Shower Energy Reconstruction using a Convolutional Neural Network in MicroBooNE

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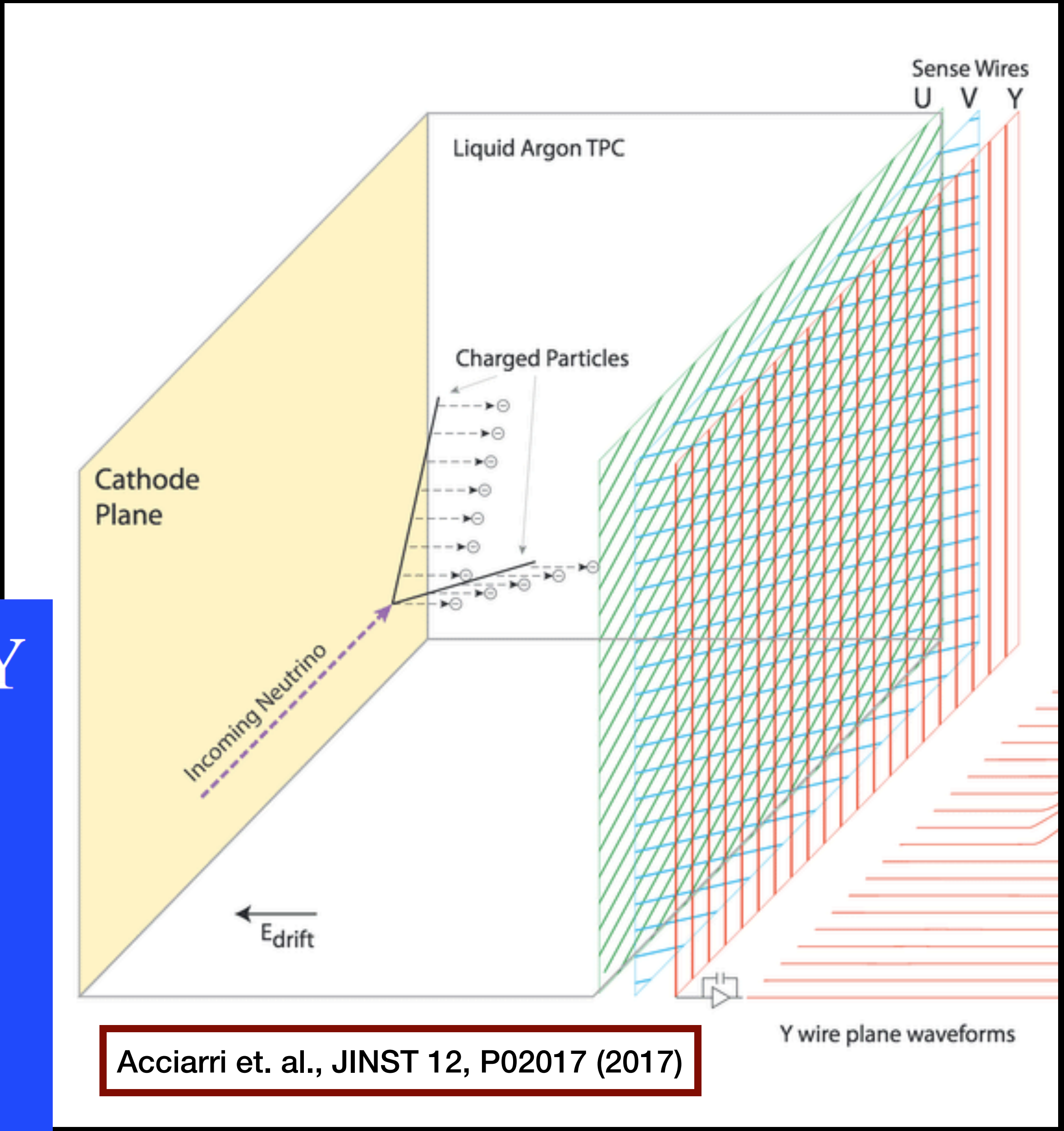
Overview

This talk will:

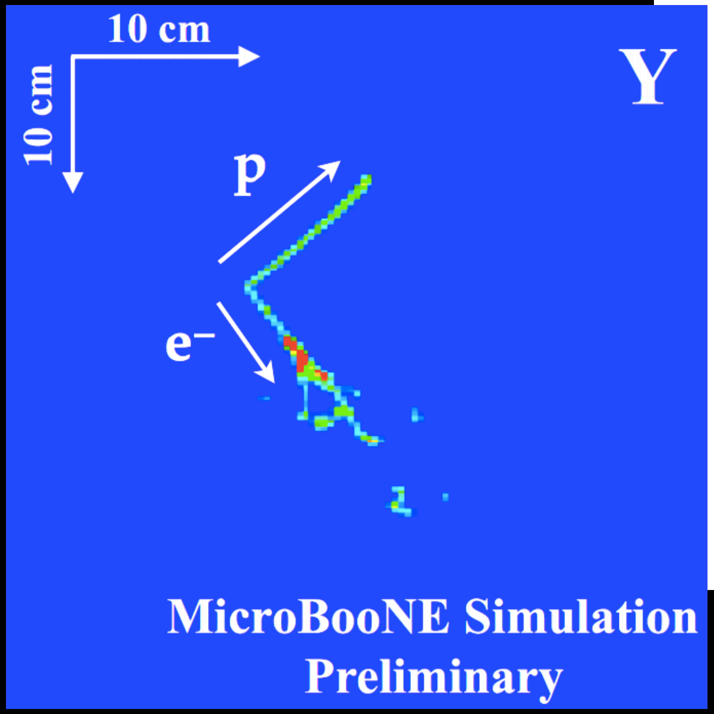
1. Review the traditional shower energy reconstruction method in MicroBooNE
2. Motivate the use of a convolutional neural network (CNN)
3. Describe the current structure of the shower energy CNN
4. Compare the CNN and the clustering algorithm
5. Explore avenues of improvement for the CNN

The MicroBooNE Detector

- Charged particles passing through MicroBooNE create ionization electrons, which are drifted through an electric field to three wire planes
- Electrons and photons will create electromagnetic showers in the detector, which appear as “clusters” of charge in the wire plane images

