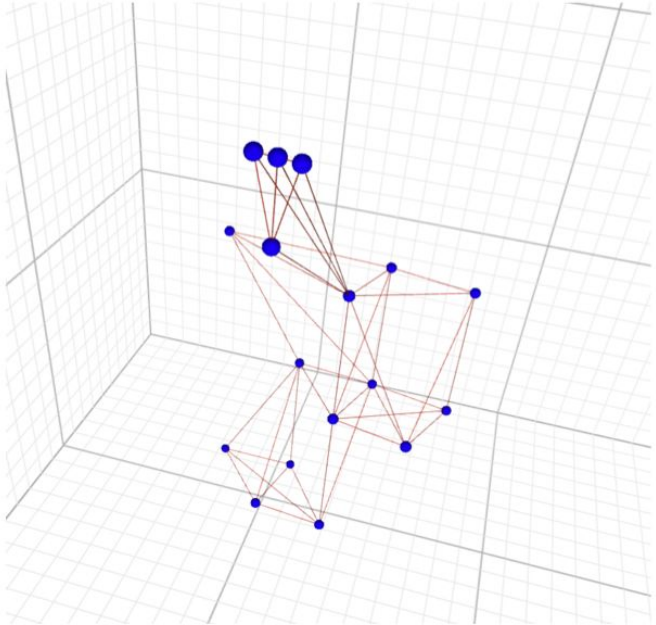
Point Cloud Deep Learning Methods for Pion Reconstruction in the ATLAS Detector



