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

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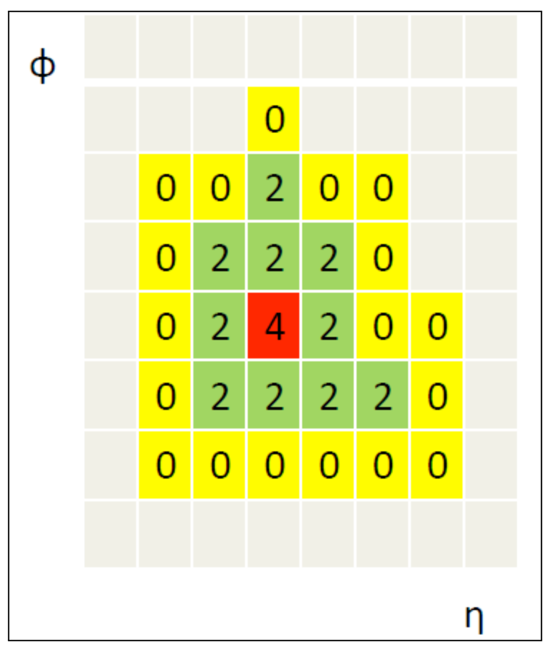
Overview

The reconstruction and calibration of hadronic final states in the ATLAS detector present complex experimental challenges. One important aspect of the reconstruction chain is the identification and calibration of energy deposited in the calorimeters by charged and neutral pions, to account for the calorimeter systems' different responses to electromagnetic (EM) and hadronic showers. Building on previous work with neural networks [1], we present results from using point cloud-based methods – specifically *Graph Neural Networks* (GNNs), *Deep Sets* and *Transformer* methods – to identify and calibrate energy deposits, as alternatives to the existing Local Cell Weighting (LCW) method [2]. These point cloud methods are also presented in a corresponding note [3].

Inputs & Point Clouds

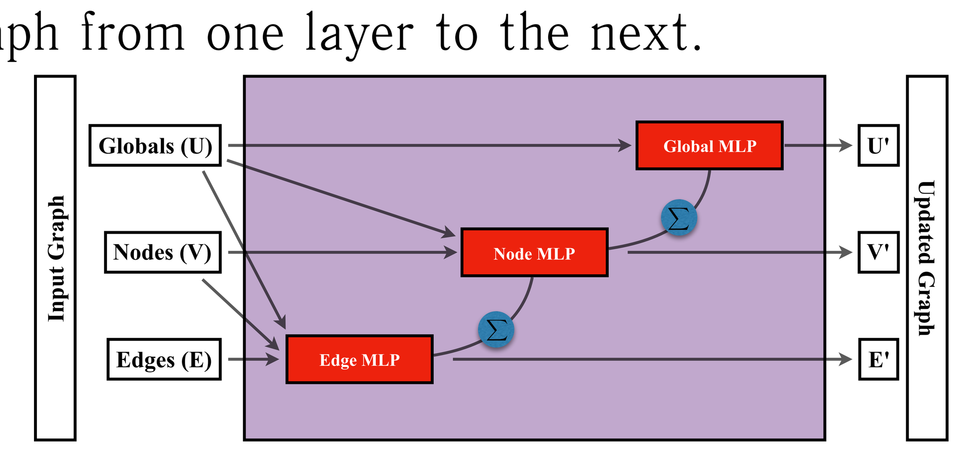
These methods use *topo-clusters* and *tracks* as inputs. Topo-clusters are clusters of calorimeter cells seeded and built using signal significance thresholds, and tracks are reconstructed from hits recorded in the silicon tracker.

EM and hadronic showers typically differ in shape, and may produce multiple such clusters. These methods, which operate on cell-level data, may exploit such differences for identifying and calibrating the showers.



Network Designs

GNN: Each topo-cluster is represented as a graph whose nodes correspond to its calorimeter cells. Multi-layer perceptrons act separately on edge, node, and global features to update the graph from one layer to the next.



