Deep Learning for Event Reconstruction at DUNE

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Introduction

Reconstruction steps: Vertex, Clustering, Tracking, Particle Momentum, Particle ID, Event Energy, Event ID

Variables need to be reconstructed:

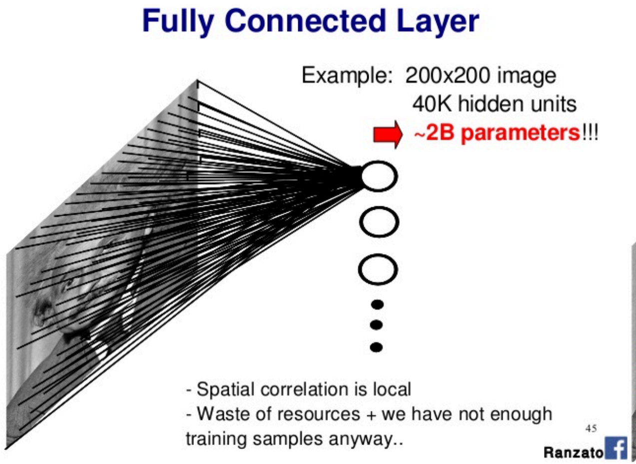
Vertex → Regression
Particle Momentum → Regression
Particle ID → Classification
Event Energy → Regression
Event ID → Classification

Use deep learning to solve both regression and classification problems in reconstruction

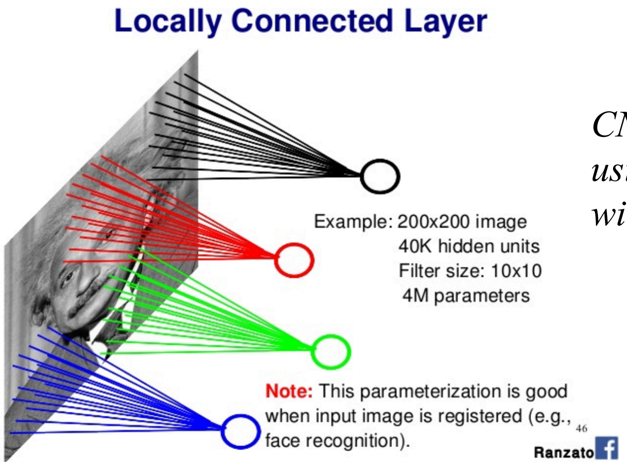
A combination of regression CNN and classification CNN can solve above reconstruction tasks
This talk → focus on Energy and Vertex reconstruction with regression CNN

Convolutional Neural Network

- Convolutional Neural Networks (CNNs) with raw pixel inputs have demonstrated success in **Classification** problems such as event identification (CVN identifier in NOvA and DUNE, image segmentation/prong identifier at MicroBooNE, vertices plane identifier at MINERvA)
- Developing **Regression** CNN based method for energy and vertex reconstruction at DUNE
- Extend regression CNN to solve other reconstruction in DUNE can form a full reconstruction chain



