PROCEEDINGS OF SCIENCE

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

Dilia María Portillo Quintero, on behalf of the ATLAS Collaboration[a,*]

[a] *TRIUMF,*
4004 Wesbrook Mall, Vancouver, BC V6T 2A3, Canada

E-mail: dilia.maria.portillo.quintero@cern.ch

The reconstruction and calibration of hadronic final states in the ATLAS detector at the LHC present complex experimental challenges. For isolated pions in particular, classifying π^0 versus $\pi^\pm$ and calibrating pion energy deposits in the ATLAS calorimeters are key steps in the hadronic reconstruction process. The baseline methods for local hadronic calibration were optimized early in the lifetime of the ATLAS experiment. This publication presents a significant improvement over existing techniques using machine learning methods that do not require the input variables to be projected onto a fixed and regular grid. Instead, Deep Sets and Graph Neural Network architectures are used to process calorimeter clusters and particle tracks as point clouds, or a collection of data points representing a three-dimensional object in space. This note demonstrates the performance of these new approaches as an important step towards a low-level hadronic reconstruction scheme that fully takes advantage of deep learning to improve its performance.

41st International Conference on High Energy physics - ICHEP2022
6-13 July, 2022
Bologna, Italy

*Speaker

PoS(ICHEP2022)1076

ATL-PHYS-PROC-2022-105
06 November 2022

1. Introduction

A fundamental task in hadronic final state reconstruction in the ATLAS detector [1] at the Large Hadron Collider (LHC) is the identification and calibration of the detector response to single particles. As the hadronic showers produced in proton-proton collisions at the CERN Large Hadron Collider (LHC) are primarily generated by pions, it is essential to accurately characterize the calorimeter response to both charged and neutral pions. Neutral pions (π^0) decay promptly to photons and develop compact showers with relatively small intrinsic fluctuations. These showers are mostly captured by the electromagnetic calorimeter. On the other hand, showers emanating from charged pions ($\pi^\pm$) generally fluctuate more dramatically in the course of their development. They also penetrate deeper into the detector than electromagnetic showers, thereby necessitating an additional hadronic calorimeter outside of the electromagnetic calorimeter to measure their energy deposits.

In the ATLAS experiment, three-dimensional clusters of topologically-connected calorimeter cell signals called topo-clusters are employed as the baseline signal definition used in the reconstruction of hadronic final states [2]. The ATLAS calorimeters are non-compensating, meaning that their response to hadrons is smaller than their corresponding response to electrons and photons depositing the same amount of energy. The hadronic calibration for topo-clusters is a multi-step process called Local Cell Weighting (LCW) that aims to correct this non-compensating calorimeter response to hadrons [2].

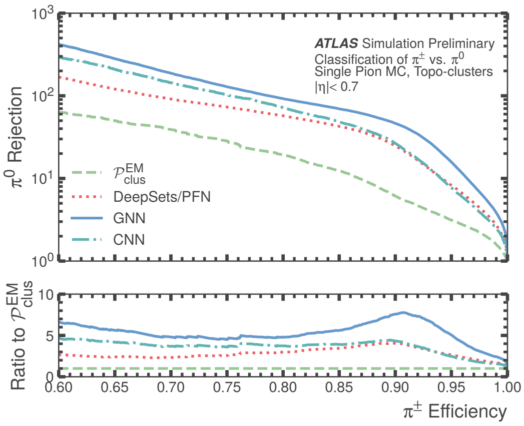
The results presented here explore new perspectives for pion identification and energy calibration using Deep Learning techniques.

2. Methods

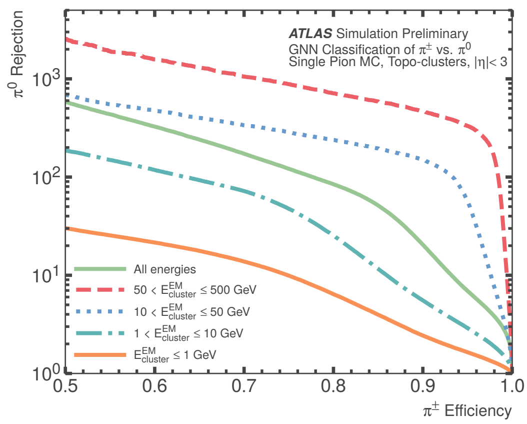
One of the the most powerful advantages of deep learning techniques is the ability to process large numbers of correlated inputs. For the hadronic calibration task, each cell of a topo-cluster can be treated as a potential input variable.

To date, the deep learning approaches to pion classification and calibration in ATLAS have only considered image-based representations of pions. Densely-connected neural networks (DNNs) and convolutional neural networks (CNNs) were explored for image-based pion classification and energy regression in the context of the complex ATLAS detector geometry in the central barrel region [3]. However, this image-based approach may be suboptimal, considering that calorimeter layers have different spatial granularities, deposition geometries are irregular, and calorimeter images are sparse with most cells not passing the selection criteria. Furthermore, image-based representations of the calorimeter restrict studies to using calorimeter information only.

Pion deposits in the ATLAS detector can also be thought of as point clouds, or collections of points in space, often representing a three-dimensional object. Each point in a point cloud representation has unique position coordinates. In this view, pions are represented not as a series of images, but as a complex three-dimensional form composed of many individual topo-cluster cells. All topo-clusters are used, and each of them is considered separately for the classification and regression tasks. The methods considered here are Deep Sets and Graph Neural Networks (GNNs). Details on the architecture used can be found in Reference [4].



