Calorimeter signal calibration using machine learning

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Overview

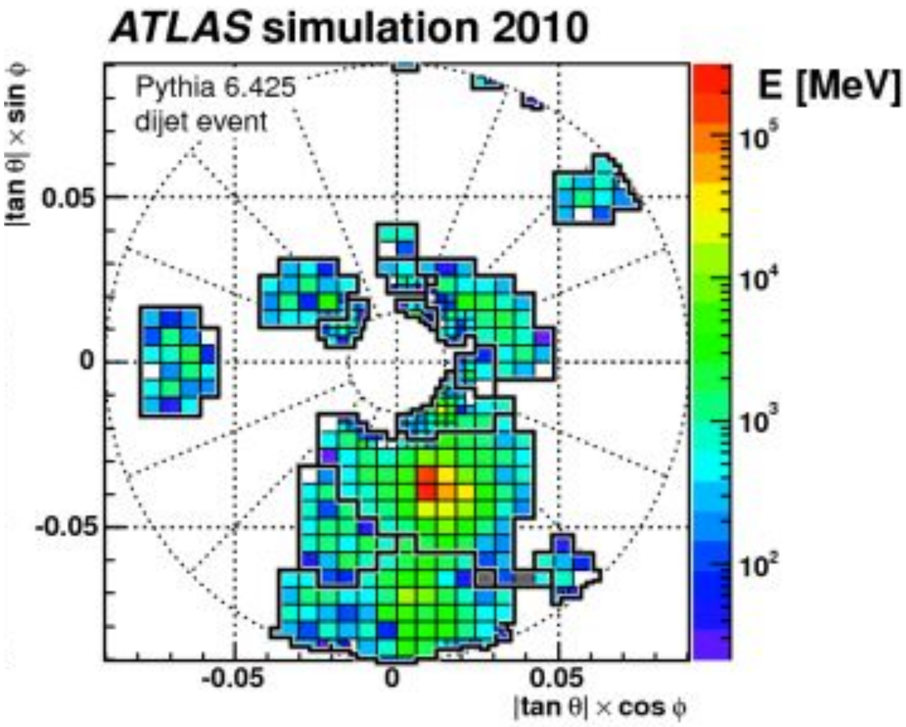
- Introduction
- Topo-clusters
  - Electromagnetic showers vs hadronic showers
- Calibration Method
- Results
  - EM probability calibration
  - Energy calibration

Introduction

- The main signal from calorimeters is related to the energy deposited in each cell.
- To extract relevant signal from noise, reconstruct particles, and reconstruct jets calorimeter signals are collected into clusters.
- Clusters are typically missing energy.
    - Missing energy is due to dead material, non-compensating calorimeter response to hadrons, and clustering strategy.

Topo-Clusters

- Cells clustered by topologically connected signals.
  - Signals are clustered into 3d energy blobs.
- Formation is controlled by cell signal significance.
- Have defined moments and shape.
- Can either represent full or fractional response to a single particle.



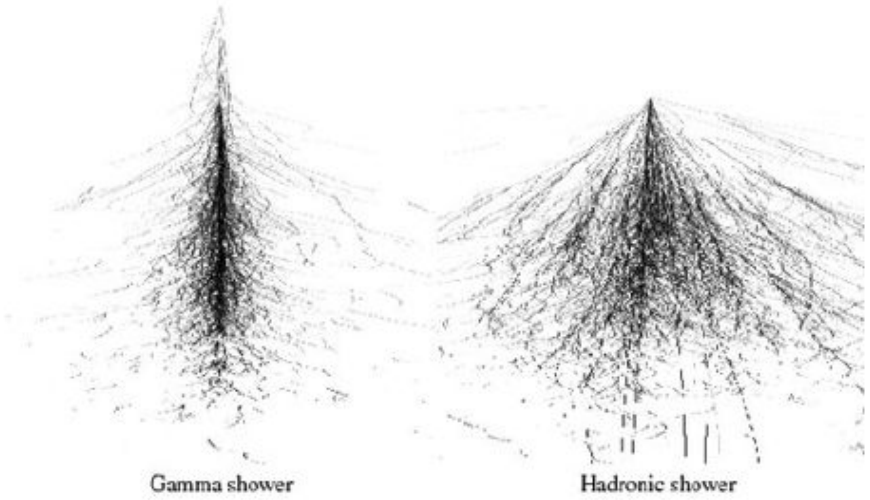
Electromagnetic showers vs hadronic showers

Electromagnetic showers

- Initiated by π^0 in simulation.
- Higher energy density.
- Energy signal close to true energy deposited.

