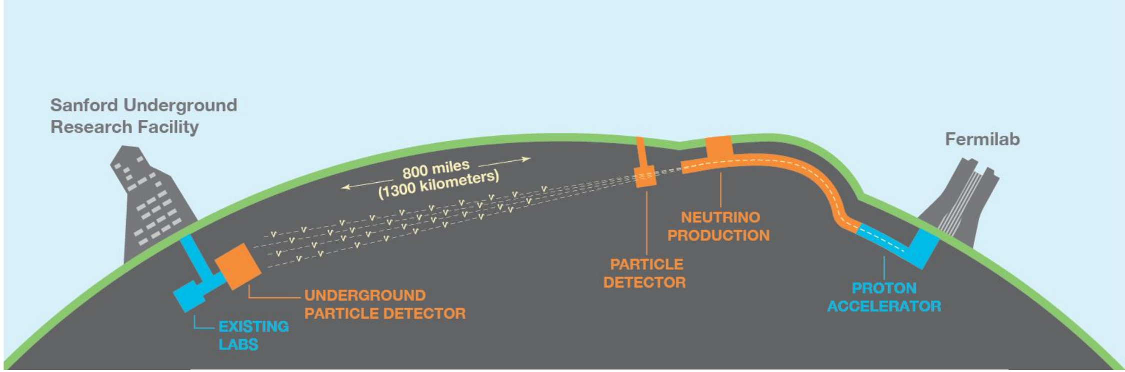
Deep Learning Event Reconstruction at DUNE

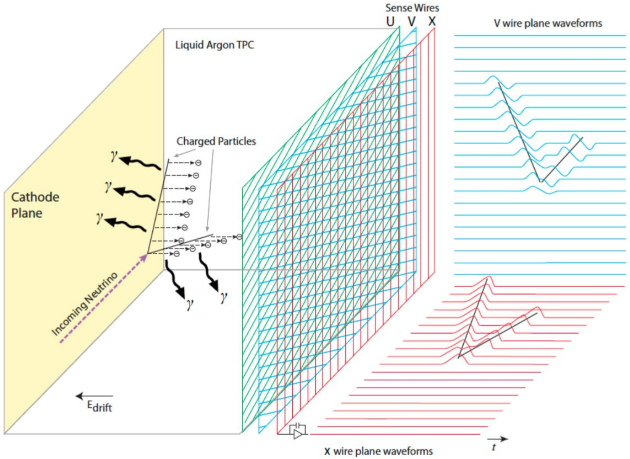
Ben Jargowsky
University of California, Irvine
For the DUNE Collaboration

DUNE

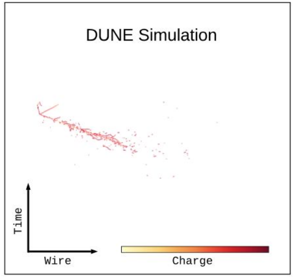
- DUNE is a long baseline neutrino oscillation experiment
- A neutrino beam will be directed at a liquid argon TPC based detector 1300 km away at SURF (comprised mostly of ν_μ or $\overline{\nu}_\mu$)
- DUNE's goal is to measure neutrino oscillation parameters
- Neutrino events in DUNE's LarTPC are projected into 3 planes (2 induction, one conduction plane)

DEEP UNDERGROUND NEUTRINO EXPERIMENT

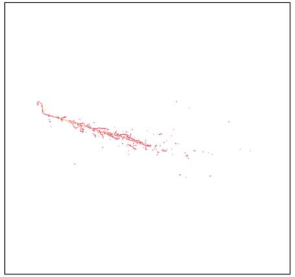




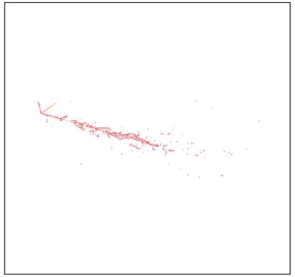
Convolutional Neural Networks



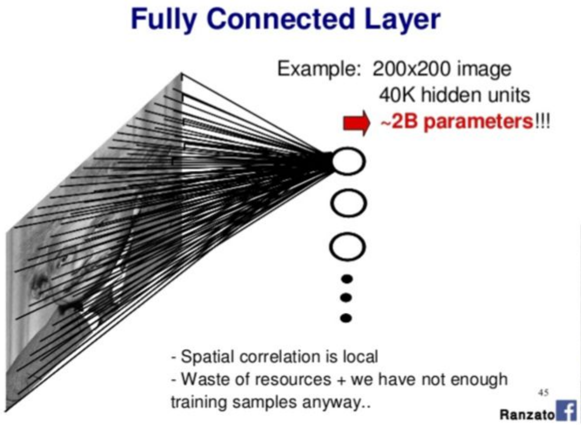
(a) View 0: Induction Plane.



