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

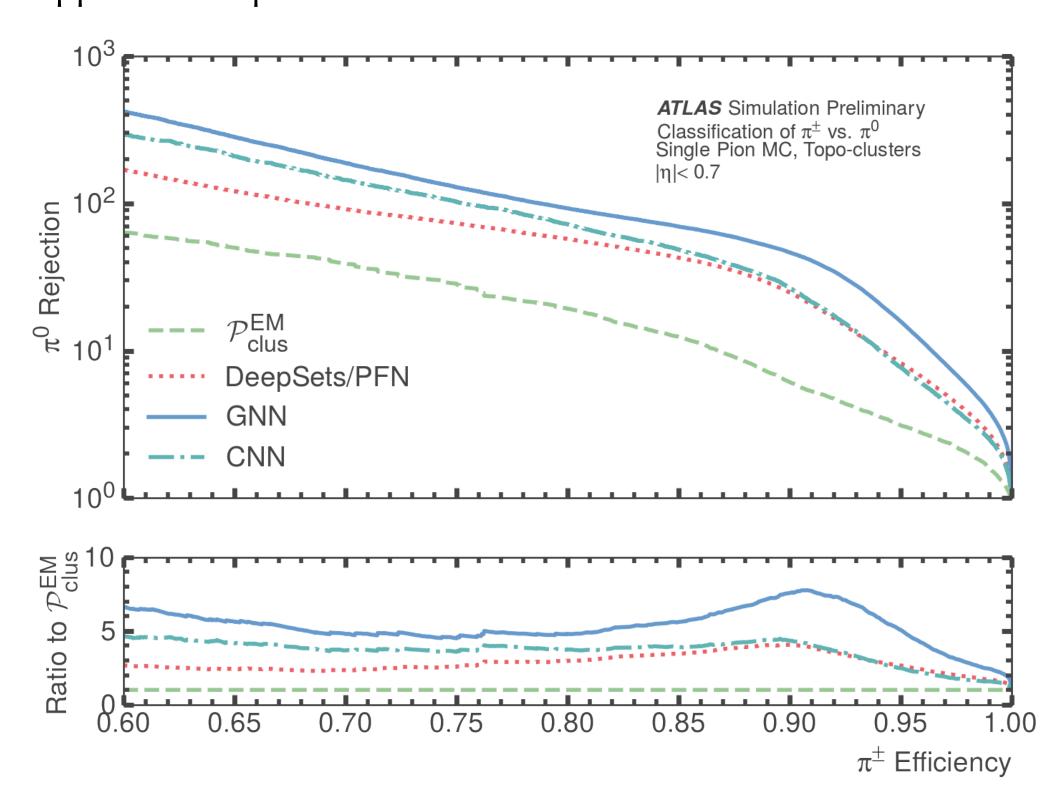
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Pions are the most common particle to emerge from *pp* collisions at the Large Hadron Collider (LHC). It is therefore essential to reconstruct them accurately. The pion reconstruction process requires us to distinguish charged pions from neutral pions, due to differing detector responses for each, as well as calibrate their energies.

