Machine Learning for Event Reconstruction with the ATLAS Detector

CDMPP Early Career Research Workshop

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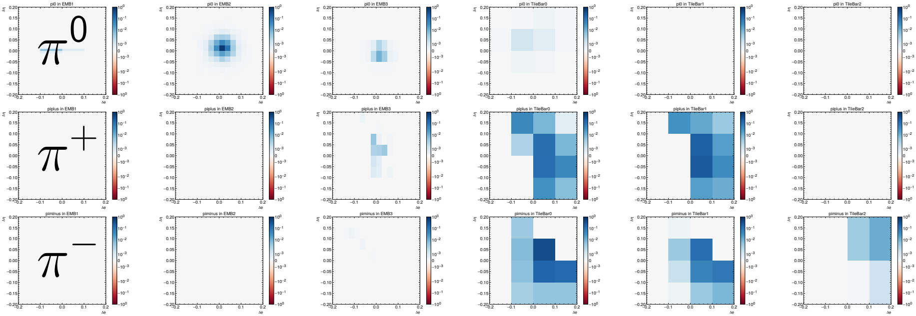
February, 2021

Introduction

- Wide variety of physics analyses performed on data recorded by the ATLAS Detector at the LHC
- Many BSM searches (eg supersymmetric models) have dark matter candidates
- Accuracy of object reconstruction vital to all physics analyses

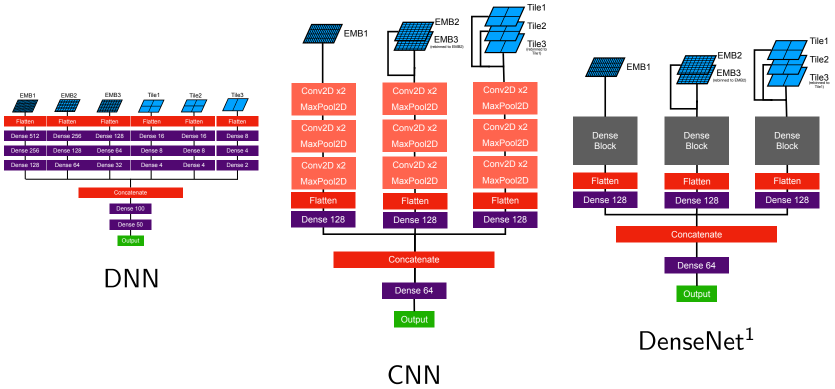
Machine Learning for Event Reconstruction

- Calorimeter calibration relies on understanding single particle response - for *pp* collisions, this is mostly pions
- Current methods for identifying and calibrating the energy of pions do not make use of distribution of energy within the calorimeter
- Lots of information in shower shape and depth - a neural network can use this!



Neural Network Architectures

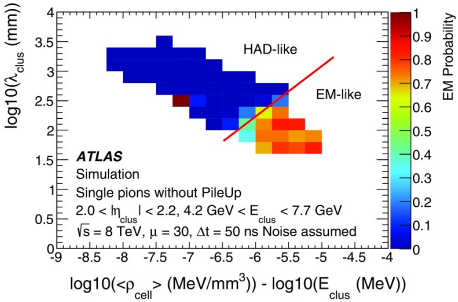
- Investigated three different neural network architectures
- Two goals: classification, and energy calibration



[1] https://arxiv.org/abs/1910.03773

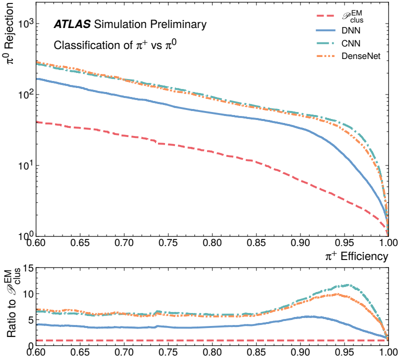
Classifier Goals

- Ultimate goal to apply the correct energy scale to each topo-cluster
- Need to classify pion events as hadronic (charged) or electromagnetic (neutral)
- Currently done using $\mathscr{P}^{\text{EM}}_{\text{clus}}$
- ML techniques can use shower shape information to improve efficiency