Traditional artificial neural network

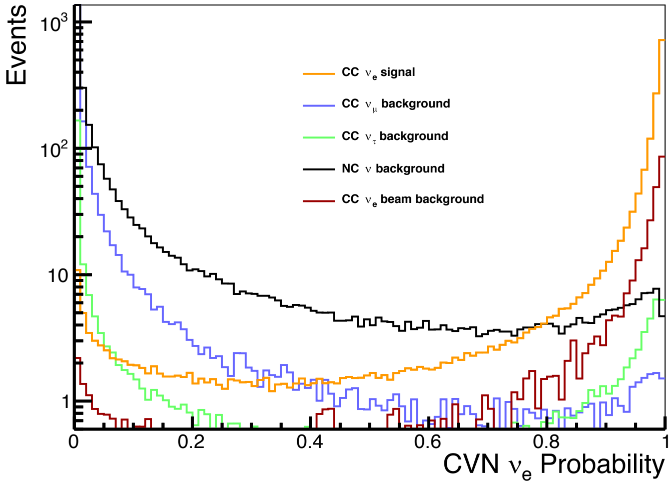


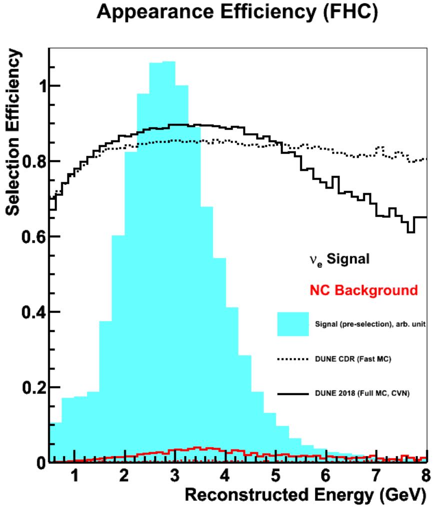
Convolutional neural network

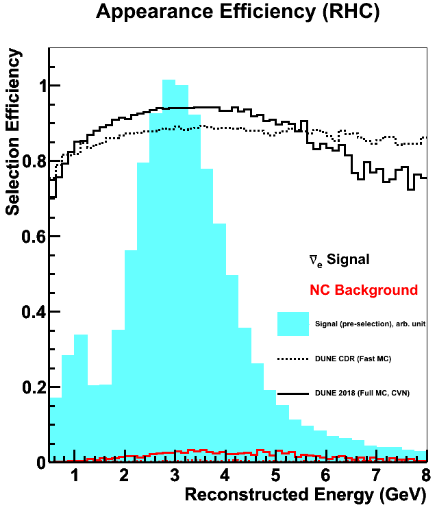
CNNs take raw pixel inputs, using all detector information with acceptable computing cost

Classification CNN identifier in DUNE

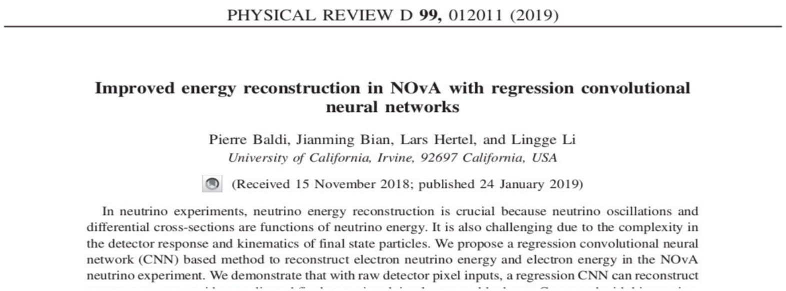
- Classification Convolutional Neural Network has been implemented at DUNE for event identification (CVN)
- Identify ν_μCC, ν_eCC and NC events
- Performance is better than DUNE CDR assumptions







Regression CNN Architecture for energy


PHYSICAL REVIEW D **99,** 012011 (2019)

Improved energy reconstruction in NOvA with regression convolutional neural networks