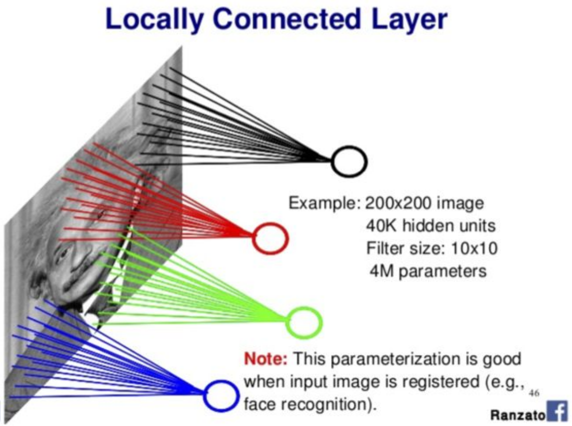
(b) View 1: Induction Plane.



(c) View 2: Collection Plane.



Traditional artificial neural network



Convolutional neural network

- We then have 3 “images” of each event
- CNNs are neural networks specialized to taking images, using a set of translationally invariant filters
- This serves as an ideal application of deep learning techniques

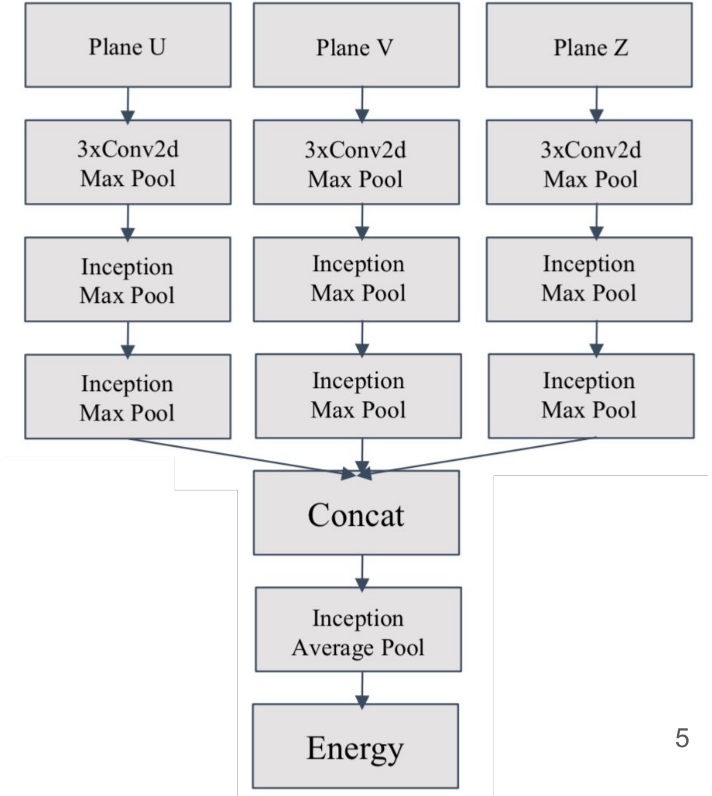
What to Do with CNNs?

- CNNs can be used for either regression or classification tasks
- Regression:
  - Outputs any real number or a list of real numbers
  - Fitting for particle energy, event energy, or event vertex
- Classification:
  - Outputs a number between 0 and 1, for binary classification
  - Also can output many numbers between 0 and 1, for classification into an arbitrary number of classes
  - For things like particle ID or event ID
- First we focus on energy regression