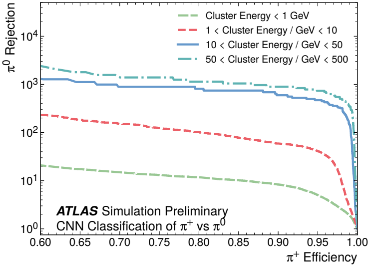


Classifier Results

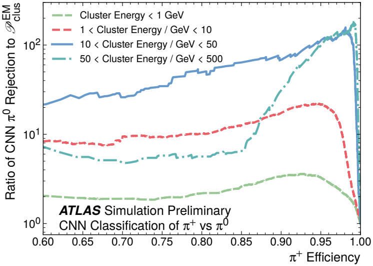
- π^0 rejection vs π^+ efficiency
- Vastly improved performance with all architectures!
- eg at 90% π^+ efficiency, DNN gives 5 times better π^0 rejection while CNN and DenseNet give around 8 times improved rejection over $\mathscr{P}^{EM}_{clus}$



Classifier Results



CNN efficiency

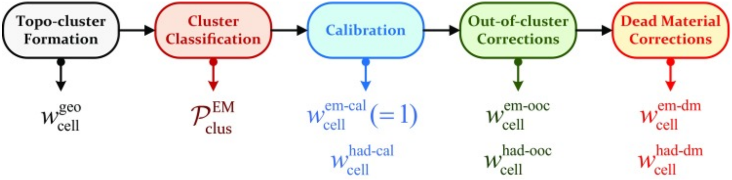


CNN / $\mathscr{P}^{\text{EM}}_{\text{clus}}$

- Increasingly better performance at higher energies
- Not explicitly trained on energy - variation in shower shape with energy enough to give good separation in every energy range

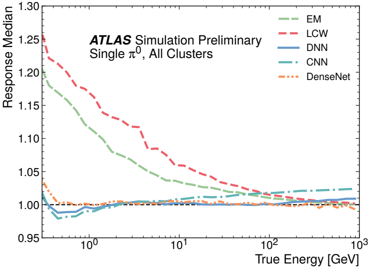
Regression Goals

- After identifying a pion as hadronic/EM, need to convert the signal into an energy measurement
- LCW calibration splits this over three steps: hadronic calibration, signal loss correction and dead material correction
- ML techniques may improve performance by better utilising cell information

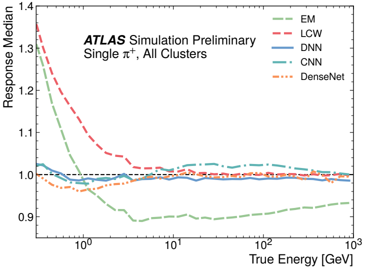


Regression Results

- x-axis: true energy, y-axis: median response
- All networks showed greatly improved performance at low energy
- CNN diverges slightly at high energy



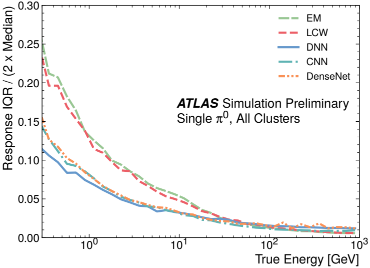
π^0



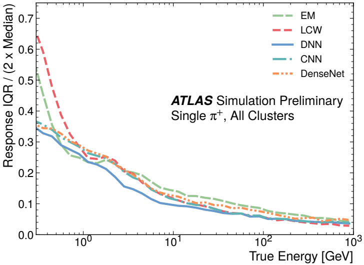
π^+

Regression Results

- x-axis: true energy, y-axis: half-width response IQR / median (resolution)
- Improved resolution at low energy
- Comparable resolution at high energy



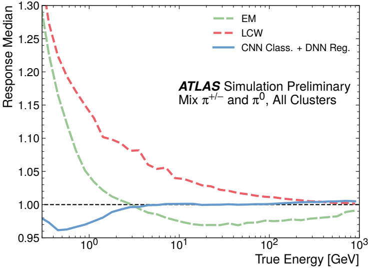
π^0



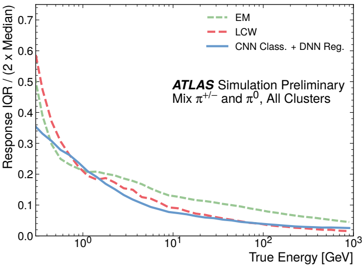
π^+

Regression Results

- Mixed sample of π^+ and π^0 as approximation of real jets
- Again, much improved performance across all energy bins



