Regression CNN Based Energy and Vertex Reconstruction at DUNE

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For the DUNE Collaboration
2019-09-17

Reco & ML in Neutrino Experiment Workshop, DESY, Hamburg

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

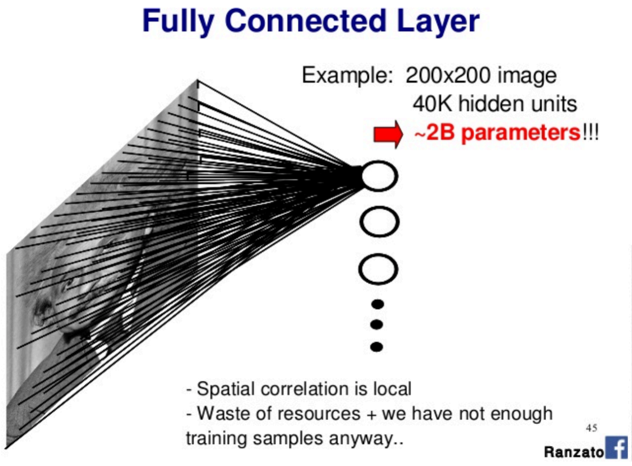
Use deep learning to solve both regression and classification problems in reconstruction

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

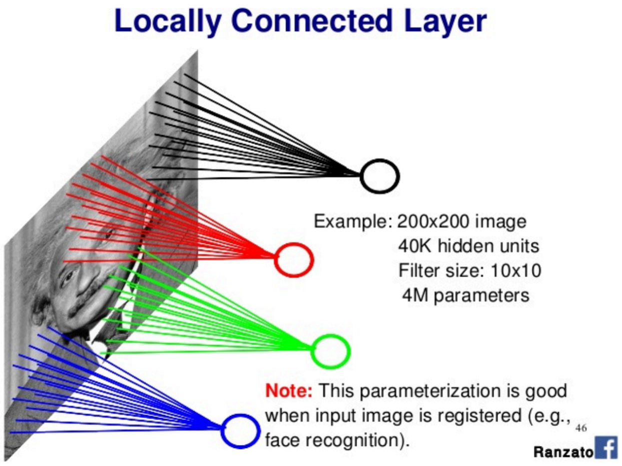
Convolutional Neural Network

- 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

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



Traditional artificial neural network

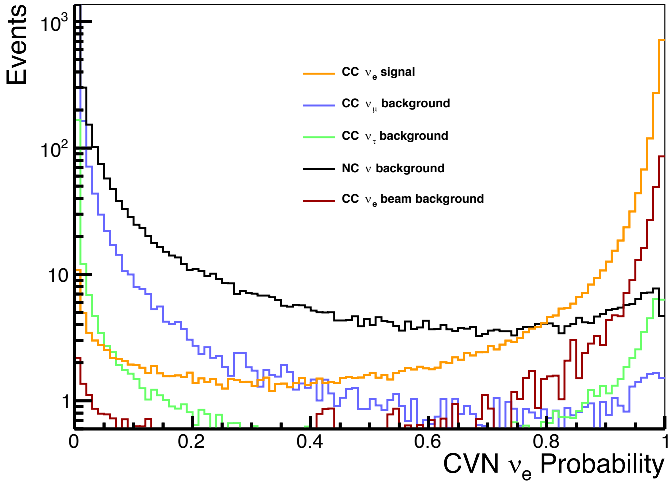


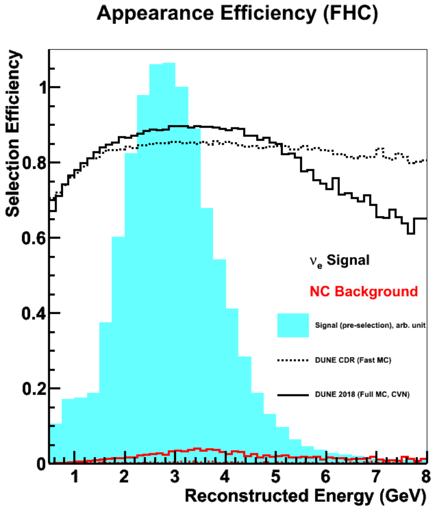
Convolutional neural network