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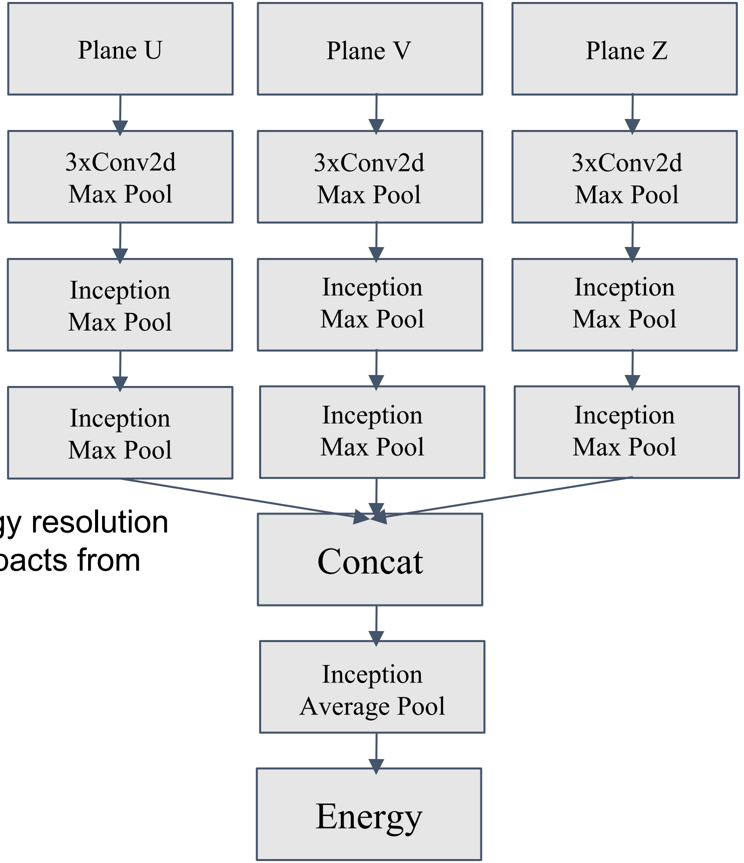
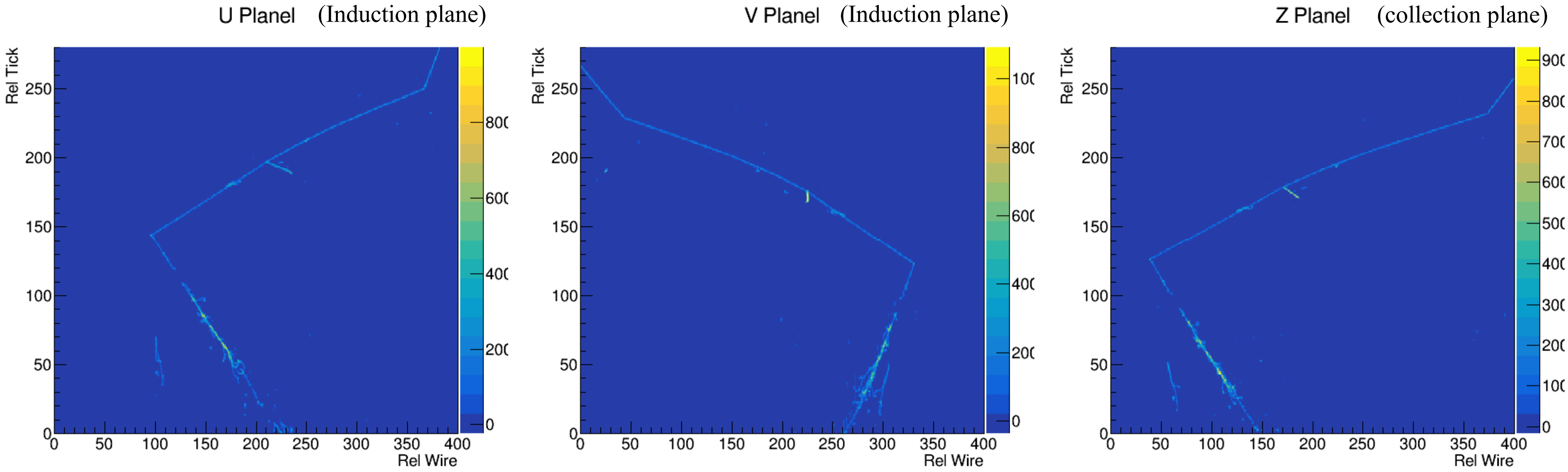
In neutrino experiments, neutrino energy reconstruction is crucial because neutrino oscillations and differential cross-sections are functions of neutrino energy. It is also challenging due to the complexity in the detector response and kinematics of final state particles. We propose a regression convolutional neural network (CNN) based method to reconstruct electron neutrino energy and electron energy in the NOvA neutrino experiment. We demonstrate that with raw detector pixel inputs, a regression CNN can reconstruct

- Architecture modified from UCI's NOvA Regression CNN energy estimator (Pierre Baldi, Jianming Bian, Lars Hertel, Lingge Li, PhysRevD.99.012011)
- Loss: $$L(\mathbf{W}, \{\mathbf{x}_i, y_i\}_{i=1}^{n}) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{f_{\mathbf{W}}(\mathbf{x}_i) - y_i}{y_i}\right|$$ Optimize energy resolution and reduce impacts from outliers.
- One linear output unit
- No regularization applied
- Use hyperparameter optimization software SHERPA developed by UCI's Lars Hertel' et. al. (GitHub https://github.com/sherpa-ai/sherpa)