Event Energy Regression

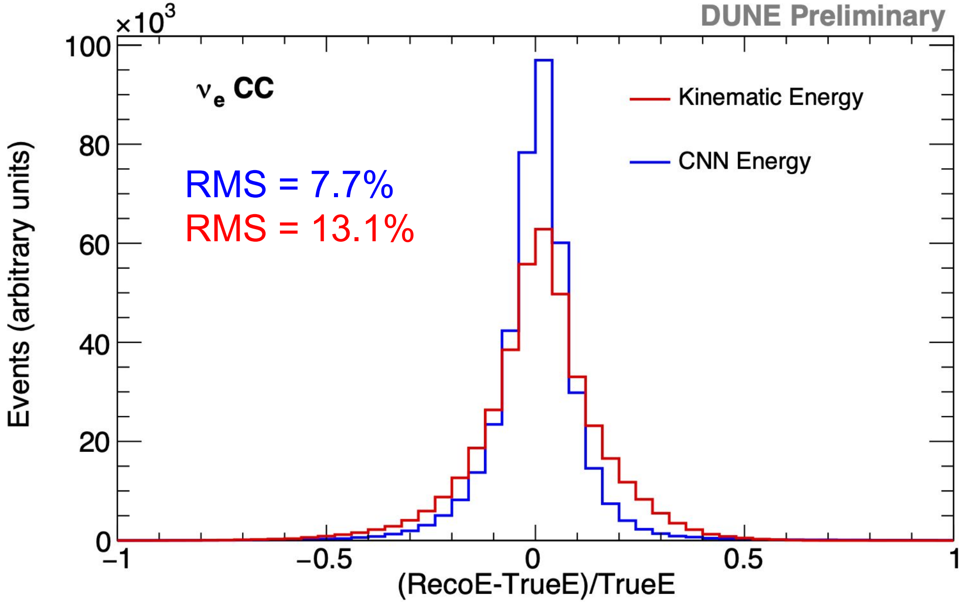
- We feed each plane image to a CNN, then concatenate the outputs which outputs an estimate of event energies
- We use mean absolute percent error as the “loss function”, which tells the CNN how close it is during training
- We use this instead of a sum of squares for robustness against outliers
- We “weight” events by energy, so network is equally likely to guess any energy

$$L(\mathbf{W}, \{\mathbf{x}_i, y_i\}_{i=1}^n) = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{f_{\mathbf{W}}(\mathbf{x}_i) - y_i}{y_i} \right|$$