Hadronic showers

- Initiated by $\pi^\pm$ in simulation.
- Energy deposited deeper in calorimeter.
- Significant energy loss due to dead material.



Method of correcting energy

- Steps to calibrate energy
  - Pick observables.
  - Predict EM probability using deep neural network.
    - Calorimeter has better response to EM scale.
    - Could be done all in the regression network.
  - Calibrate energy using regression neural network.
    - Use EM probability as extra input to regression network.

Cluster Observables

EM probability

Cluster observables.

- Depth
- Energy Density
- Energy
- Pseudorapidity
- PTD
    - Measure of spatial signal compactness

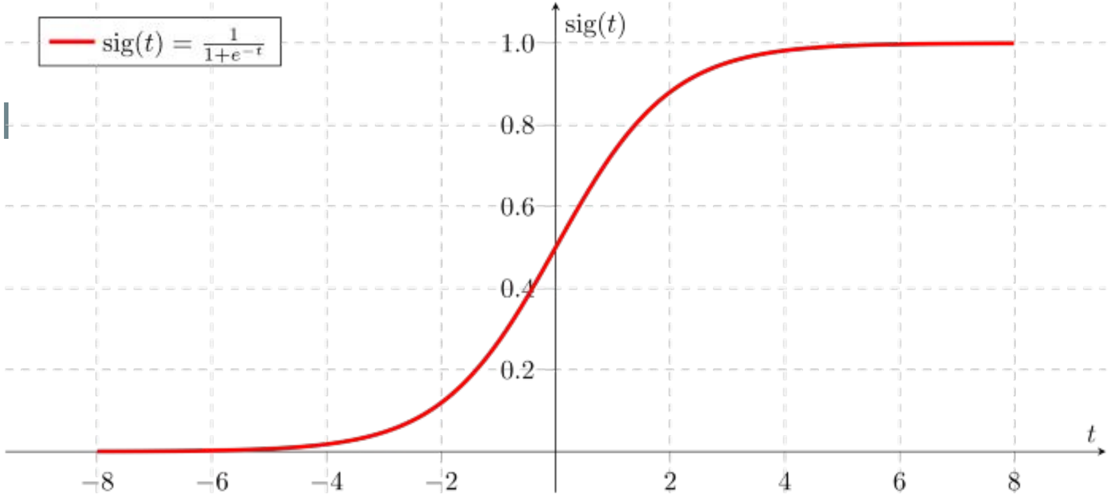
Energy calibration

Cluster Observables

- Depth
- Energy Density
- Energy
- Pseudorapidity
- PTD
    - Measure of spatial signal compactness
- EM probability
- Longitudinal energy dispersion
- Lateral energy dispersion