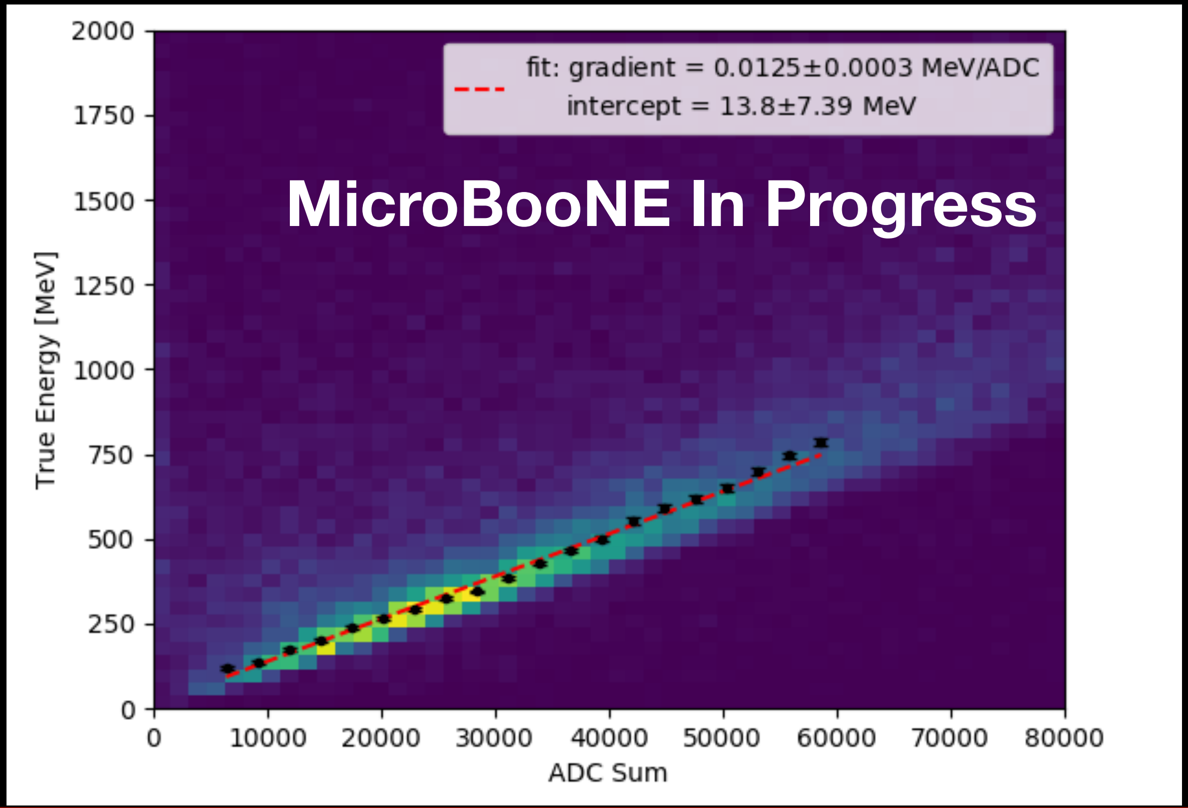


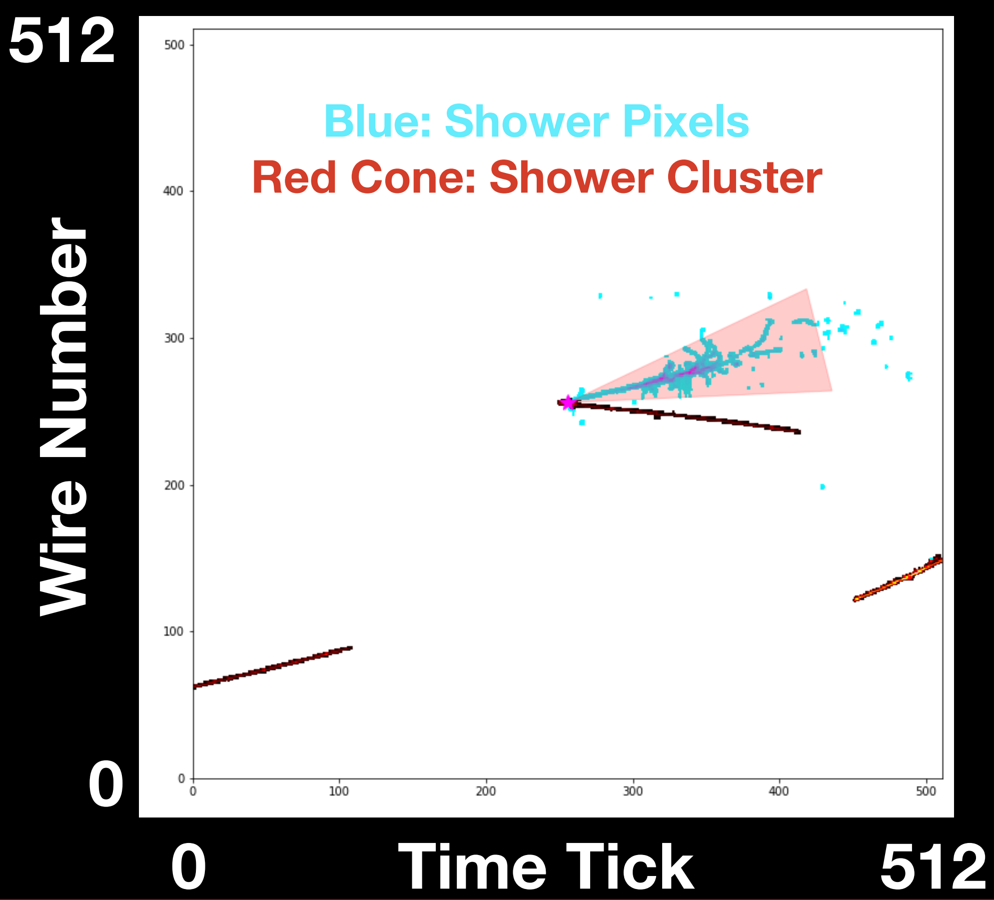
Acciarri et. al., JINST 12, P02017 (2017)



Traditional Clustering Algorithm

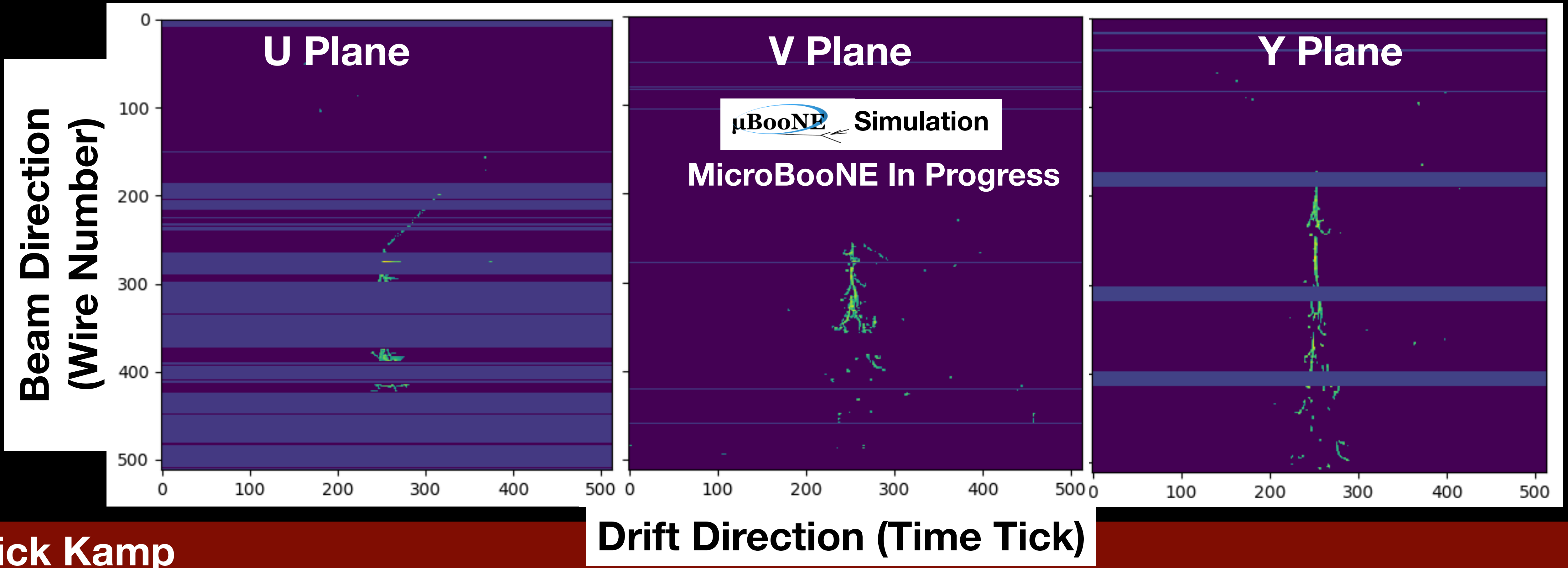
1. Take a given reconstructed Y-plane vertex and center a 512x512 pixel box around that vertex
2. Remove pixels with an ADC value < 10 and a shower score < 0.05 (from the "sparse semantic segmentation" network)
3. From the vertex, find the optimal direction, length, and opening angle of a cone in order to capture the maximum number of shower pixels
4. Fit for calibration parameters between the total charge in the cone and true energy of the electron



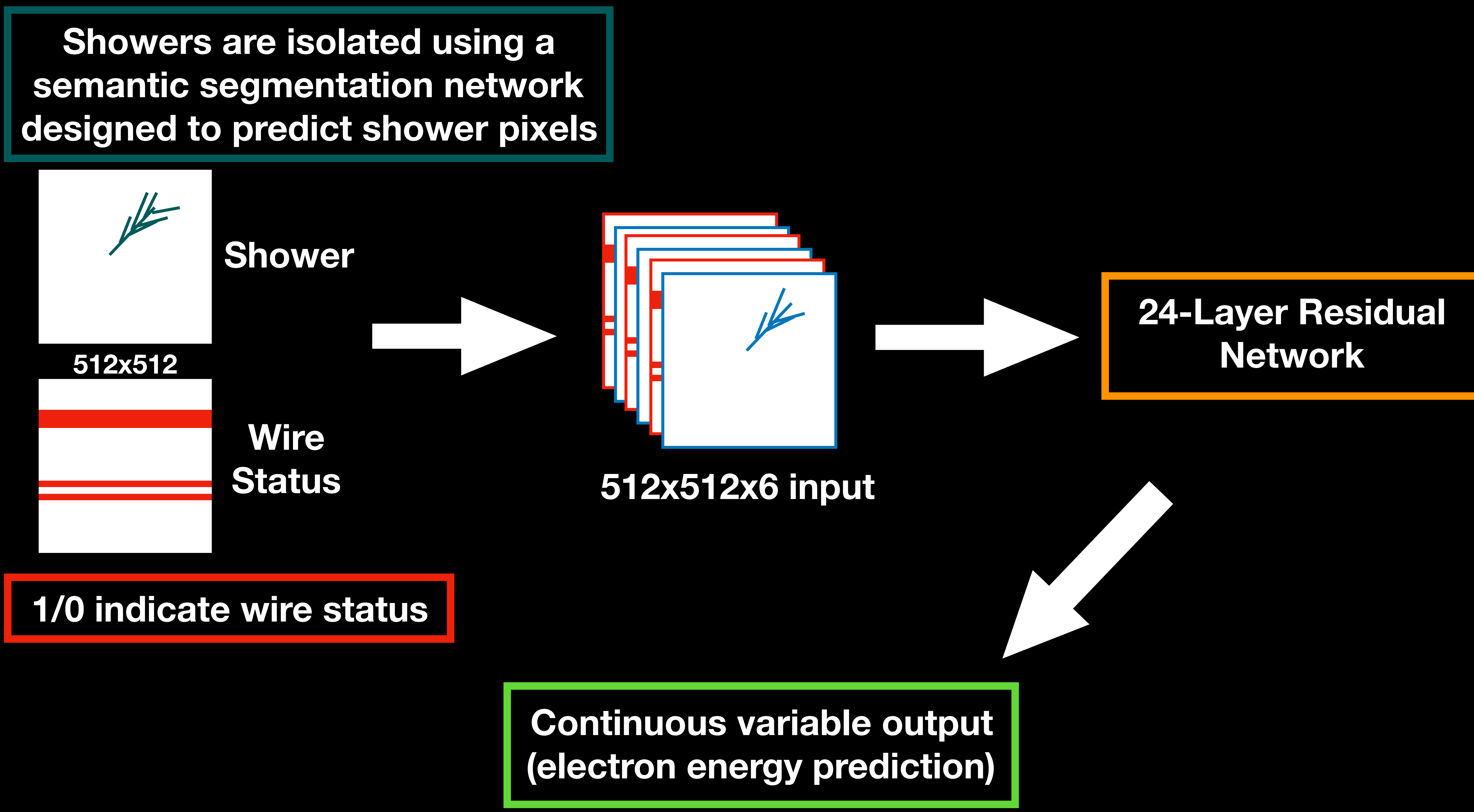


Failure Modes

- Due to the nature of a linear calibration, the cluster algorithm loses efficiency for electrons that deposit a below-average fraction of their energy into shower charge
  - This happens most frequently for showers that pass through non-responsive wire regions
- A convolutional neural network may be able to account for the lost charge in these situations, especially if it knows which wires are non-responsive

