Neutrino Energy Reconstruction with a Regression CNN in DUNE

Neutrino Physics and Machine Learning (NPML)

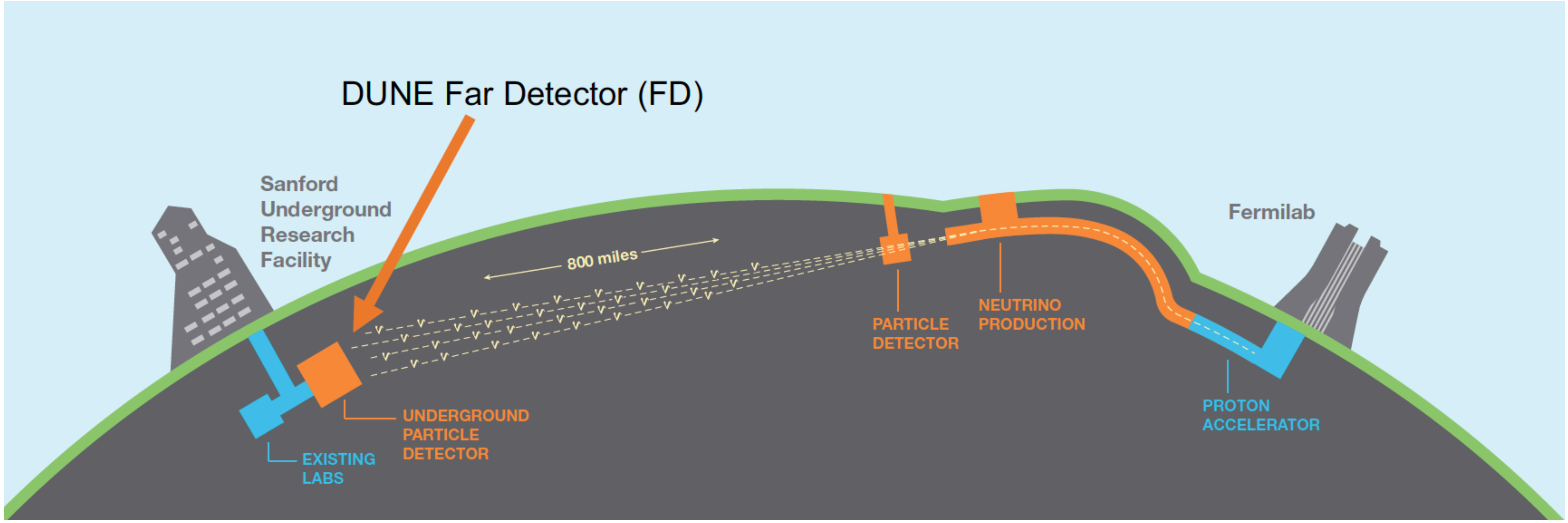
Wenjie Wu (For the DUNE collaboration)

University of California, Irvine

Jul. 22, 2020

Introduction

- DUNE is a long baseline neutrino experiment
- The primary goals is to address the CP-violating phase, the neutrino mass ordering and the octant of θ_{23} by measuring the oscillation patterns of ν_μ and $\bar{\nu}_\mu$ over a range of energies spanning the first and second oscillation maxima
- It requires precisely reconstructed neutrino energies

