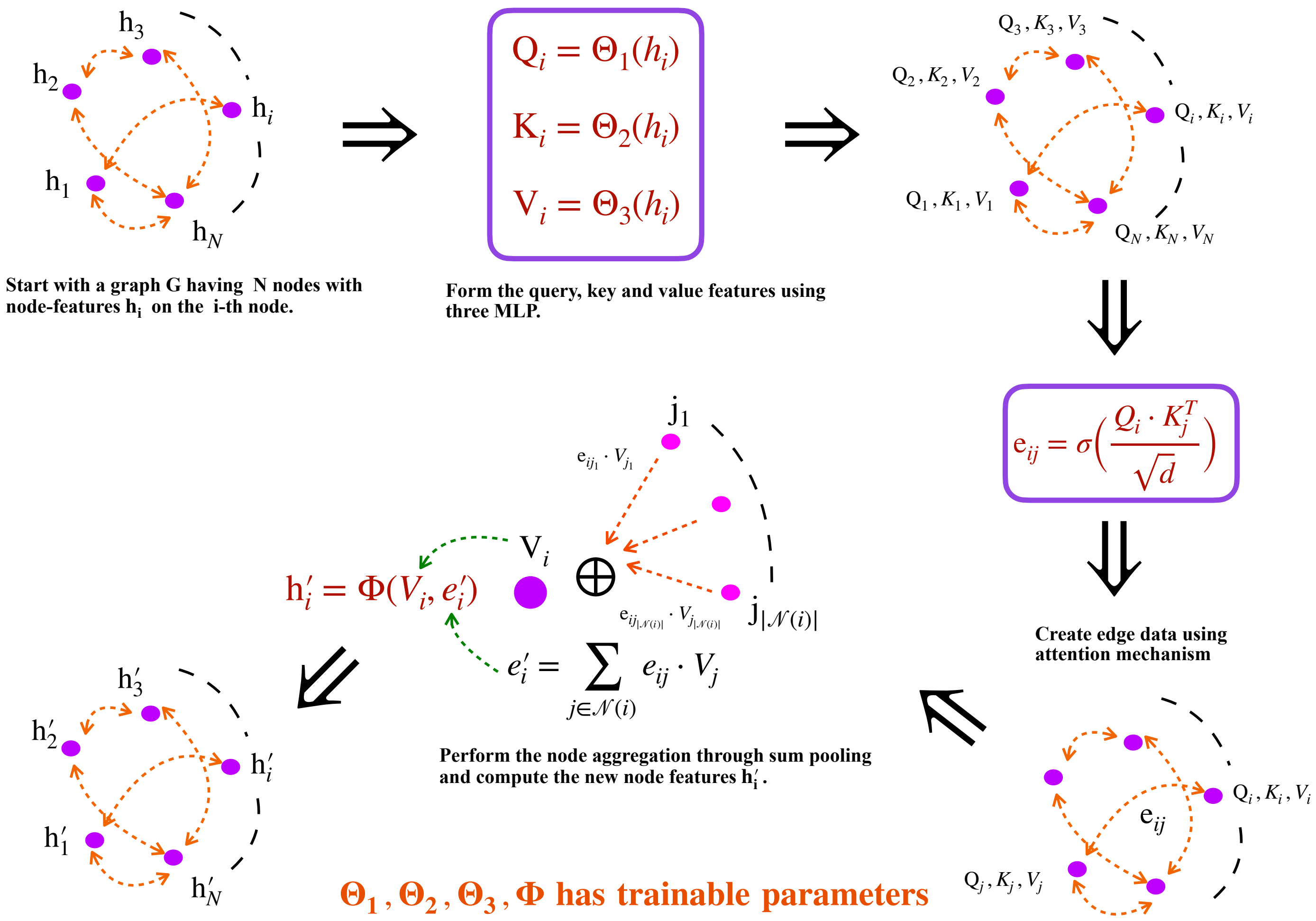
Tracking + Calorimetry

- Calibrating calorimeter alone has intrinsic limitations due to hadronic shower fluctuations
  - Tracker is natural counterpart: better resolution at low energy
- Point cloud networks can be easily extended to include tracking information
  - Track considered just another "node" in the point cloud; include binary mask to label input as track or calo cell

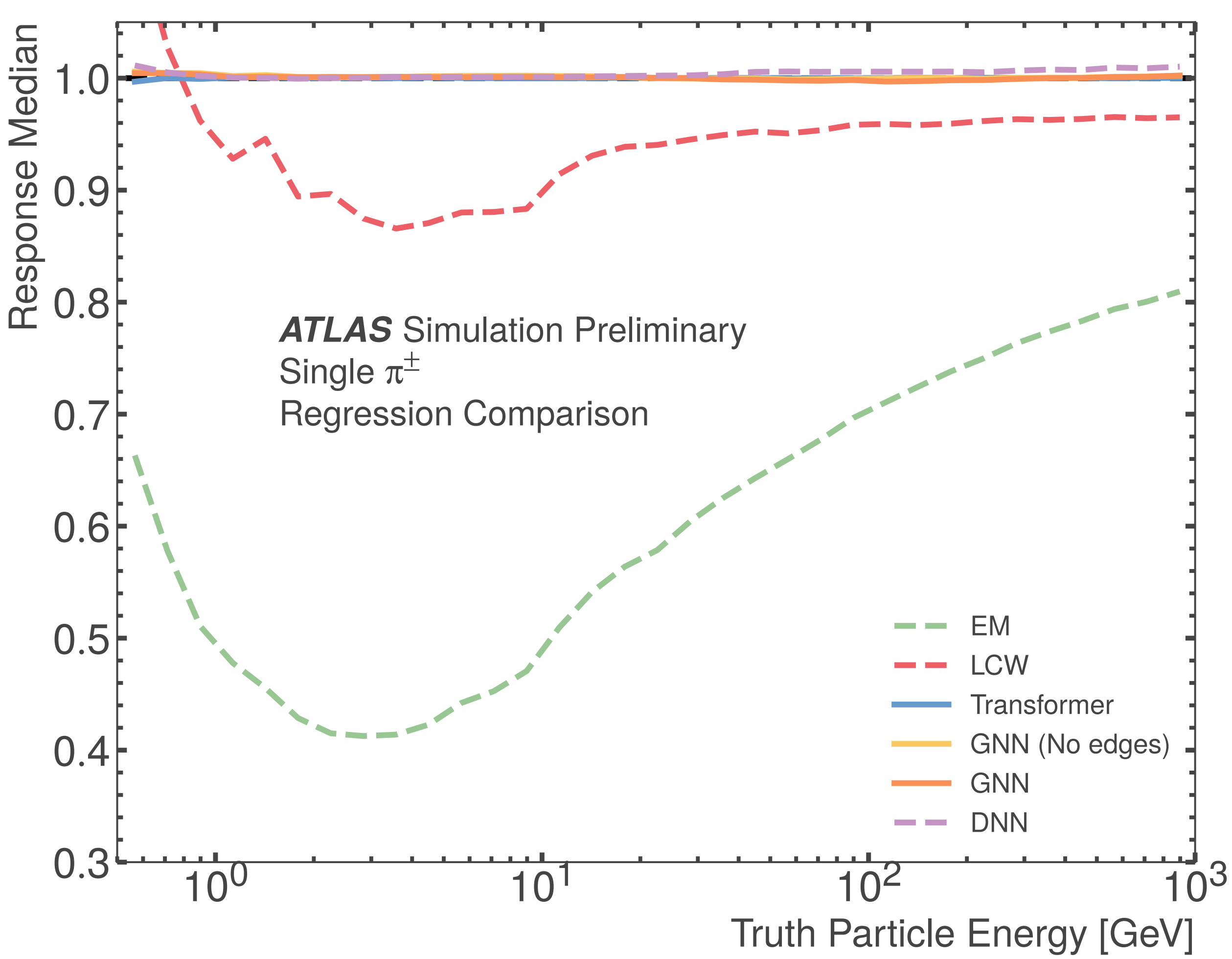


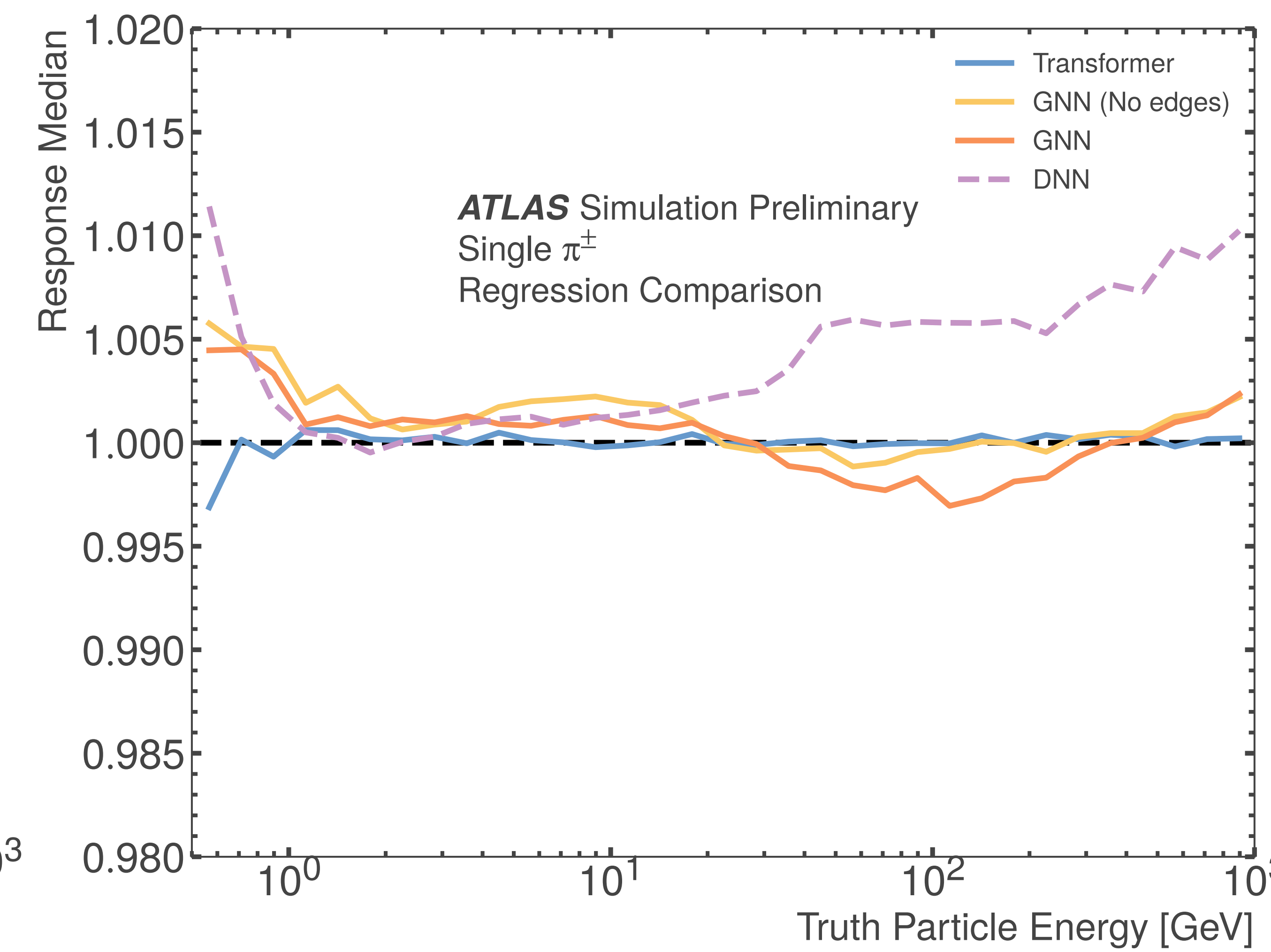
Architectures

- GNN and DeepSets continue to be studied
  - Very simple DNN (simple MLP) also implemented to compare performance
- Also explore "transformer" algorithm
  - Several iterations of "Message passaging layer" (displayed on right) helps model learn relationships between nodes via attention mechanism; nodes ultimately summed in pooling layer
  - Similar methods developed by Nilotpal et al (previous talk)