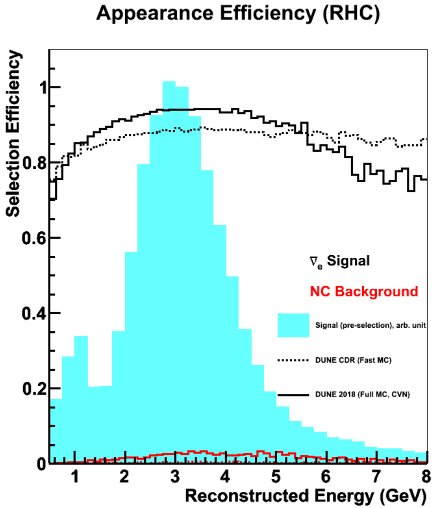
- A. Aurisano et al [NOvA), JINST 11, no. 09, P09001 (2016).
- E. Racah, et al [Daya Bay], arXiv:1601.07621 [stat.ML].
- R. Acciarri et al. [MicroBooNE], JINST 12, no. 03, P03011 (2017).
- J. Renner et al. [NEXT], JINST 12, no. 01, T01004 (2017).
- S. Delaquis et al. [EXO], JINST 13, no. 08, P08023 (2018).
- G. N. Perdue et al. [MINERvA], JINST 13 (2018) no.11, P11020.

Classification CNN identifier in DUNE

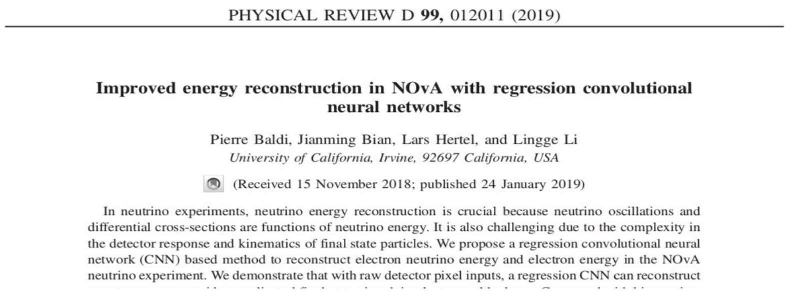
- Classification Convolutional Neural Network has been implemented at DUNE for event identification (CVN)
- Identify ν_μCC, ν_eCC and NC events
- Performance is better than DUNE CDR assumptions







Regression CNN Architecture for energy



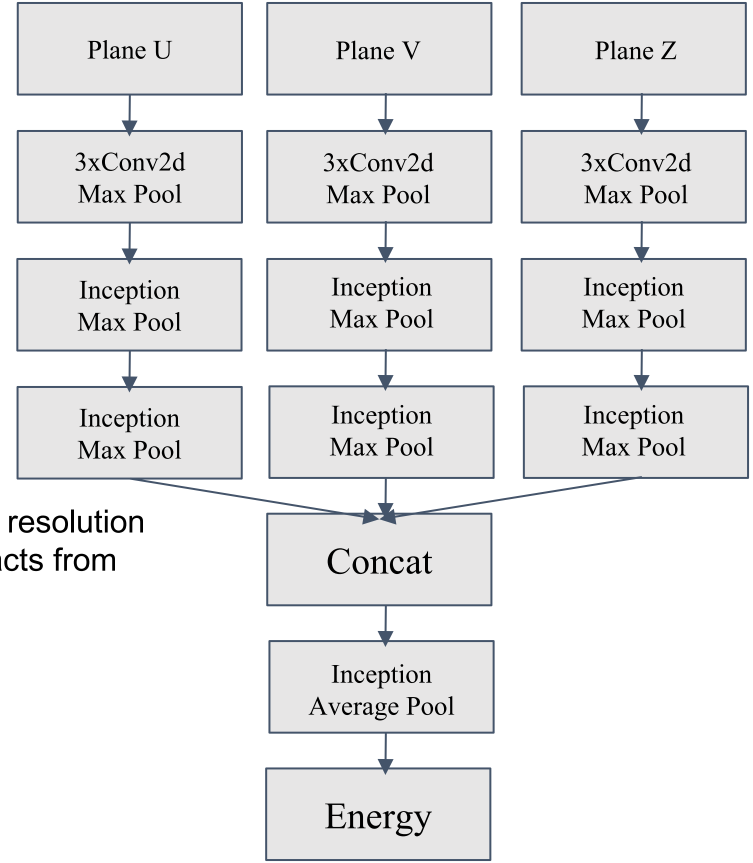
PHYSICAL REVIEW D **99,** 012011 (2019)