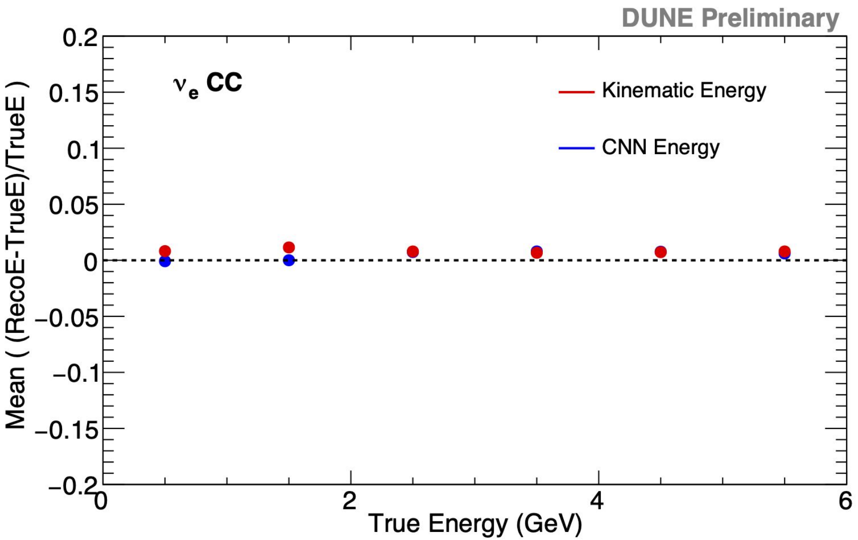
ν_e CC Event Energy

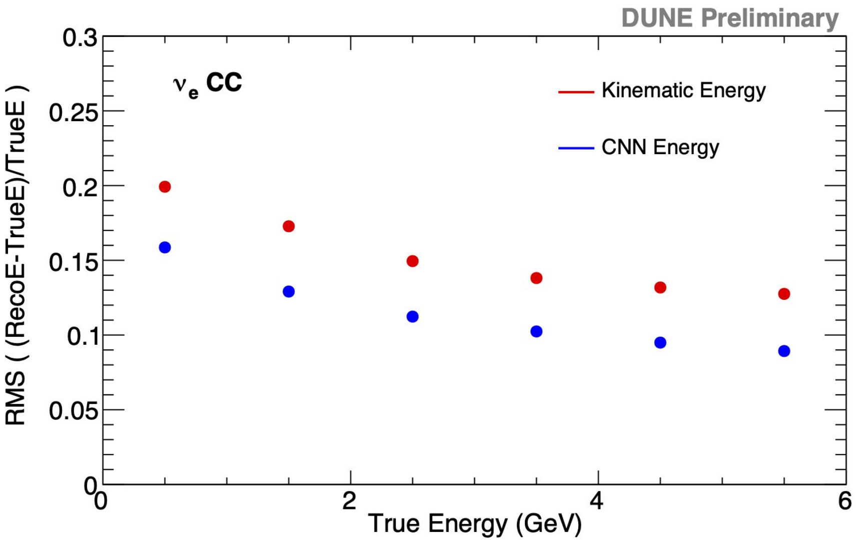
- Here is the resolutions applying our CNN's resolution to the traditional method for ν_e CC events
- Traditional method is found by adding leptonic and hadronic energy, individually calibrated after adding up corresponding hit energies



ν_e CC Event Energy

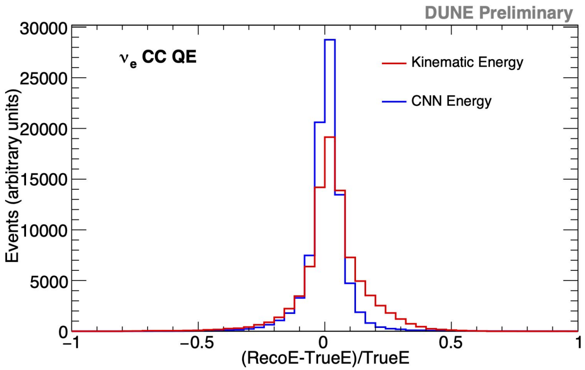
- Resolution is not only better overall, but also over different ranges of true event energy
- Bias is also better or comparable everywhere

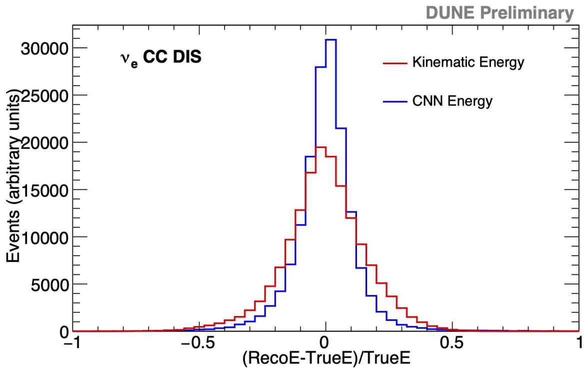


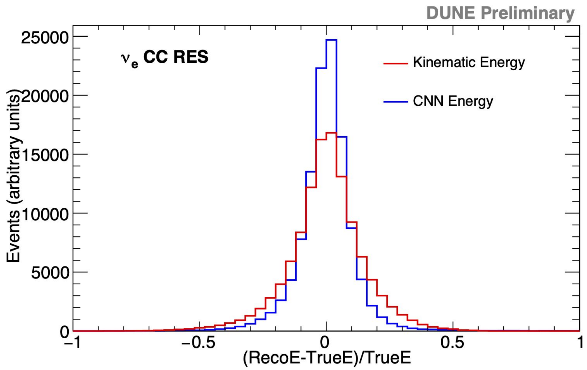


ν_e CC Event Energy

- CNN also robust to different types of neutrino interactions (quasi-elastic, deep inelastic scattering, resonance)
- CNNs having a high number of degrees of freedom to allow this