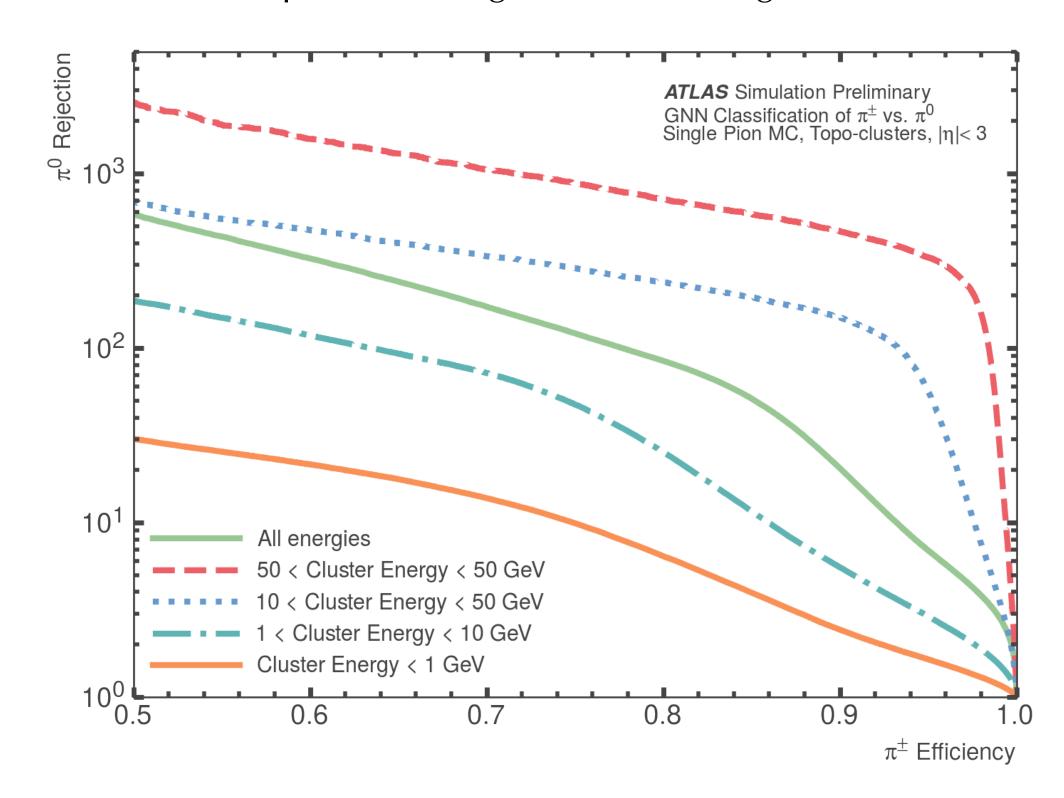
Recently, image-based deep learning techniques [1] demonstrated significant improvements over baseline methods for pion identification (EM cluster probability) and calibration (Local Cell Weighting or LCW) that do not use machine learning. These studies [2] are an extension of that work using point cloud methods that do not require calorimeter topo-clusters [3] to be projected onto a fixed and regular grid. Particle Flow Network/Deep Sets (PFN) [4] and Graph Neural Network (GNN) [5] architectures are used to process calorimeter clusters as point clouds – an important step toward a fully deep learning-based low-level hadronic reconstruction. These point cloud approaches outperform the baseline hadronic calibration, demonstrating the potential of deep-learning-based low-level hadronic calibrations to significantly improve the quality of particle reconstruction in the ATLAS calorimeter.

π^0 vs. π^{\pm} Classification

The GNN & PFN point cloud approaches far outperform the baseline EM cluster probability used in the LCW ($\mathcal{P}_{\text{clus}}^{\text{EM}}$) — over 5 times the background rejection at 90% efficiency. They also perform on par with or better than the image-based CNN approach for pion classification.



For both the GNN & PFN point cloud approaches, classification performance increases with cluster energy due to better statistics and calorimeter responses for higher cluster energies.

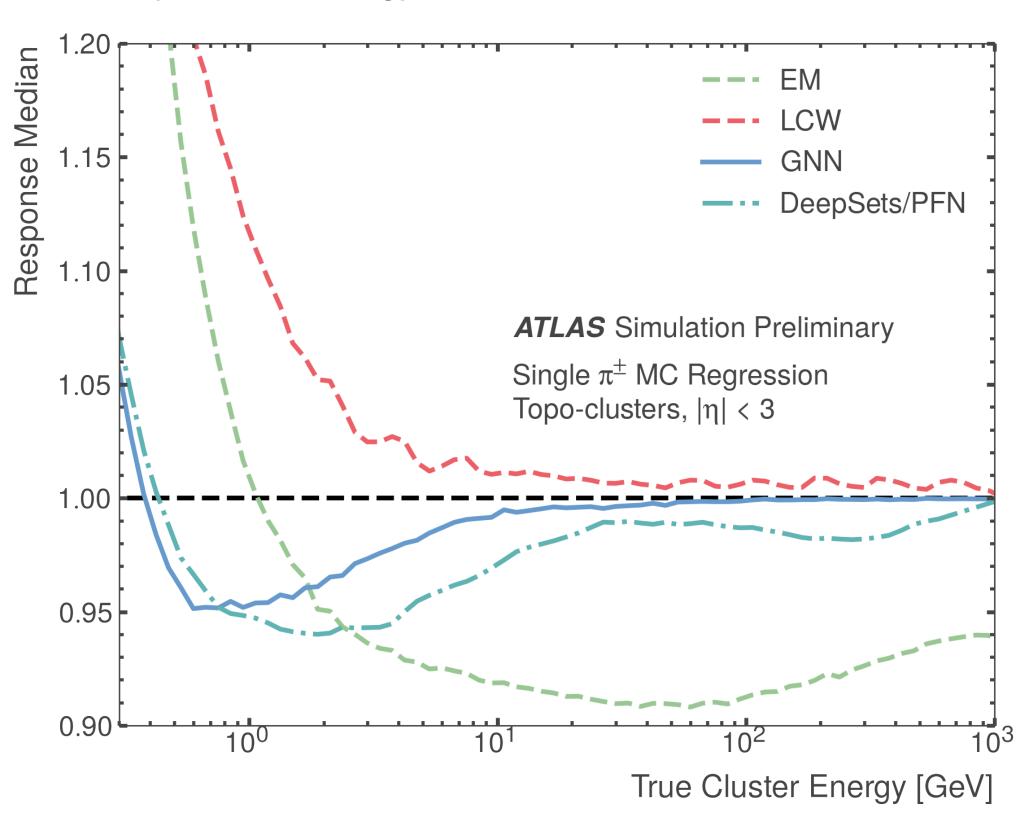


[1] ATLAS Collaboration, Deep Learning for Pion Identification and Energy Calibration with the ATLAS Detector, ATL-PHYS-PUB-2020-018, 2020, URL: https://cds.cern.ch/record/2724632.