Improved energy reconstruction in NOvA with regression convolutional neural networks

Pierre Baldi, Jianming Bian, Lars Hertel, and Lingge Li
University of California, Irvine, 92697 California, USA

(Received 15 November 2018; published 24 January 2019)

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

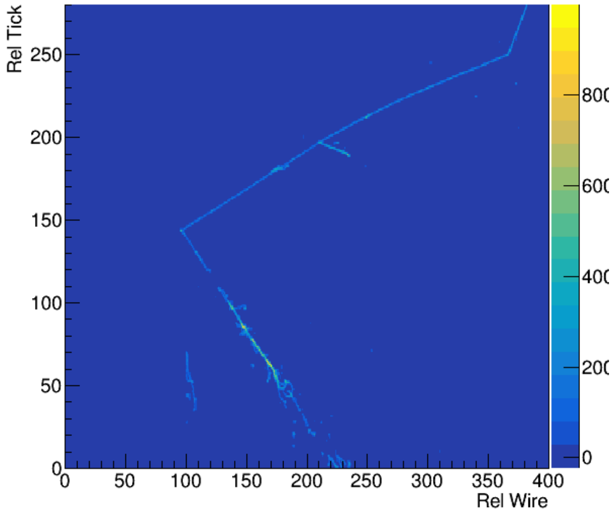


- Architecture modified from UCI's NOvA Regression CNN energy estimator (Pierre Baldi, Jianming Bian, Lars Hertel, Lingge Li, PhysRevD.99.012011)
- Loss: $L(\mathbf{W}, \{\mathbf{x}_i, y_i\}_{i=1}^{n}) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{f_{\mathbf{W}}(\mathbf{x}_i) - y_i}{y_i}\right|$ Optimize energy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

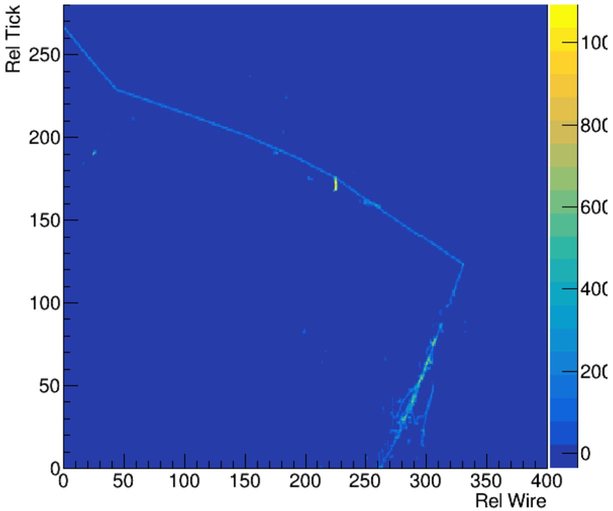
Pixel Map inputs for ν_e

- 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

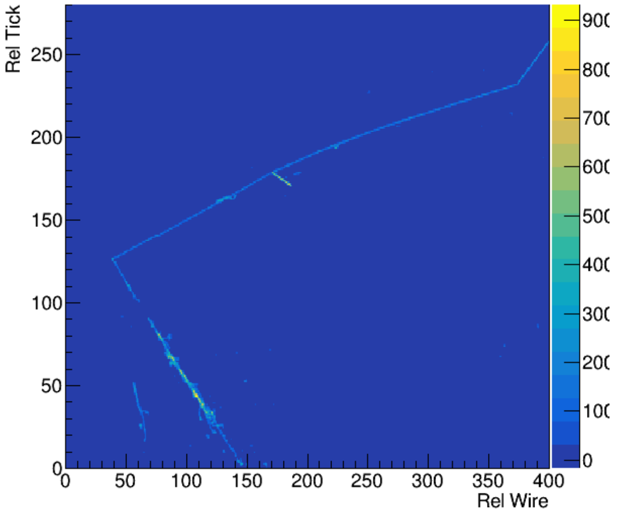
U Planel (Induction plane)