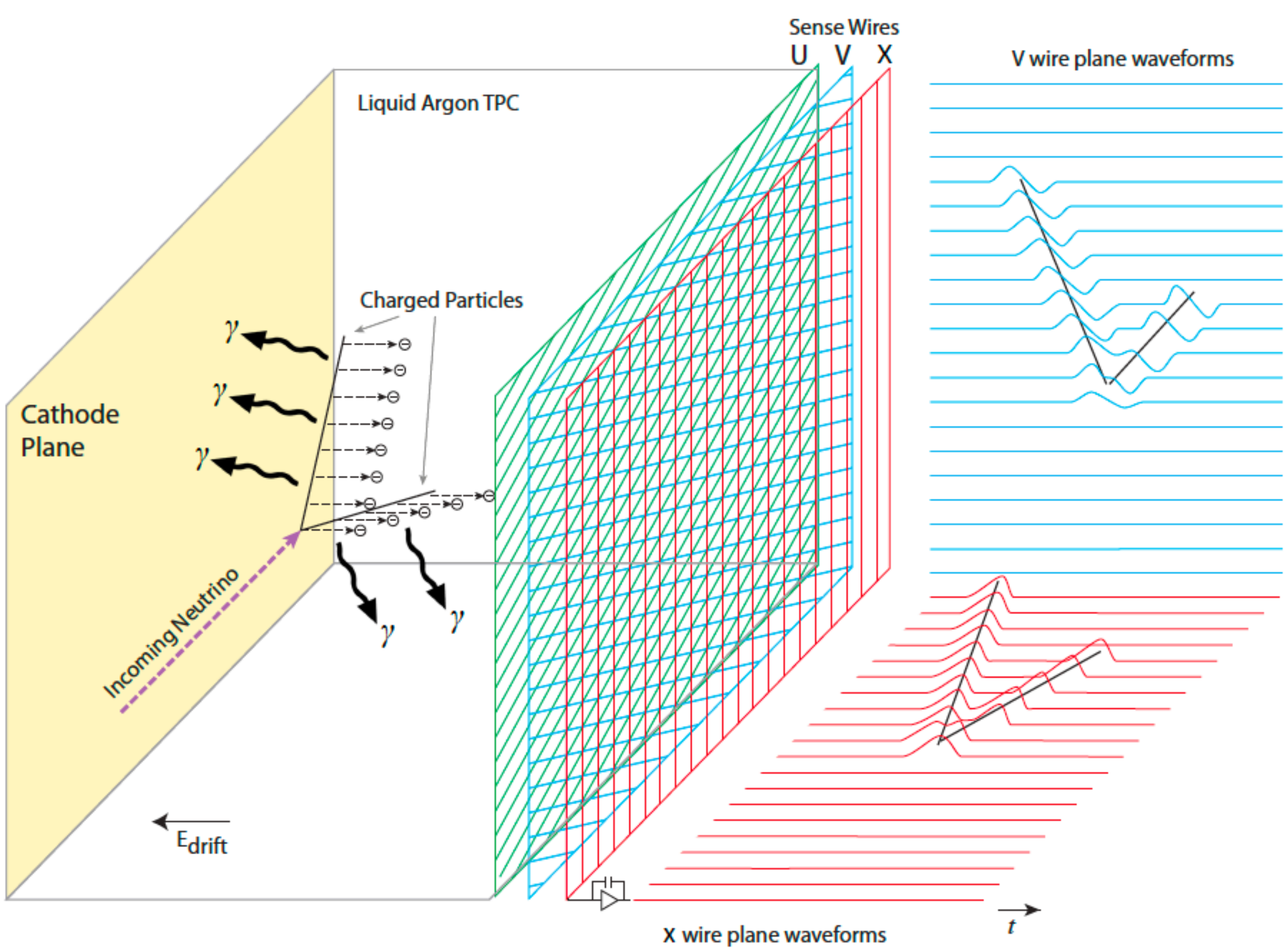


Introduction

- Kinematic-based method
  - Charged lepton and hadronic shower energies are reconstructed separately and then summed
  - Using MC truth to find correction factors to visible lepton and hadronic energy
- Energy reconstruction has many challenges due to missing energy caused by argon impurities, nonlinear detector energy responses, invisible energy, hadron identities (mass), and overlaps between lepton and hadron interactions
- Our approach:
  - Neural networks have shown state of the art performance in HEP classification and regression tasks in problems with high dimensionality
  - Use a convolutional neural network directly on the pixel maps

Data Generation

- In the DUNE FD module, three wire readout planes collect the ionization charge that is generated when charged particles traverse the liquid argon volume
- Raw detector waveforms are deconvolved to obtain the charge information
- The position of the charge observed in each of the three planes is combined with the drift time to create three views of each interaction

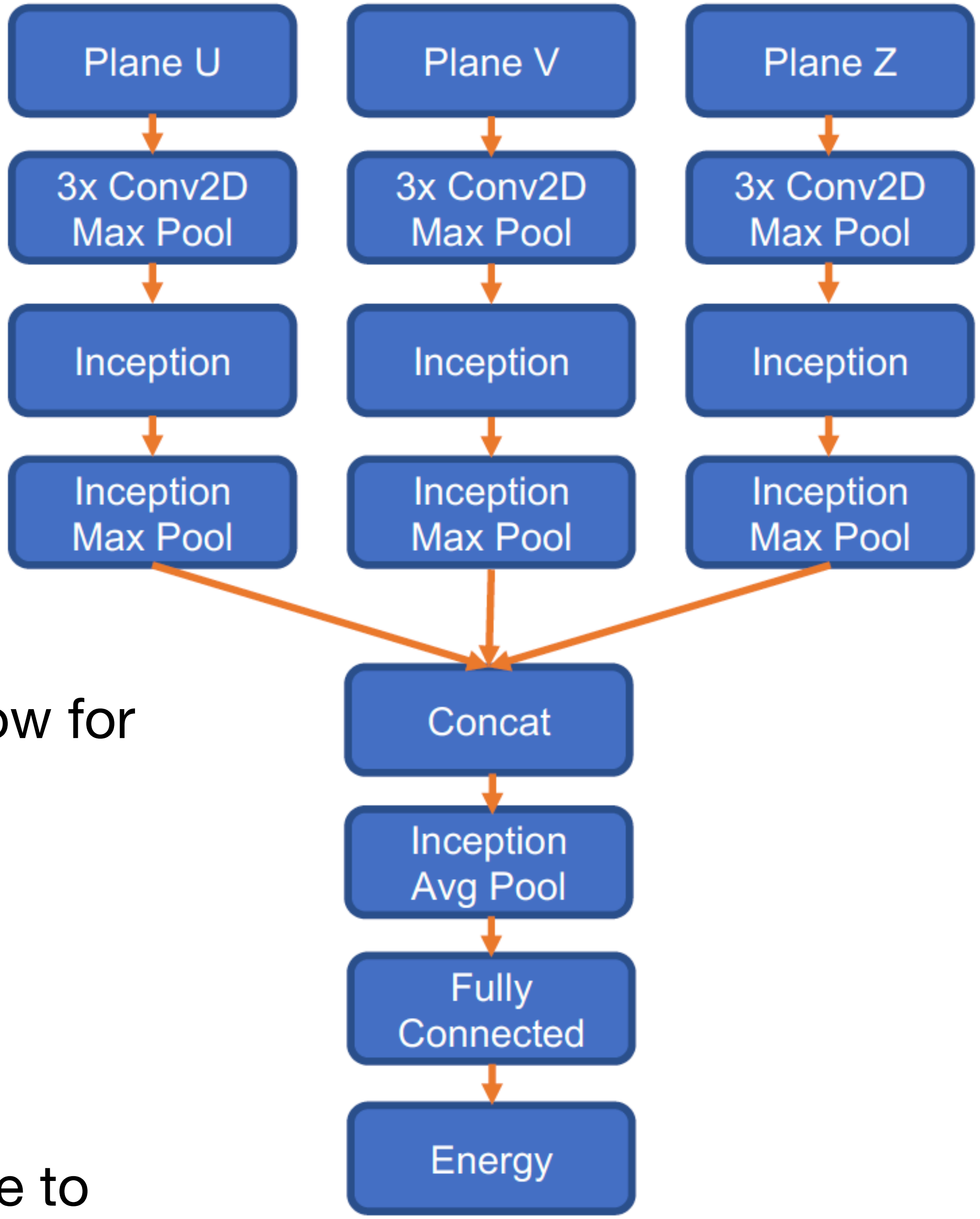


Regression CNN Architecture

- Architecture modified from UCI's NOvA Regression CNN energy estimator (Phys. Rev. D. 99.012011)
- Mean absolute percentage error