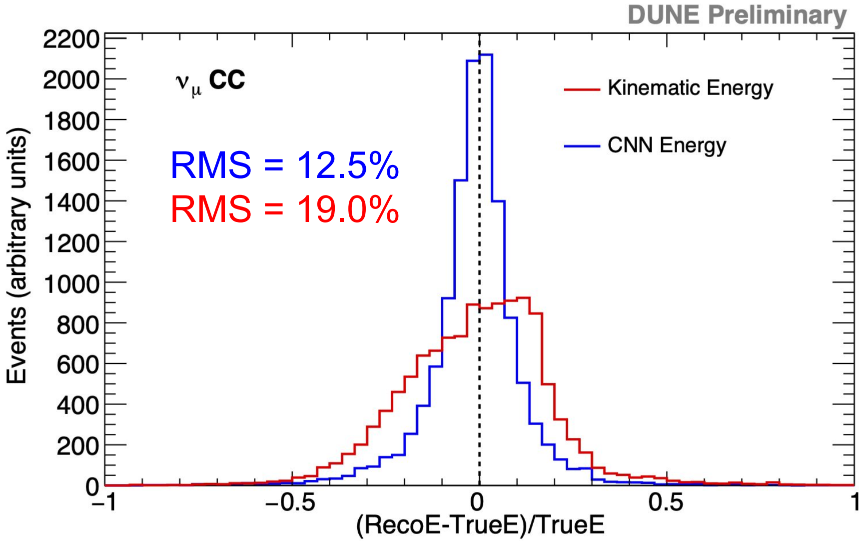






ν_μ CC Event Energy

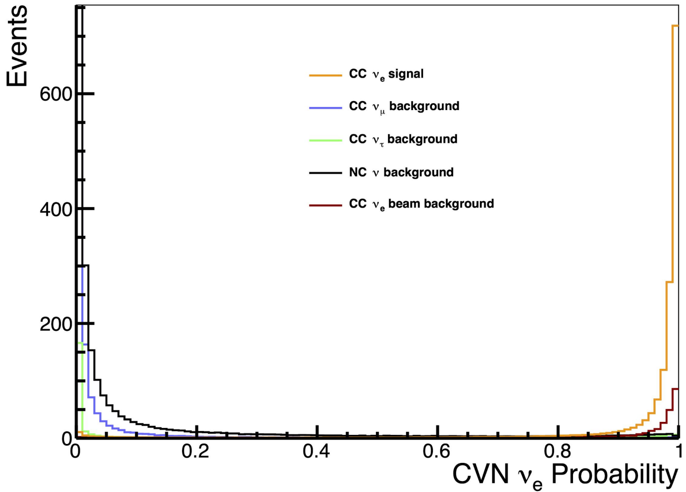
DEEP UNDERGROUND NEUTRINO EXPERIMENT

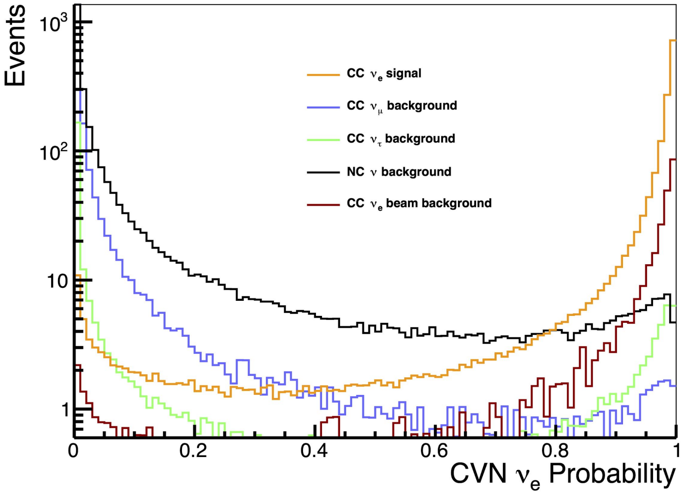


- This CNN technology can also be used for ν_μ CC event energy
- The CNN has better resolution than traditional method, again based on adding up hadronic and leptonic parts
- Traditional energy of muon tracks based on track length