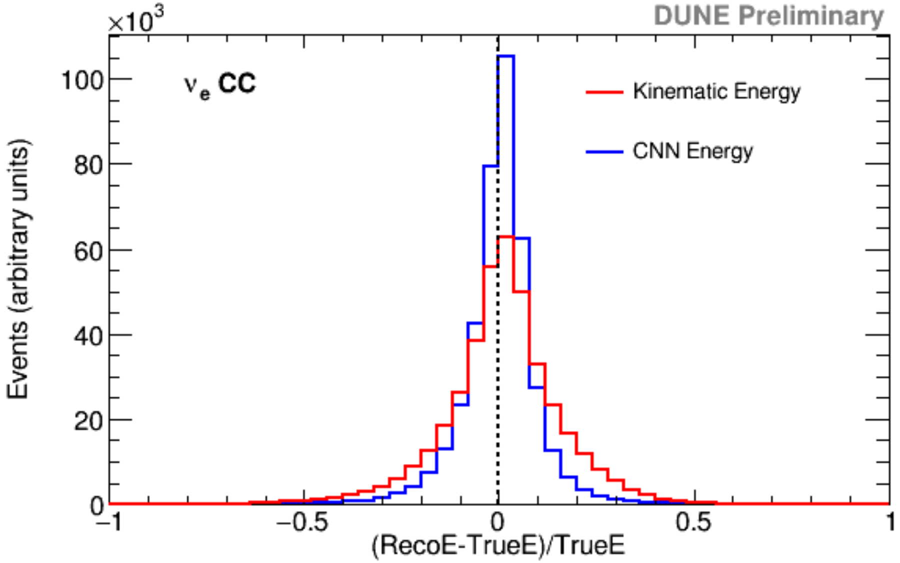
Pixel Map inputs for ν_e

- Use ADC counts and TDC units from Wire instead of using the reconstructed hits
- Three input pixel maps: U-T, V-T, and Z-T Pixel map size has been chosen to contain 90% of hits on average
- Coarsed TDC ticks to make same physical dimensions of the x- and y-axis of the pixel map
- Pixel map size: 280x400 (actual covered space: 1680 ticks x 400 wires) → 6 ticks are merged



NueCC Energy Resolution

- Applied the trained model to the official Nue MC samples
- Fiducial volume is defined with the true vertex
- Fit with Gaussian within (-1,1)
- Sigma of Kinematic-based method: 13.1% and RegCNN: 7.2%

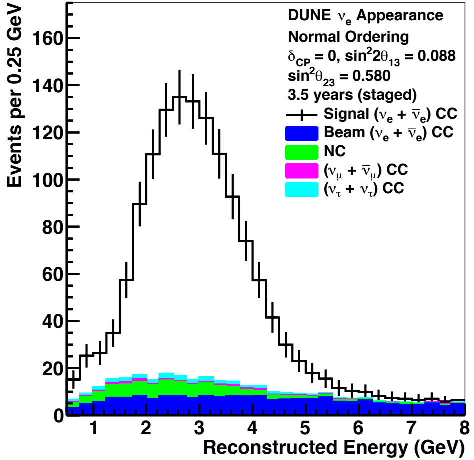


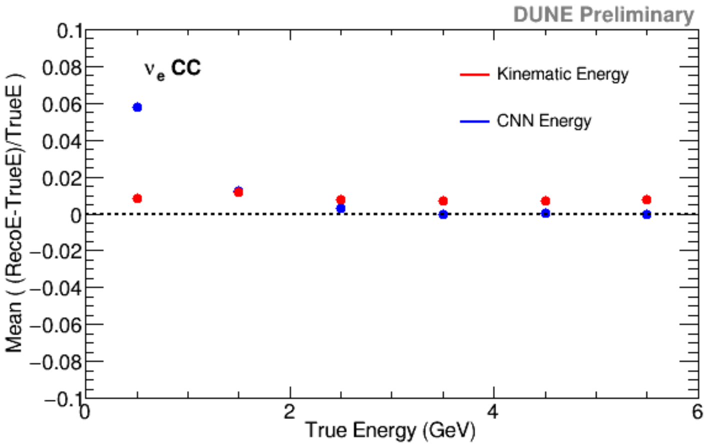
Kinematics Energy reconstructed by
$E(\nu) = E_{lep}^{cor} + E_{had}^{cor}$
Using MC truth to find correction factors to visible lepton and hadron energy

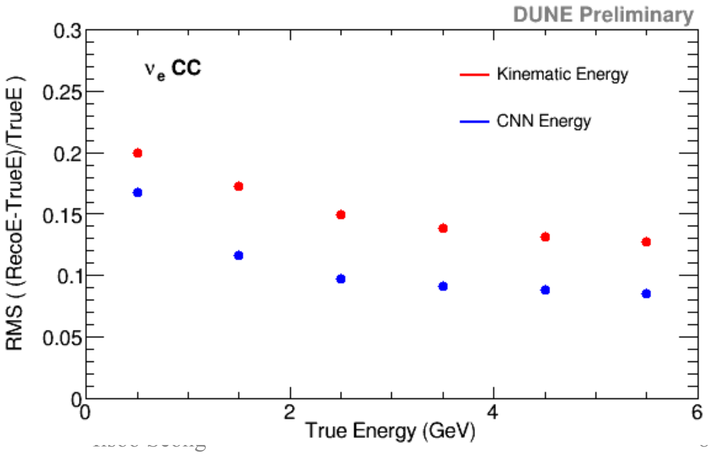
CNN Energy is reconstructed by regression CNN

Energy Resolution Vs. True Energy

- Mean and RMS of energy resolution
- RegCNN has smaller RMS and over-estimates for low energies
- Bias is due of low statistics in low energy in the training samples
- To reduce the bias, flat energy spectrum is best option
- At this stage, re-weighted individual events to give the impression of flat energy spectrum samples