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

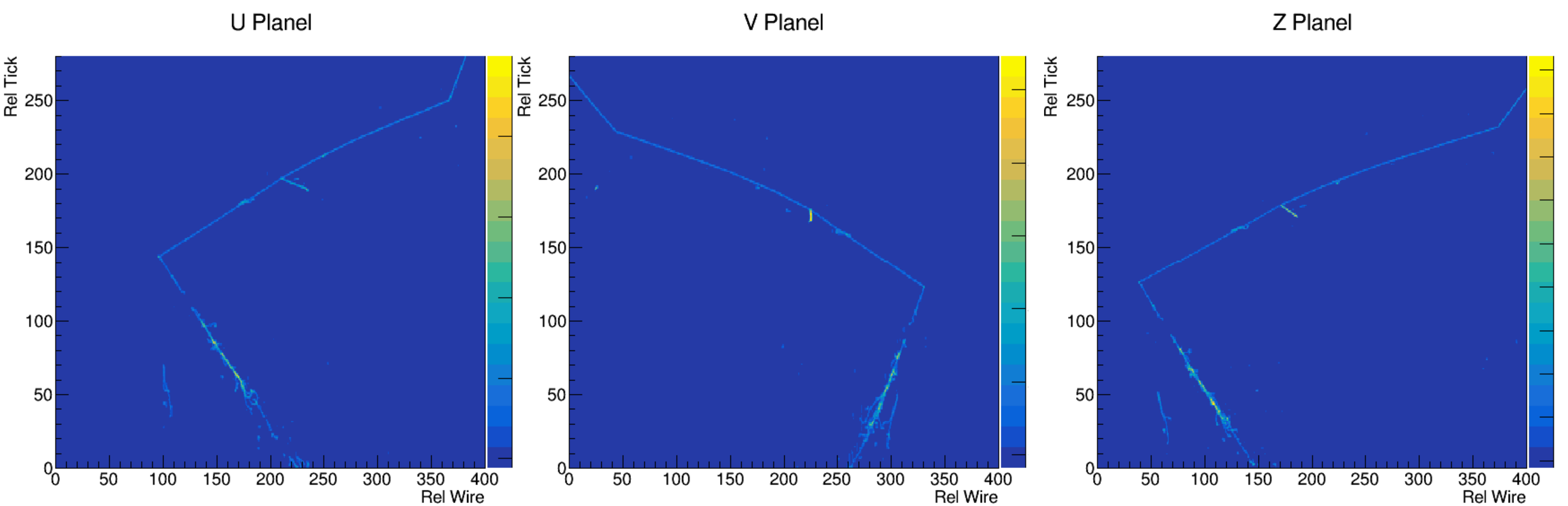
- Images are concatenated as channels to allow for extra convolutional layers afterwards
- All convolutional layers use ReLU
- No regularization applied
- Hyper-parameters are not fully optimized due to computational constraints



Inception: https://arxiv.org/abs/1409.4842

Input Images for ν_e

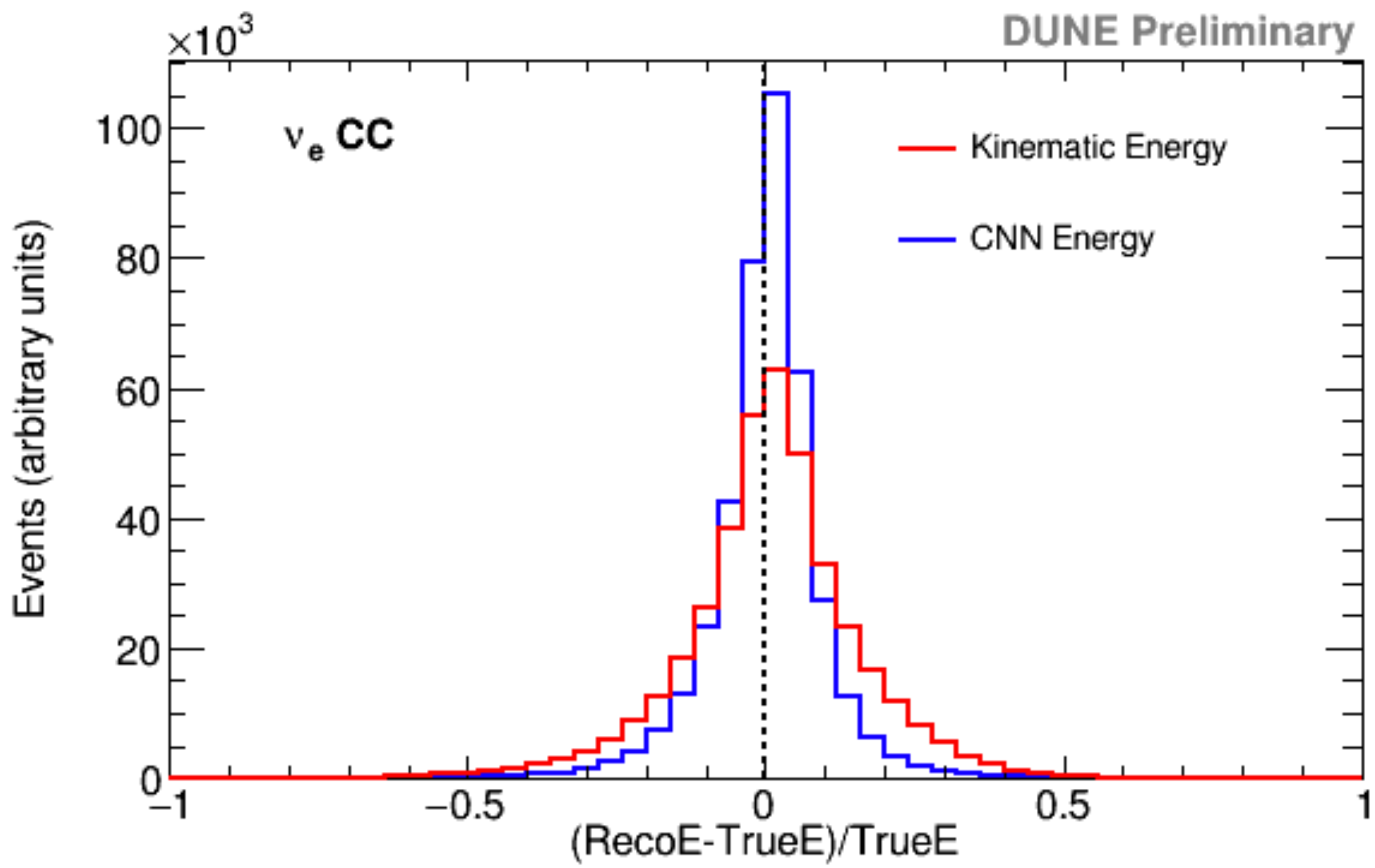
- Use ADC counts and TDC units from Wire instead of using the reconstructed hits
- Three pixel maps: 280x400
- Merged 6 TDC ticks: real covered space is 1680 ticks and 400 wires
  - Make the same physical dimensions of the x- and y-axis
- The pixel map size is chosen to contain 90% of hits on average