ν_e CC Interaction Classification

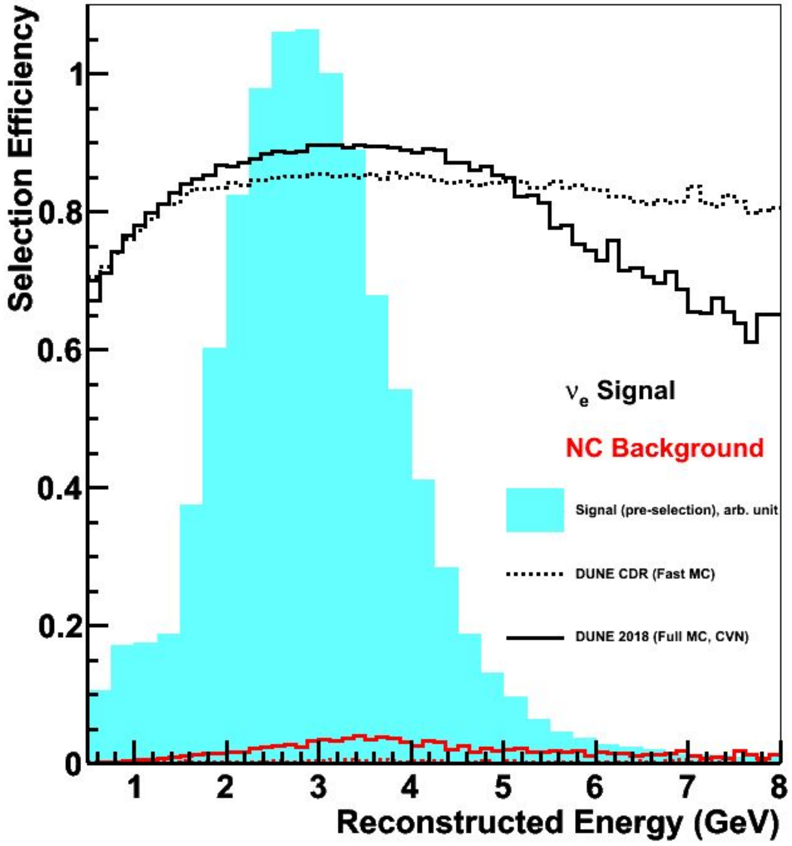
- A binary classification CNN for ν_e CC event classification was also developed (arXiv:2006.15052)
- Here we show results for neutrino beam (not antineutrino)
- A number closer to 1 shows an event more likely to be ν_e CC
- An event with classifier > 0.85 is chosen as a ν_e CC event
- Linear and log scaling shown





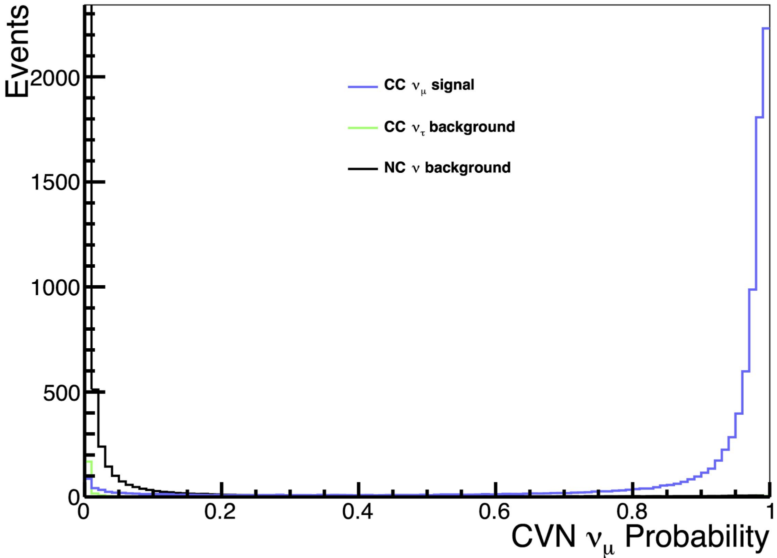
ν_e CC Interaction Classification

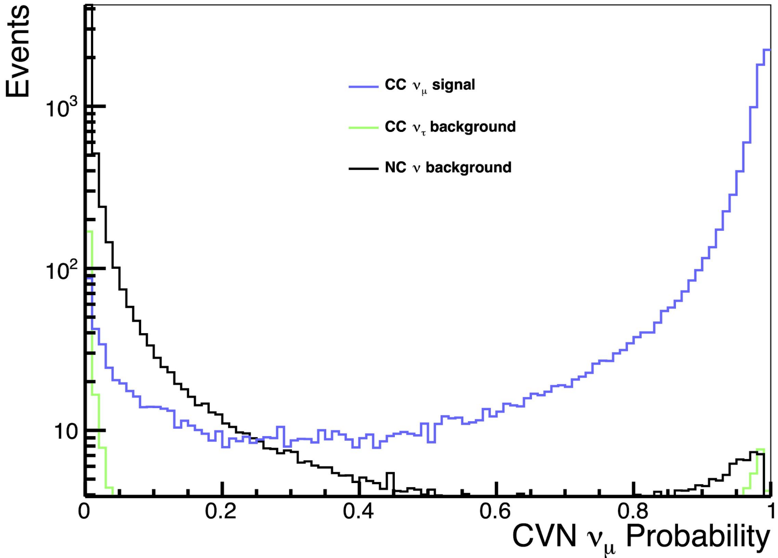
- Here we see selection efficiency over range of reconstructed event energy for neutrinos
- We see a maximum efficiency of around 90% near the flux peak
- Slightly better efficiency in antineutrino beam