Mariel Pettee

on behalf of the ATLAS ML4Pions Team

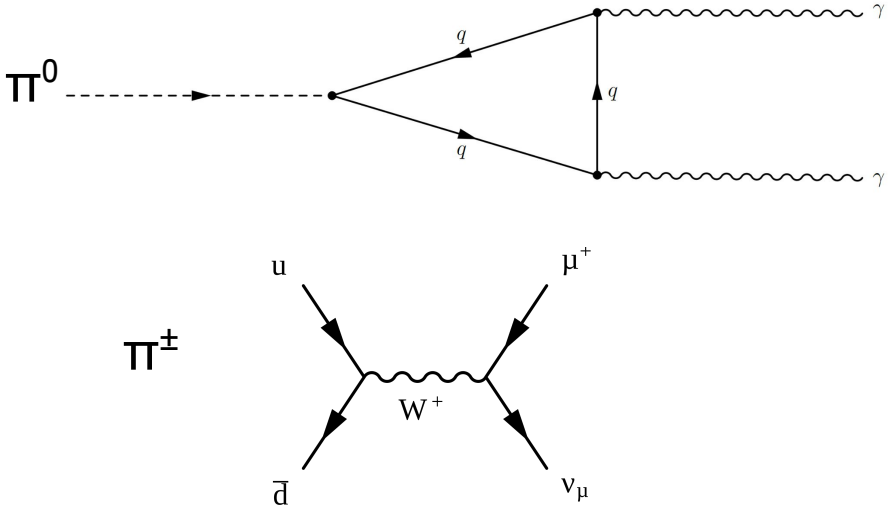
IML 2022 • May 13th, 2022

ATLAS EXPERIMENT

BERKELEY LAB

Pion Reconstruction in the ATLAS Detector

Classification task:
π^0 vs. π^+



Regression task:
Predict pion energy

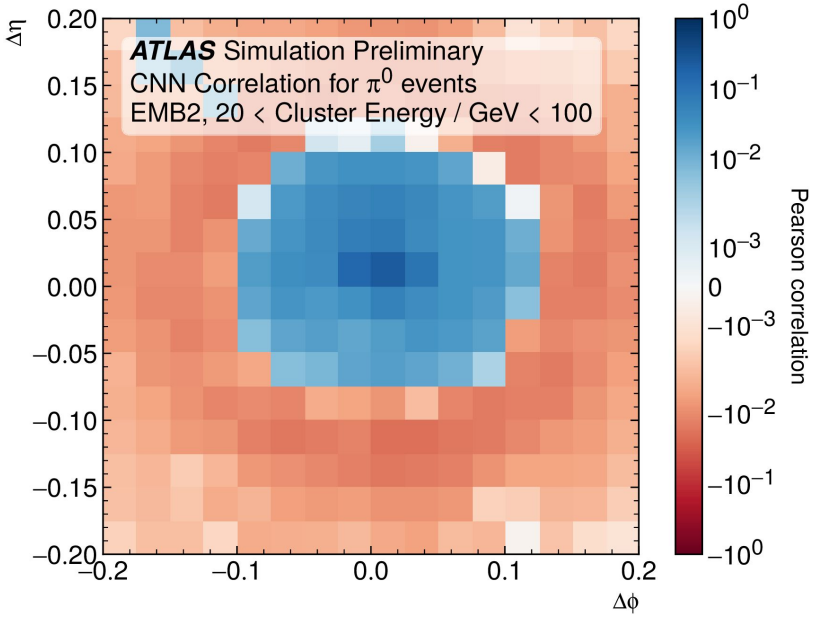


Image-based ML Methods

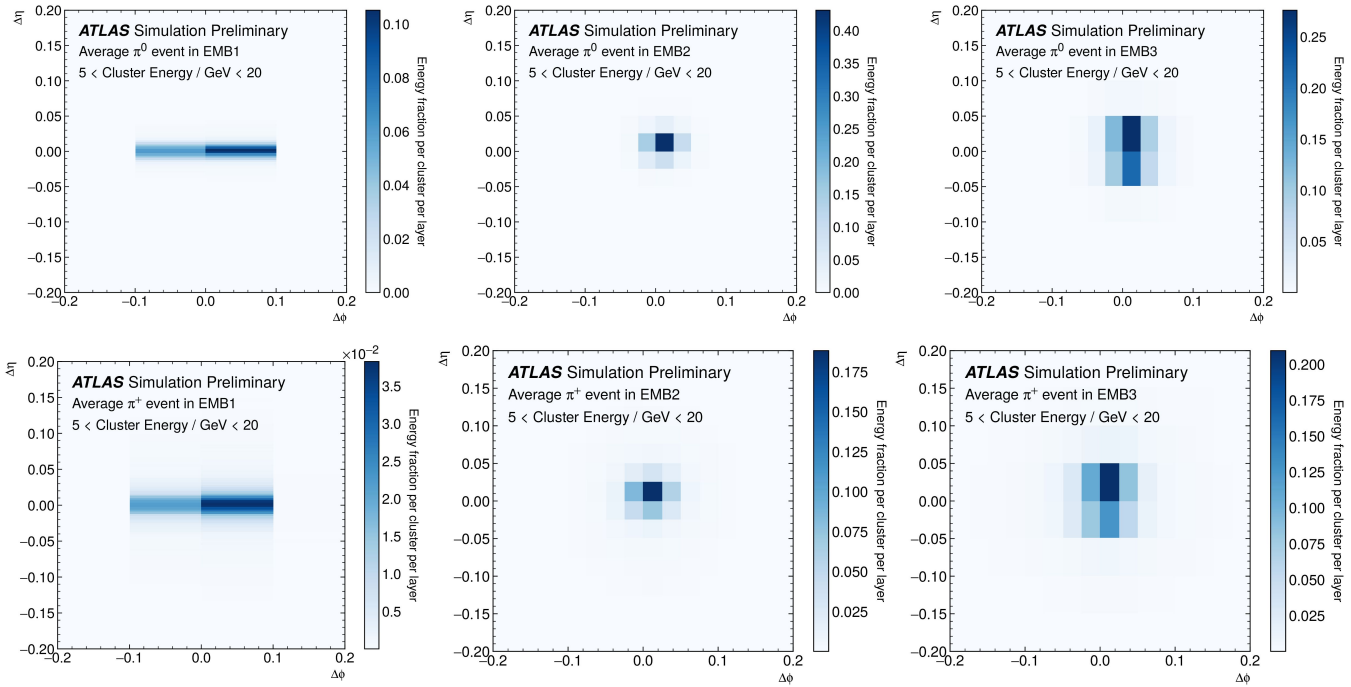
ATLAS Collaboration, Deep Learning for Pion Identification and Energy Calibration with the ATLAS Detector, ATL-PHYS-PUB-2020-018, 2020. http://cdsweb.cern.ch/record/2724632/.

Image-based Representations of Pions

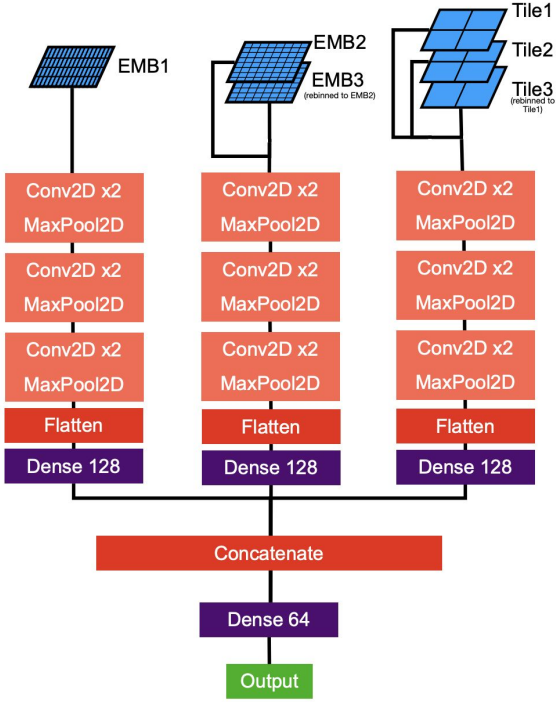
Each calorimeter layer is treated like a "color" in an image classification problem. The varying geometries of the calorimeter layers make it nontrivial to combine these images, as the binning varies widely.

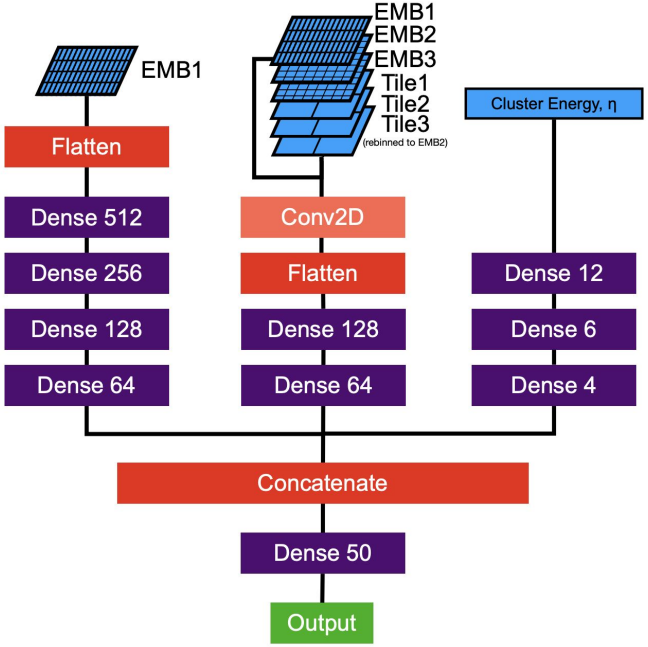
π^0

$\pi^\pm$



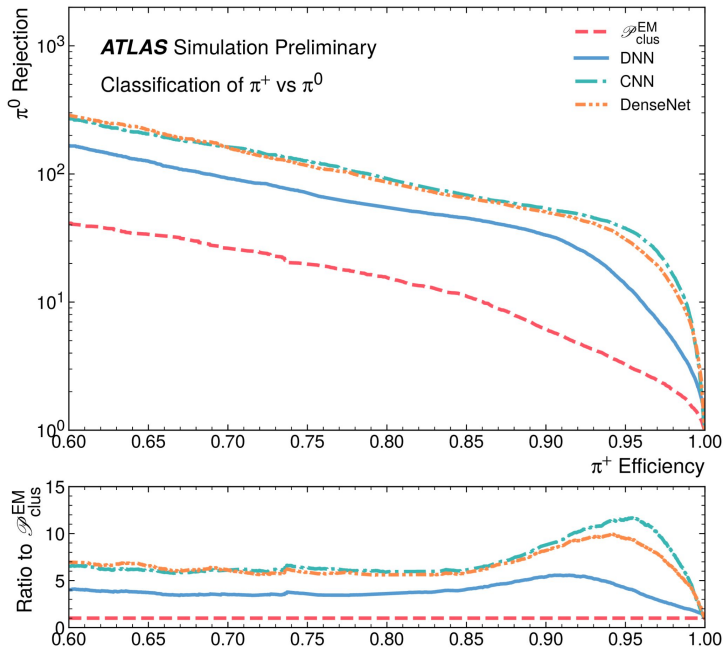
Convolutional Neural Network (CNN)