ν_e CC Energy Reconstruction

Energy resolution

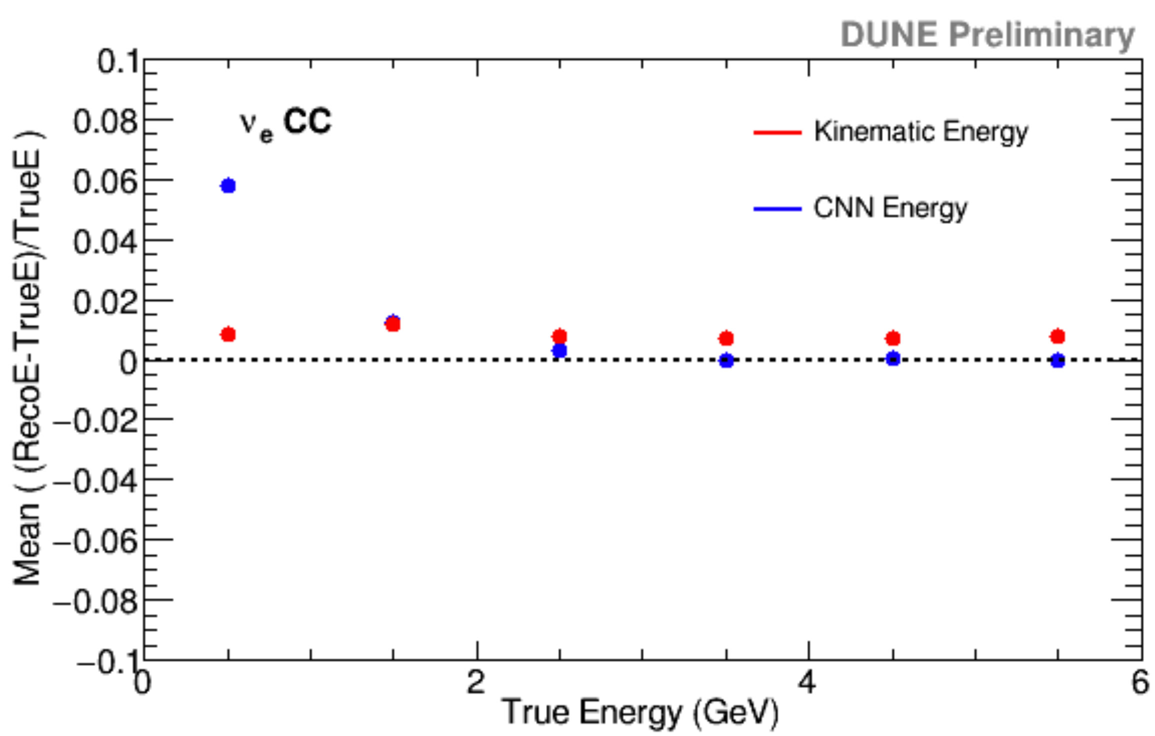
- Applied the trained model to the official ν_e MC samples
- Fiducial volume cut is applied with true vertex information
- Fit with Gaussian in the range (-1, 1)
  - Kinematic-based method: $\sigma = 13.1\,\%$
  - RegCNN: $\sigma = 7.2\,\%$