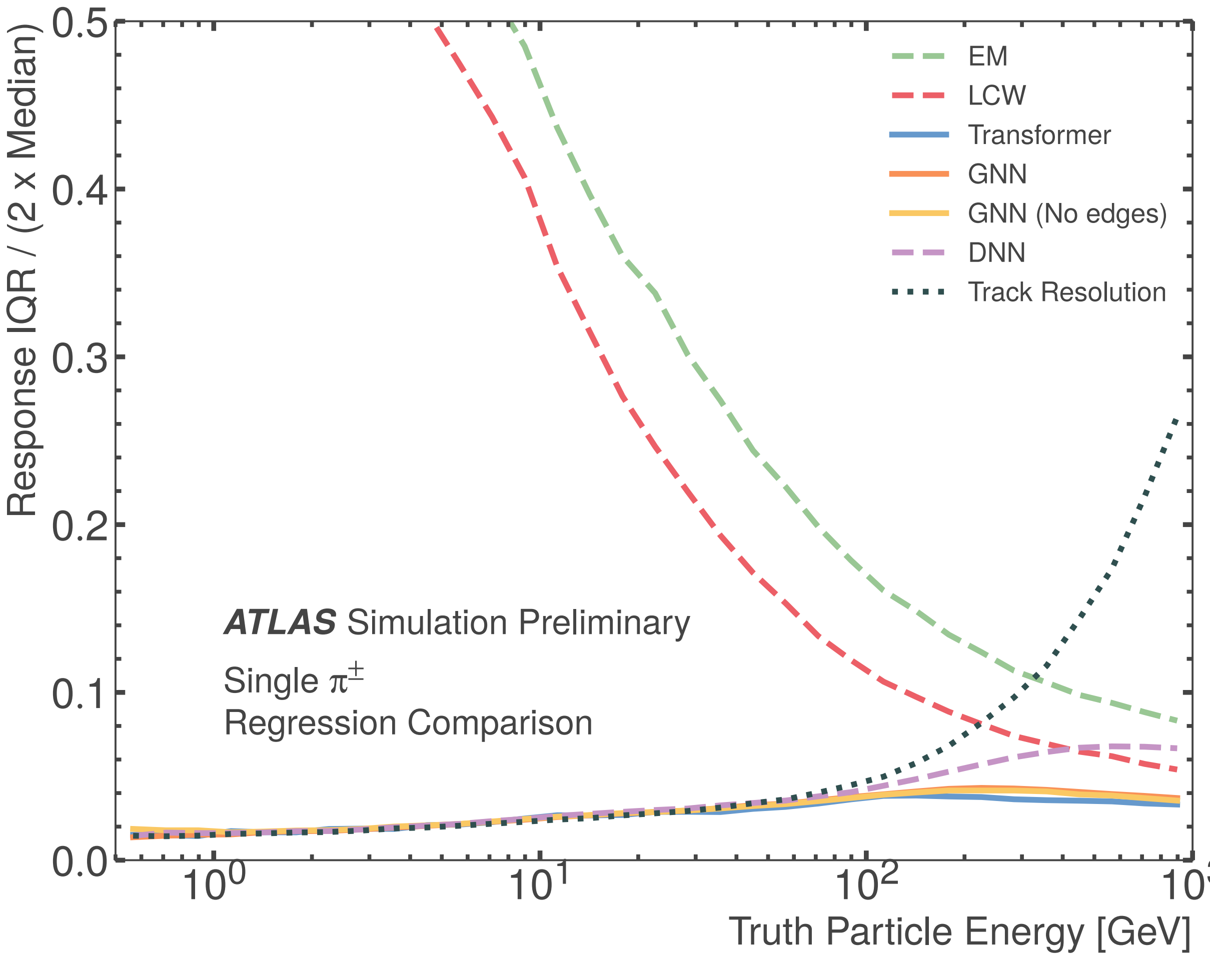
Calibration Results

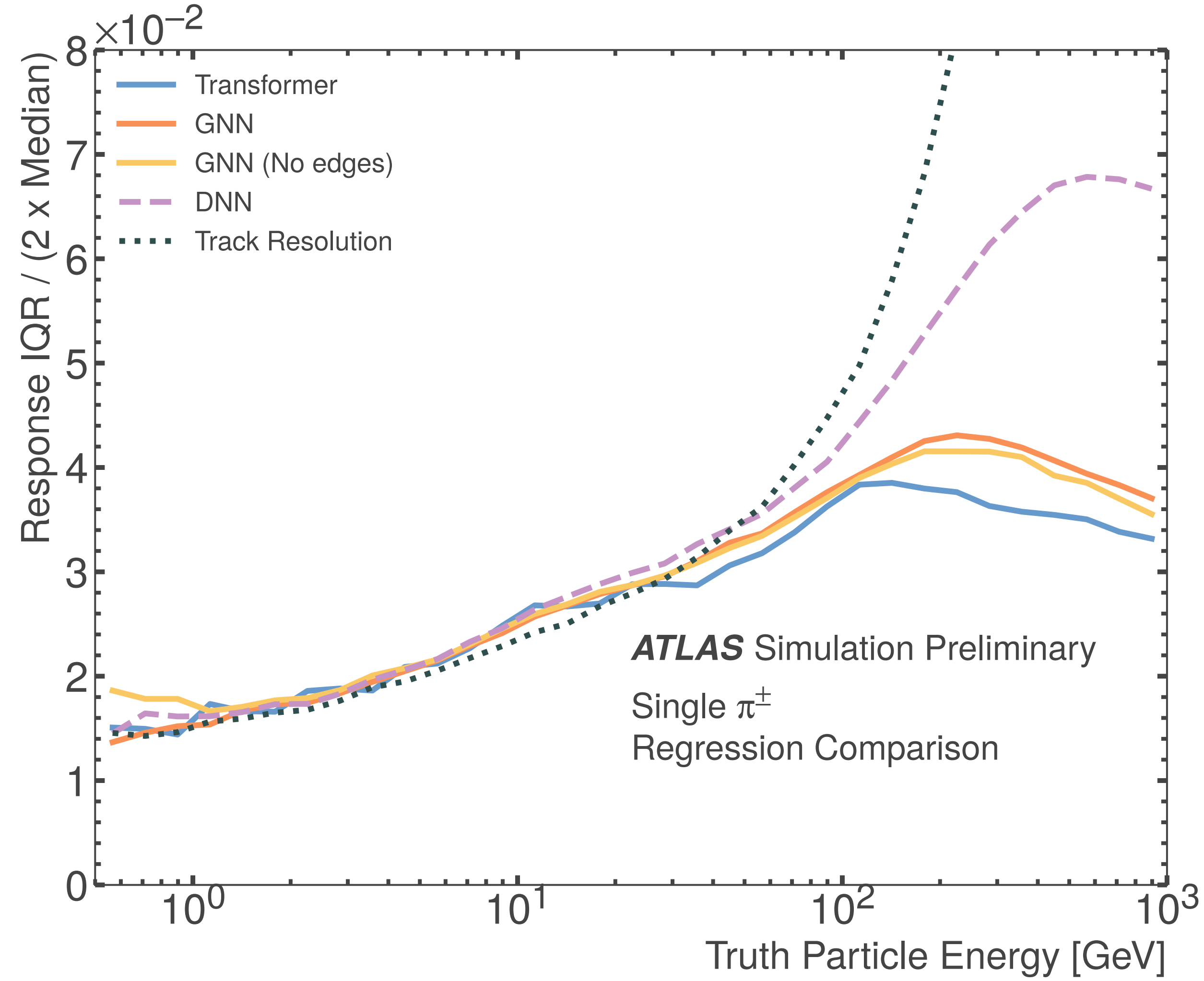




- All ML architectures deliver significantly improved energy reconstruction over full energy range

Resolution Results





- Here, compare resolution of ML techniques to Calo-only and tracker-only results
- ML results all significantly improve over baselines
  - Transformer and GNN significantly improve over DNN: graph/message layers matter!
- **ML can successfully combine information from different detectors**

Conclusions

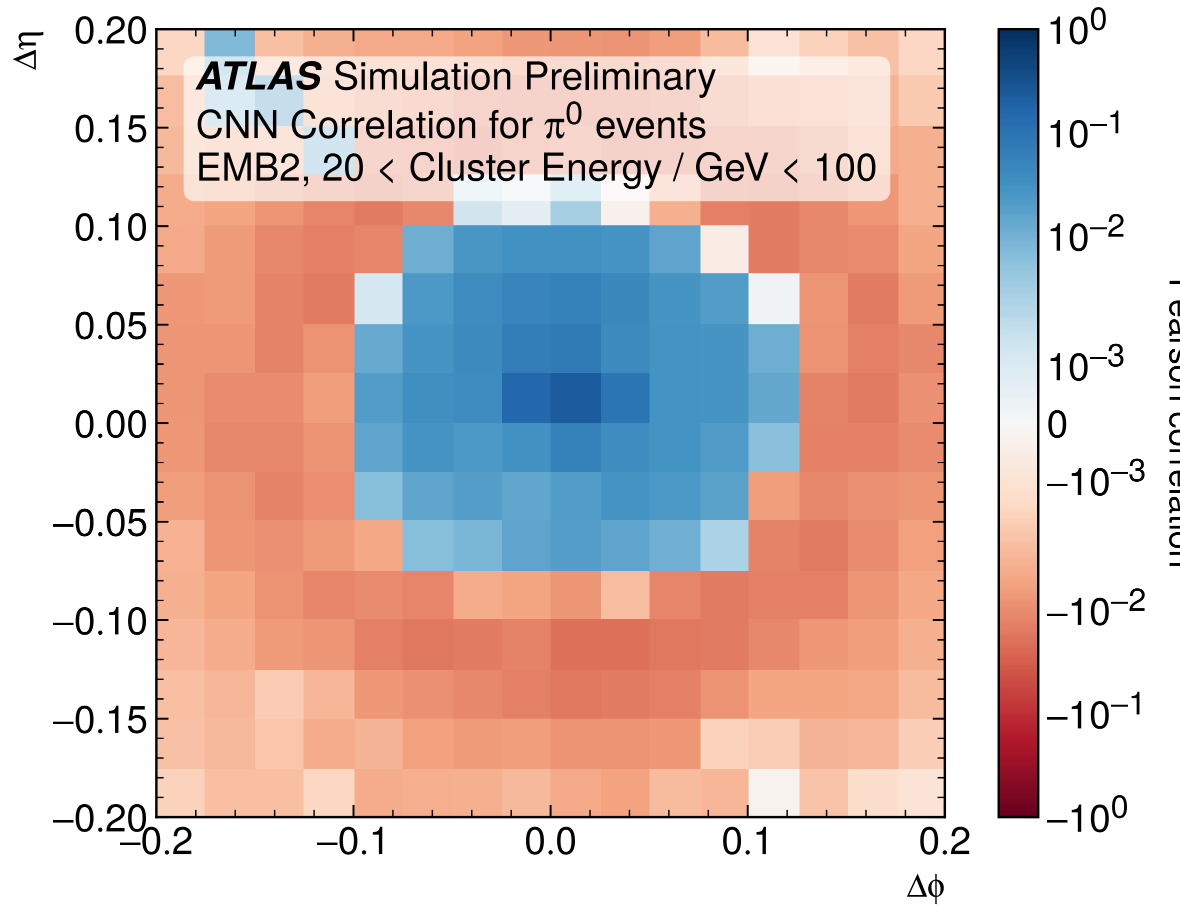
Conclusions

Better resolution can enable better physics at the LHC

We are tackling *low-level inputs to jets*: can we use our exquisite detector granularity to help jets catch up to other final states?

Our step-by-step approach has shown improvements over baseline in several key metrics already

Results on more complete "PFlow" to come soon!