ν_μ CC Interaction Classification

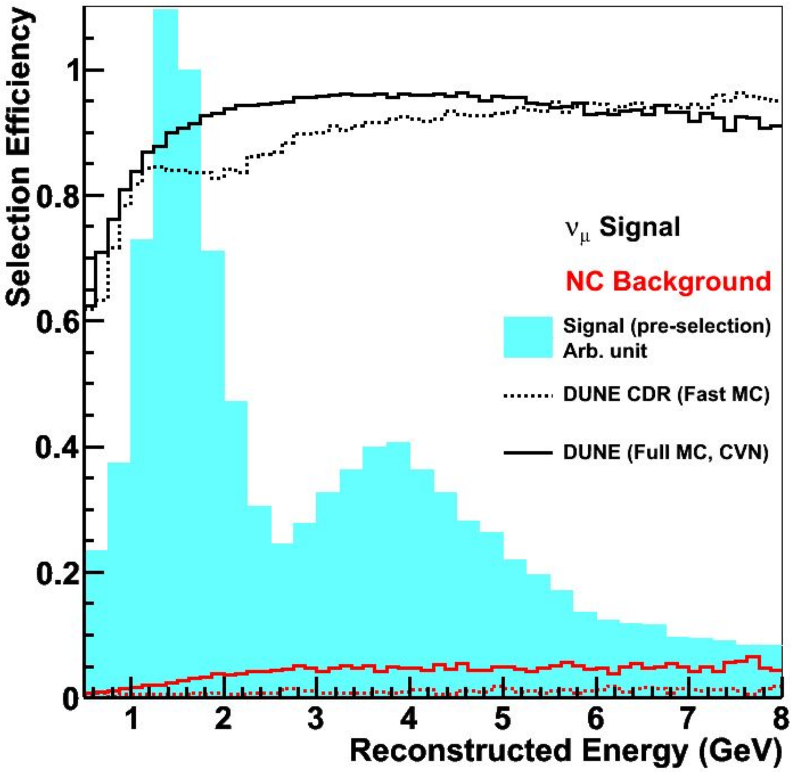
- We can do the same for ν_μ CC event classification
- Again, neutrinos are shown hear (antineutrinos have slightly better performance)
- If an event has a classifier > 0.5, we interpret it as a ν_μ CC event





ν_μ CC Interaction Classification

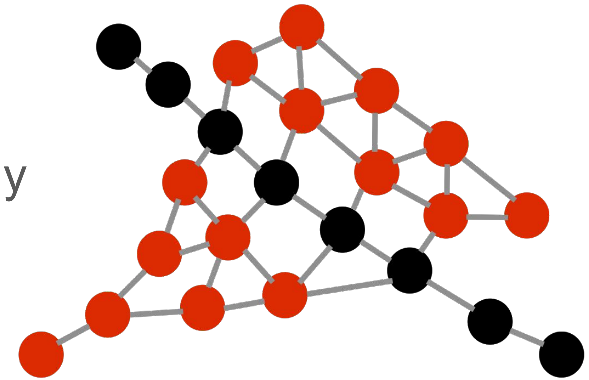
- Here is the selection efficiency over range of reconstructed event energy
- The efficiency if greater than 90% at maximum



Other Methods Being Developed

DEEP UNDERGROUND NEUTRINO EXPERIMENT

- Sparse CNNs for Semantic Segmentation
  - Takes advantage of sparseness of hits in 3D pixelmaps
  - Has shown promise for identifying individual pixels as part of tracks or showers
- Graph Neural Networks
  - Breaks up hits into “graph” comprised as connected nodes with information such as geometry and energy composition
  - Feeds these graphs to a NN which labels individual nodes
  - Has shown promise in ProtoDUNE



Summary

- CNN based energy regression has better performance for both ν_e CC and ν_μ CC events
- CNN based event classifiers have been shown to have very good efficiency, greater than 90% for both ν_e CC and ν_μ CC events in FHC and RHC beam configurations
- GNNs and Sparse CNNs have shown promise in reconstructing tracks and showers