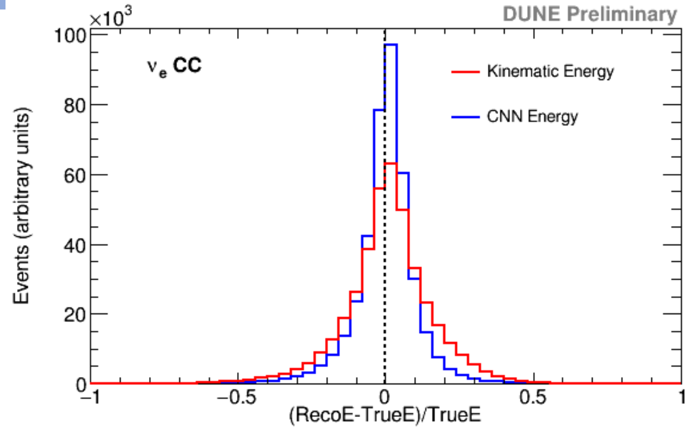


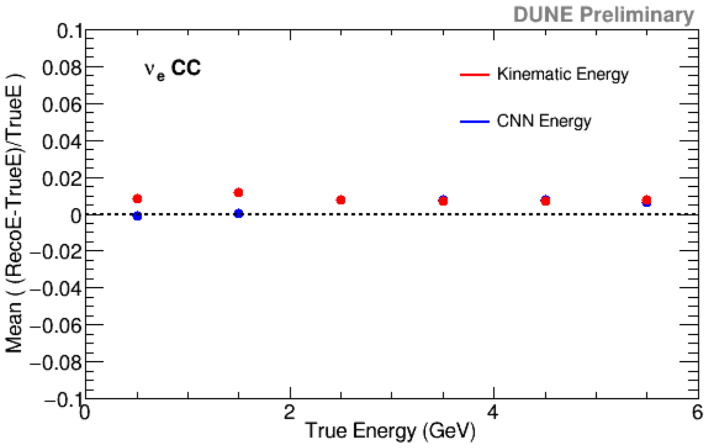
Weighted Training and Result

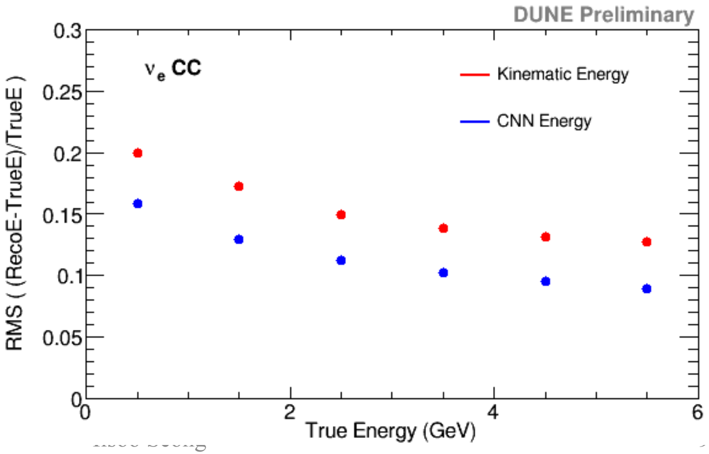
- Redefined the loss function

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

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



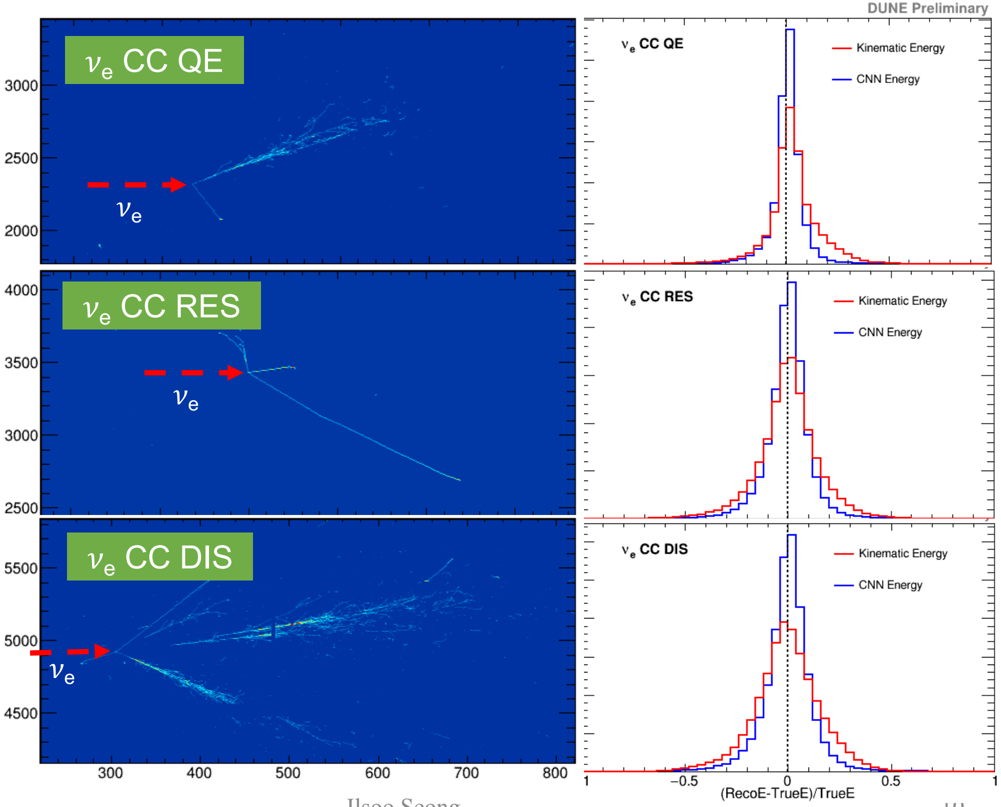