Backup

Calorimeter-Only Pion Reconstruction With Deep Learning

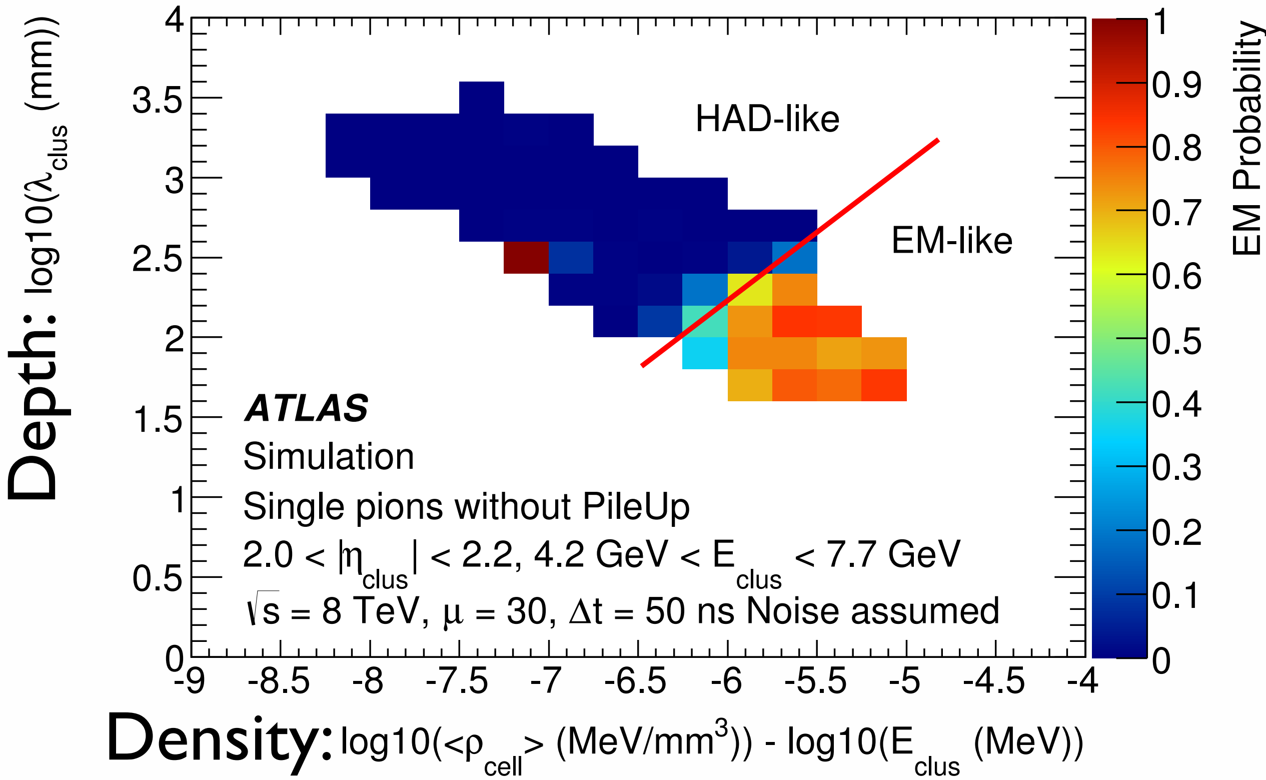
ATLAS-PHYS-PUB-2020-018

Calorimeter-Only Calibrations

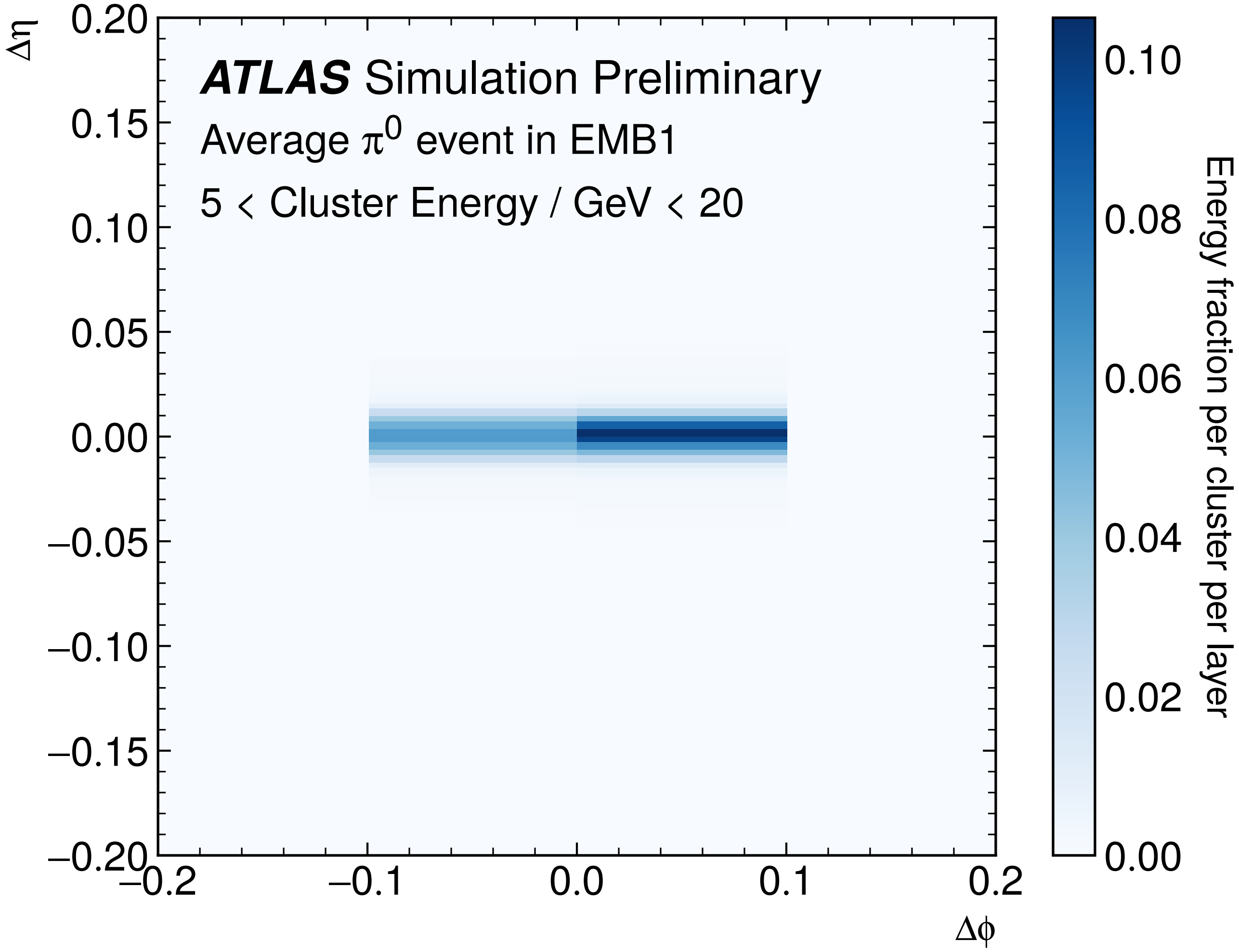
Traditionally, ATLAS has used the "Local Cell Weighting" technique for calorimeter-only jet reconstruction

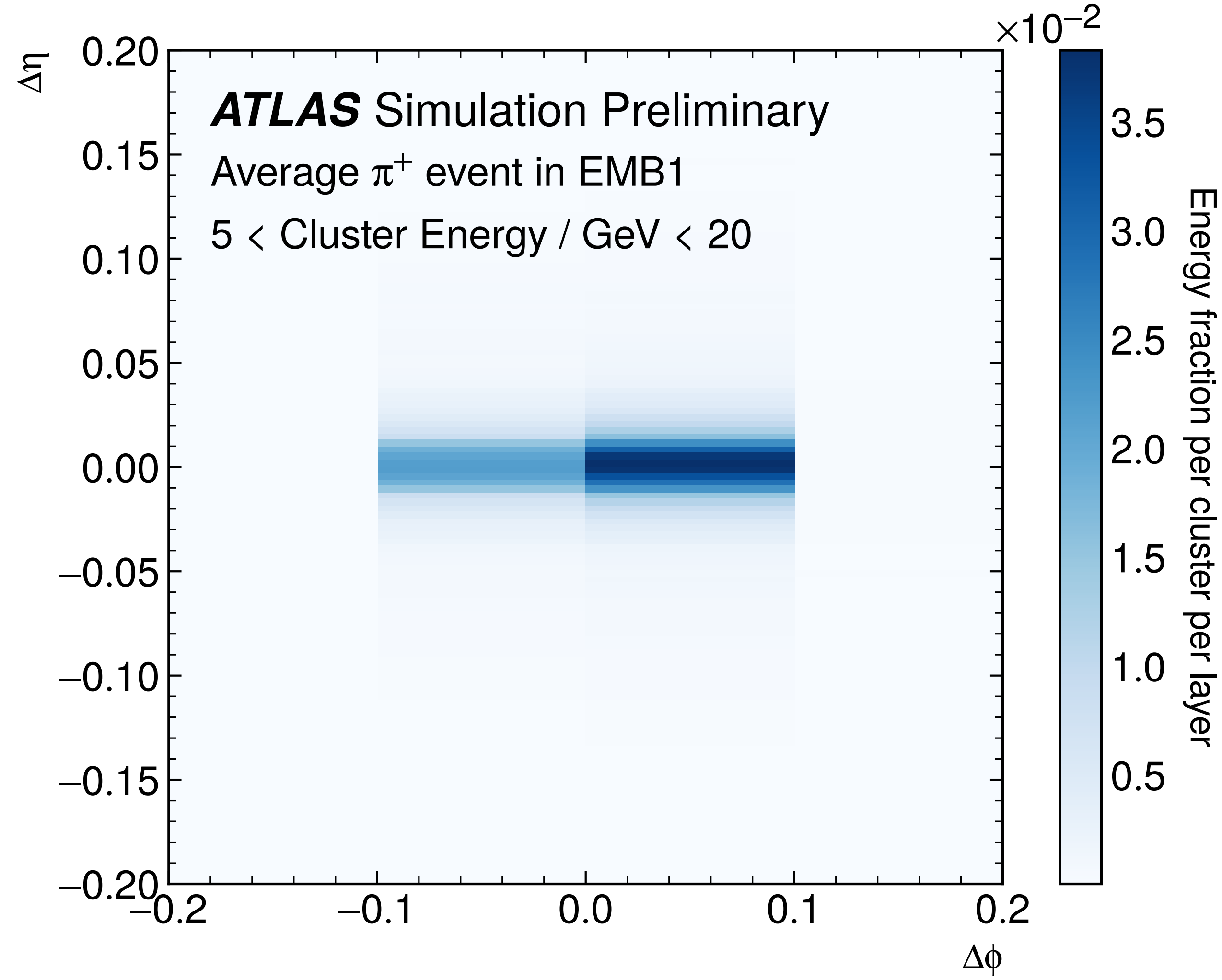
1. Classify topo-clusters as "EM-like" or "Hadronic-like"
2. Apply a calibration appropriate for EM or Hadronic pions

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



Average Pions



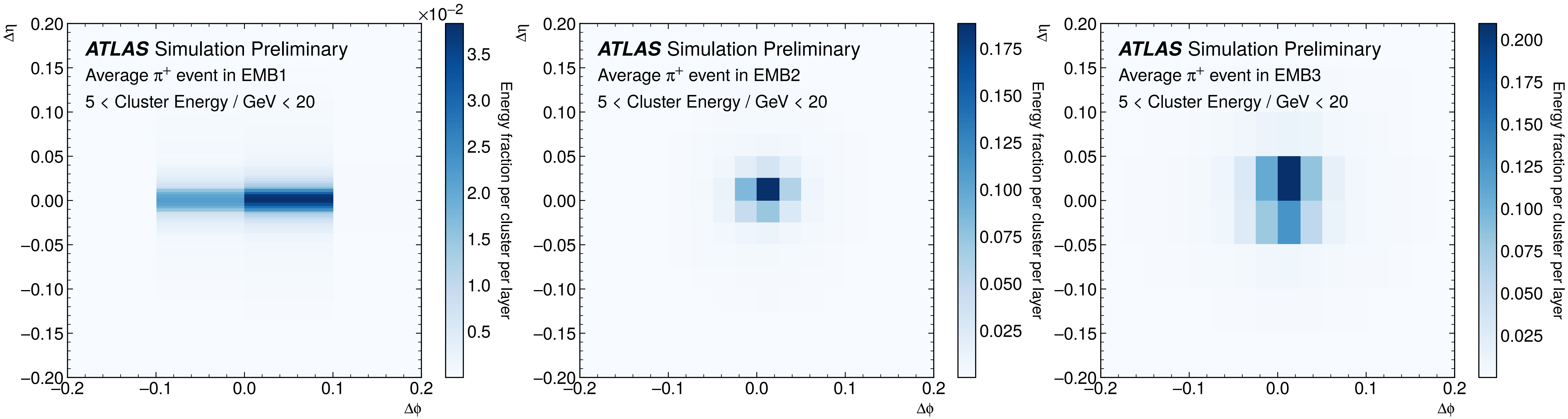


Treat energy in each 'cell' of topocluster as pixel intensity

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



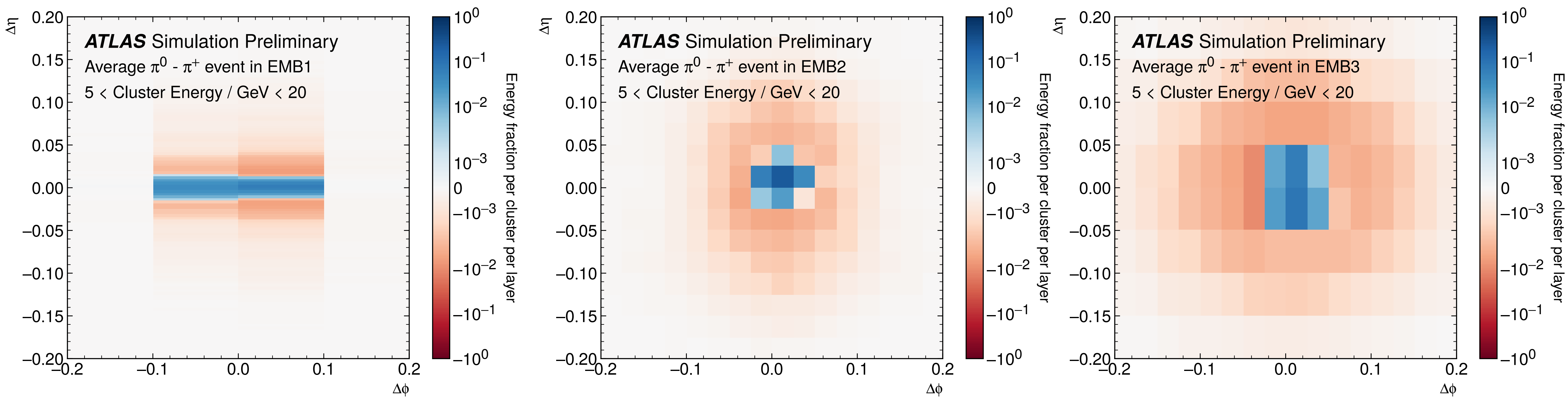
Different calorimeter layers have different granularity

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

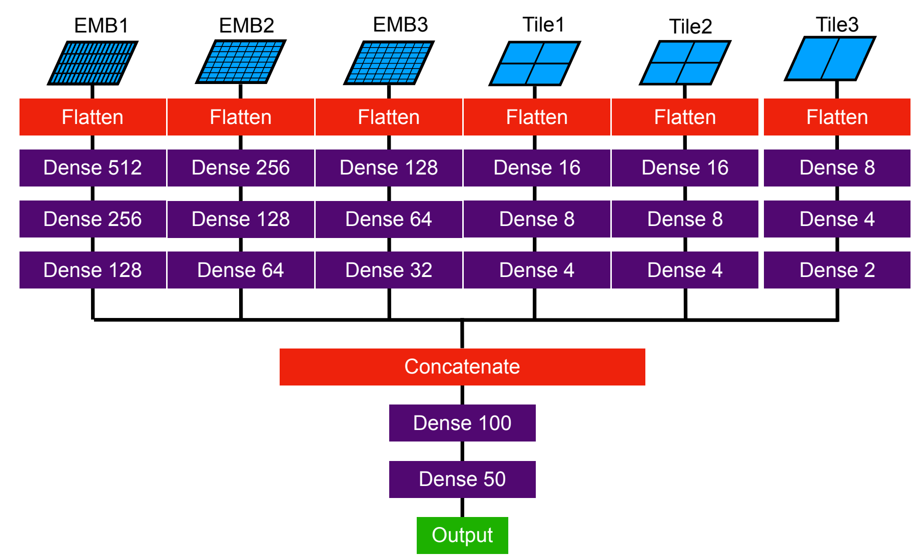
Can deep learning classifiers use this information?