Deep Sets: An implementation of the *Deep Sets* framework [4], the Particle Flow Networks (PFNs) [5] can generalize any permutation-invariant observable as

$$O\left(\{p_1, \ldots p_M\}\right) = F\left(\sum_{i=1}^{M} \Phi\left(p_i\right)\right),$$

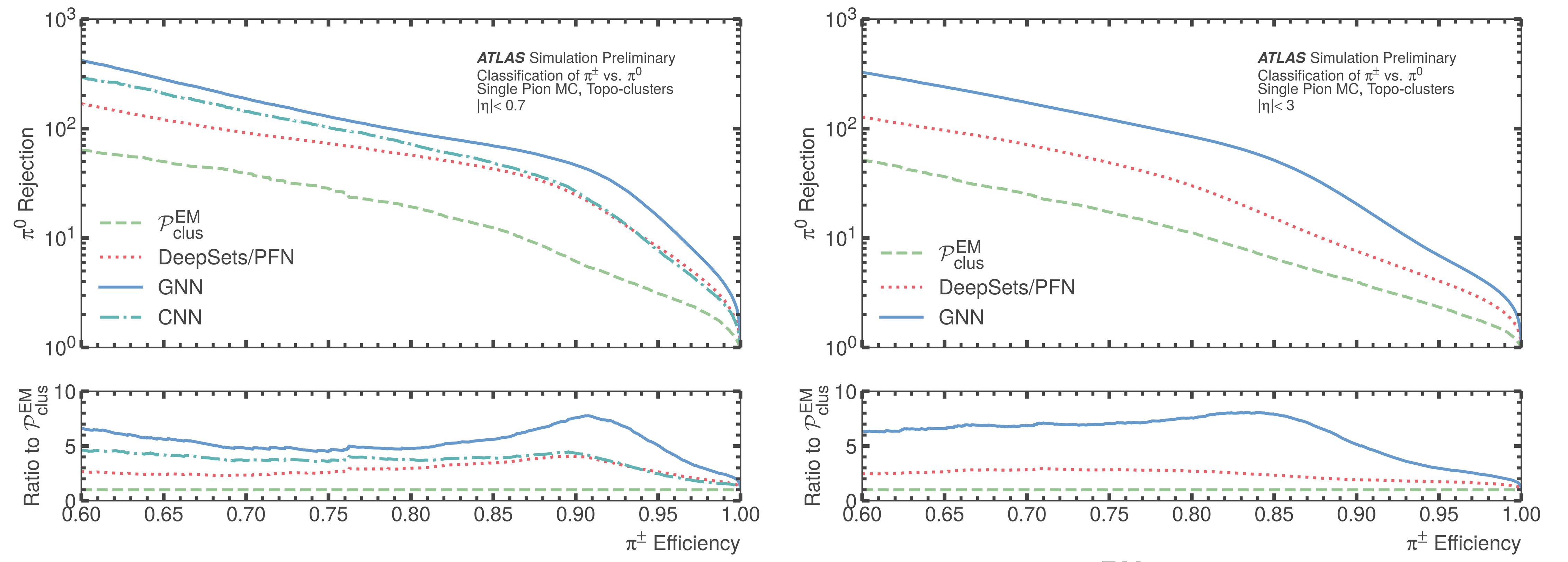
with Φ and F parametrized by neural networks.

Transformer: The transformer acts on graphs of topo-cluster cells that are updated via the *self-attention* mechanism [6], allowing the model to learn the mutual importance of calorimeter cells for predicting calibrated topo-cluster energy.

The GNN and PFN studied here are used for simultaneous cluster classification and energy calibration, whereas the transformer is only used for energy calibration.

Classification Performance

Here, we show charged vs. neutral pion classification performance, using only cluster (calorimeter) information. The CNN shown in the left figure corresponds to results from Ref. [1].