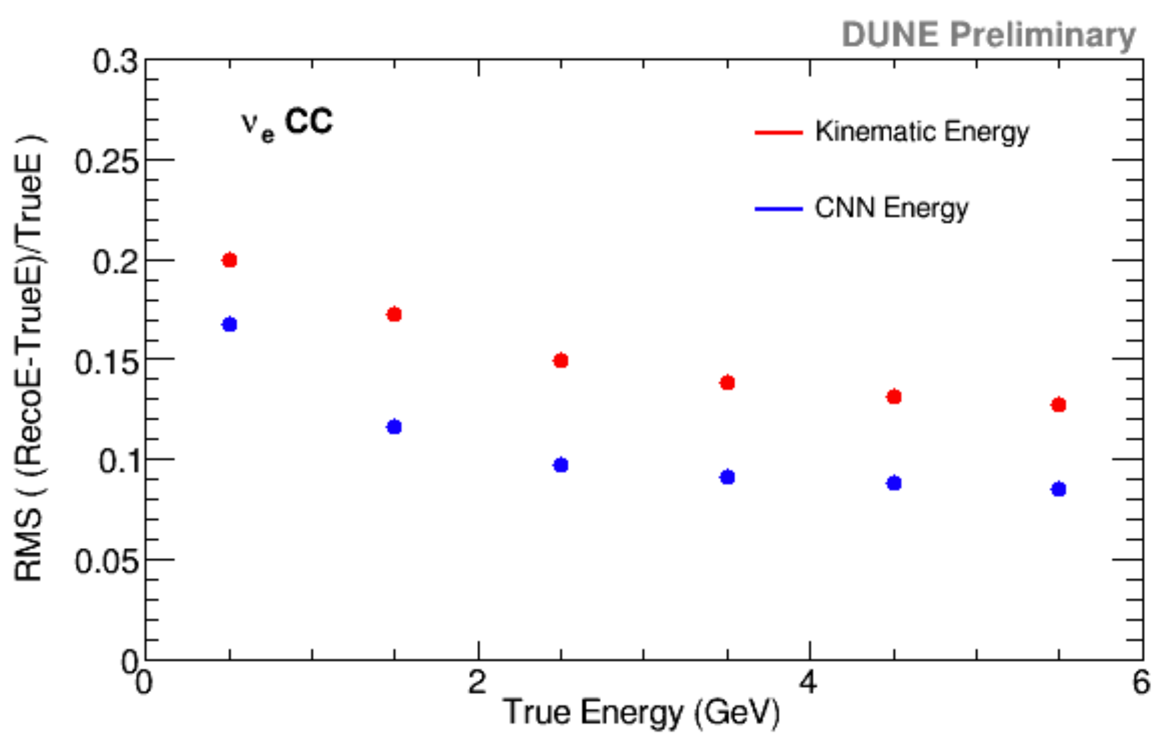


ν_e CC Energy Reconstruction

Energy resolution vs. True energy

- Mean and RMS of each True energy bin
- RegCNN has smaller RMS over the energy range (0, 6) GeV
- RegCNN over-estimates for low energies due to low statistics
- Re-weighted individual events based on the energy distribution in order to reduce the bias for low energy events