Classification

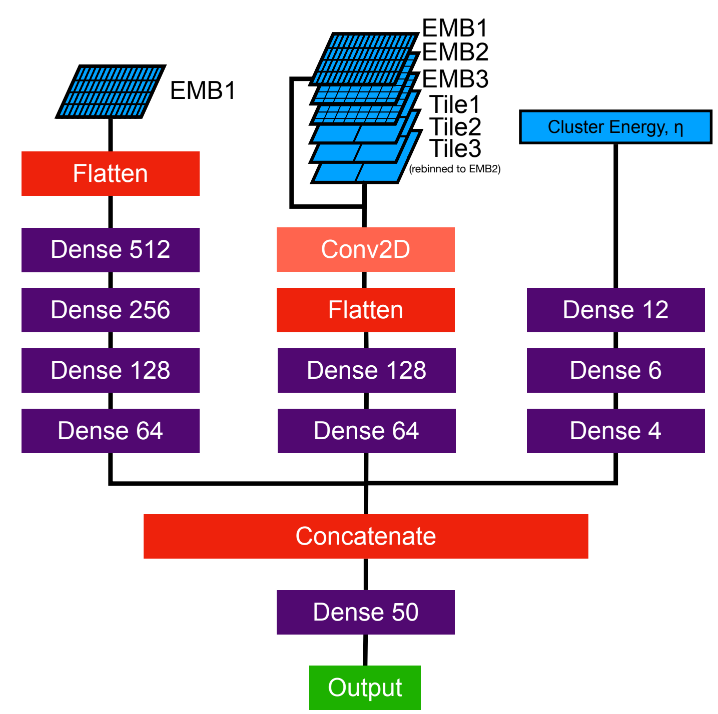
Architectures

Three general classes of NN architecture studied

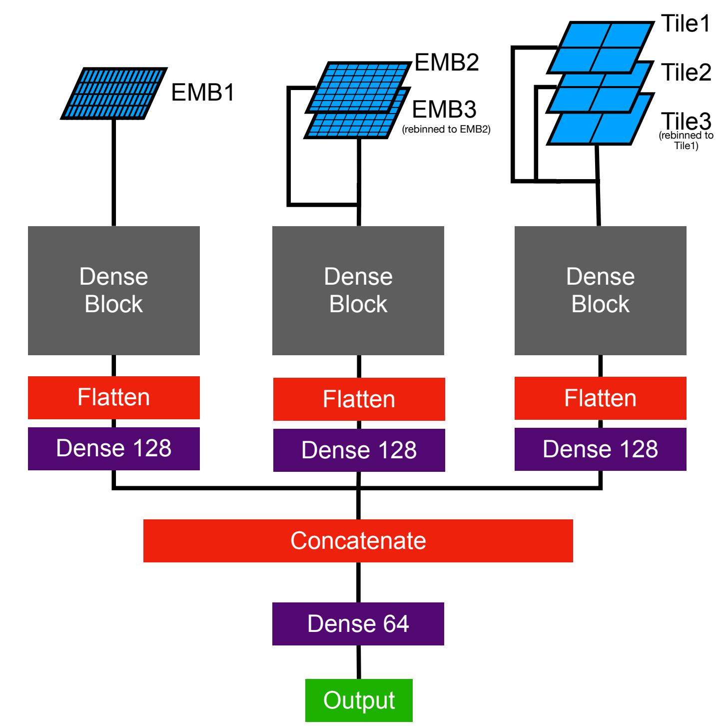
DNN: Large, deep networks with cells as direct inputs



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



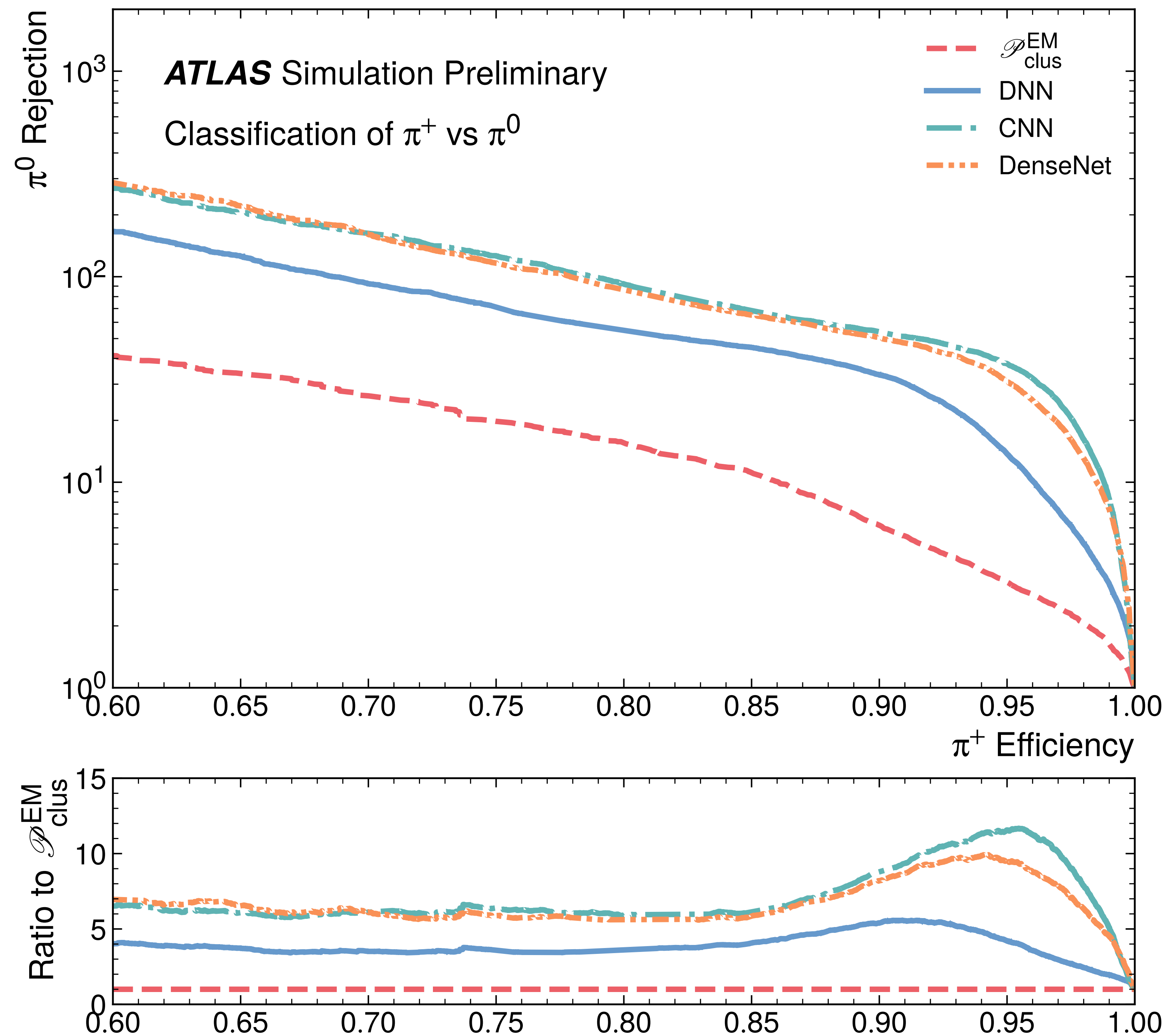
DenseNet: Industry-designed, sophisticated CNN with information propagation



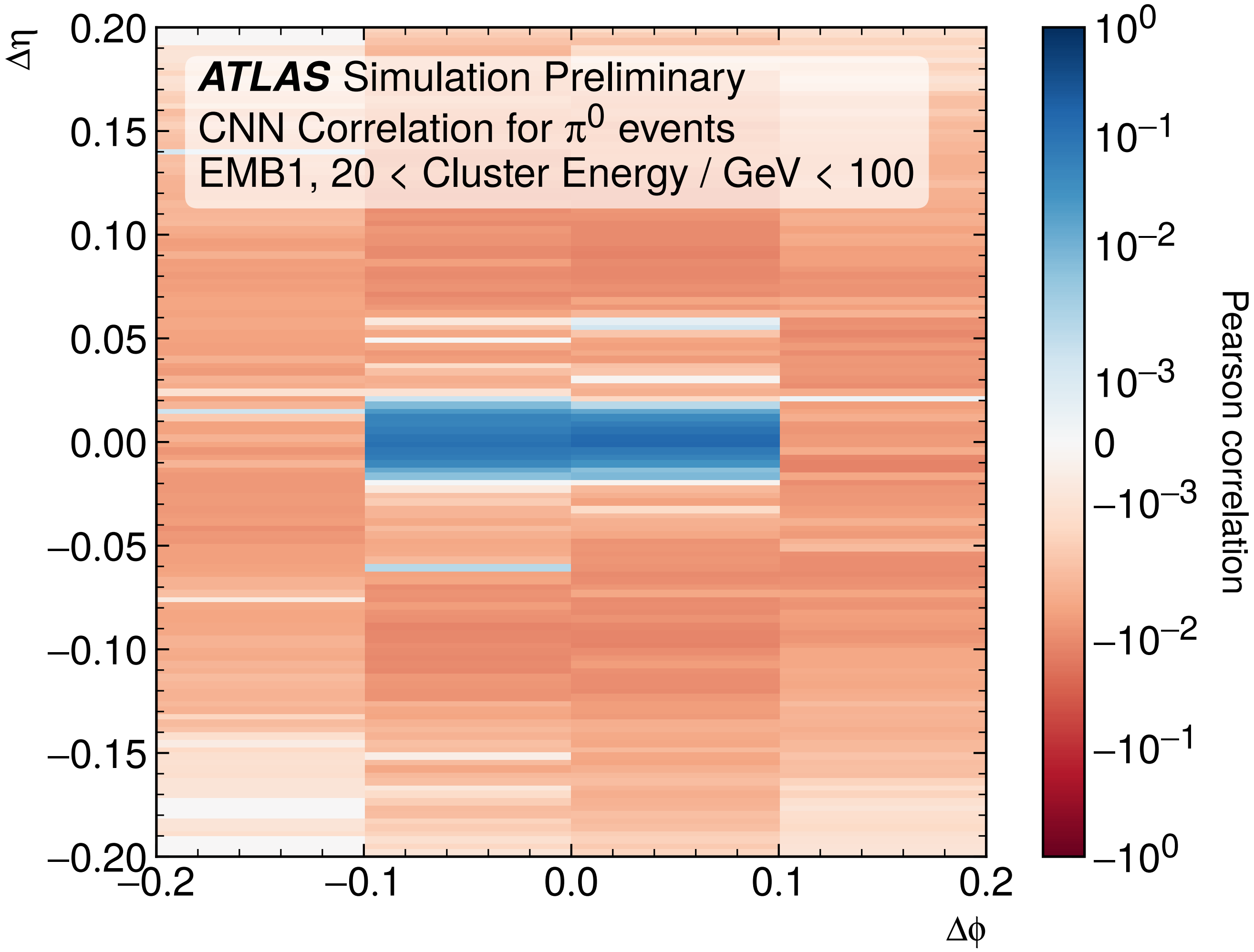
Classification ROC

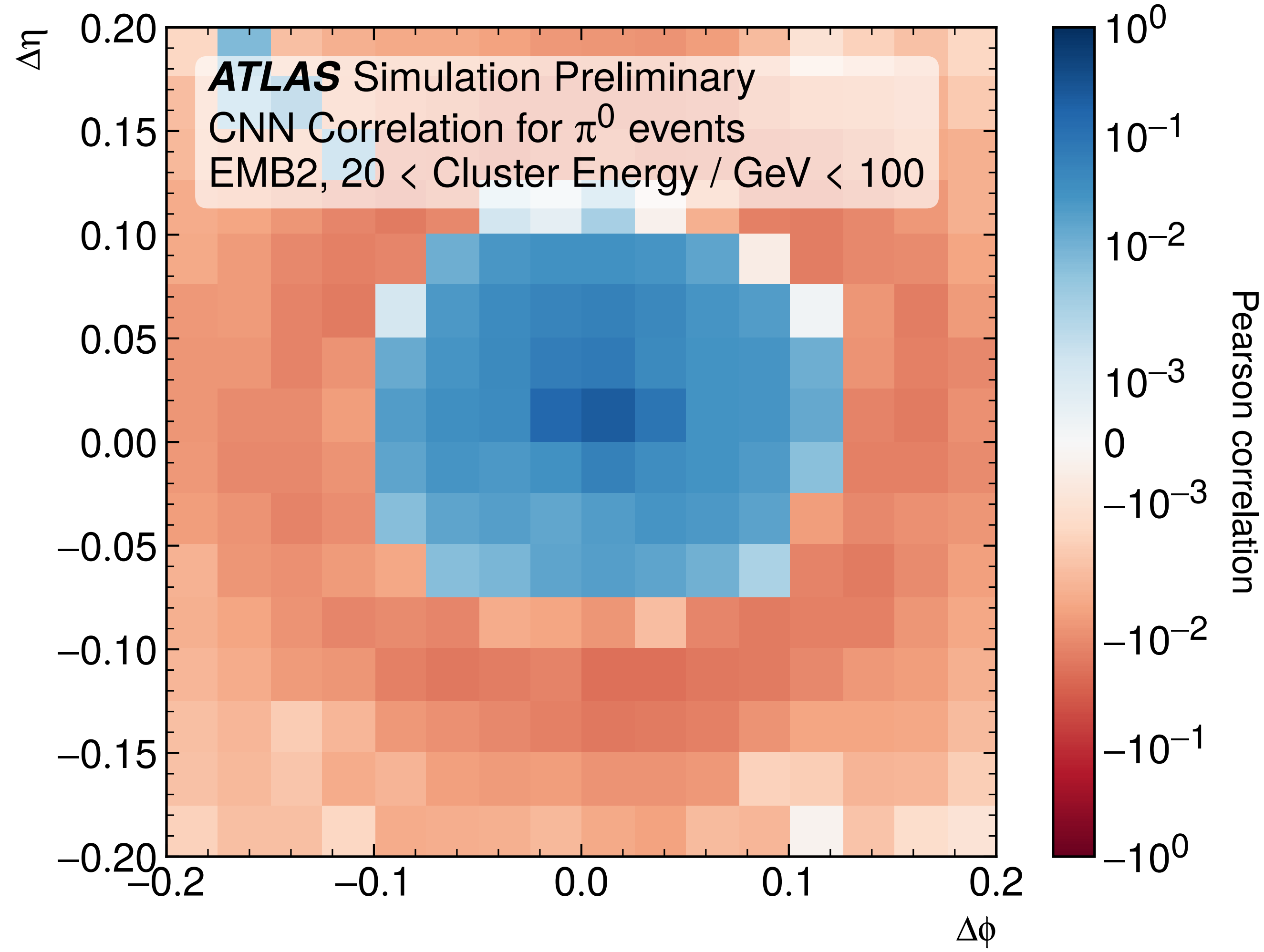
Compare π^+ efficiency vs π^0 rejection (1/efficiency) for different algorithm