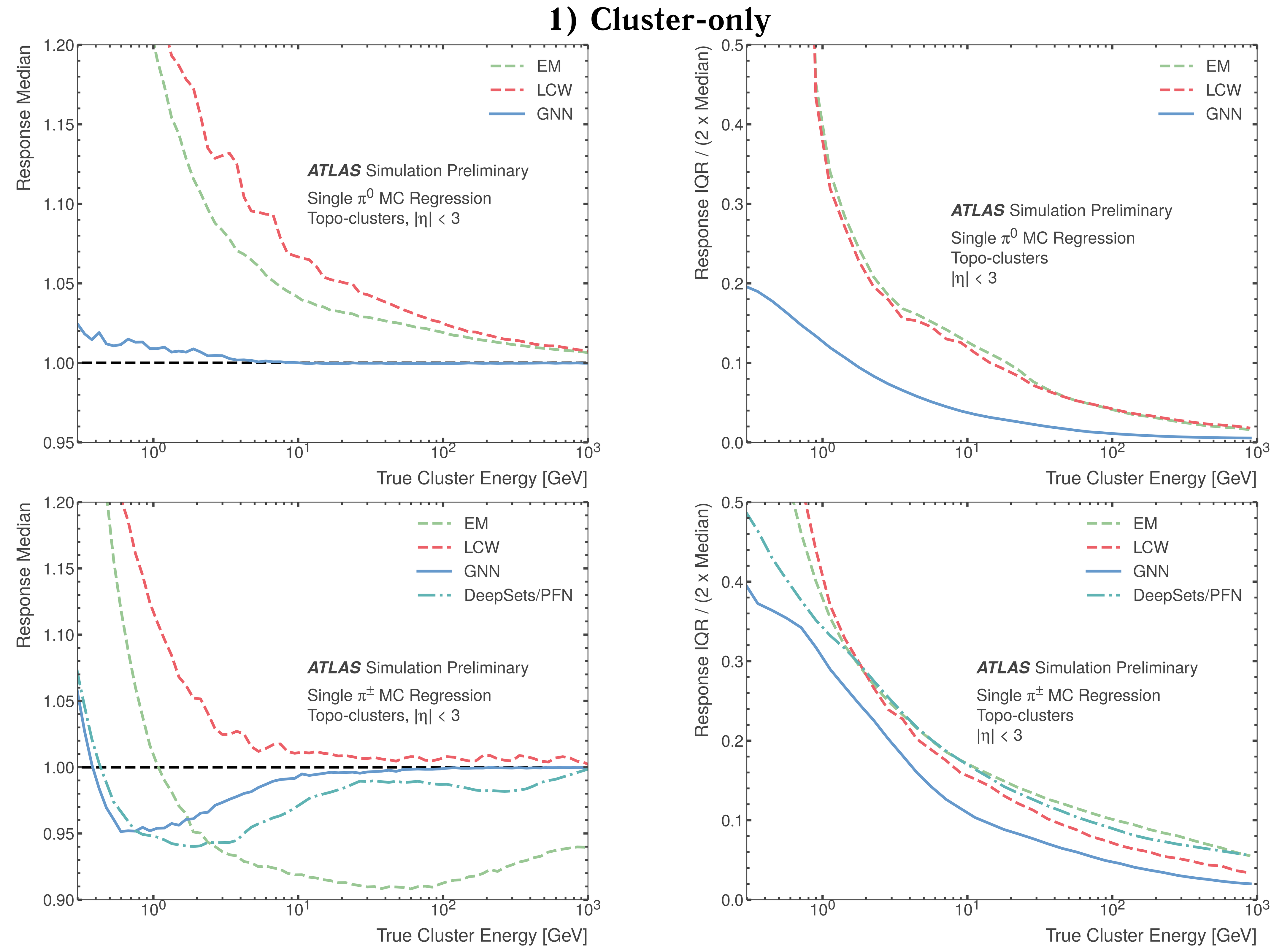


All of the point-cloud methods significantly outperform the baseline $\mathcal{P}^{\mathrm{EM}}_{\mathrm{clus}}$ in classification strength.