Convolutional Neural Network (CNN)

The CNN model trained on calorimeter cluster images shows a high rejection of π^0 vs. π^+ (**classification**) and accurately reconstructs the true pion energy (**regression**).



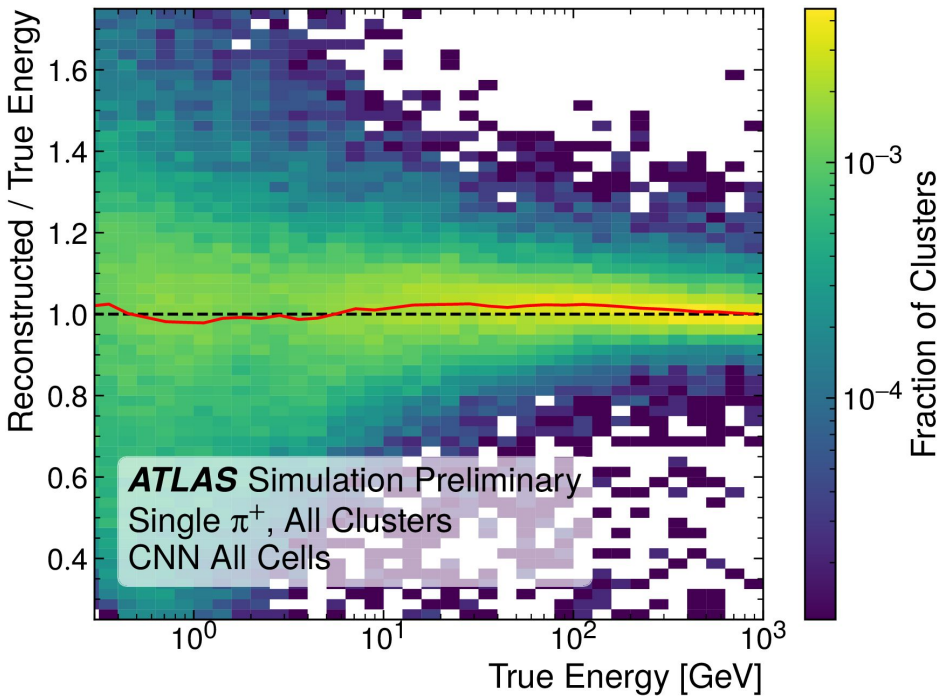
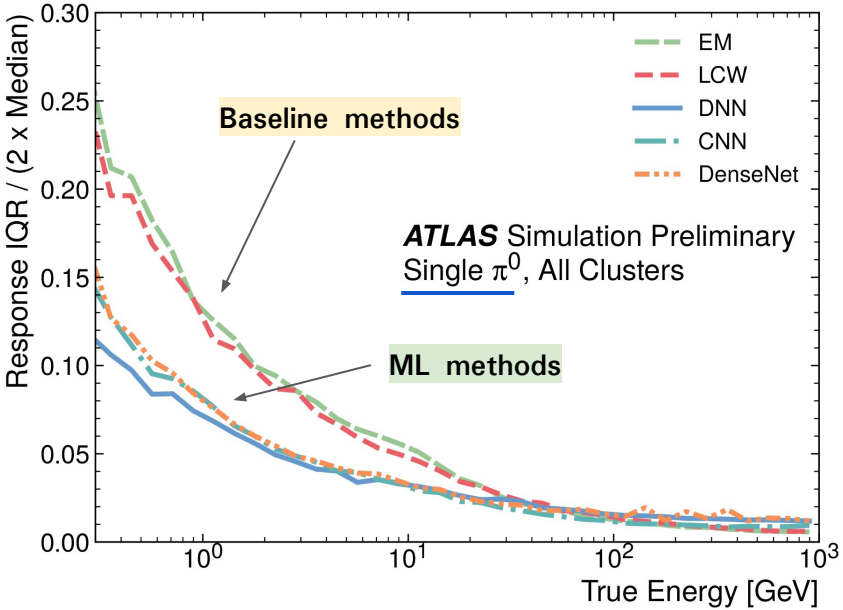
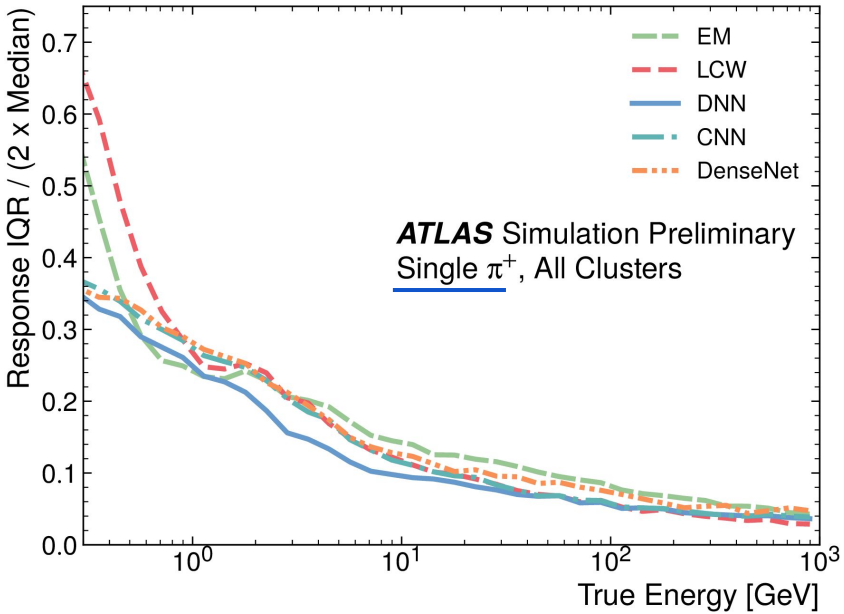