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



Classifier Correlation: π^0





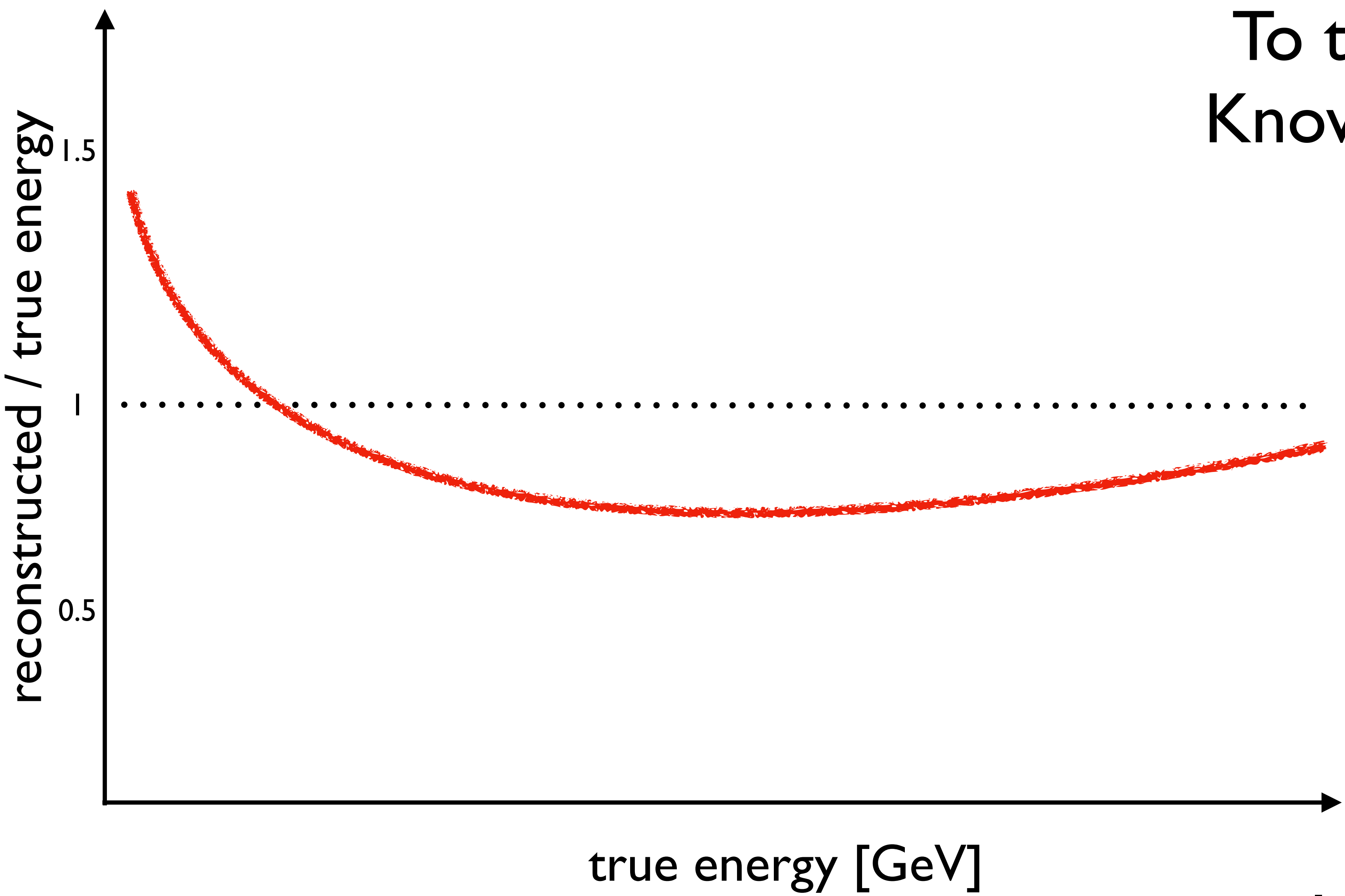
Here, calculate the correlation coefficient between each pixel and the classifier

Can visualize (very roughly) what the CNN is learning

Can see the physics we expected from the images!

Energy Regressions

Understanding Calibrations

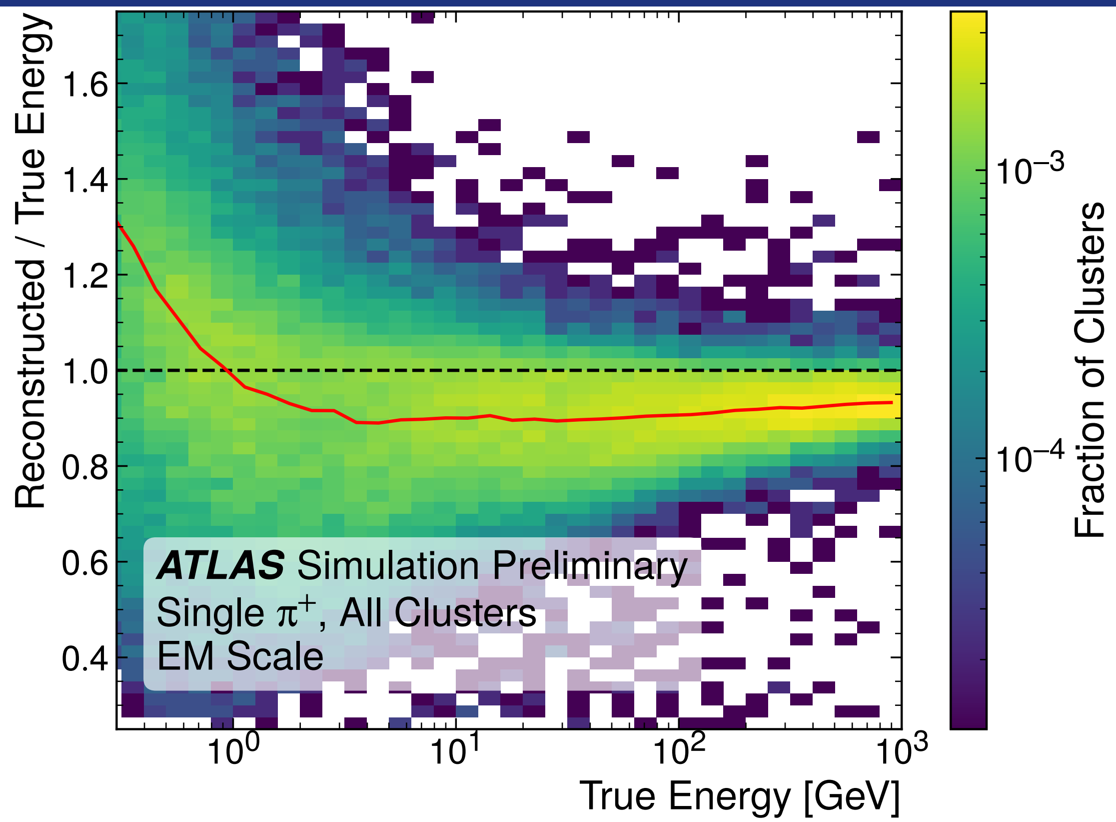


Use simulated data
To test energy calibrations:
Know ‘truth’ from simulation

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

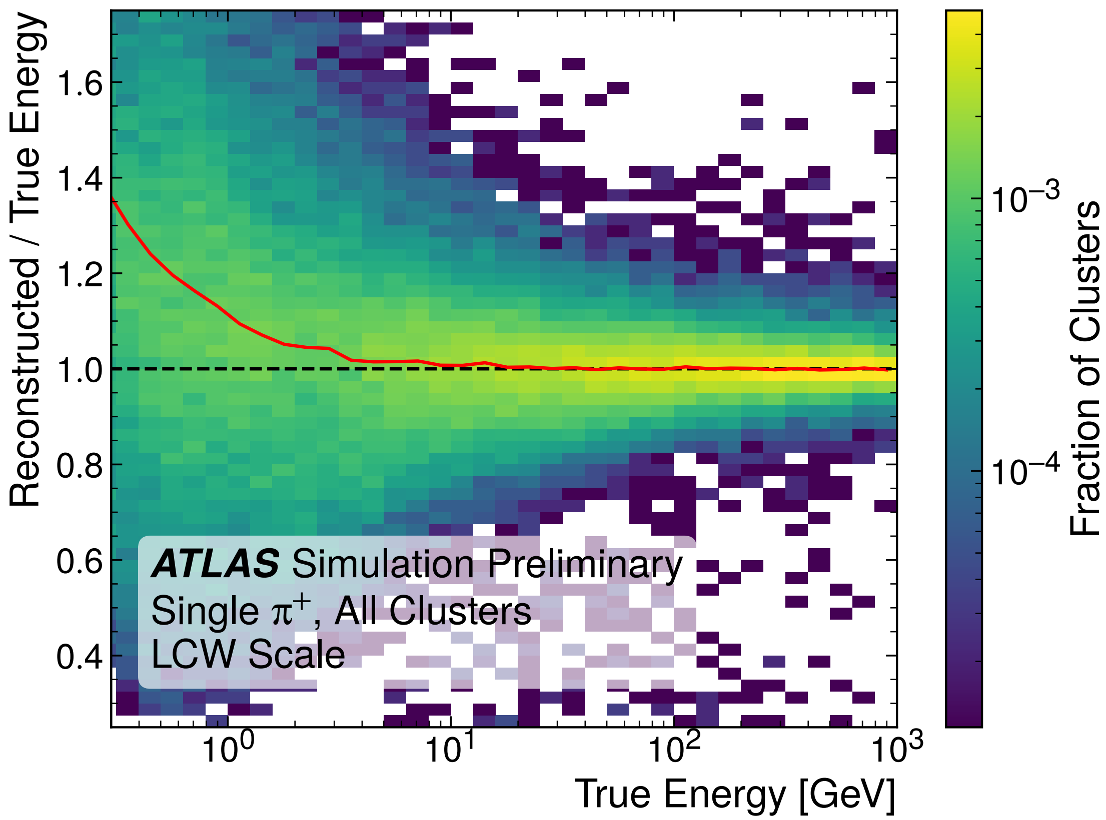
Ideally: close to 1, and narrow distributions

Correcting π^+



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

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



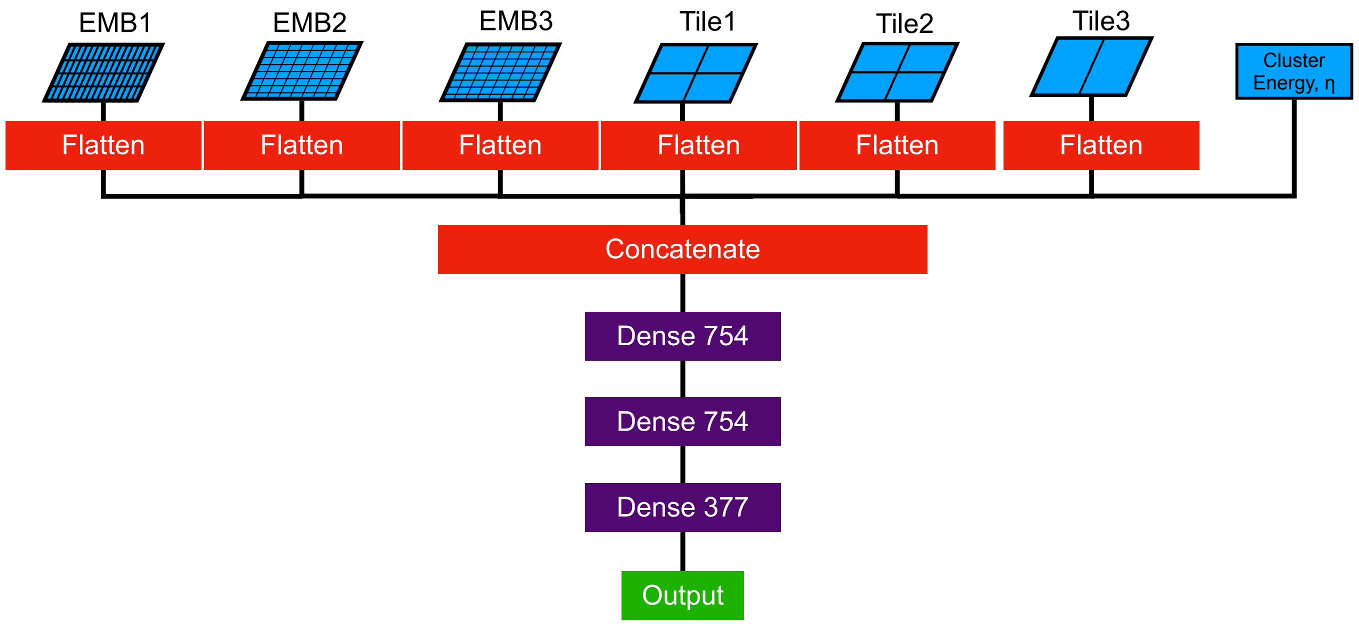
Feature-based method corrects for this: see 'correct' energy scale for wide range of true energy, but over-compensation at low energy