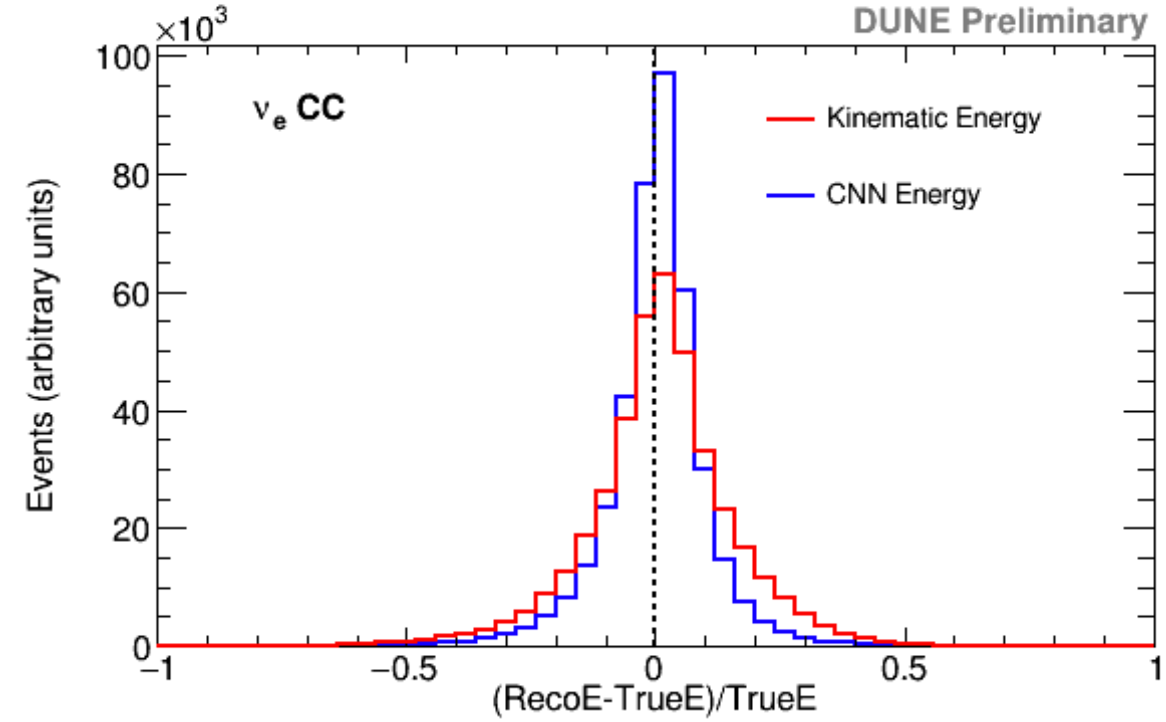
ν_e CC Energy Reconstruction

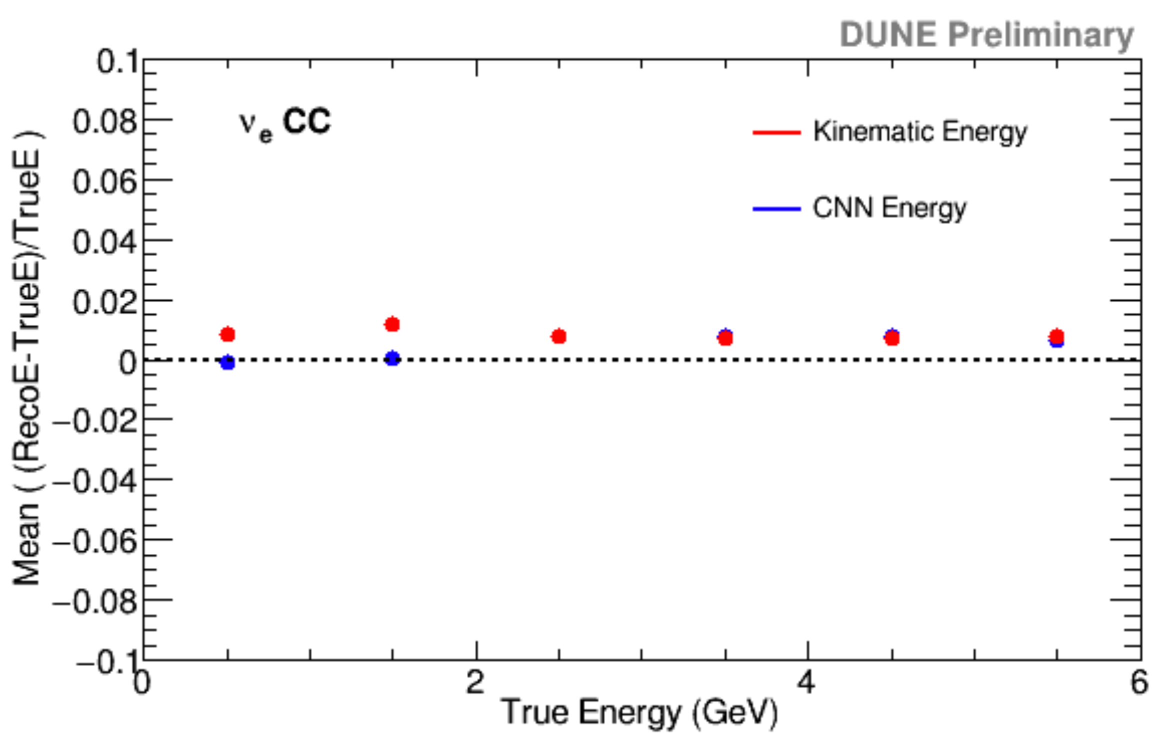
Weighted training and result

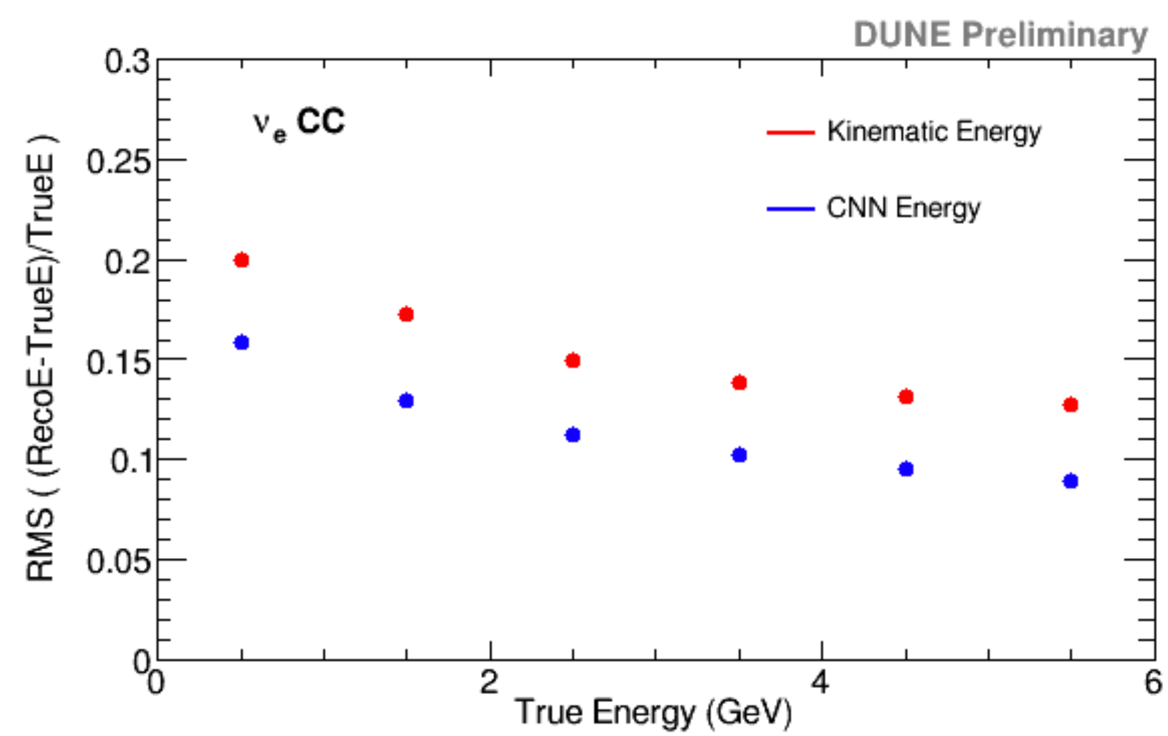
- Redefined the loss function

$$L\left(\mathbf{W}, \{\mathbf{x}_i, y_i\}_{i=1}^{n}\right) = \frac{1}{\sum_j^n \sqrt{\omega_j}} \sum_i^n \sqrt{\omega_i} L\left(\mathbf{W}, \mathbf{x}_i, y_i\right)$$