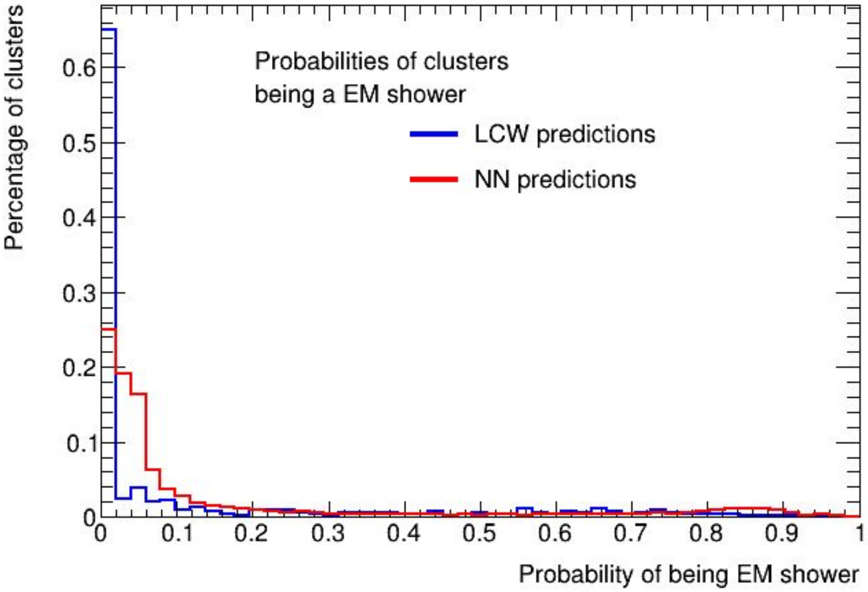
Neural Network

- Deep Neural Network implemented using Keras.
- Benefit of low computational cost.
- Final activation for EM probability of sigmoid.
  - Chosen to make results have similar distribution to original.
- No final activation for energy calibration.