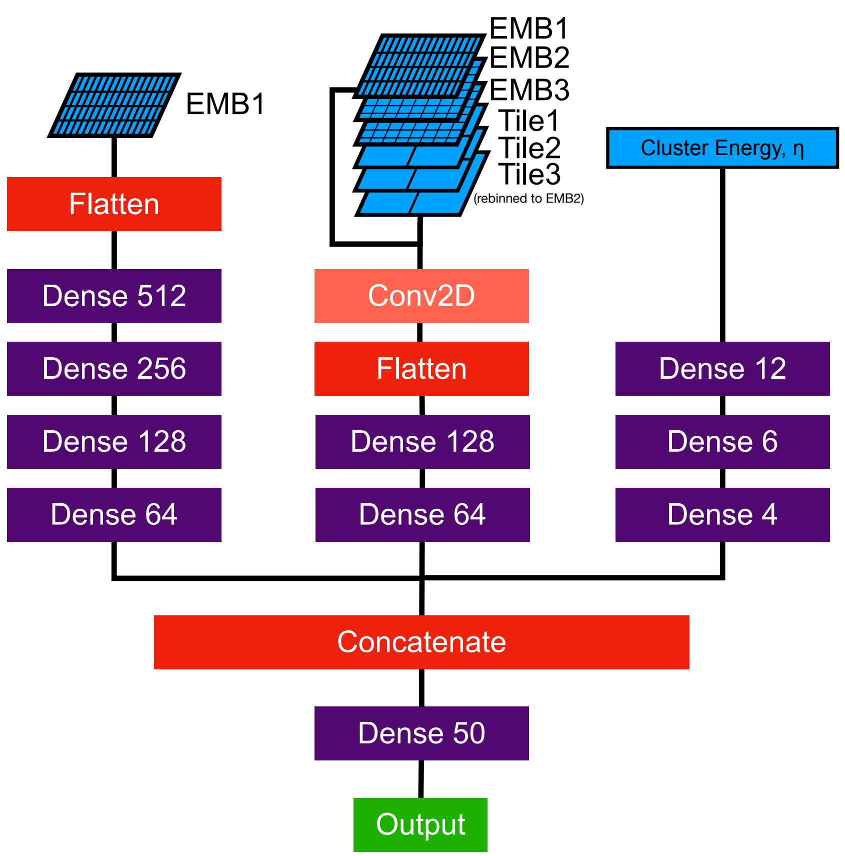
Regression Architectures

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

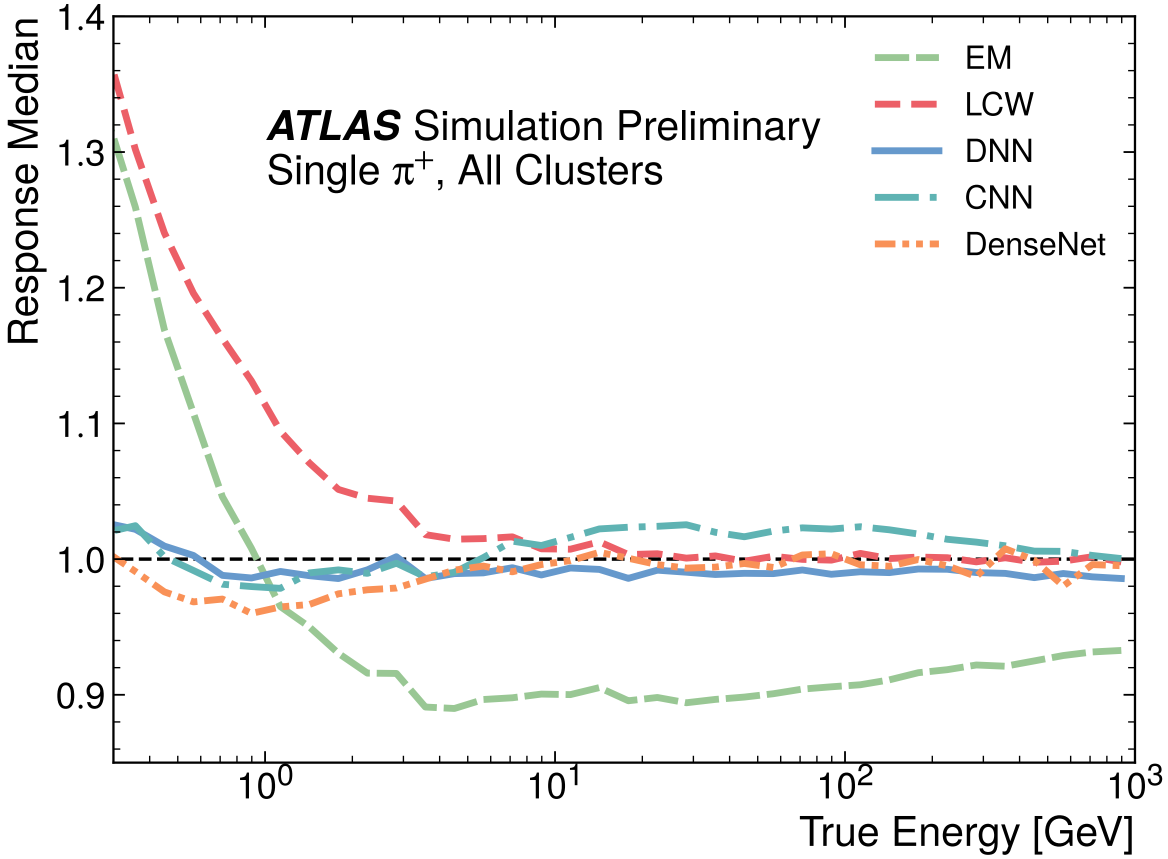
Target: ‘true’ energy from simulation

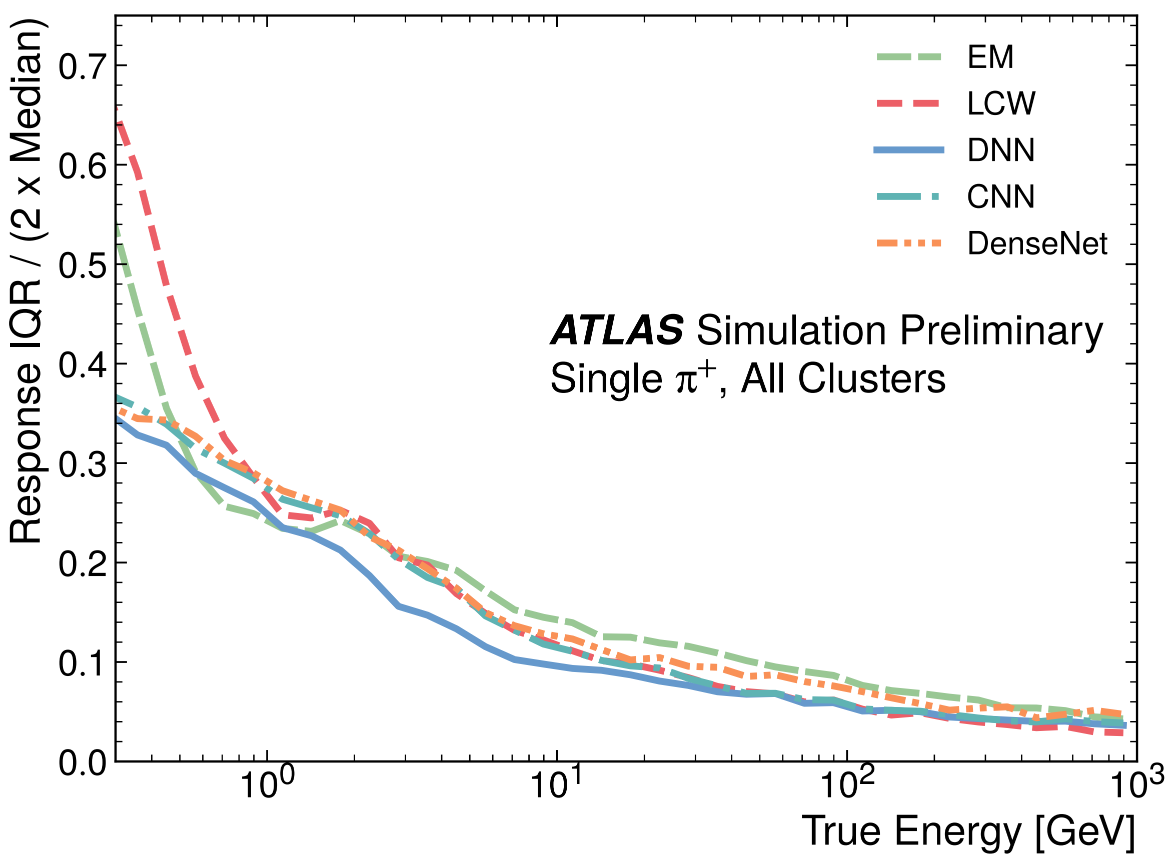
Use similar NN architectures as for the classifier, but also include ‘raw’ energy





Comparing Results





Scale goal: get close to 1

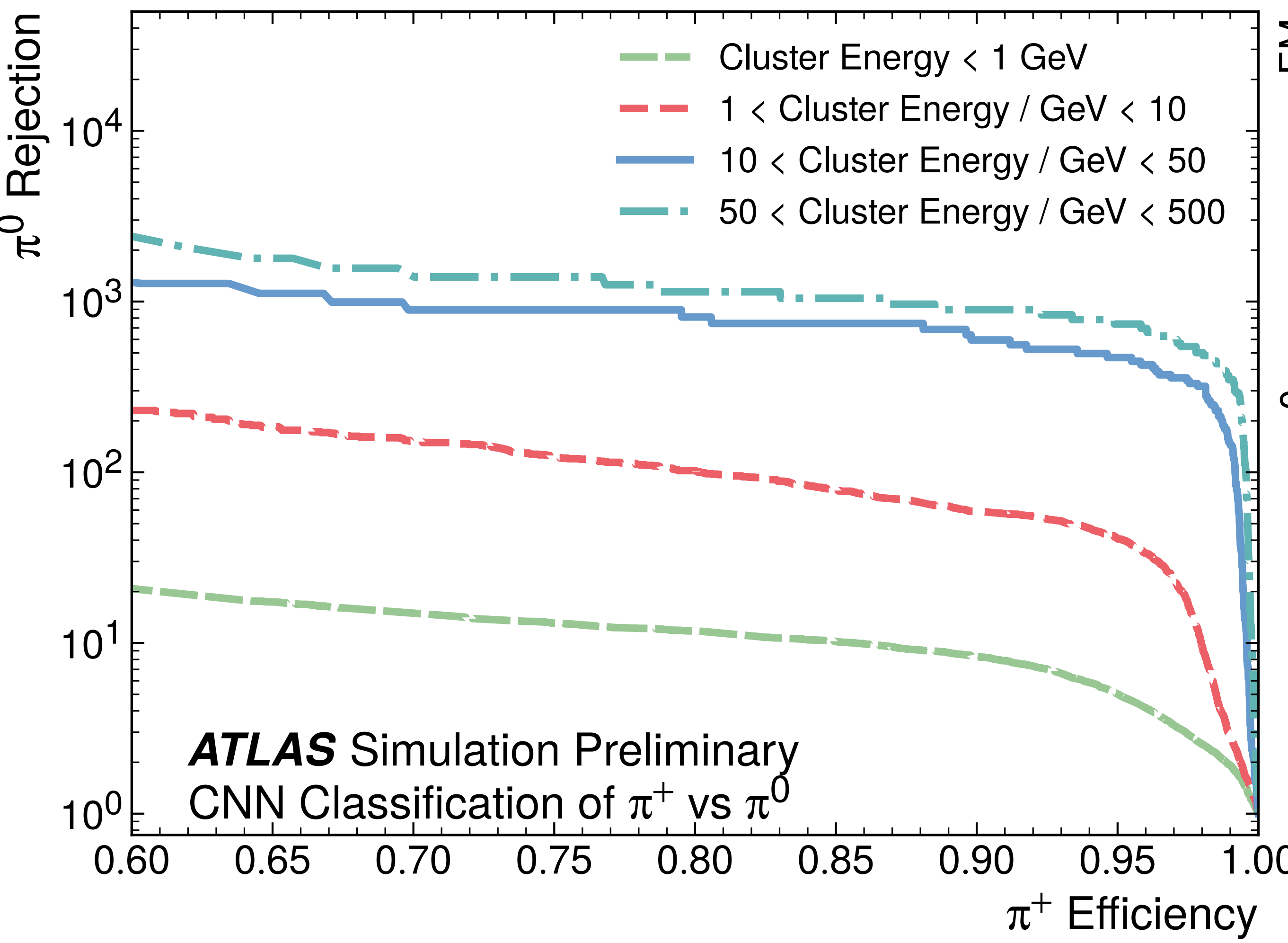
DNN outperforms default, and 'feature-based' correction!