- Similar energy resolution: 7.2%→7.3%
- Reduced bias in low energy region





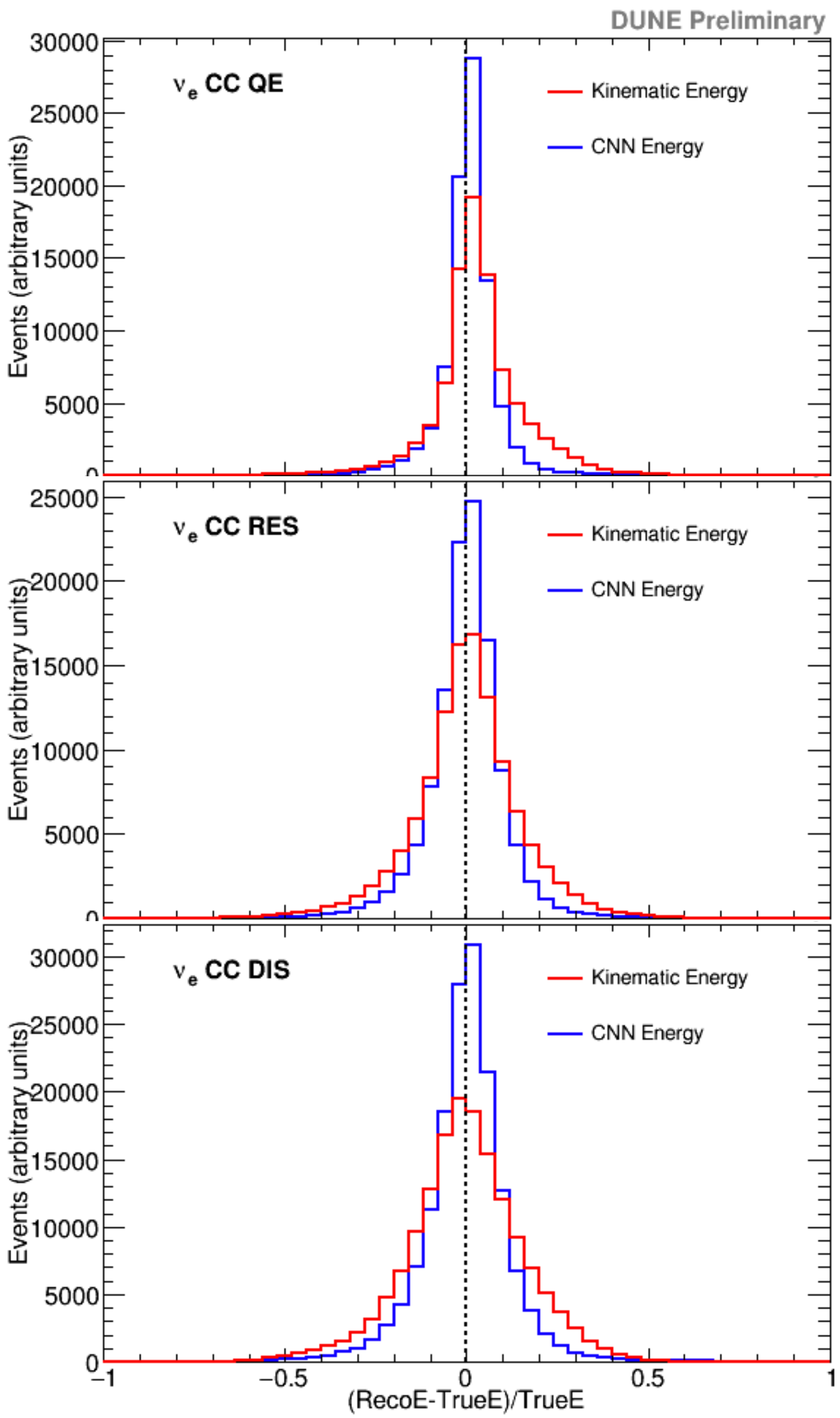


ν_e CC Energy Reconstruction

Energy resolution with different interaction modes

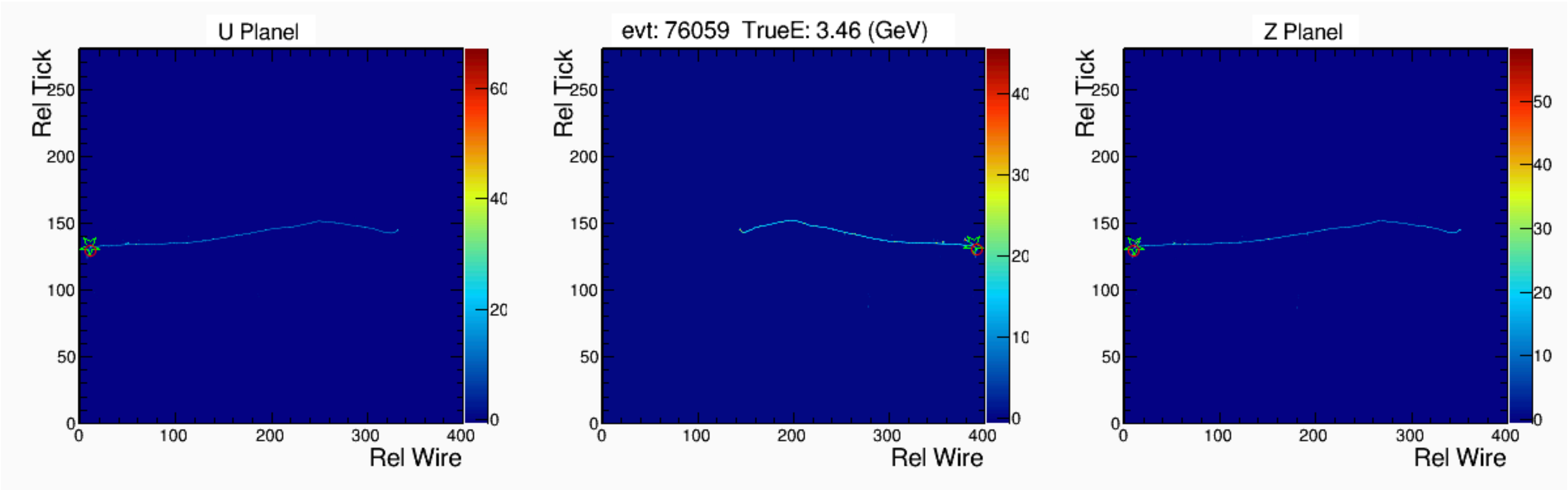
- RegCNN shows good performance for different interaction modes
- Fit with Gaussian in the range (-1, 1)