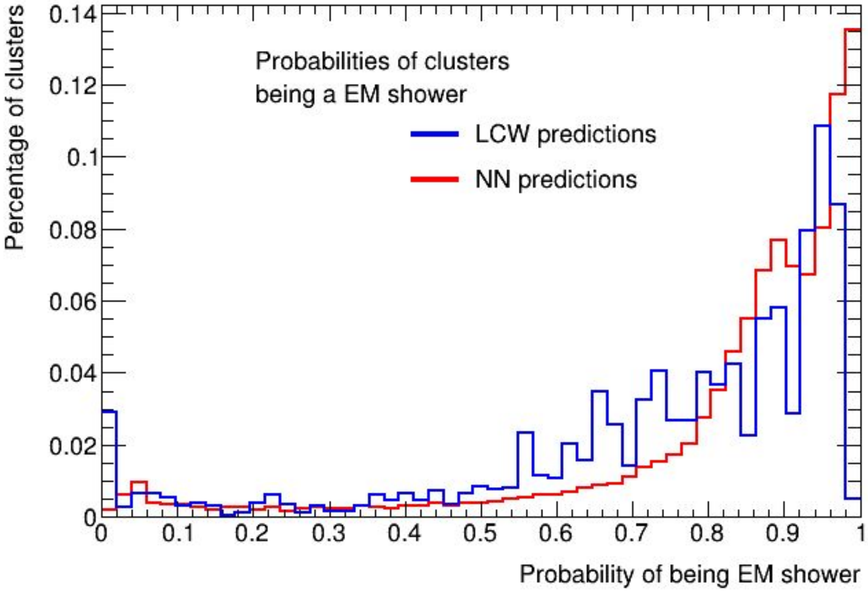


EM probability results

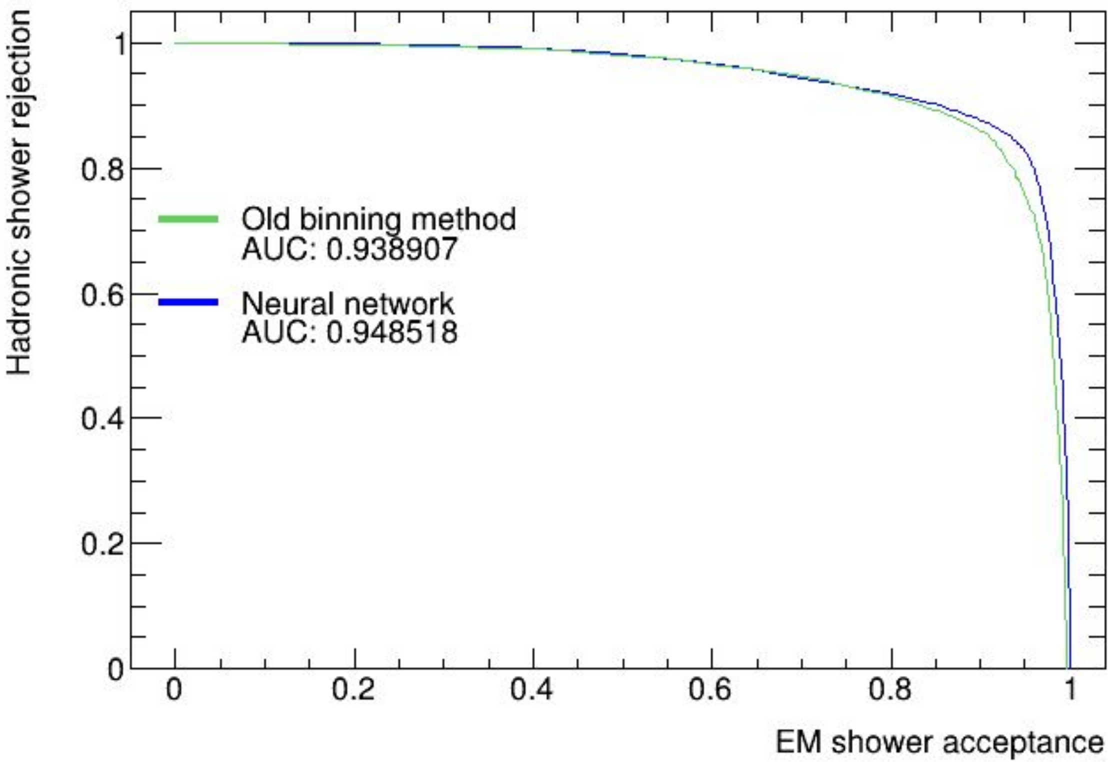
Results for hadronic showers ($\pi^{\pm}$)



Results for electromagnetic showers (π^{0})