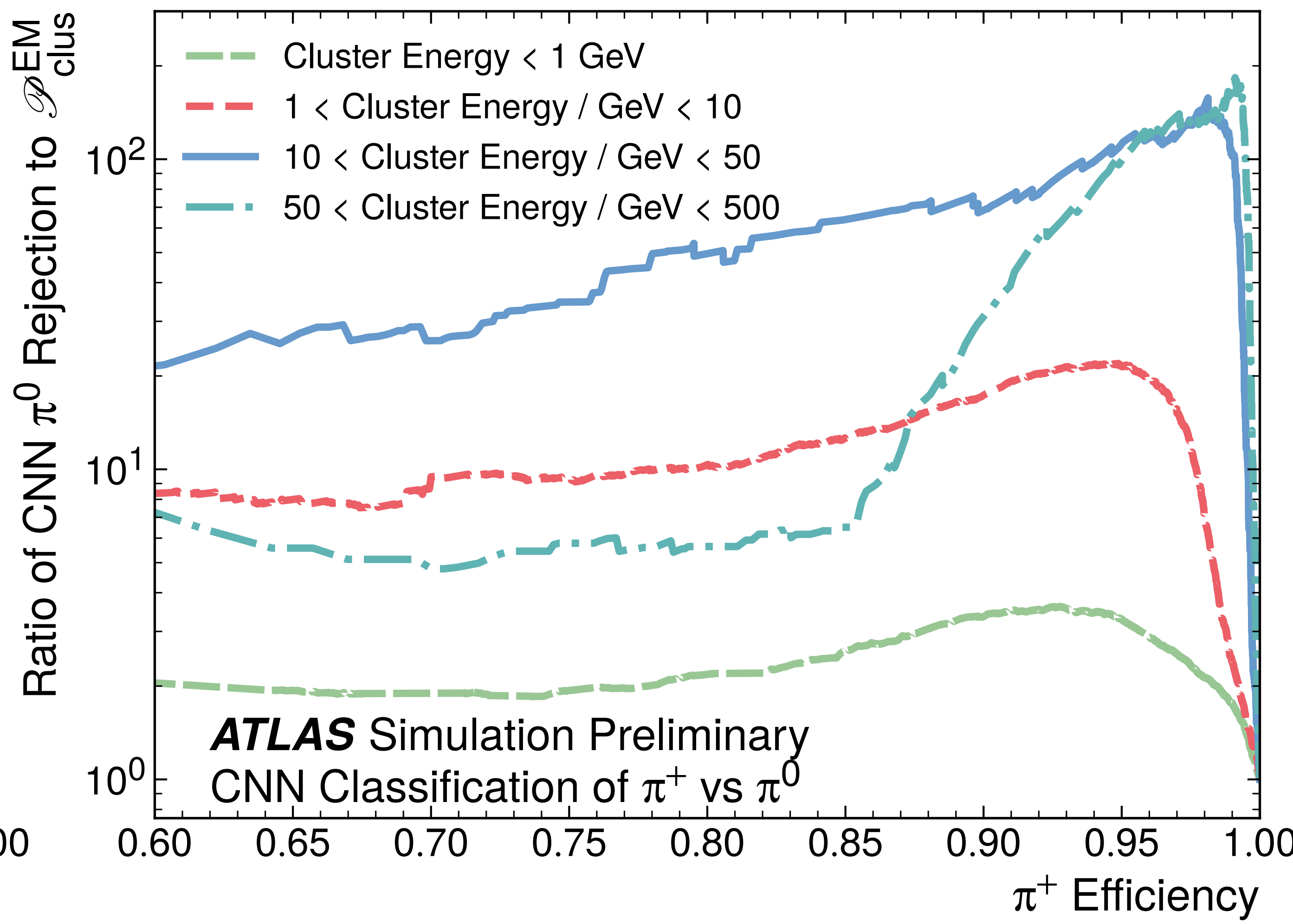
Resolution goal: get close to 0

DNN again outperforms other methods

Thank you!

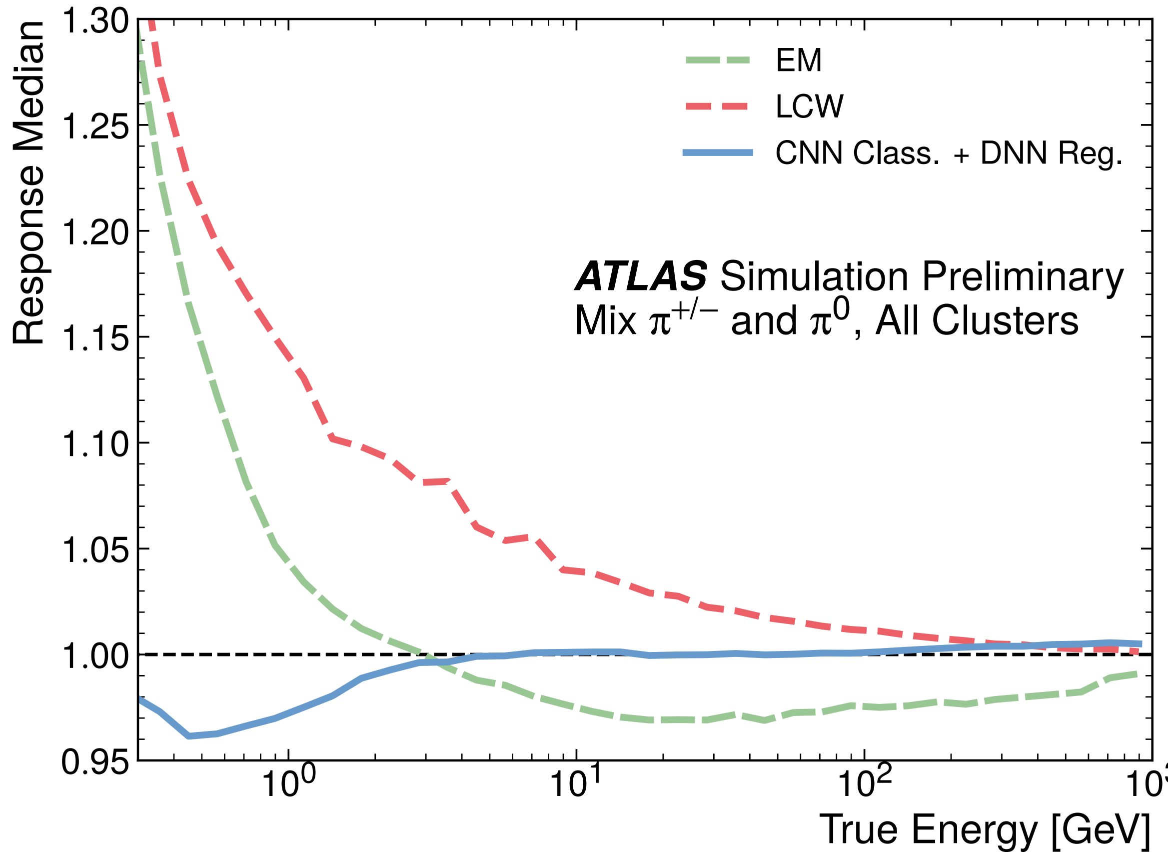
Binned Performance

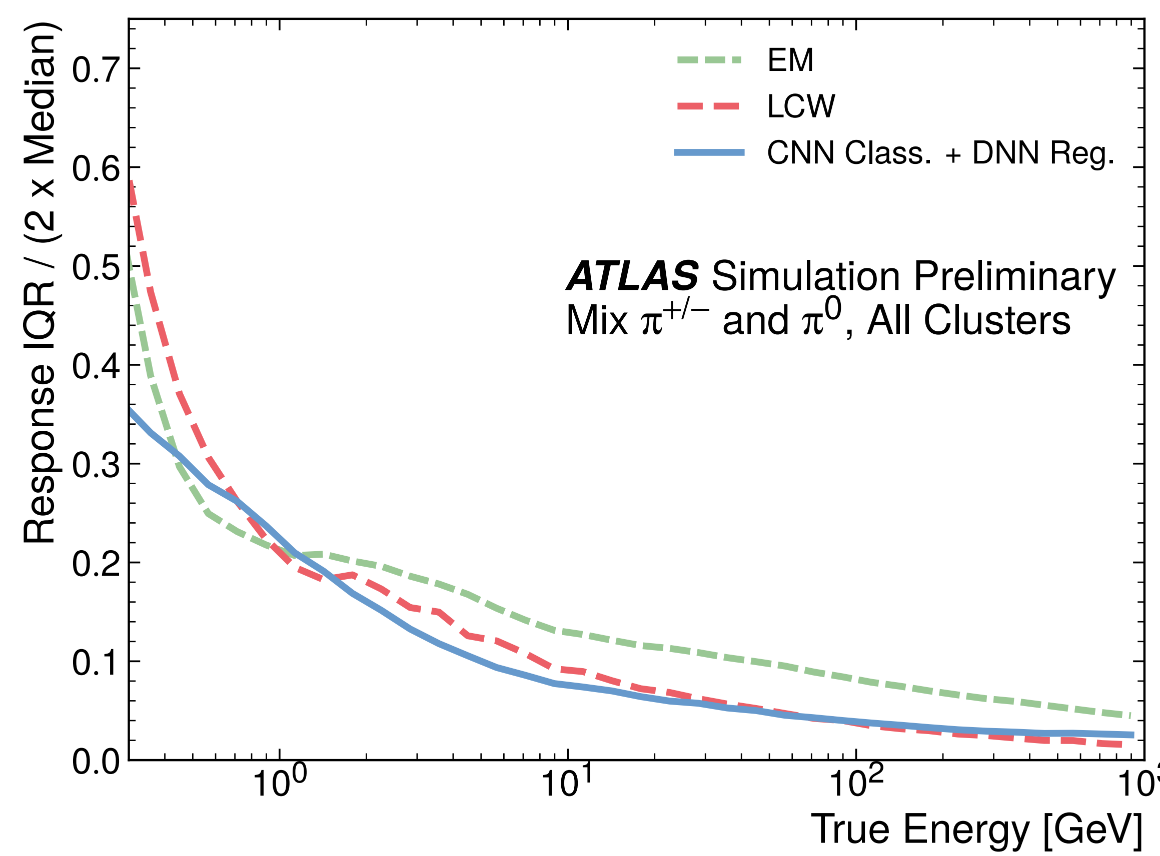




- Also show the CNN (best architecture) performance in bins of energy
    - And compare to LC in bins of energy
- Results are encouraging: good performance over all energies!
    - Factor of 100x improvement for 10-50 GeV π^0 rejection!

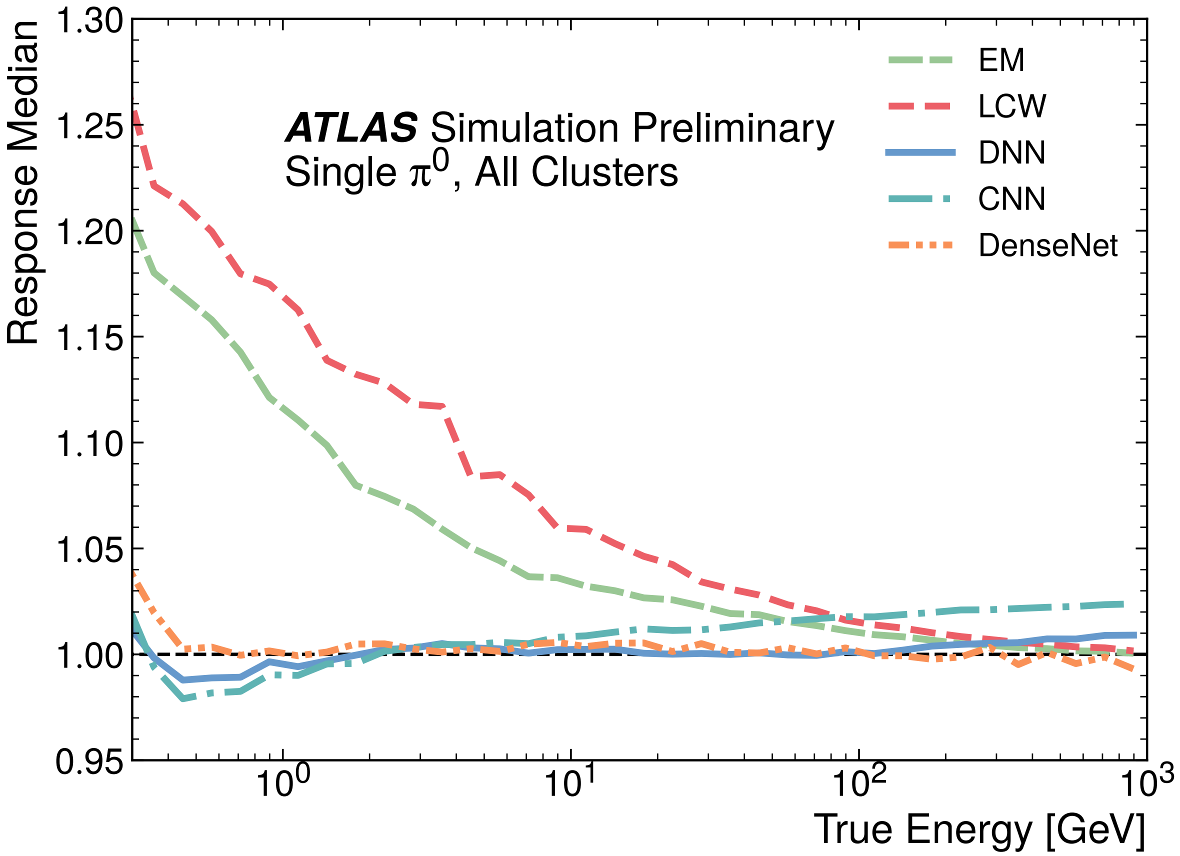
Combining in a Mixed Sample

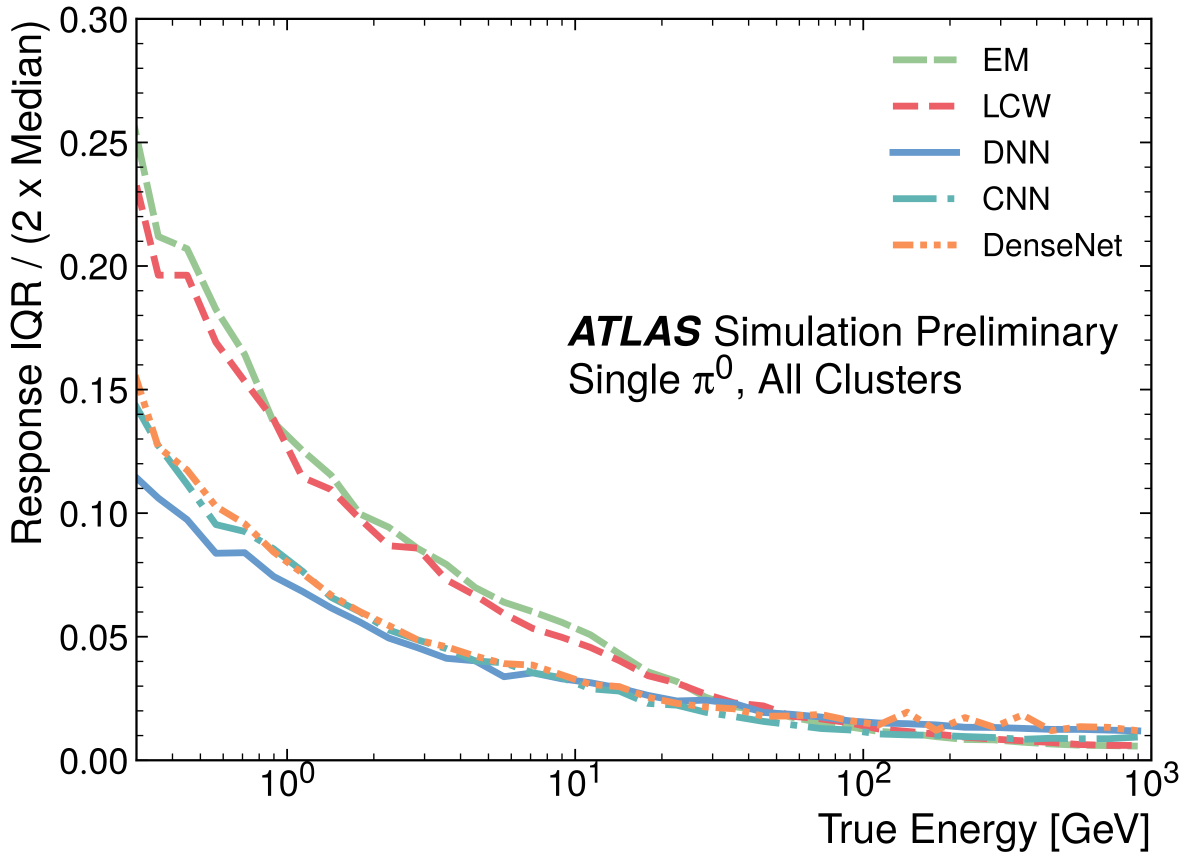




- So far, evaluated only in pure samples
- Can also mix charged and neutral pions in 2:1 ratio to mimic jets
- Apply classifier at ~95% π^+ efficiency, and then apply chosen regression
- Good performance! Better median and resolution than defaults