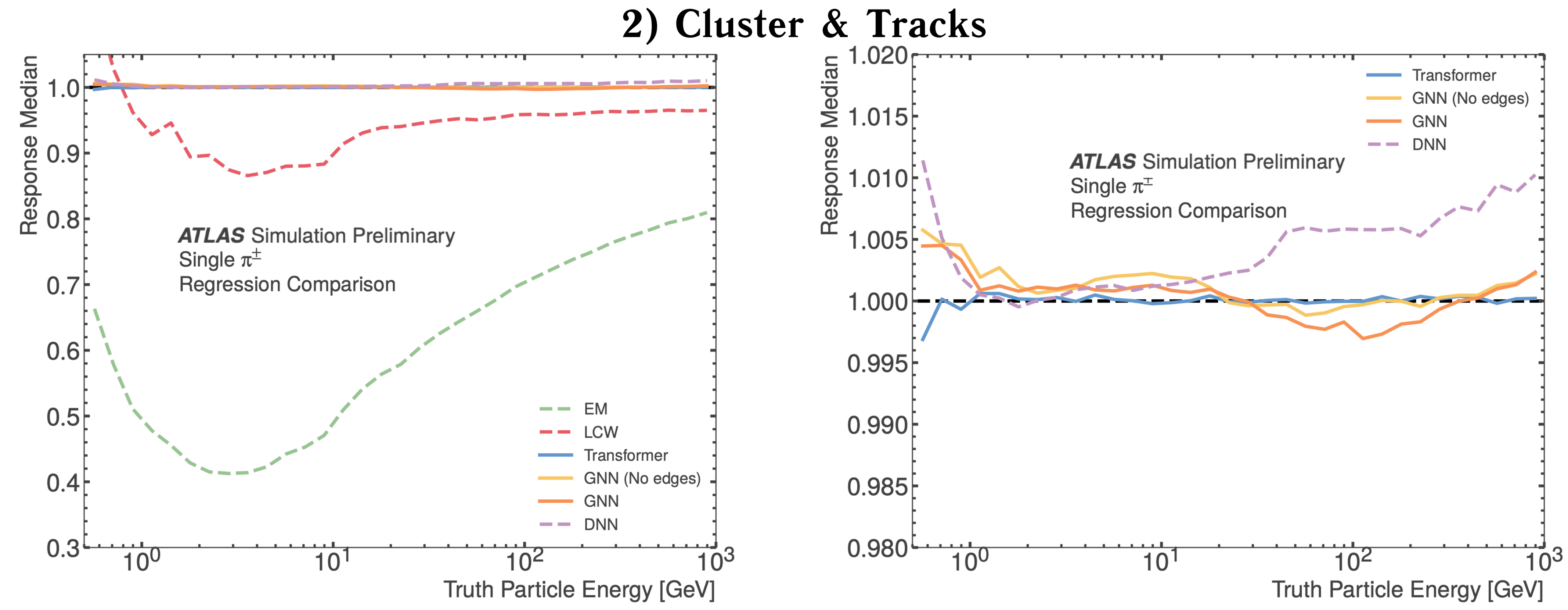
Calibration Performance

Here, we show energy calibration performance, for charged and neutral pions – a separate instance of each network is trained for each of the two types – for networks using only cluster information, as well as those using both clusters and tracks as input.

1) Cluster-only



2) Cluster & Tracks



All the point cloud methods outperform LCW in reconstructing the median cluster (or pion) energy, as well as achieving a smaller spread in energy response, showing that deep learning techniques are promising tools for low-level hadronic reconstruction.

References

[1] ATLAS Collaboration, *Deep Learning for Pion Identification and Energy Calibration with the ATLAS Detector*, 2020, https://cds.cern.ch/record/2724632.
[2] ATLAS Collaboration, *Topological cell clustering in the ATLAS calorimeters and its performance in LHC Run 1*, Eur. Phys. J. C **77** (2017) 490, arXiv:1603.02934 [hep-ex].
[3] ATLAS Collaboration, *Point Cloud Deep Learning Methods for Pion Reconstruction in the ATLAS Detector*, 2022.
[4] M. Zaheer et al., *Deep Sets*, Adv. Neural Inf. Process Syst. **30** (2017), arXiv:1703.06114 [cs.LG].
[5] P. T. Komiske et al., *Energy Flow Networks: Deep Sets for Particle Jets*, JHEP **01** (2019) 121, arXiv:1810.05165 [hep-ph].
[6] A. Vaswani et al., *Attention Is All You Need*, Adv. Neural Inf. Process Syst. **30** (2017), arXiv:1706.03762 [cs.CL].