Response



Resolution

Conclusion

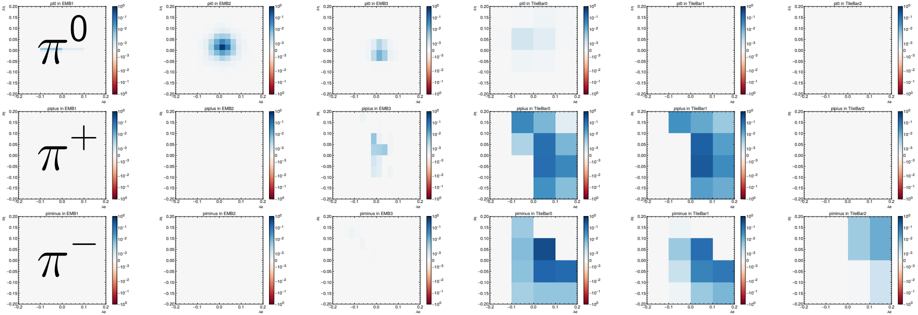
- Neural networks to classify pions as charged or neutral - great performance improvement over traditional methods
- Neural networks to perform energy calibration - significant improvement in both energy scale and resolution for classified pion events
- Combining the two types of networks leads to some very promising results
- All of this possible by better leveraging the information contained in the shapes of showers as they pass through the various calorimeter layers

See the ATLAS public note for more details: https://cds.cern.ch/record/2724632?ln=en

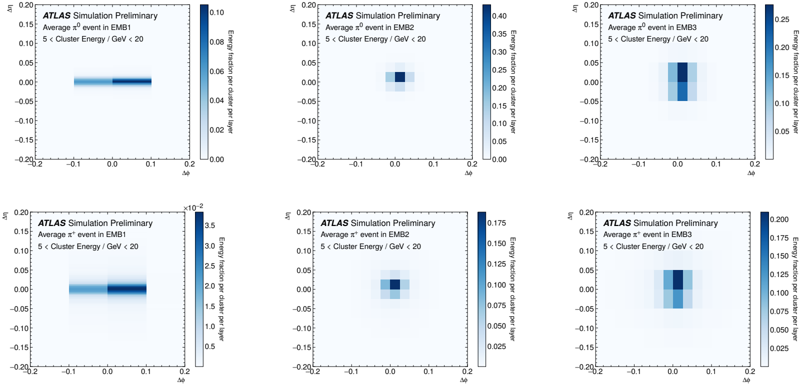
Backup Slides

Dataset Details

- Single pion samples in barrel region ($|\eta| < 0.7$)
- Generate a 2D 'image' for each topo-cluster in each calorimeter layer (EMB1,2,3 and Tile1,2,3)
- x- and y-axes are the ϕ and η coordinates relative to the cluster centroid

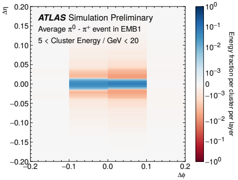


Average Pion Images



- π^+ have slightly wider distributions, but difficult to see from just looking at the 'average' images

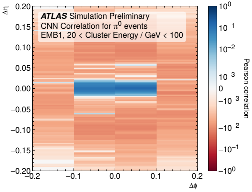
Average Difference Images



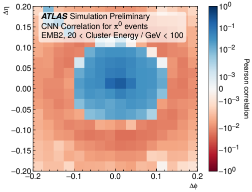
- Wider showers are associated with charged pions, smaller showers with neutral pions as expected
- Let's see how well the neural networks can leverage this information!

Classifier Correlation

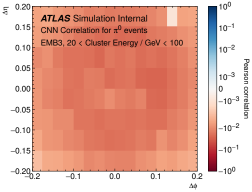
- Pearson correlation between average π^0 image and CNN classifier score
- Width and depth of shower are important to the CNN, as expected



EMB1



EMB2



EMB3

CNN Visualisation

- Visualisations of ‘features’ that the CNN has learned to look for
- Difficult to interpret, but generally captures the shape of showers in each layer
- Axes are in arbitrary units (related to cell index)