Image-based ML Methods

- Interquantile range (IQR) = a measure of the spread of the regression energy response around the median value
  - Ideally, we want this to be as small as possible throughout a range of energies
- By construction, since calorimeter data is used, performance improves with increasing energy
- The ML methods used all outperform the EM & LCW energy calibration baselines, particularly for neutral pions

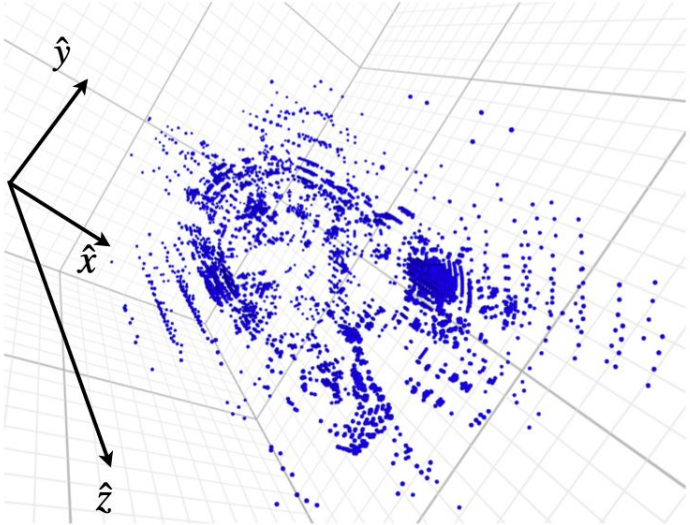


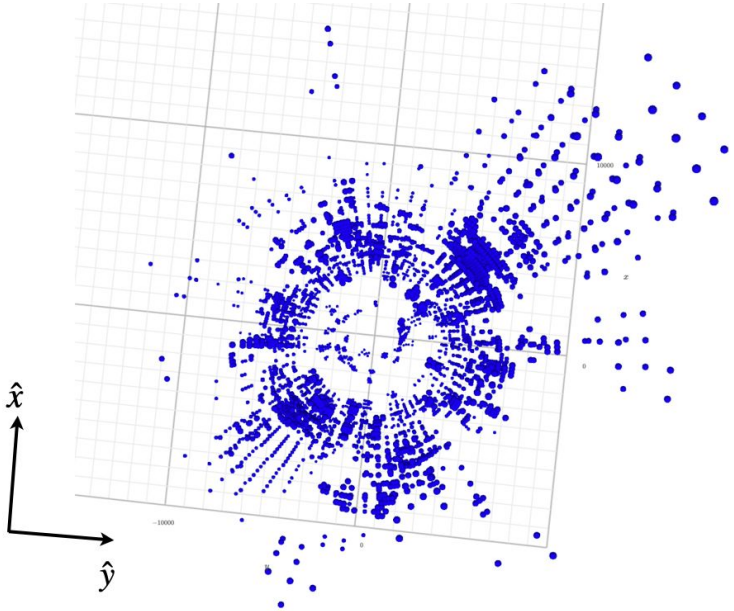


Point Cloud ML Methods

Point Cloud Representations of Pions

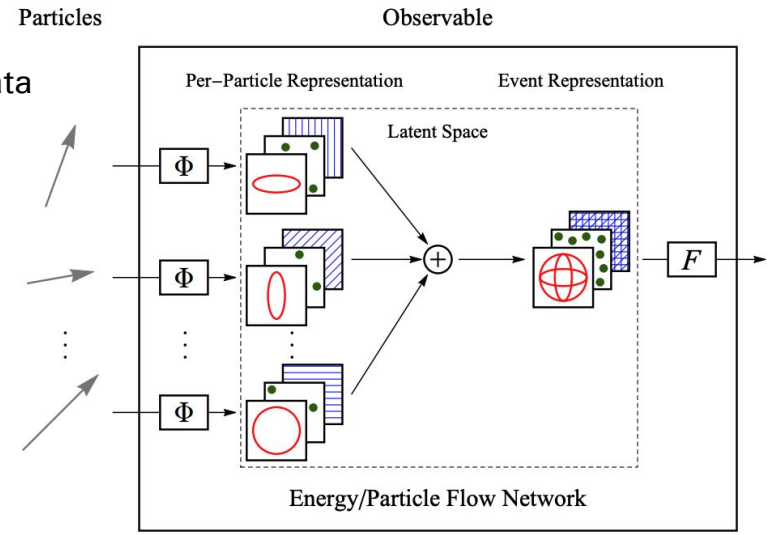
Advantages: a more natural representation of the nonuniform 3D structure of calorimeter topo-clusters than a series of images, and more flexible as an input structure. Doesn't require workarounds for the different layer geometries/granularities.





Deep Sets

- Deep Sets are designed for permutation-invariant & variable-length data
  - Each set element (topo-cluster) can have multiple attributes (cell energy, η, ϕ, etc.)
- Particle Flow Network (PFN)
  - Adapts the Deep Sets framework for particle physics data
  - Per-particle Φ dense networks
  - Network output = direct sum (permutation-invariant)
  - Direct sum is passed through a final NN
- Separate models for classification & regression
  - Regression model is only trained on charged pions