V Planel (Induction plane)

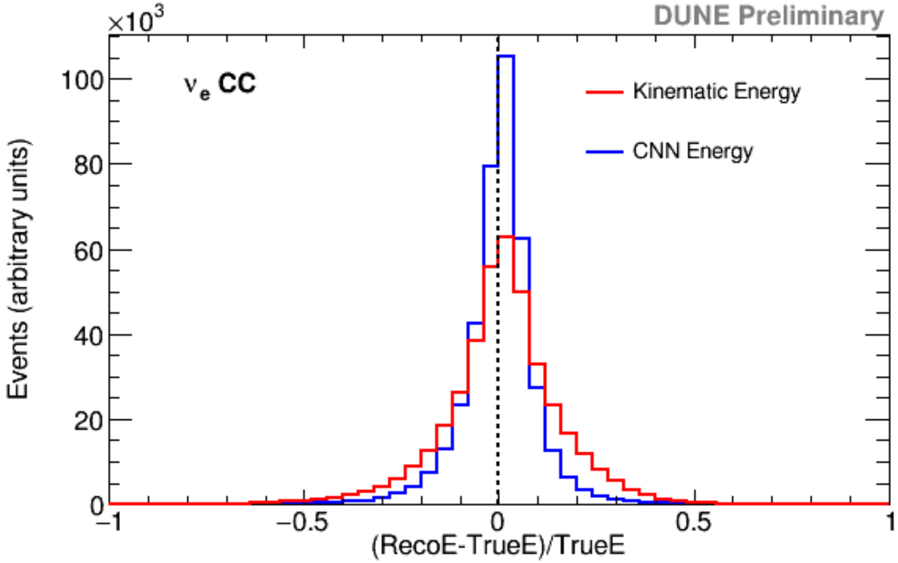


Z Planel (collection plane)



ν_e CC 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%



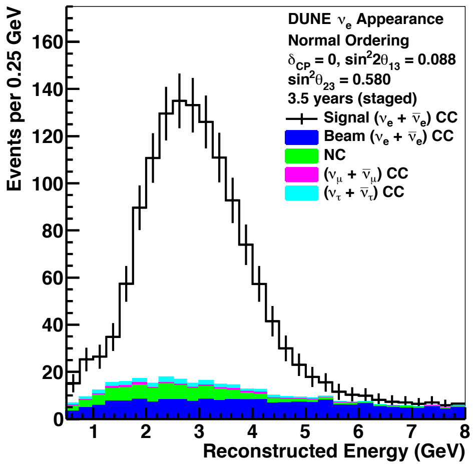
Kinematics Energy reconstructed by
$E(\nu) = E_{lep}^{cor} + E_{had}^{cor}$
Using MC truth to find correction factors to visible lepton and hadron energy

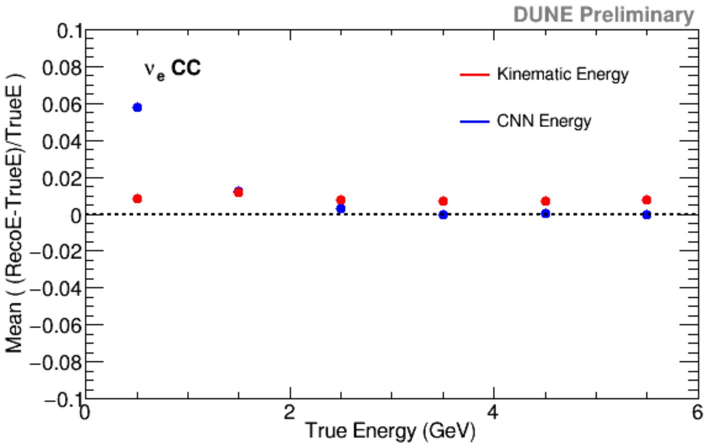
CNN Energy is reconstructed by regression CNN