Energy Resolution with Different Interaction Modes

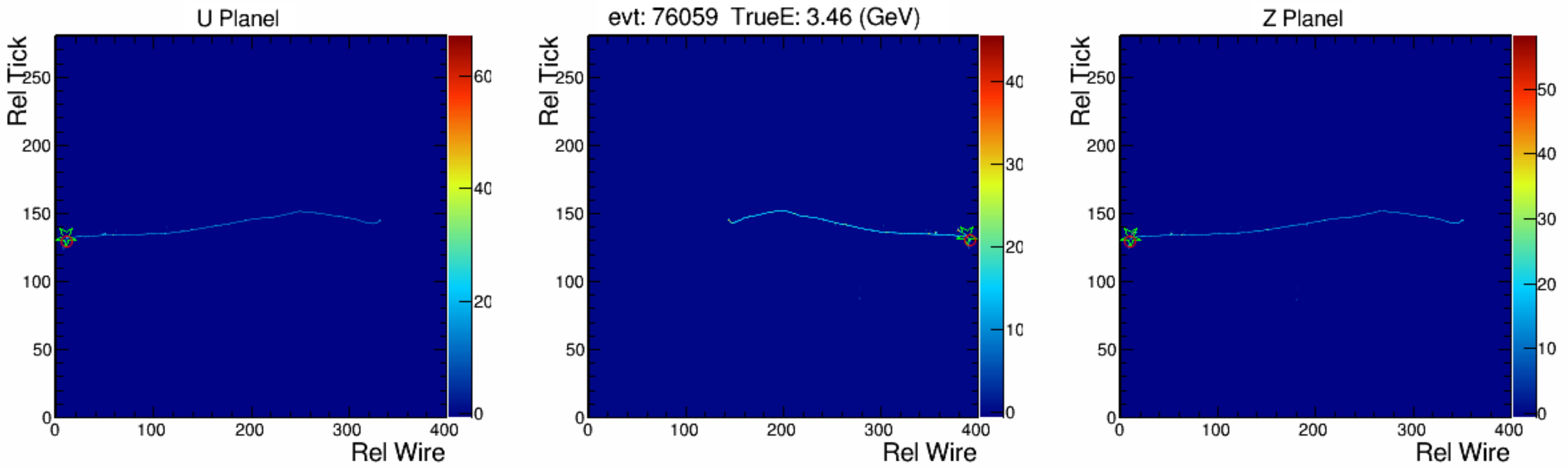
- RegCNN shows good performance for different interaction modes

- Sigma of Gaussian fit:
  - RegCNN: 5.2% (QE), 8.3% (RES), 9.4% (DIS)
  - Kinematic-based: 9.5% (QE), 13.1% (RES), 15.2% (DIS)



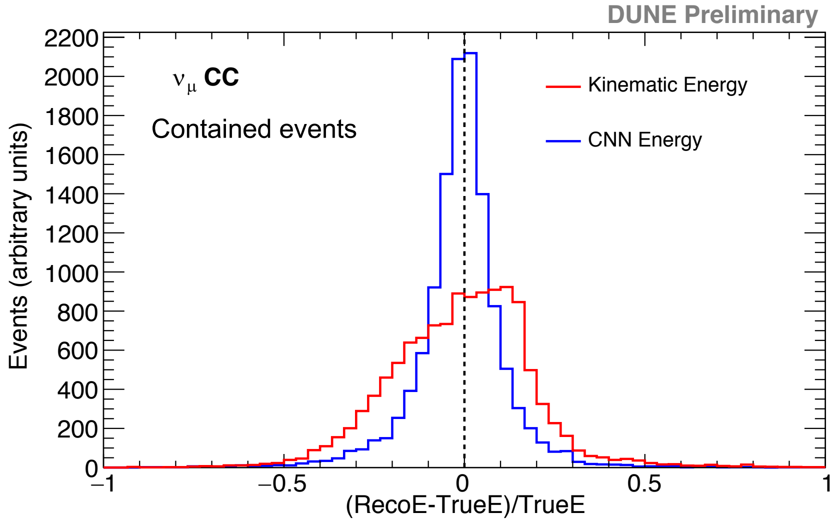
Low-resolution Pixel Map inputs for ν_μ Energy