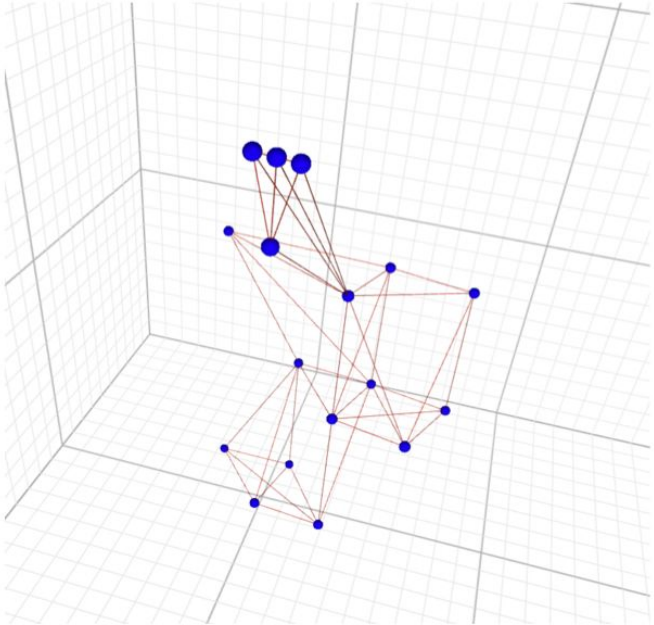
arXiv:1810.05165 [hep-ph]

Graph Neural Network (GNN)

- Simultaneous classification & energy regression:

$$\mathcal{L} = (1-\alpha)\mathcal{L}_{\text{classification}} + \alpha\mathcal{L}_{\text{Regression}}$$

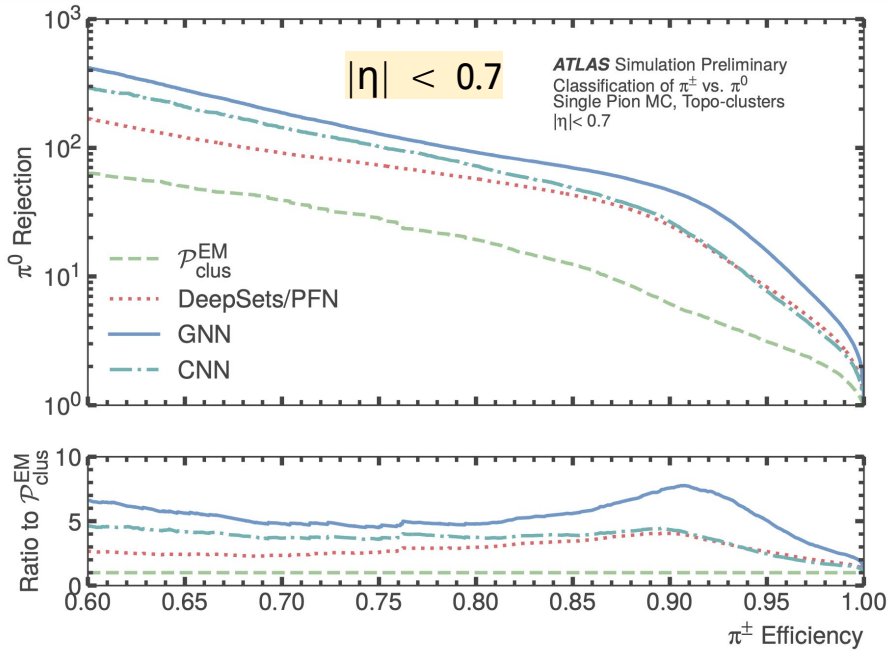
- Represent each pion topo-cluster as a graph
  - Nodes = individual cluster cell features
  - Edges = cell geometry information
  - Global feature = cluster energy
- 4 GNN blocks, then use global features to predict pion type and energy as 2 outputs

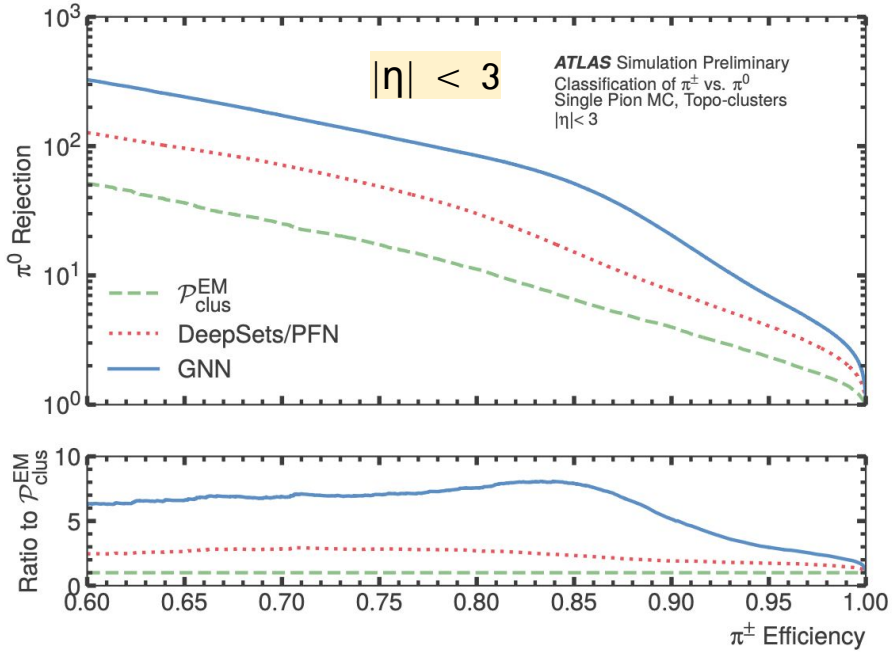


Classification Results

The PFN outperforms the CNN baseline up until around 90% efficiency, then is comparable to the CNN.