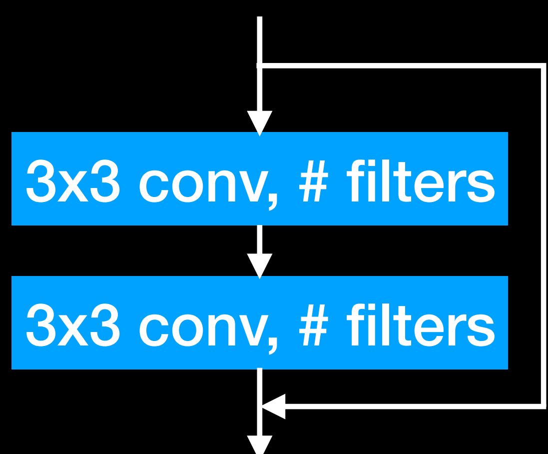


Network Overview

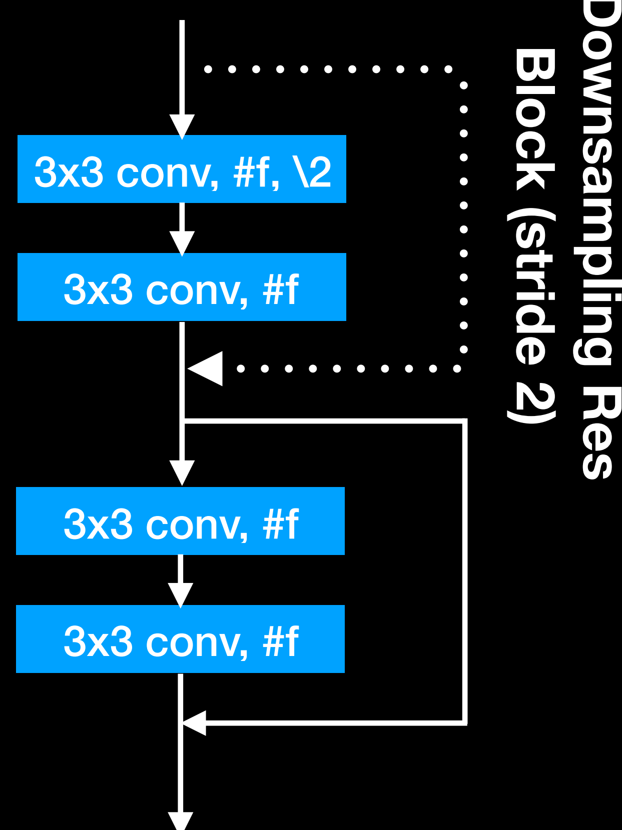


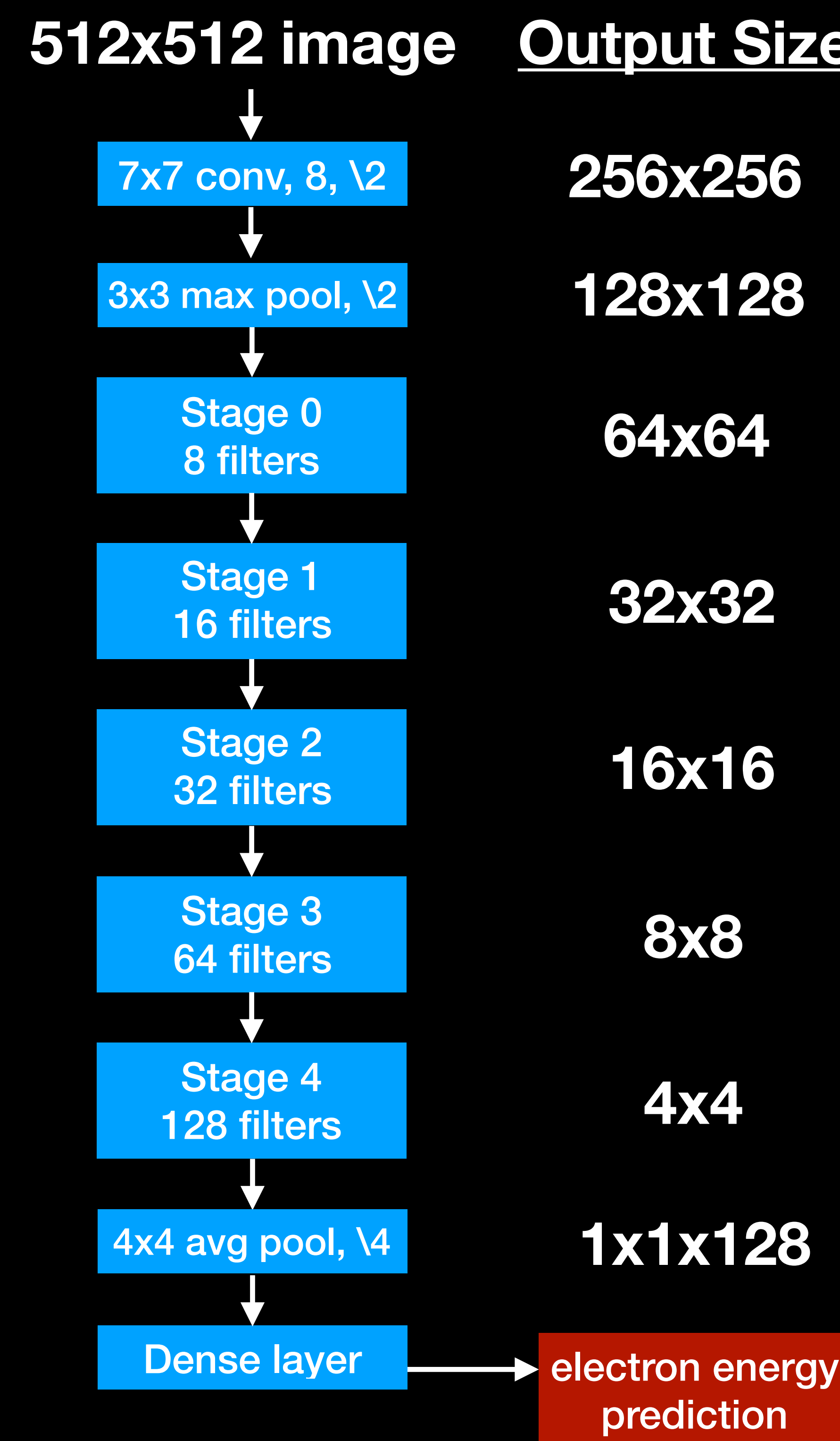
Network Architecture

Residual Block



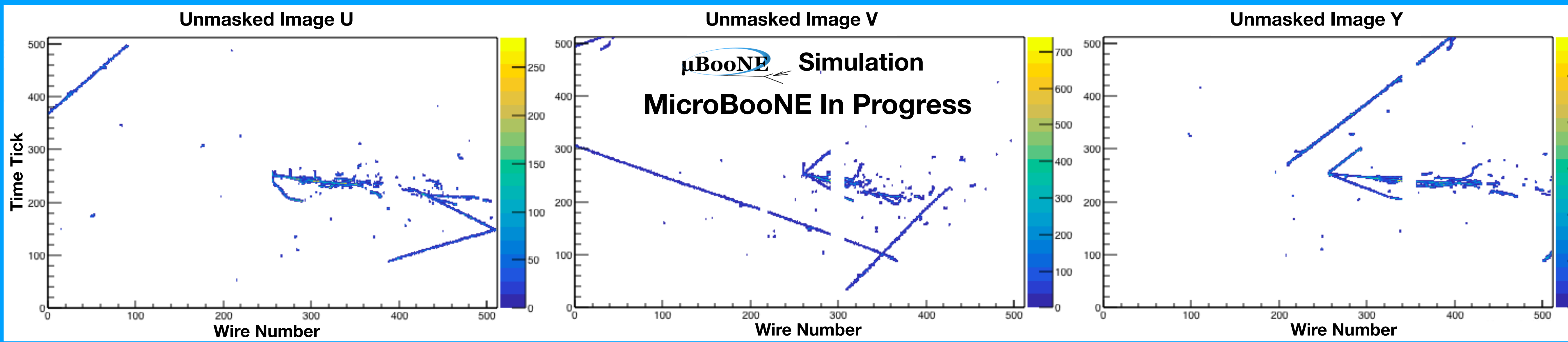
Stage



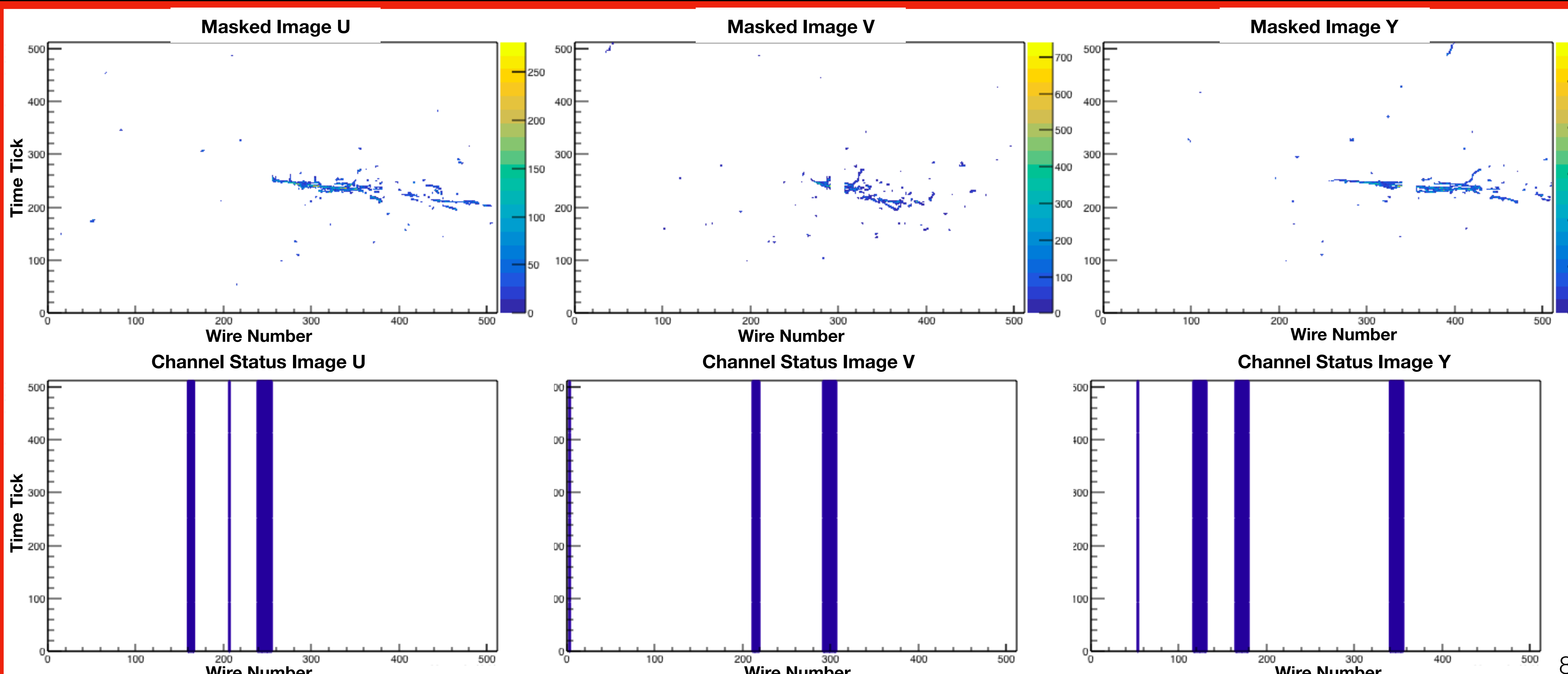


Currently trained using stochastic gradient descent on the L1 loss

Before Shower Masking



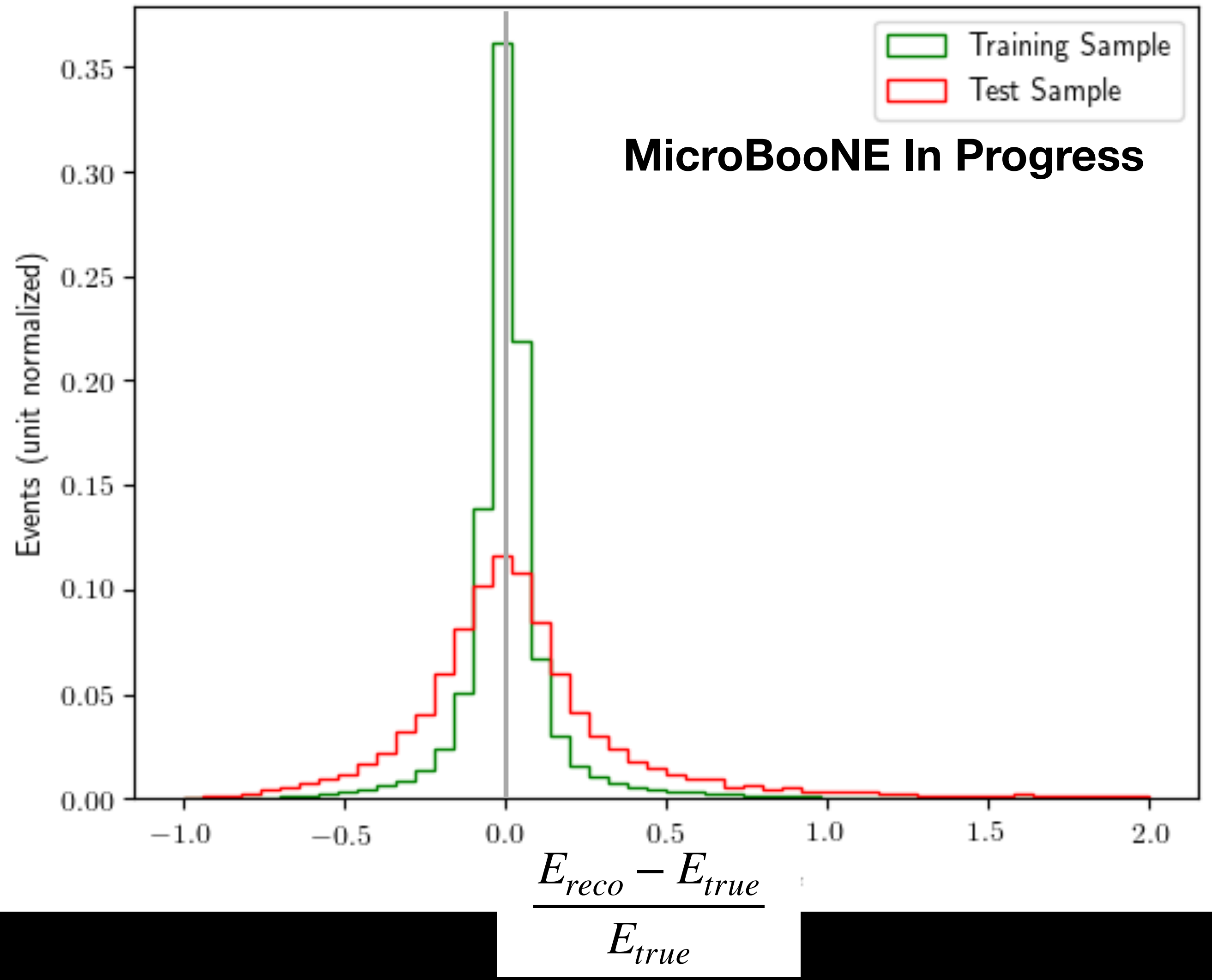
Actual Network Input



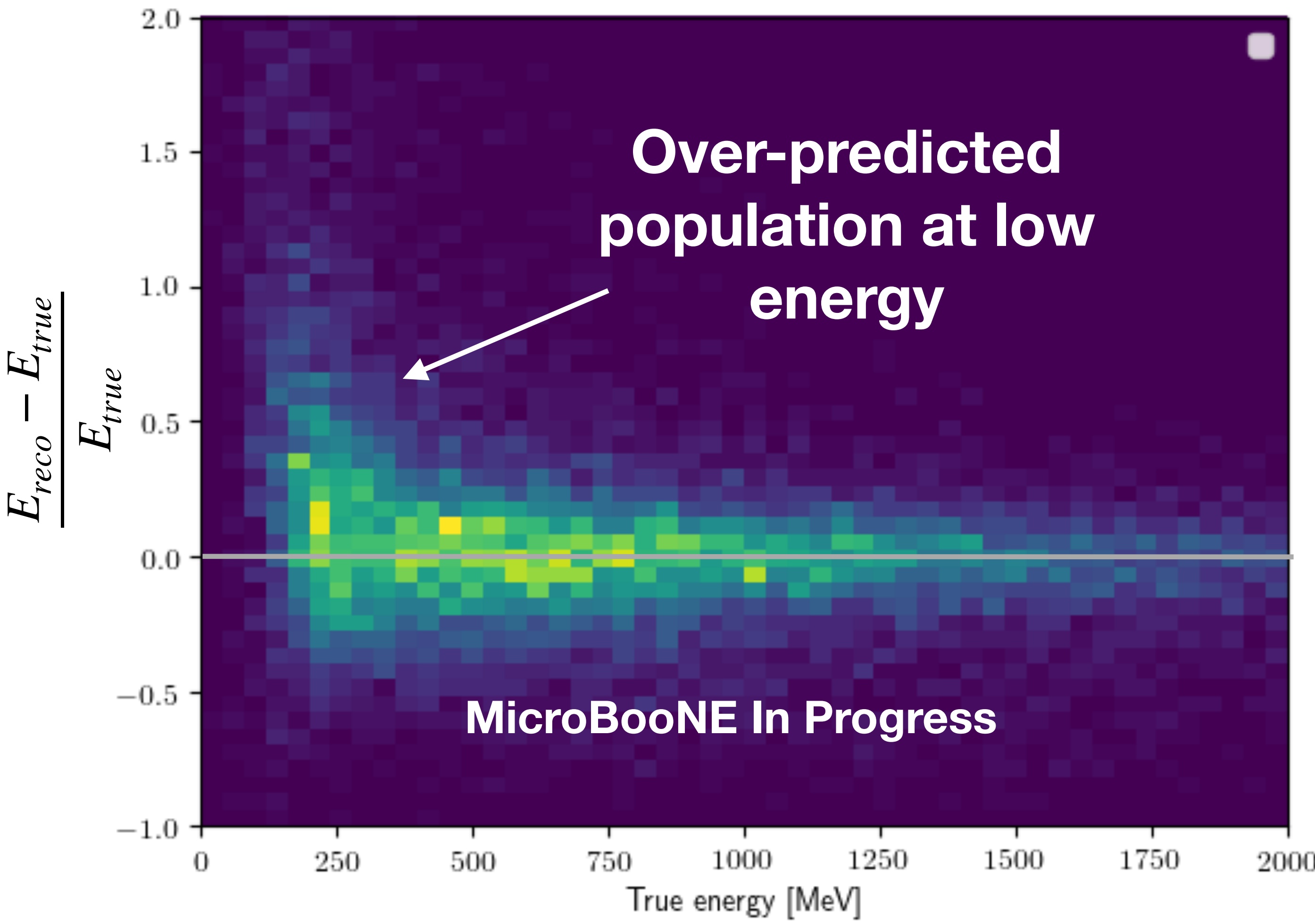
Network Training

- Training/validation sample consists of roughly:
    A. 57000/14000 shower images from the **standard** MicroBooNE simulation sample of electrons from ν_e interactions
    B. 5700/1400 shower images from a **low energy** version of the same sample
- Cuts:
    1. Take only the reconstructed vertex closest to the true electron vertex in each event
    2. Require the reconstructed vertex to be in fiducial volume
    3. Require $|\vec{r}_{reco} - \vec{r}_{true}| < 5$ **cm**