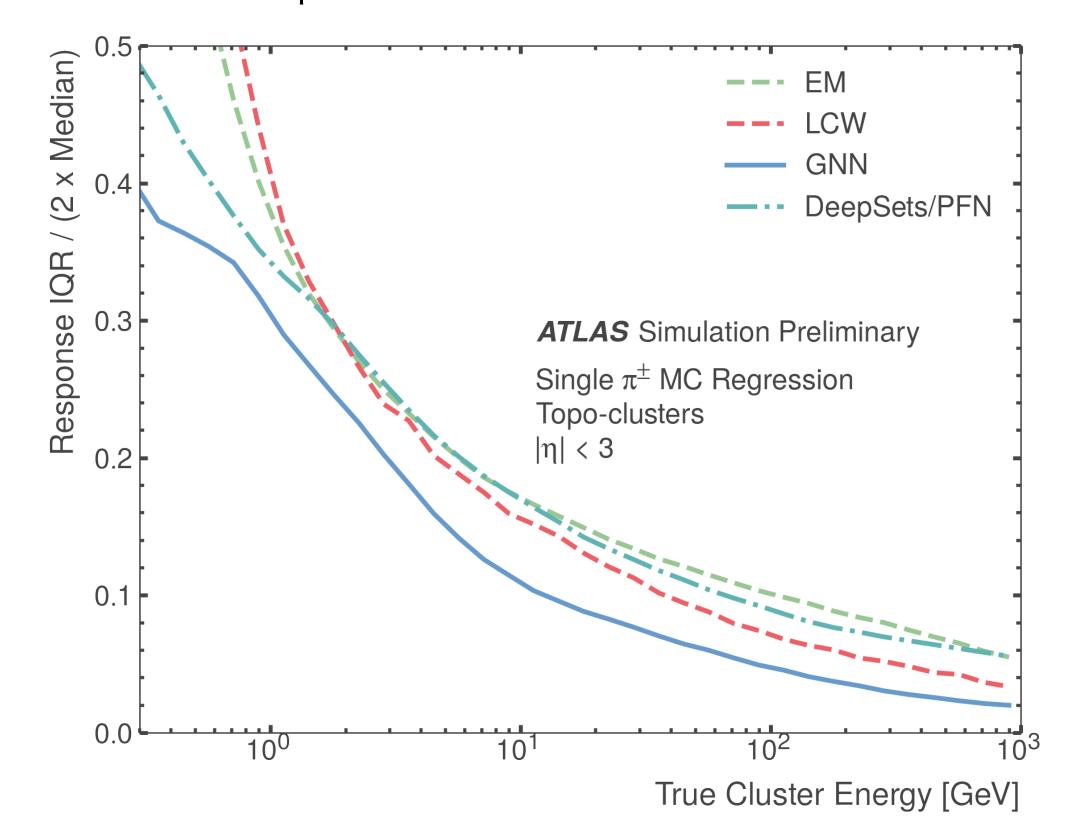
[3] ATLAS Collaboration, *Topological Cell Clustering in the ATLAS Calorimeters and its Performance in LHC Run 1*, Eur. Phys. J. C 77 (2017), arXiv: 1603.02934 [hep-ex].

π^0 & π^{\pm} Energy Regression

The median predicted ratios of predicted to true cluster energy from the GNN & PFN point cloud are closer to one than the EM scale (raw cluster energy) or LCW calibration (baseline calibrated energy), particularly for low-energy clusters below 1 GeV.



The interquartile (68%) ranges quantifying the pion energy resolution of the GNN & PFN models also indicate comparable or narrower response curves than the EM and LCW baselines.



[4] P. T. Komiske, E. M. Metodiev and J. Thaler, *Energy Flow Networks: Deep Sets for Particle Jets*, JHEP 01 (2019), arXiv: 1810.05165 [hep-ph].

[5] P. W. Battaglia et al., Relational Inductive Biases, Deep Learning, and Graph Networks, arXiv preprint arXiv:1806.01261 (2018).

^[2] https://atlas.web.cern.ch/Atlas/GROUPS/PHYSICS/PLOTS/JETM-2022-002/