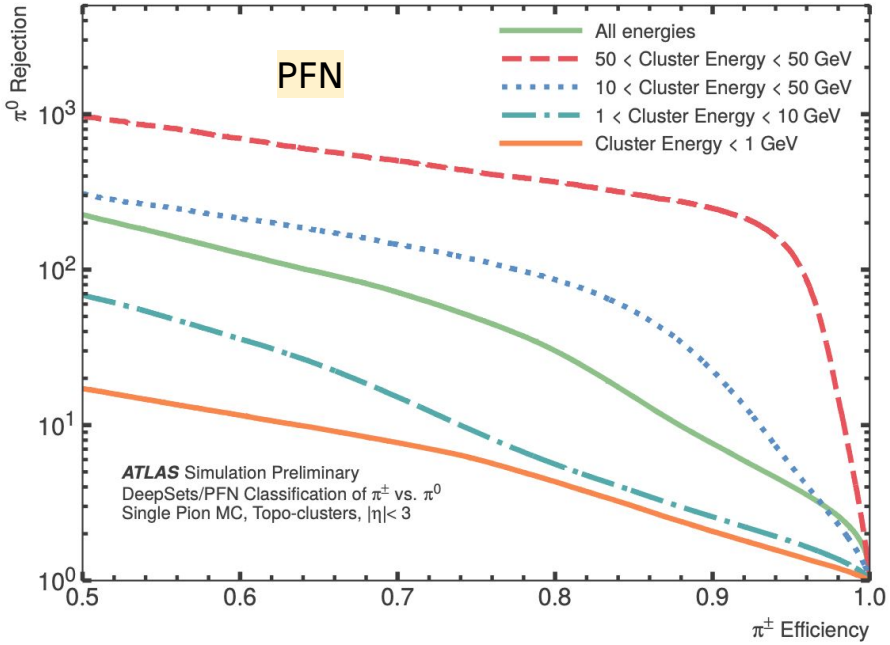
The GNN outperforms the PFN & CNN throughout the full range of efficiencies.

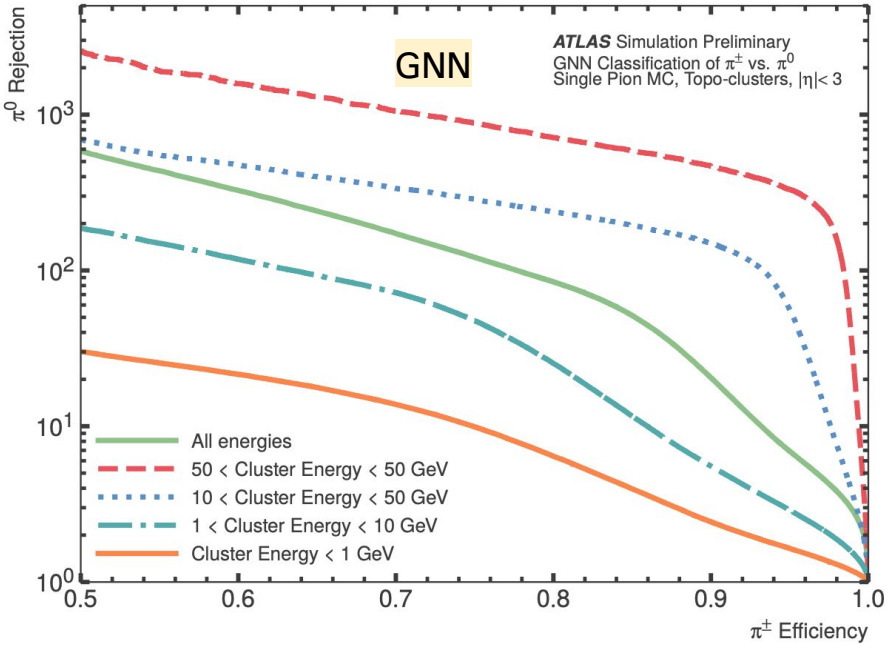




Classification Results

Both the PFN & GNN classifiers perform better as cluster energy increases due to higher statistics and better calorimetry responses:

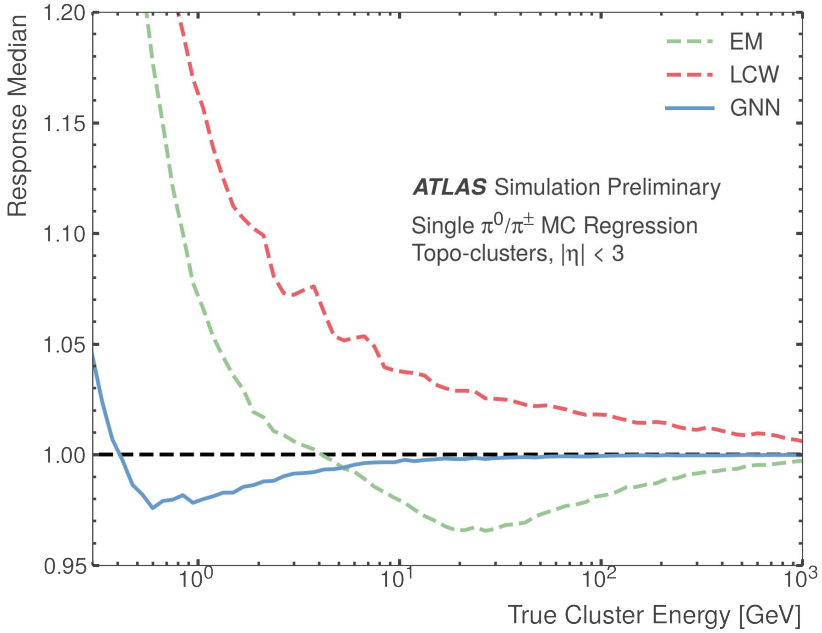




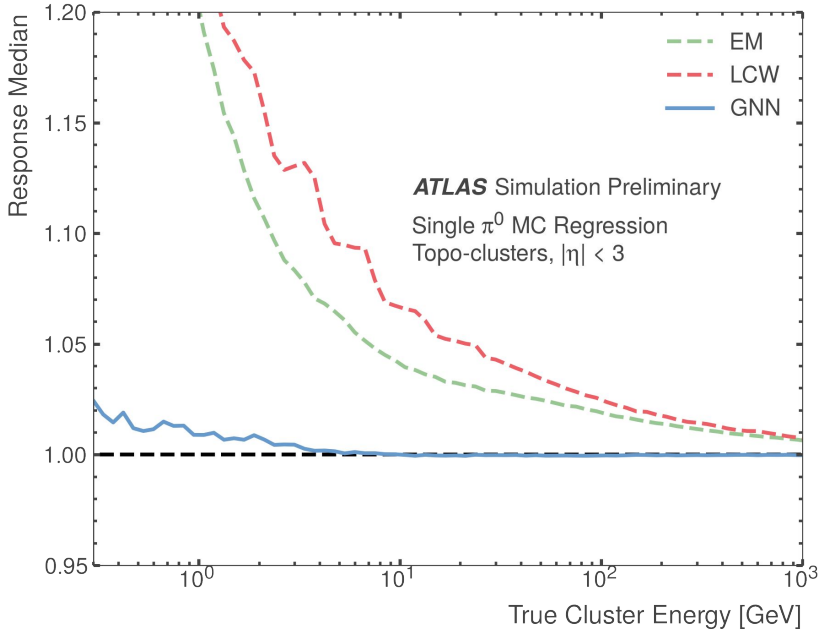
Energy Regression Results

Median ratio of predicted to true cluster energy is much closer to 1 for the GNN than for the EM or LCW baselines:

Combined neutral & charged pions:



Neutral pions only:

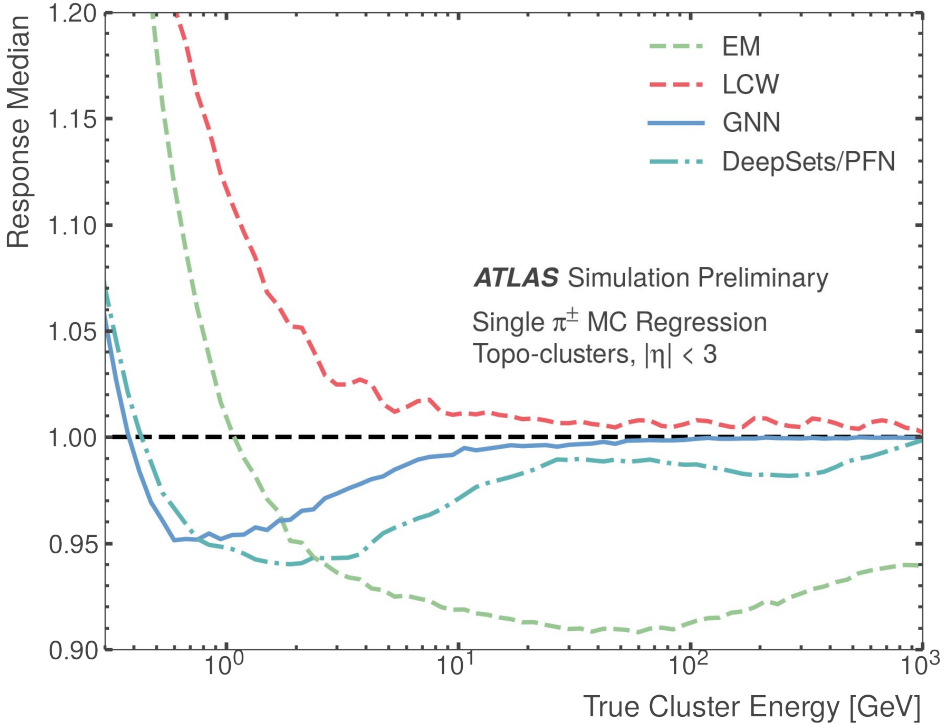


Energy Regression Results

For charged pions, the GNN and PFN have similar median ratios of predicted to true cluster energies below ~1 GeV. Both significantly outperform the EM & LCW baselines in this regime.

Above ~1 GeV, the GNN outperforms the PFN, but both significantly outperform the EM calibration. In this regime, the point cloud methods are comparable to or better than the LCW calibration, which was designed to mitigate the non-compensating nature of the ATLAS calorimeters for hadronic showers.

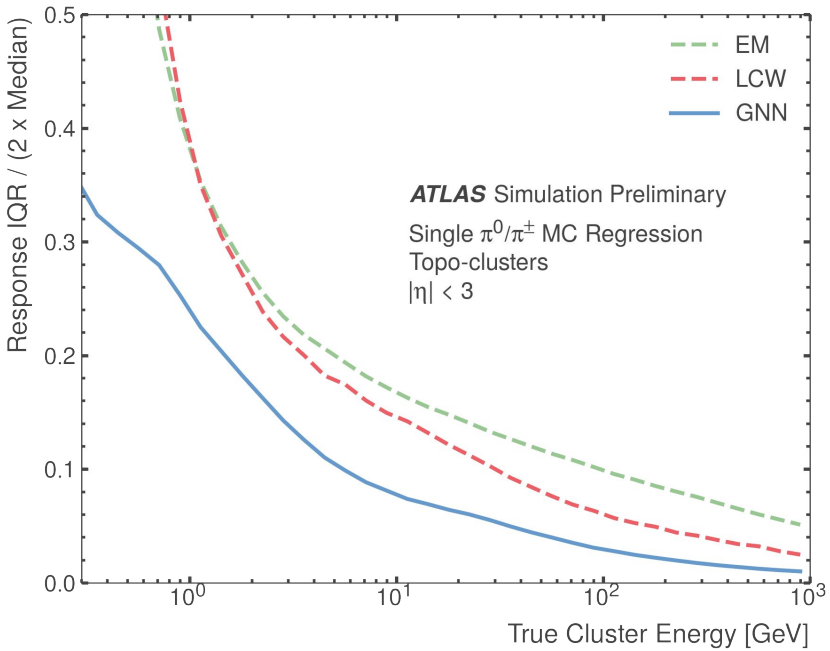
Charged pions only:



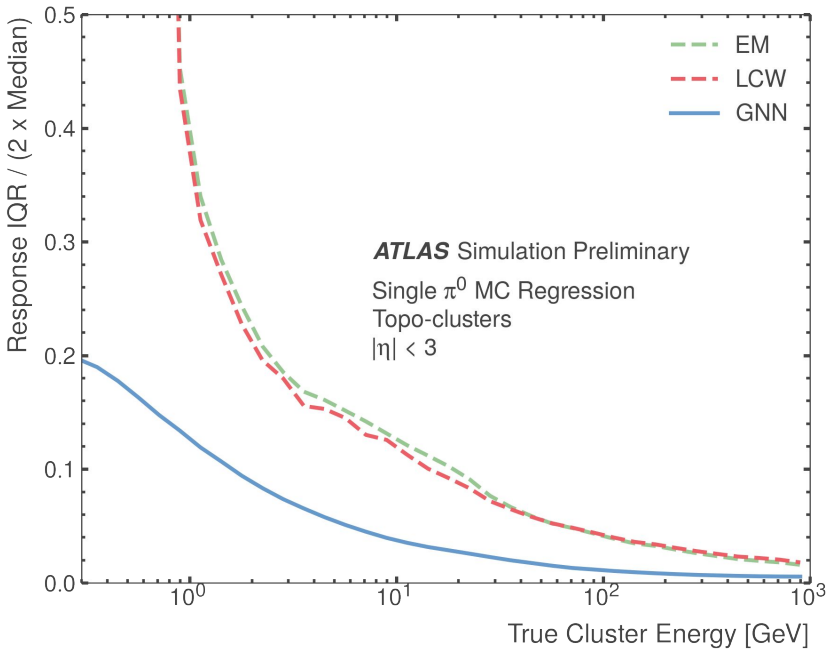
Energy Regression Results

The interquartile range (middle 68%) indicates a far narrower spread for GNN predictions than for the EM/LCW baselines:

Combined neutral & charged pions:



Neutral pions only:

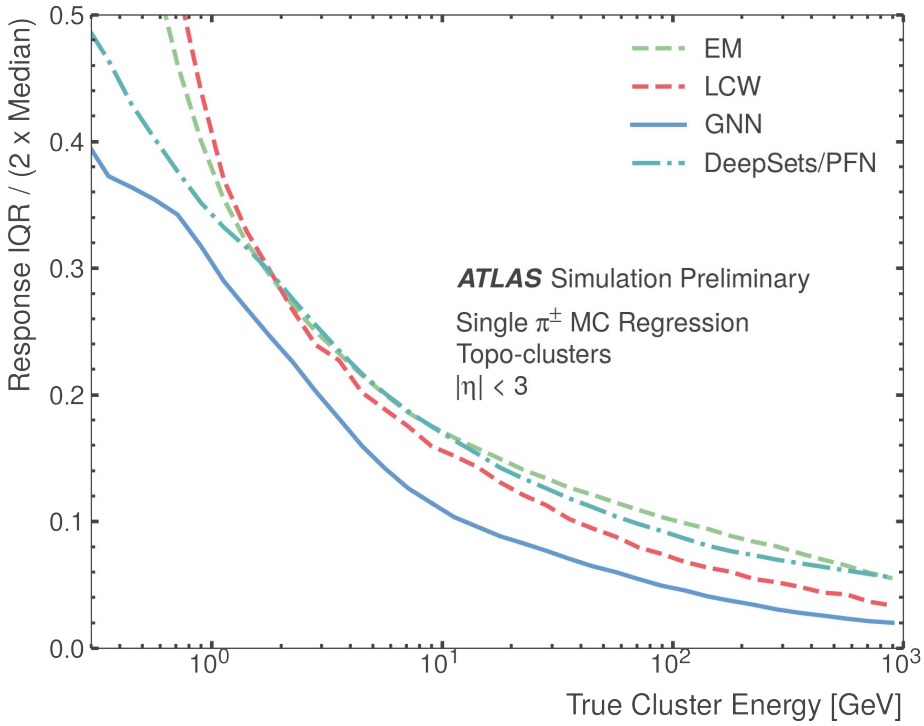


Energy Regression Results

For charged pions, the energy response for the PFN model has a narrower spread than the baseline EM and LCW calibration schemes below energies of about 1 GeV, and has a comparable spread to the baselines for energies above about 1 GeV.

The GNN model has a significantly smaller spread than those of the baseline EM or LCW calibration schemes throughout the full energy spectrum.

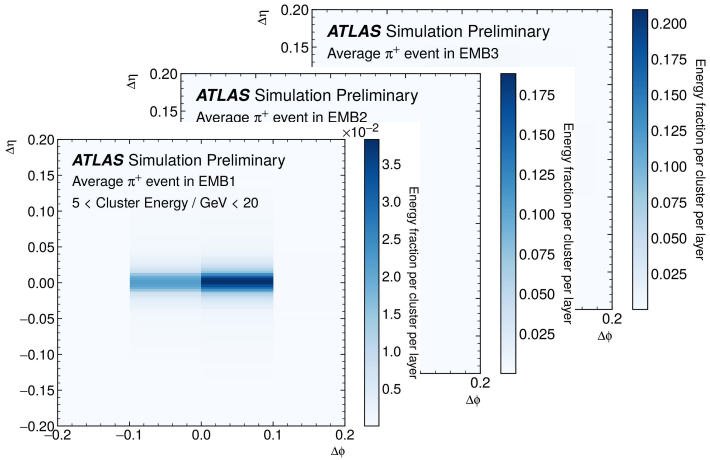
Charged pions only:

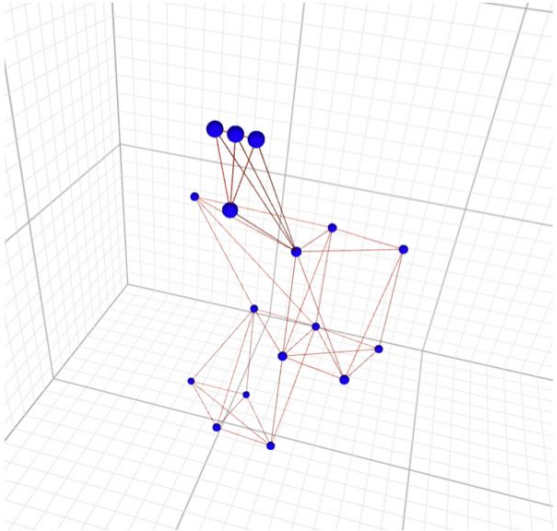


Summary

Moving from an **image-based** description of pion signatures in the ATLAS detector to a **point-cloud based** description allows for better, richer representations of pion data. These point-cloud models result in more accurate pion classification and cluster energy regression predictions that are both more accurate and precise than traditional baselines.

Results available here: https://atlas.web.cern.ch/Atlas/GROUPS/PHYSICS/PLOTS/JETM-2022-002/





Thank you!