Network Performance



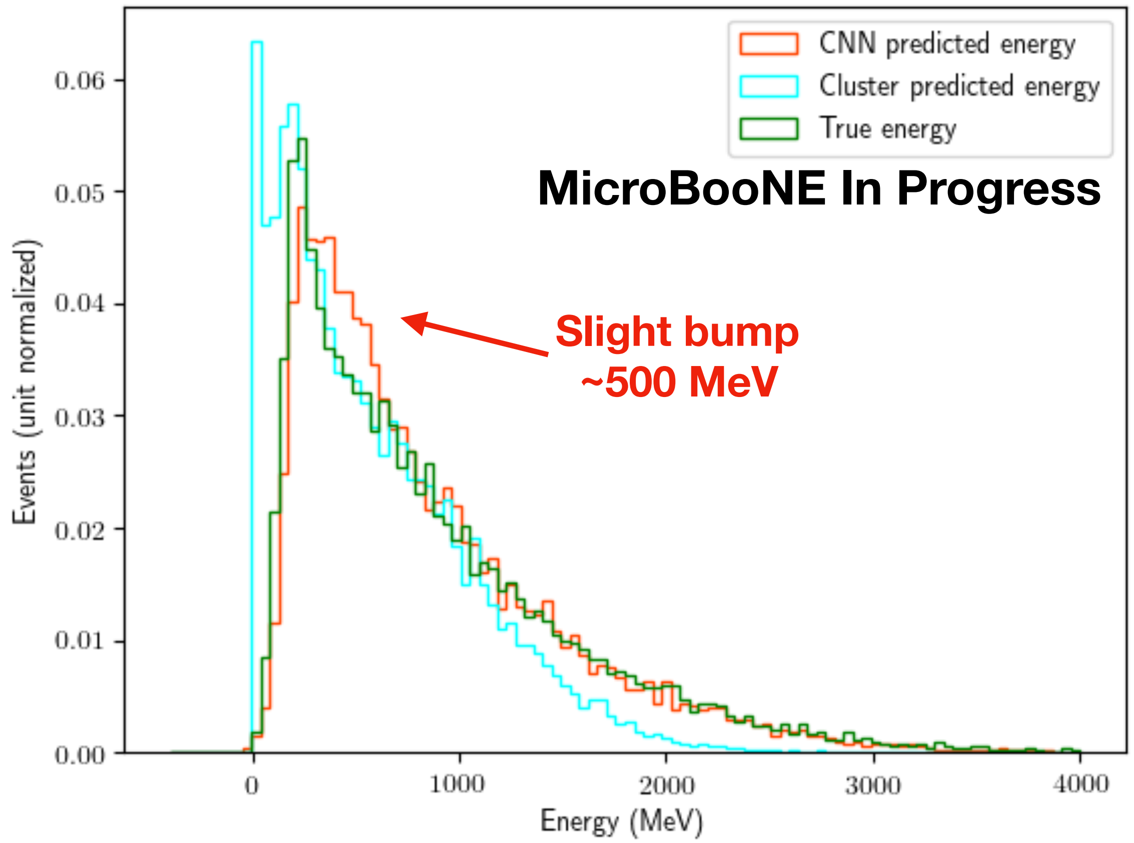
Validation sample events only

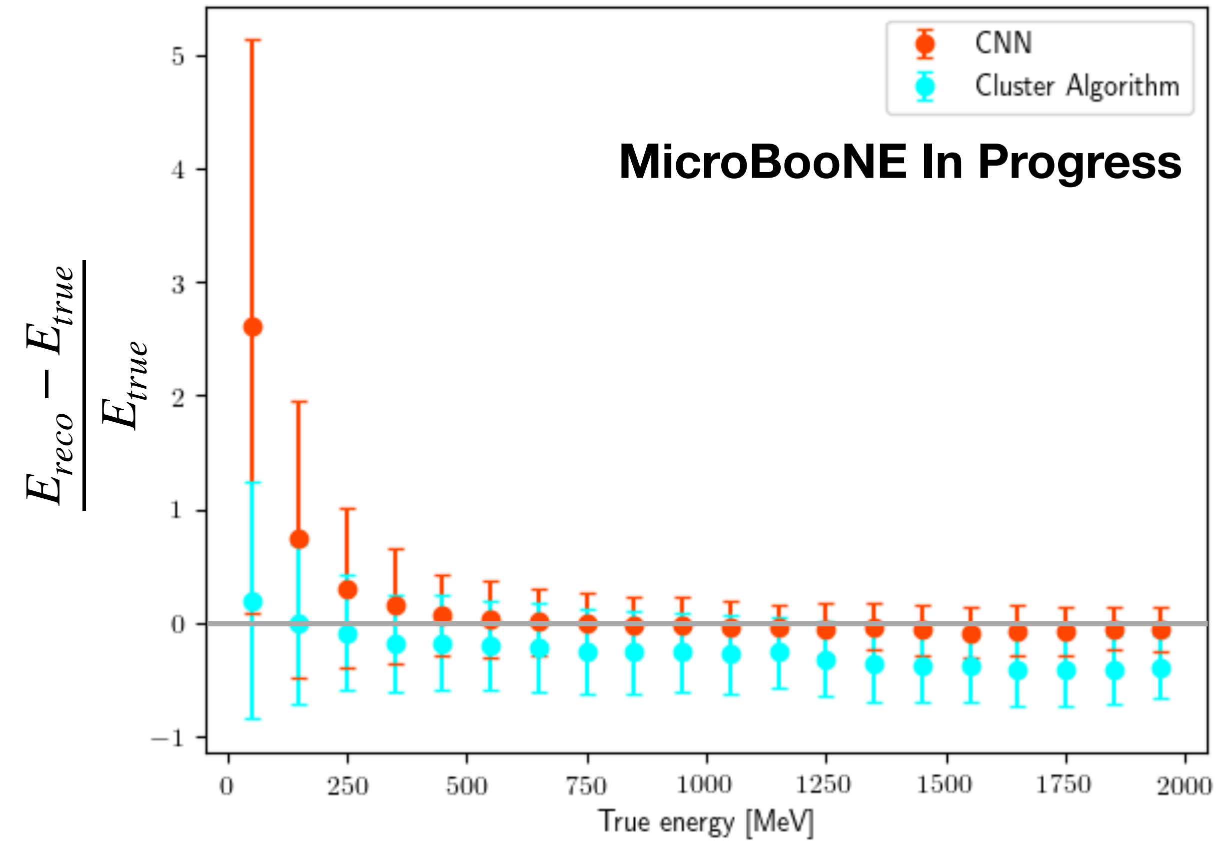


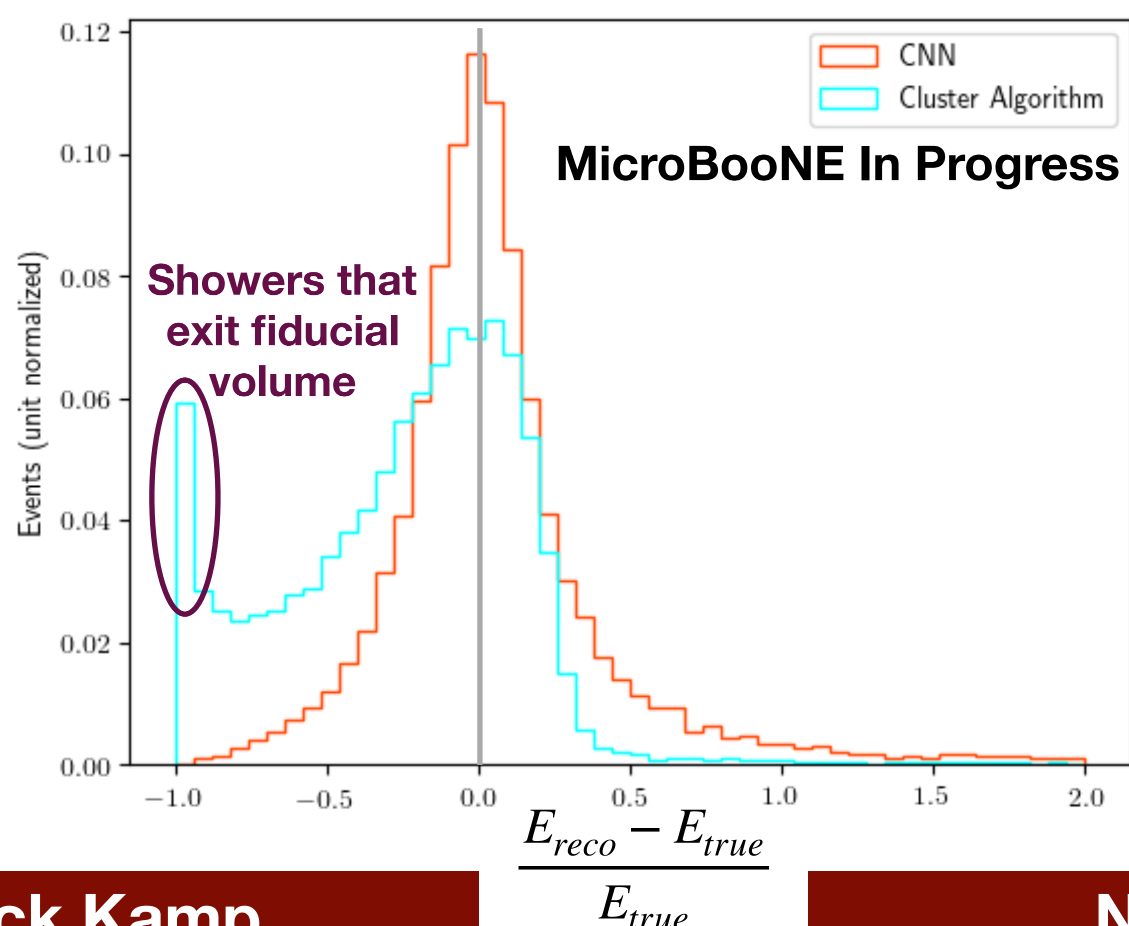
CNN v.s. Cluster Algorithm

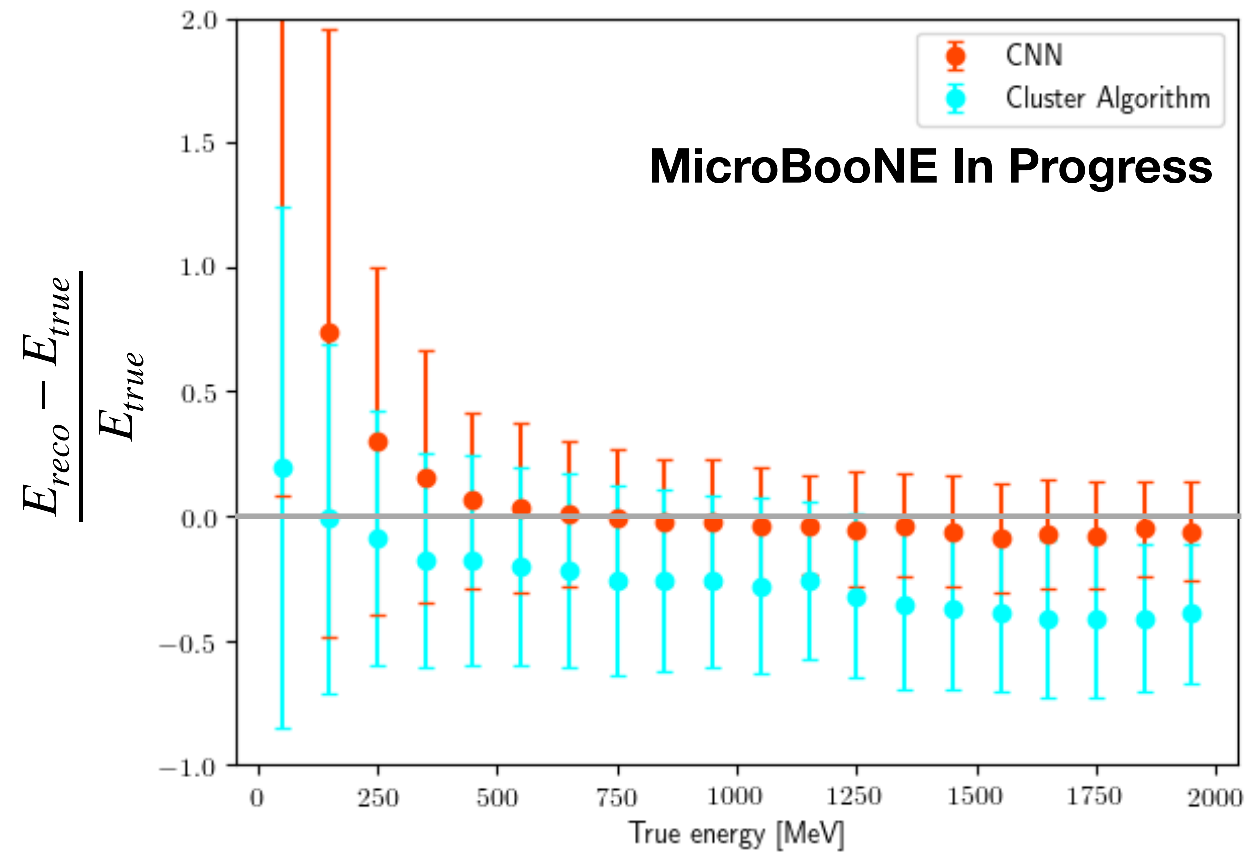
- The performance of the CNN can be compared to that of the clustering algorithm on the same set of shower images
- The plots in the following slides use the validation sample of the network
- Comparisons are divided between the standard and low energy shower image samples
- It is found that the clustering algorithm outperforms the CNN for $E_{true} \lesssim 250$ MeV, while the CNN outperforms the clustering algorithm for $E_{true} \gtrsim 250$ MeV

Full Validation Sample (Standard + Low Energy)