(a) $|\eta| < 0.7$



(b) GNN in bins of $E^{\text{EM}}_{\text{cluster}}$ for $|\eta| < 3$

Figure 1: Comparison of topo-cluster classification performance of all methods for $|\eta| < 0.7$ (1a), and for $|\eta| < 3$ in bins of topo-cluster energy, $E^{\text{EM}}_{\text{cluster}}$ (1b), for the GNN model. Performance is measured as π^0 topo-cluster rejection (defined as the inverse of π^0 selection efficiency) versus $\pi^\pm$ topo-cluster efficiency [4].

3. Results: $\pi^0/\pi^\pm$ Classification

Performance is shown as π^0 rejection (defined as the inverse of π^0 selection efficiency) versus $\pi^\pm$ efficiency with respect to all truth pions, where higher rejection indicates better classification performance for the same selection efficiency. Figure 1a shows a comparison of the classification performance for the various models. Even though the CNN model was trained for the central barrel as a point of comparison with respect to previous results [3], both the GNN and Deep Sets models were trained without any pseudo-rapidity selection. Across the full range of $\pi^\pm$ efficiencies, all machine learning models notably outperform the $\mathcal{P}^{\text{EM}}_{\text{clus}}$ baseline classifier used in the LCW calibration. At high $\pi^\pm$ efficiencies, the CNN pion classification performance is comparable to the performance of the new Deep Sets model, while the GNN shows the highest rejection across all $\pi^\pm$ efficiencies.

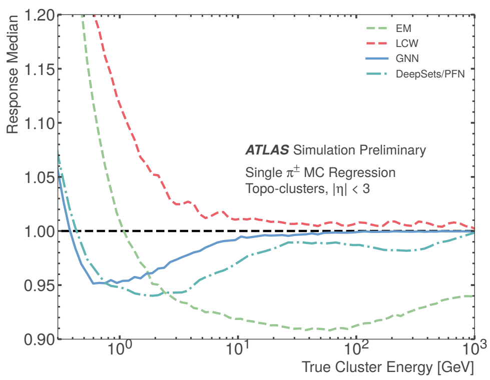
Pion topo-cluster classification performance for the GNN model is shown in Figure 1b for different exclusive ranges of $E^{\text{EM}}_{\text{cluster}}$. Performance increases with higher topo-cluster energies $E^{\text{EM}}_{\text{cluster}}$ due to both higher sampling statistics and reduced stochastic fluctuations.

4. Results: Pion Energy Regression

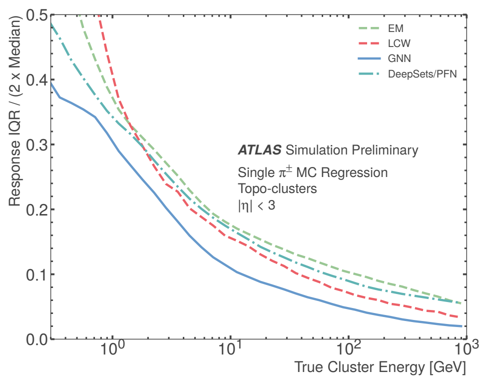
The energy calibrations for both the baseline LCW and the point cloud regression methods target the true topo-cluster energy. The true topo-cluster energy is defined as the sum of all energy deposits, as given by the Geant4 simulation, within the physical extent of the topo-cluster. The performance of the regression models can be quantified by measuring the energy response, i.e. $R = E_{\text{predicted}}/E_{\text{true}}$, as a function of E_{true}. $E_{\text{predicted}}$ should be close to the target value E_{true} after calibration, leading to a mean response R close to unity.

The energy resolution is also a relevant metric used to evaluate regression performance. An ideal calibration would have a small resolution of predicted values, meaning that its predictions are more precise and stable. The resolution of the energy measurement can be quantified with the interquantile range (IQR), representing the width of the response data from 1σ to -1σ (84% - 16%) of the median.

The performance comparison of the point cloud deep learning methods to the EM and LCW baseline are shown in Figure 2. The median energy response ratio for the GNN is significantly closer to unity throughout the full energy spectrum considered than the baselines EM or LCW calibration schemes for charged and neutral pions. The IQR is narrower for the GNN than for the baselines across both charged and neutral pions.



(a) $\pi^{\pm}$ Median Energy Response



(b) $\pi^{\pm}$ Interquantile Range (IQR)

Figure 2: Median energy response (a) and IQR (b) for the EM and LCW baselines as well as the GNN and Deep Sets as a function of true cluster energy [4].

5. Conclusion

A variety of machine learning methods designed for π^0 vs. $\pi^{\pm}$ classification and pion energy regression were studied. All of these methods outperformed the existing baseline classifier in ATLAS, $\mathcal{P}^{\mathrm{EM}}_{\mathrm{clus}}$, in terms of π^0 rejection vs. $\pi^{\pm}$ efficiency. Regarding the pion energy regression task, all the studied architectures outperform the baseline LCW calibration in terms of both the accuracy and precision of the predicted energy responses. These results show the potential of deep learning techniques for low-level hadronic reconstruction with the ATLAS detector at LHC, and are therefore an important step towards implementing a version of Particle Flow that optimally takes advantage of performance improvements from machine learning.

References

[1] ATLAS Collaboration, JINST 3 (2008) S08003

[2] ATLAS Collaboration, Eur. Phys. J. C 77 (2017) 490, arXiv: 1603.02934

[3] ATLAS Collaboration, ATL-PHYS-PUB-2020-018, url: https://cds.cern.ch/record/2724632

[4] ATLAS Collaboration, ATL-PHYS-PUB-2022-040, url: https://cds.cern.ch/record/2825379