- We start with a low resolution pixel map to include overall topology
- Three input pixel maps: U-T, V-T, and Z-T
- Pixel map size has been chosen to contain 90% of hits on average
- Coarse TDC ticks and wires
- Pixel map size: 280x400, (actual covered space: 6720 ticks x 2800 wires) → Merged 7 wires and 24 ticks



Numu CC 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.



Two stage training for Vertex

- The pixel map size (280x400) is too large for vertex training, to improve resolution we construct 2-stage architecture
- First stage: propose the vertex on each plane → crop each view and make smaller pixel map
- Second stage: reconstruct the 3-D vertex with the smaller pixel map

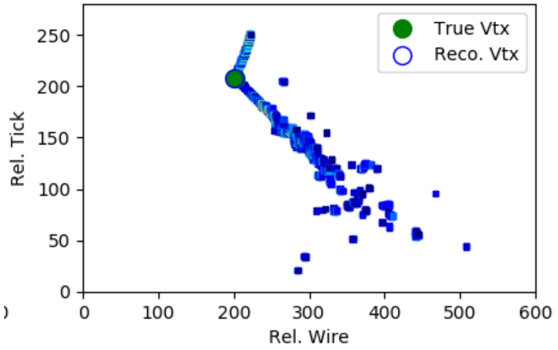
Use Pixel Map (280x**600**)
Find Vertex on Wire/Tick
for each plane

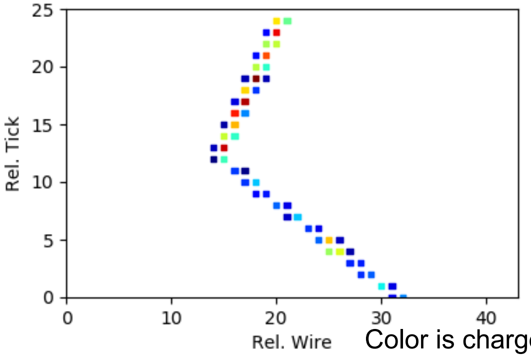
→

Crop image
Make Small Pixel Map
(24x40)