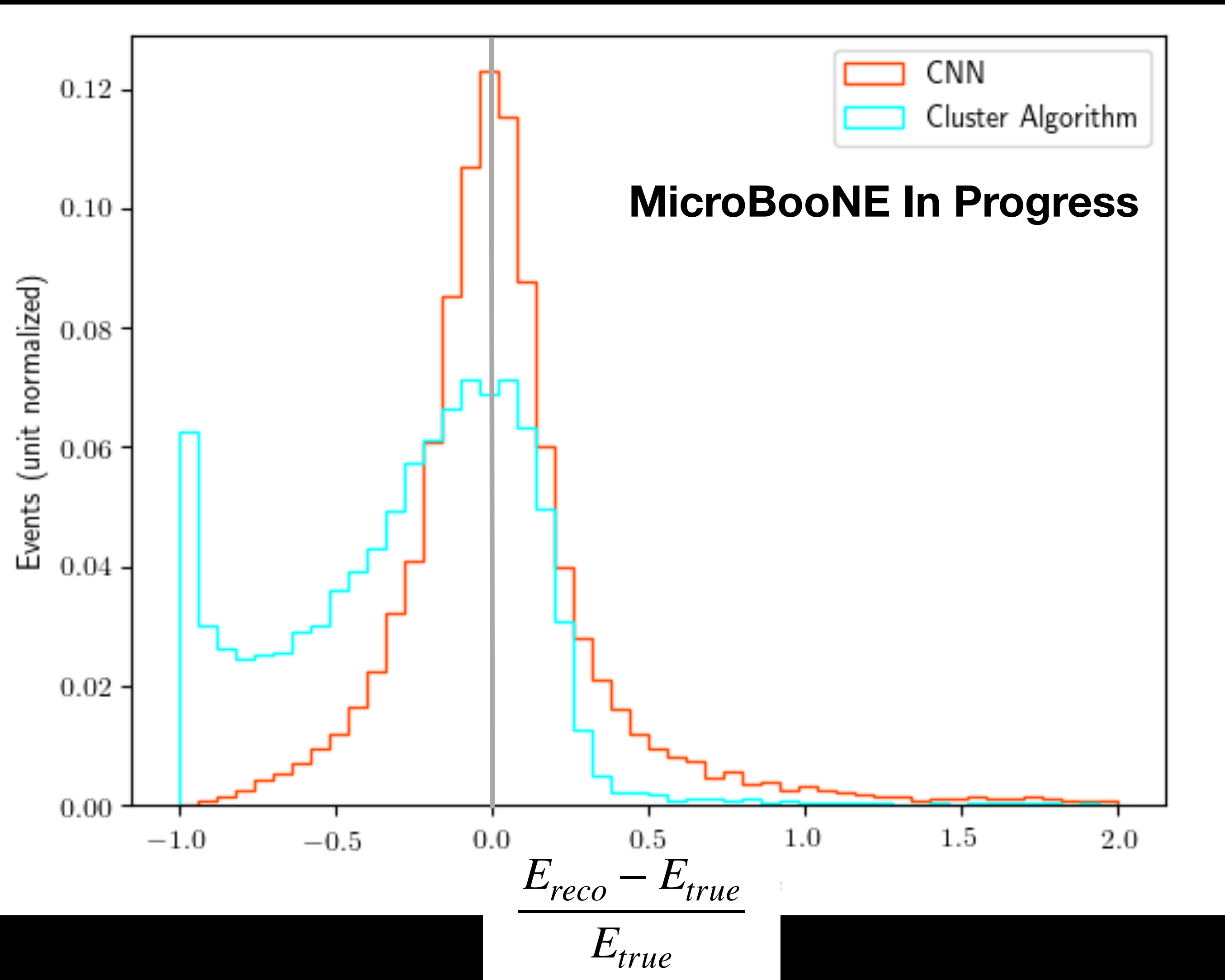


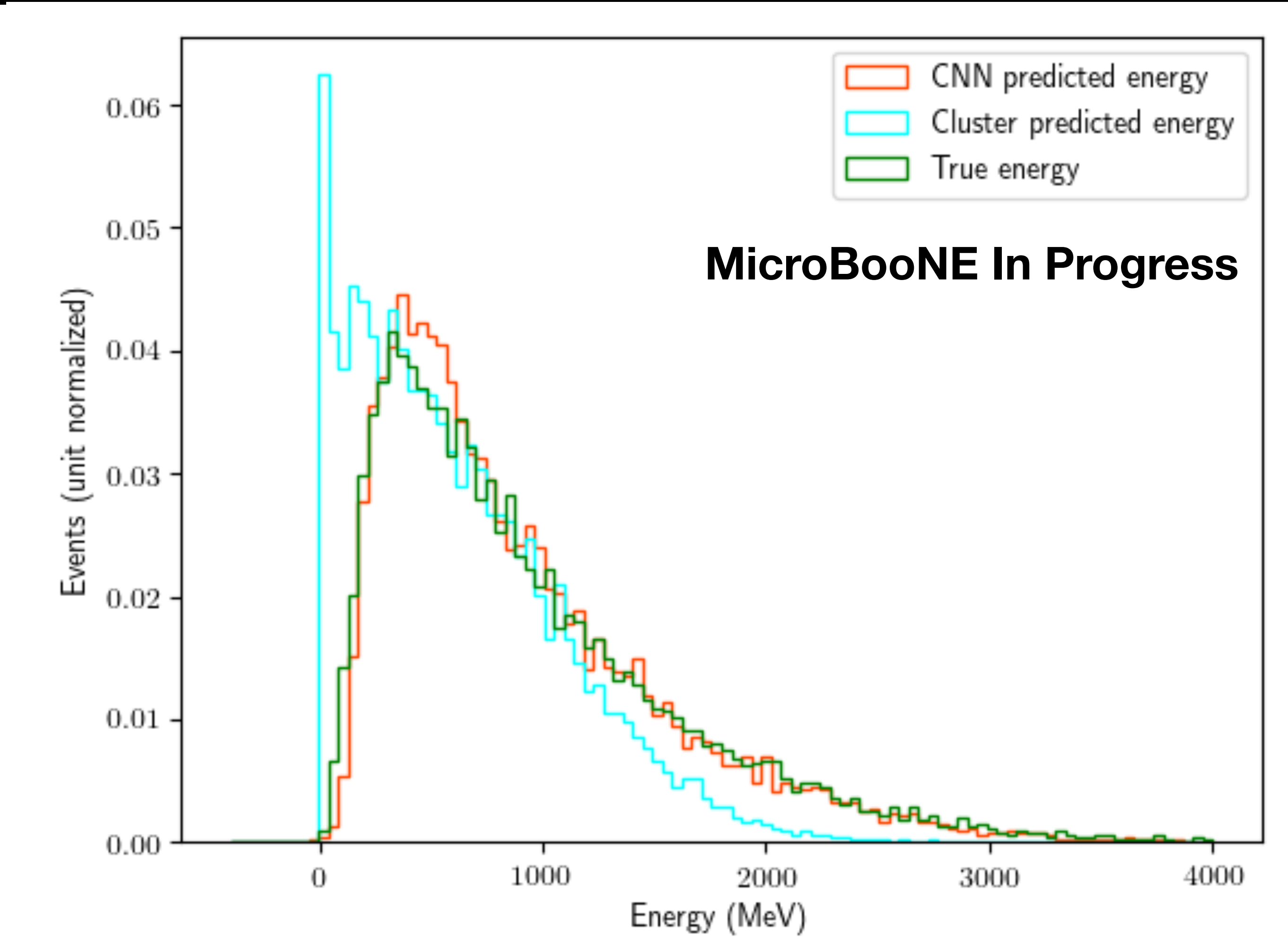






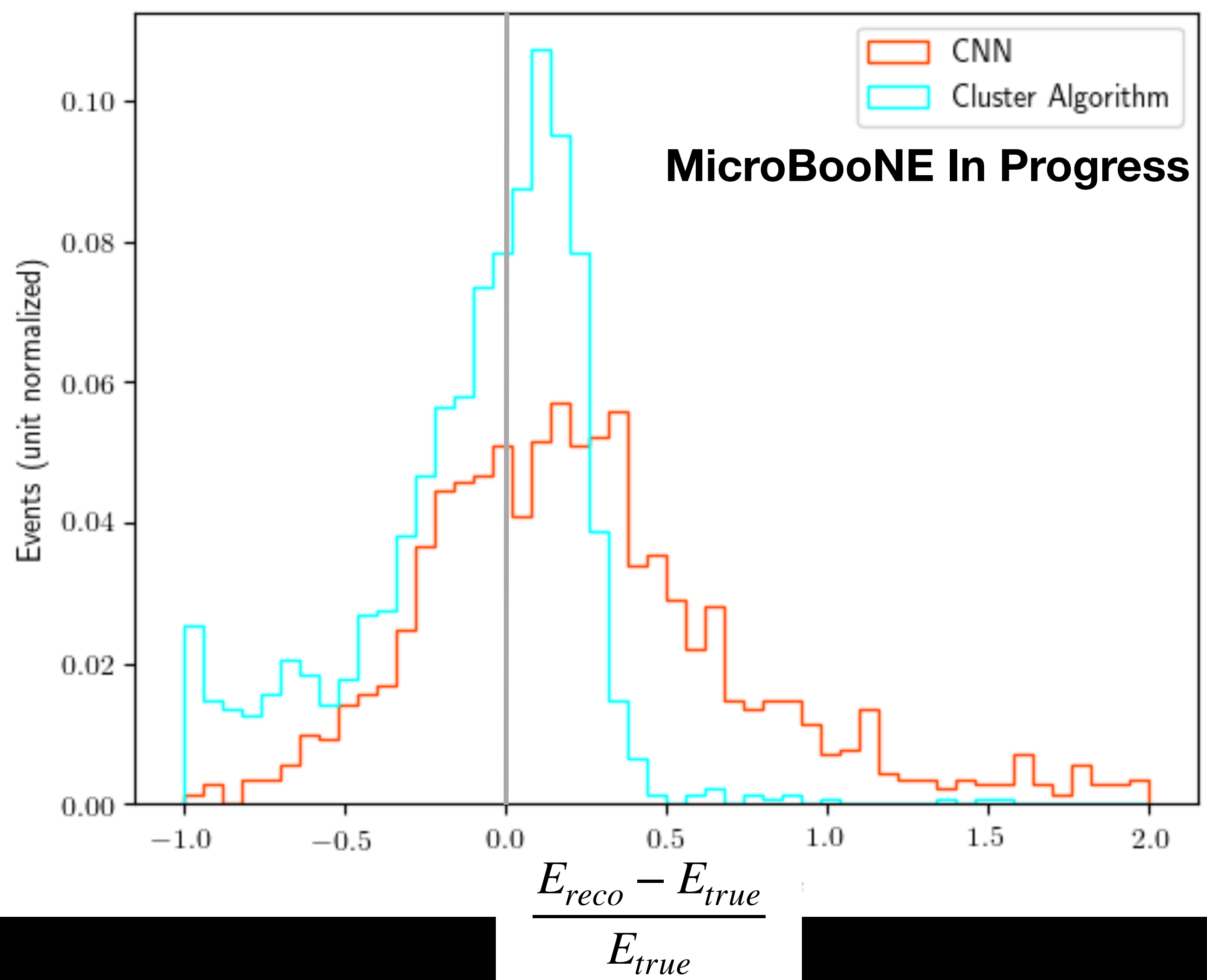
Validation Sample (Standard Only)

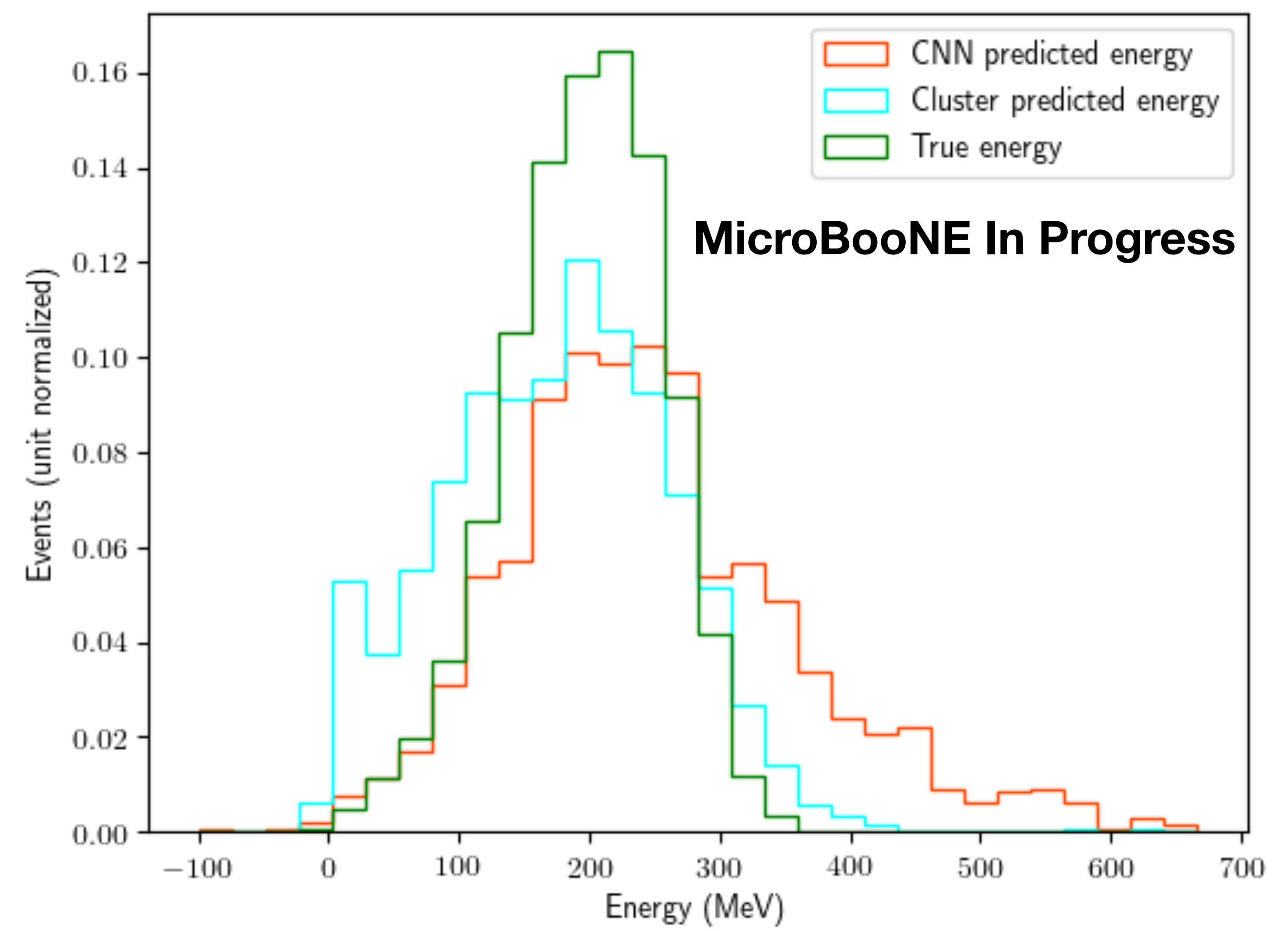




- Closely resembles full validation sample (makes sense; comprises majority of it)
- ~500 MeV bump still present in CNN predicted energy spectrum, cannot be attributed to low energy sample

Validation Sample (Low Energy Only)





- Cluster algorithm fractional error appears more sharply peaked here
- CNN has a longer tail extending to higher fractional errors / predicted energies—it is generally over predicting these showers