	RegCNN sigma	Kinematic sigma
QE	5.3%	9.5%
Res	8.3%	13.1%
DIS	9.4%	15.2%



Input Images for ν_μ

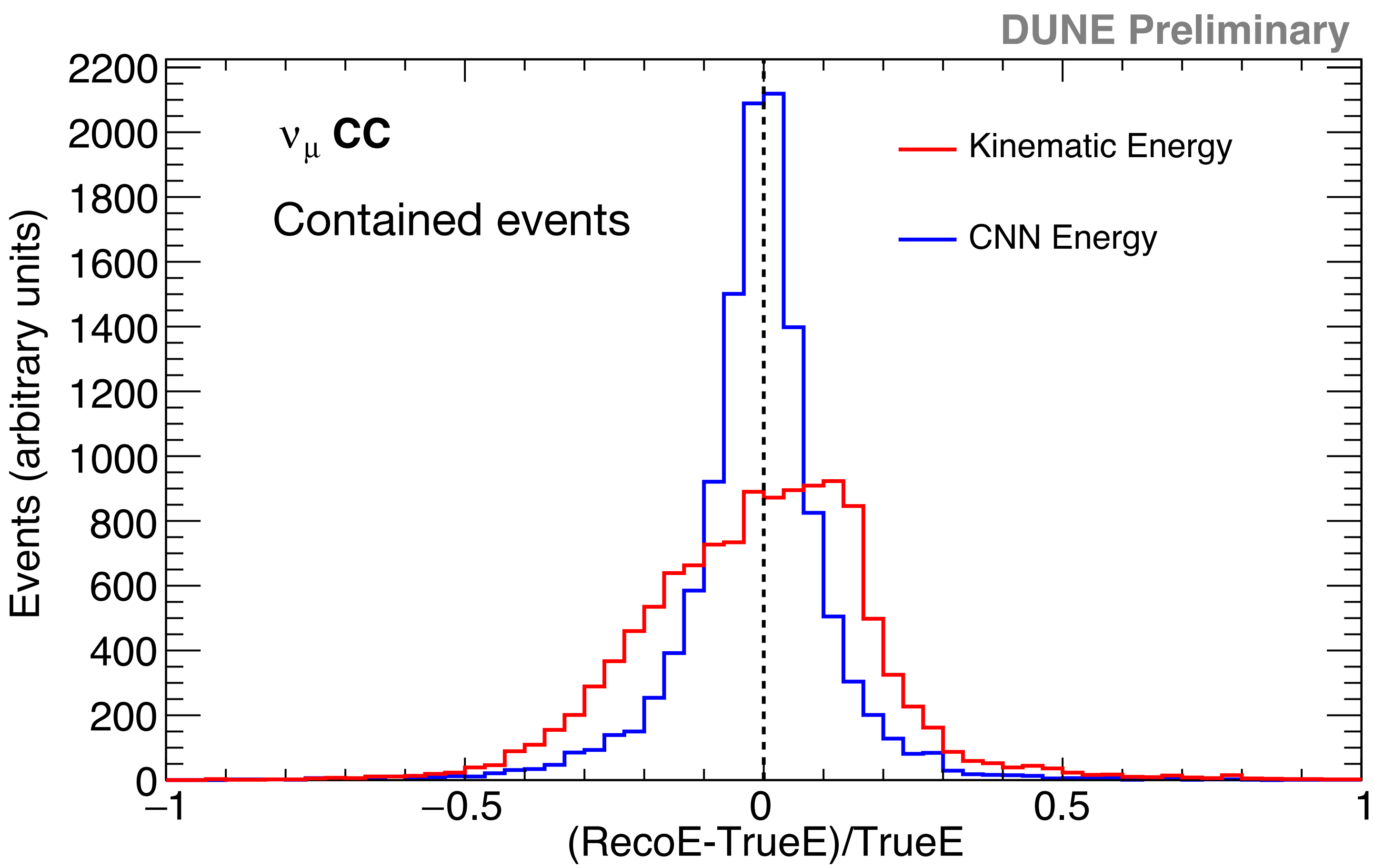
- Three pixel maps: 280x400
- For ν_μ interactions, leptonic portion is characterized by very long μ-tracks
- In order to contain most of the hits, further lower the image resolution
  - Merged 24 TDC ticks and 7 wires: real covered space is 6720 ticks and 2800 wires



ν_μ CC Energy Reconstruction

Energy resolution

- As a first step, performed the reconstruction for events with contained tracks
- RMS of kinematic-based method: 19.0% and RegCNN: 12.5%
- Moving to study events with exiting muon track



Summary

- Developed regression CNN models to reconstruct ν_e CC and ν_μ CC events
- RegCNN shows promising results with better energy resolution for both neutrinos
- For ν_e CC: 13.1%→7.3%, for contained ν_μ CC:19.0%→12.5%
- In the near future:
  - Train a model on un-contained ν_μ CC events
  - Eliminate energy dependence of bias by re-weighting during training