Comparing Results





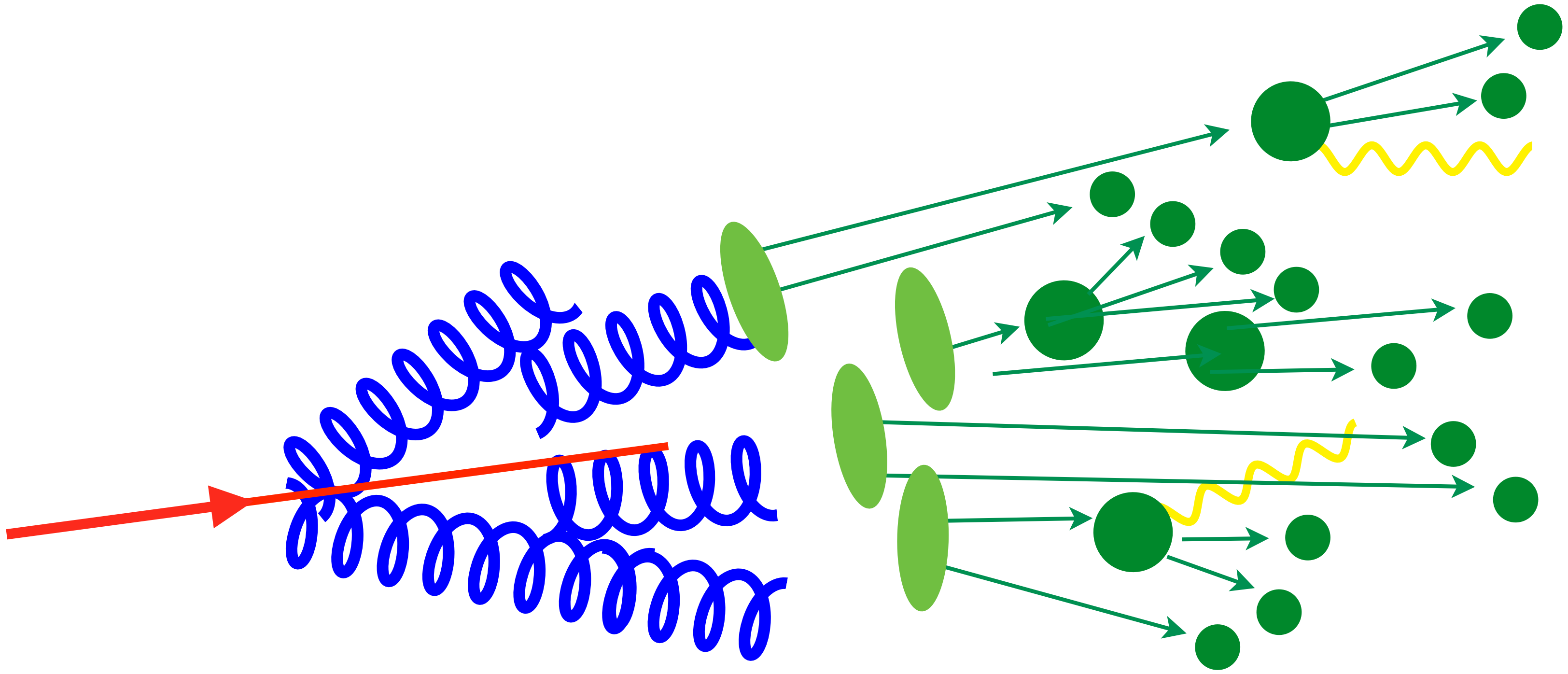
Scale goal: get close to 1

Resolution goal: get close to 0

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

DNN again outperforms other methods

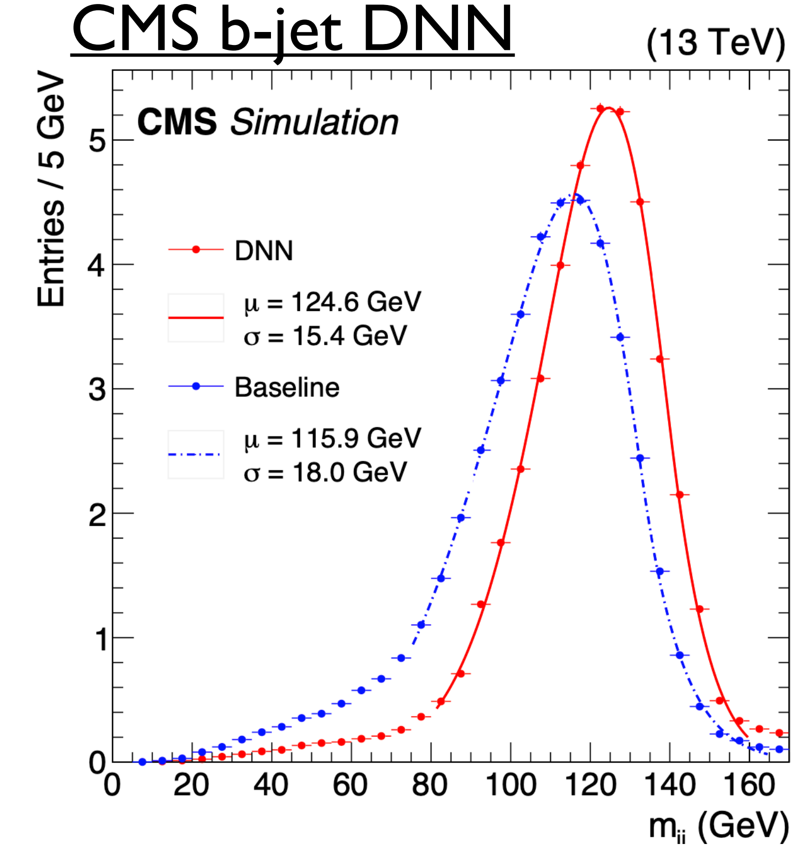
Differences in Fragmentation

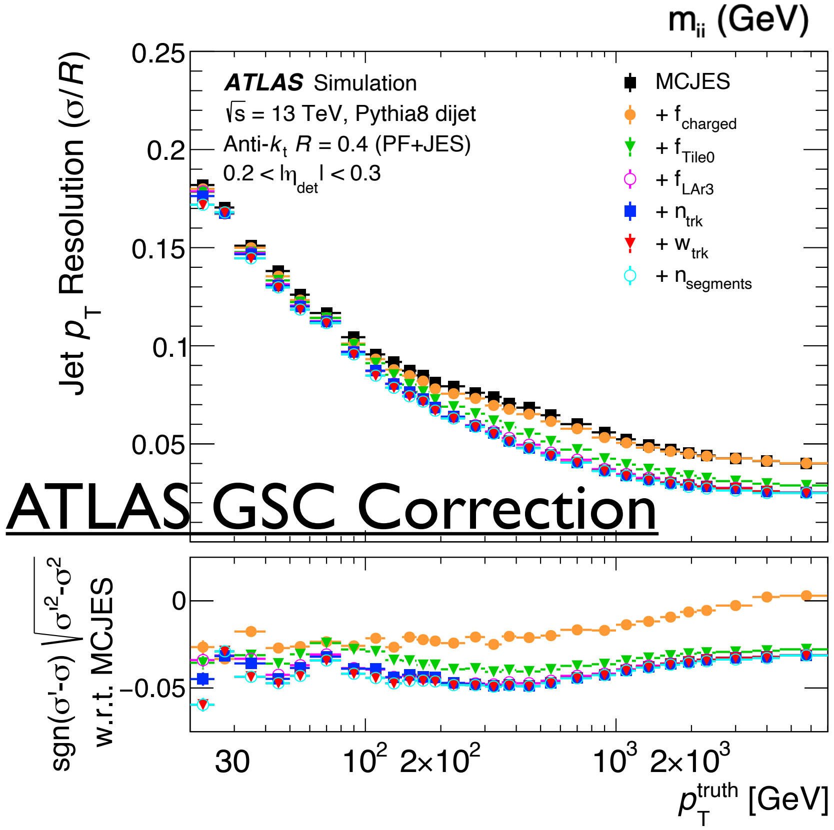


Individual particle showers fluctuate, but so do the jets themselves: the number of hadrons can vary, the types of hadrons, and so on…

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

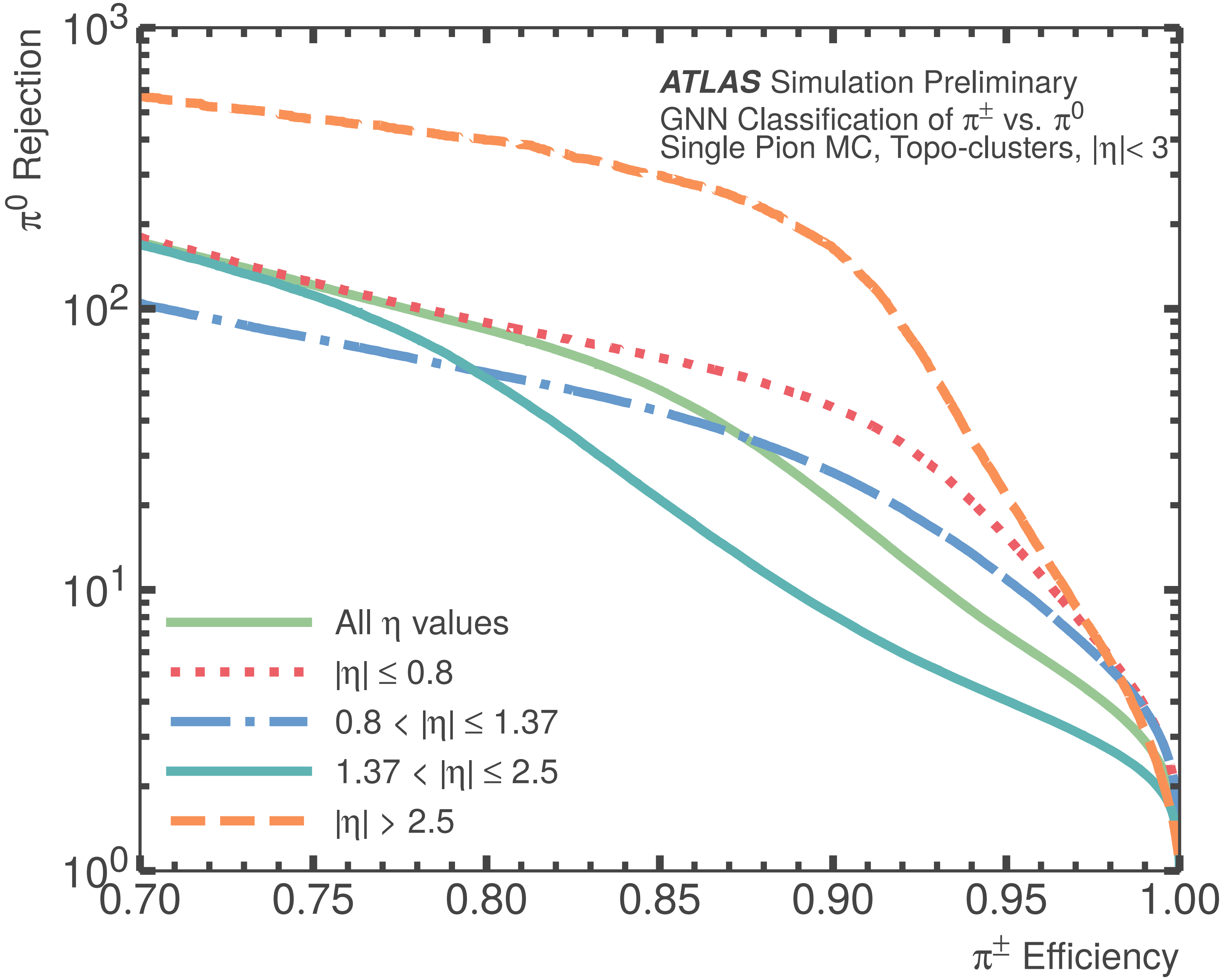
CMS b-jet DNN





ATLAS GSC Correction

GNN vs η



ATLAS Simulation Preliminary
GNN Classification of π± vs. π0
Single Pion MC, Topo-clusters, |η|< 3
π0 Rejection
π± Efficiency
All η values
|η| ≤ 0.8
0.8 < |η| ≤ 1.37
1.37 < |η| ≤ 2.5
|η| > 2.5