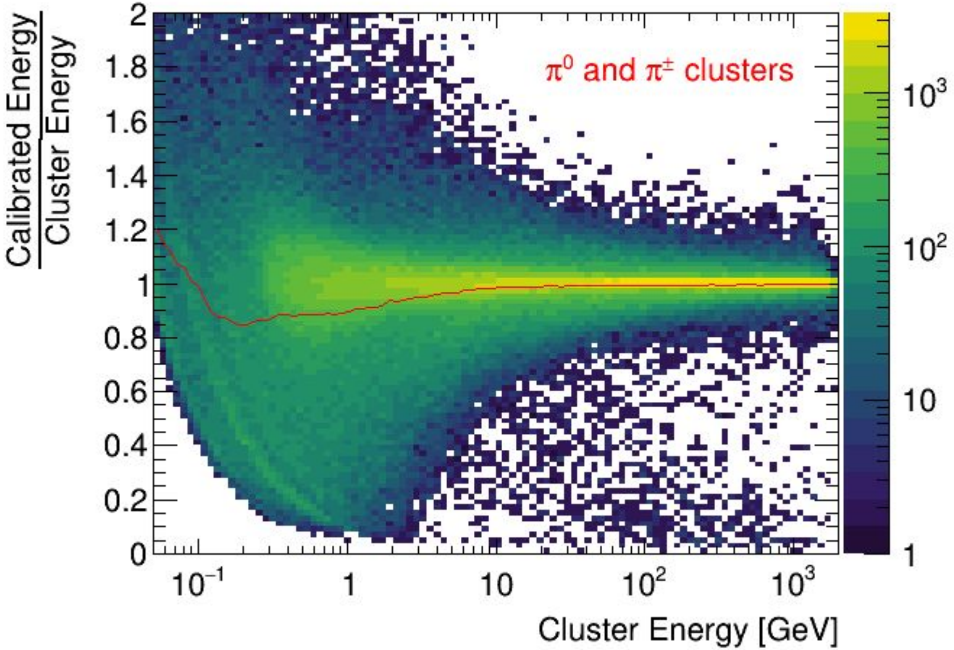


EM probabilities corrections



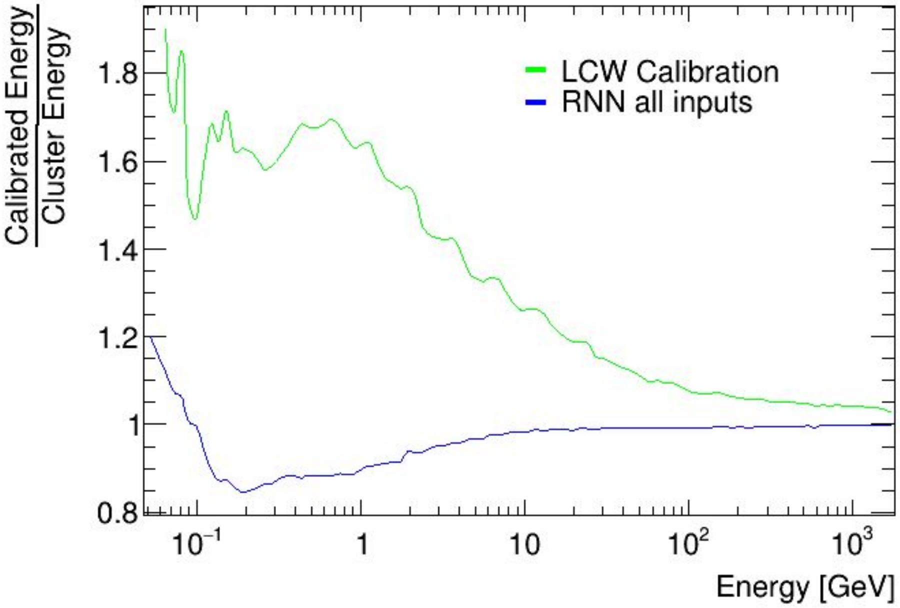
Energy Calibration

- Great results for energy > 10 GeV.
- Low energy cluster are hardest to calibrate.
- Cut clusters with cell significance < 3.



Energy Calibration Results

- Response show great improvement over LCW Calibration
- Response is within 10% for cluster energy greater than 1 GeV



Conclusion

- EM probability is improved marginally.
  - More importantly distribution of EM probability is smoother.
  - Doesn’t assign 0 probability to 3% of EM showers as old method did.
- Energy calibration is within 10% for energy above 1 GeV.
  - Work is still needed to continue improving the low energy response.
  - Further analysis is need to understand the uncertainty.

Questions

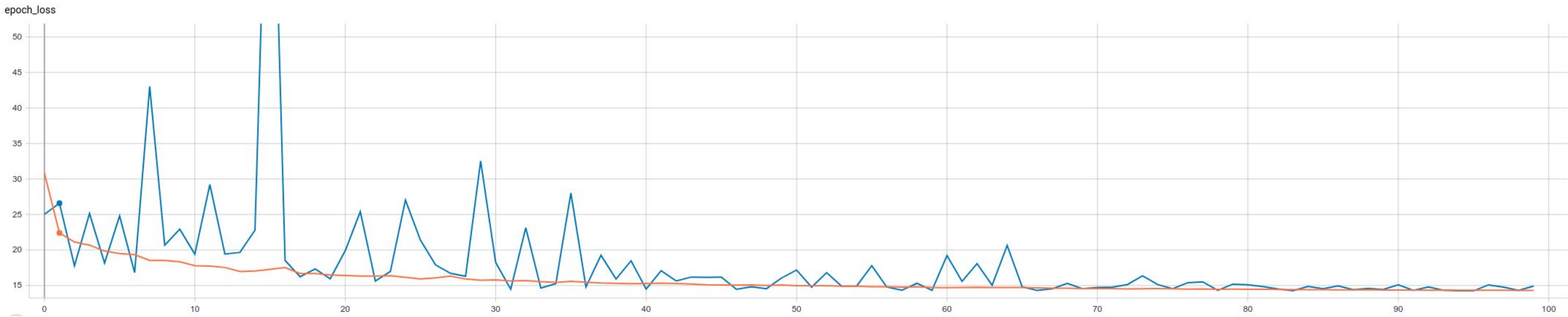
Network Specifics

EM Probability

- 1 hidden layer Relu activation 2048 nodes
- Final layer sigmoid
- Loss BinaryCrossentropy

Energy Calibration

- 2 hidden layer Relu activation 1024 nodes each
- Final no activation
- Loss Mean percentage error



Loss per epoch for energy calibration