→

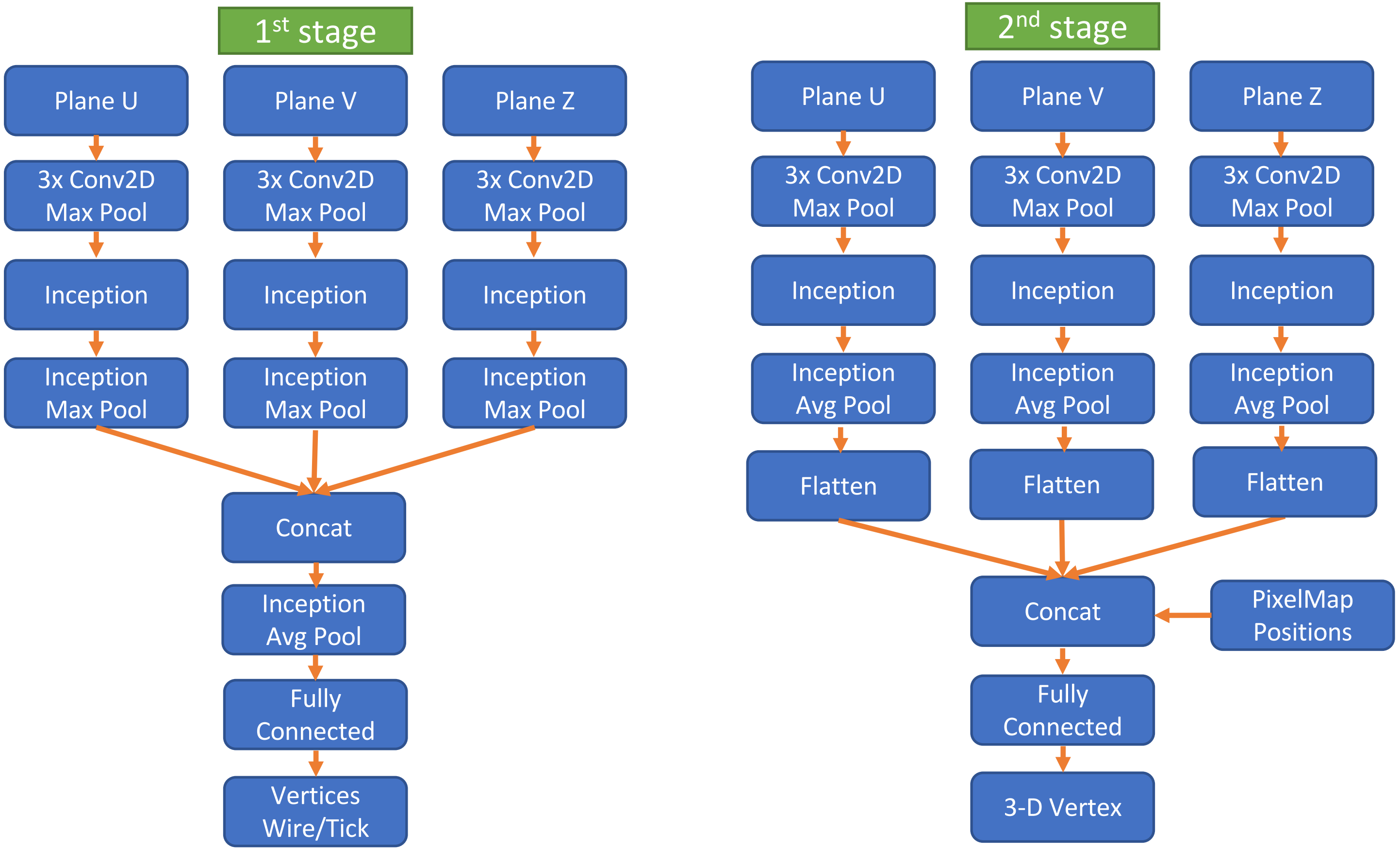
Reconstruct Vertex on
X/Y/Z





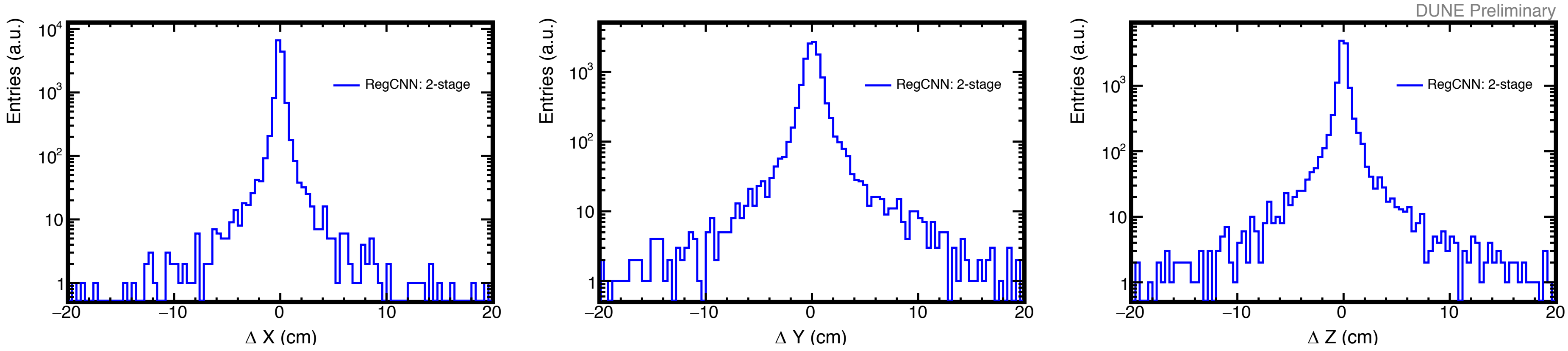
Color is charge

Vertex Regression CNN Architectures



Reconstructed 3-D Vertex

- Trained on statistical independent Nue CC samples and tested on two simulation versions with results consistent results
- Promising RMS: 0.98 cm (X), 1.98 cm (Y) and 1.67 cm (Z)



Summary

- Developed regression CNN models to reconstruct neutrino energy and vertex for DUNE
- Show promising results in the energy and vertex resolution
- For Nue CC: 13.1% → 7.3 %, for Numu CC:19.0% → 12.5 % (for contained events)
- With weighted training, energy scale shows small dependence on true neutrino energy, investigating effects from interaction modelling
- Working on systematic uncertainties and validation at ProtoDUNE

Thank you!