Near Future Next Steps

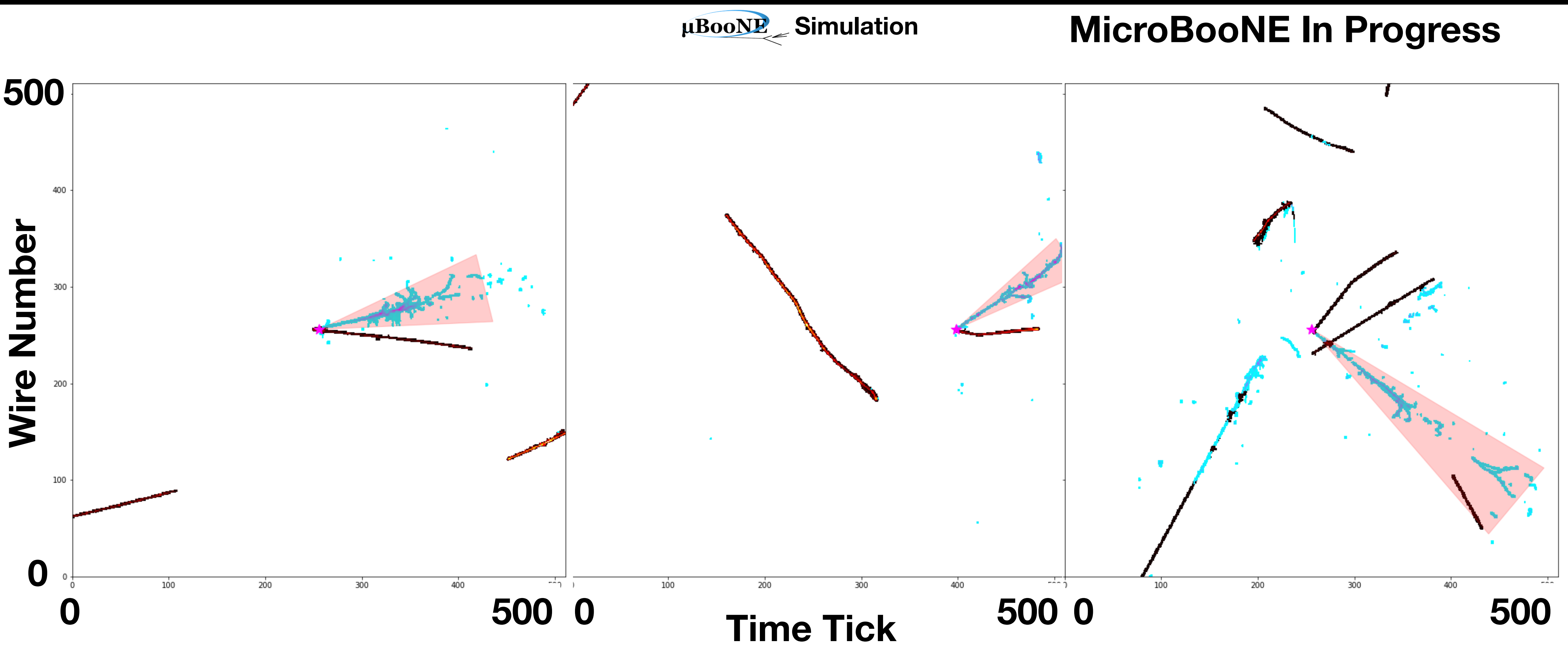
- Refine the training sample to improve performance at low energies (including increasing the weight of low energy training images)
- Reconstruct the energy of gammas from pi0 data events to obtain a mass peak
- Compare performance of different model architectures
- Evaluate detector-related systematic uncertainties of the network

Conclusion

- A CNN-based shower energy reconstruction method has been developed to address the failure modes of the traditional clustering algorithm
- The CNN currently outperforms the clustering algorithm at high energies, but tends to over-predict low energy showers
- Near-future work will focus on solving this over-prediction issue and validating the network performance on data

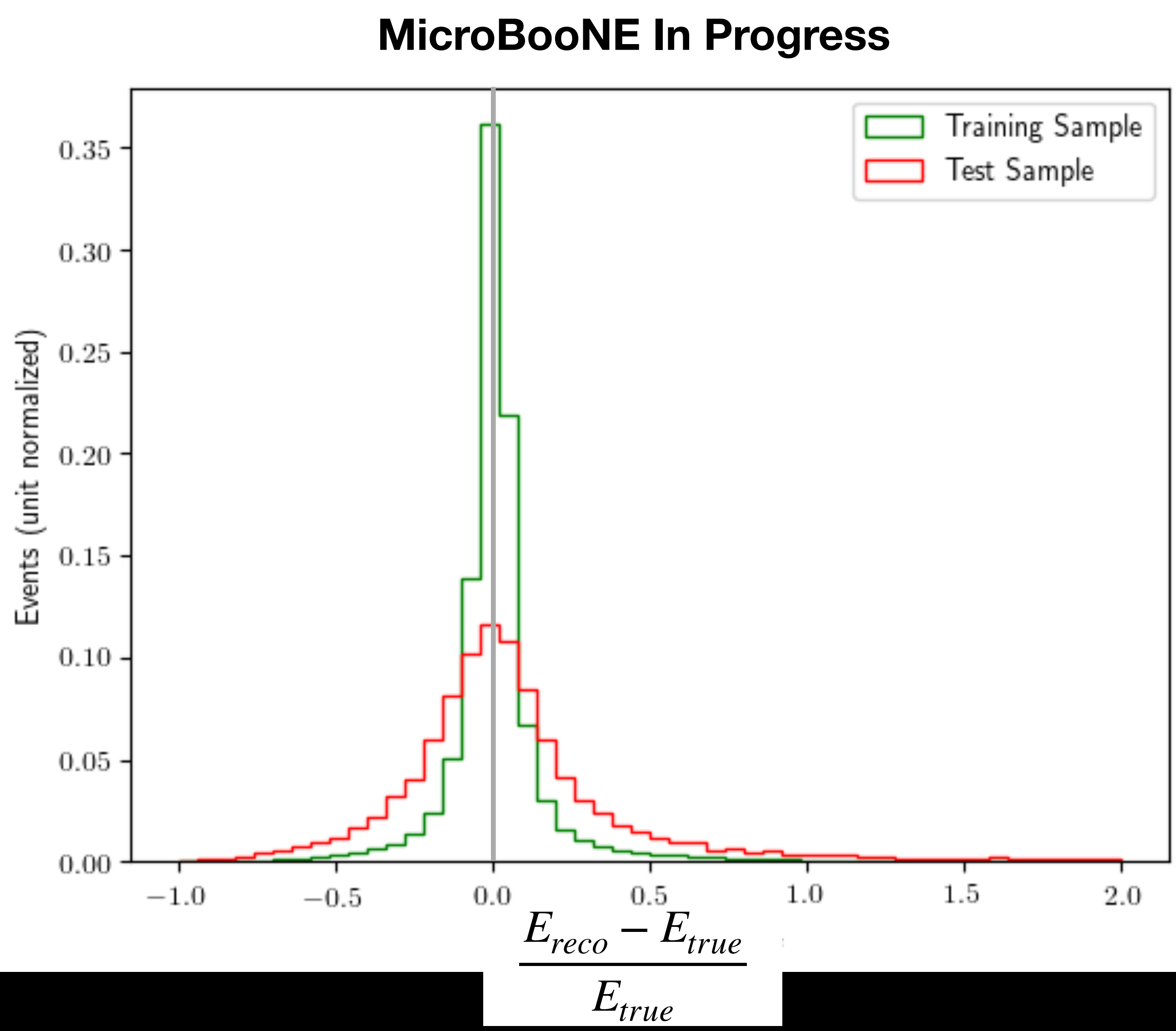
Backups

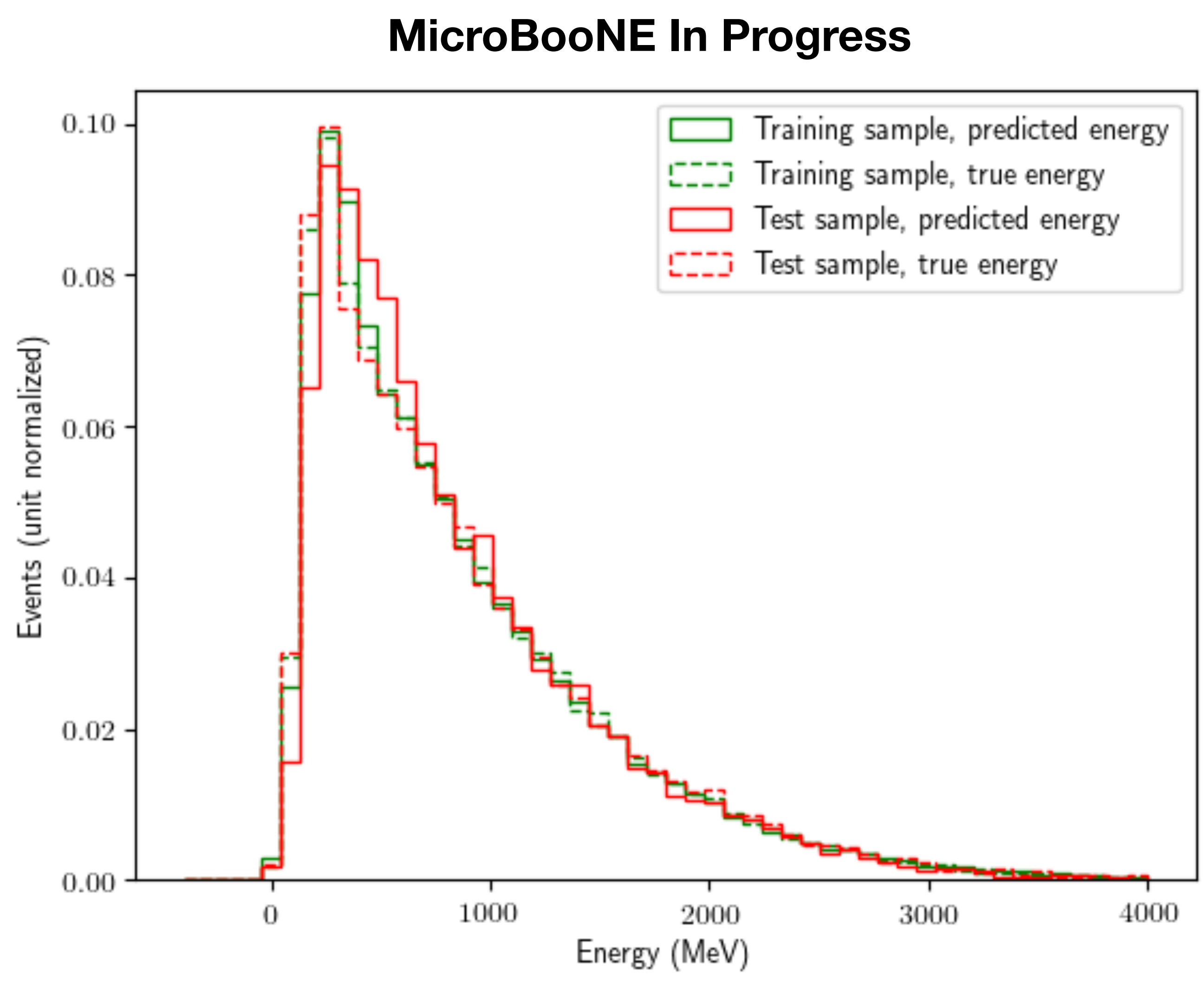
2D Clustering Y-plane Images



Blue: Shower Pixel
Black: Track Pixel
Red to Yellow: Pixel Intensity

Network Performance





Network Performance

Validation sample events only