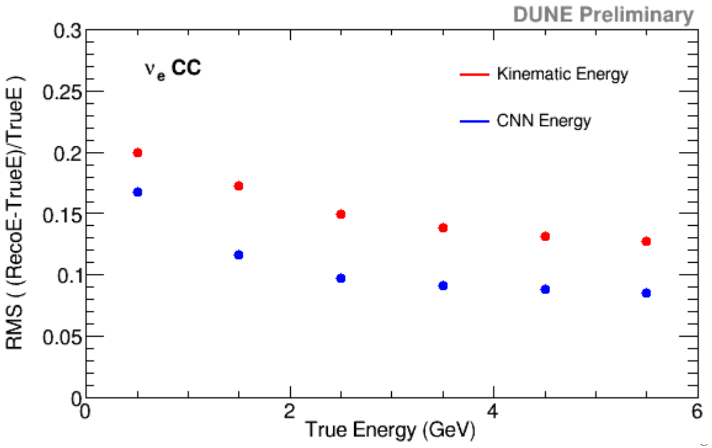
Energy Resolution vs. True Energy

- 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

DUNE CDR





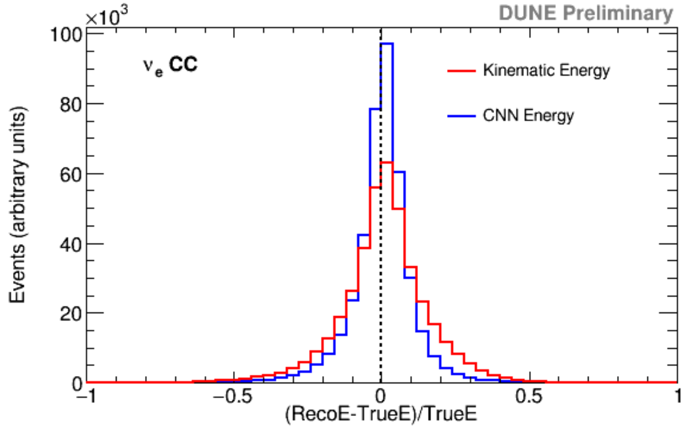


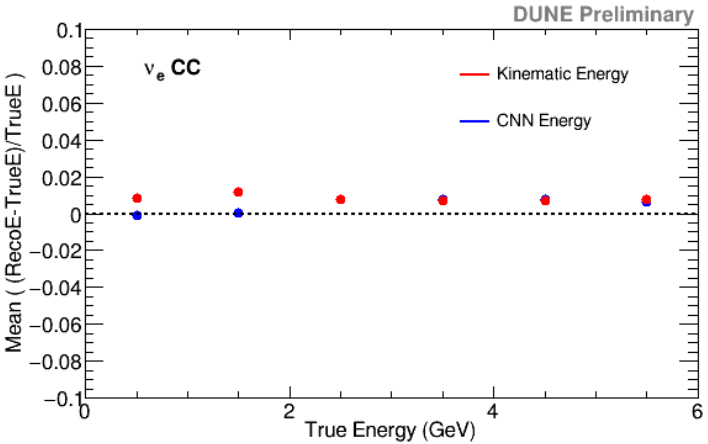
Weighted Training and Result

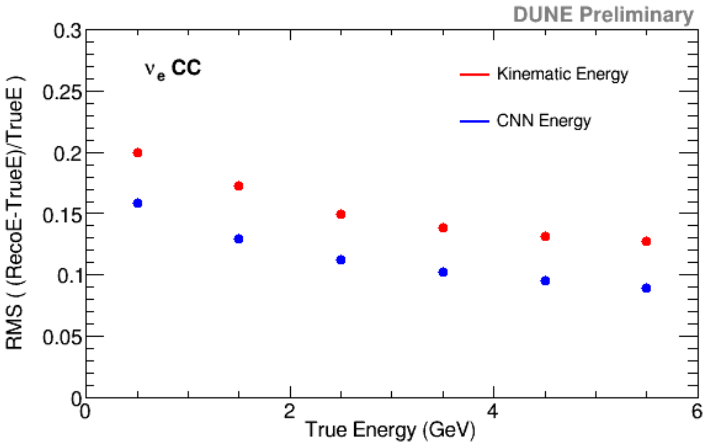
- Redefined the loss function

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

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

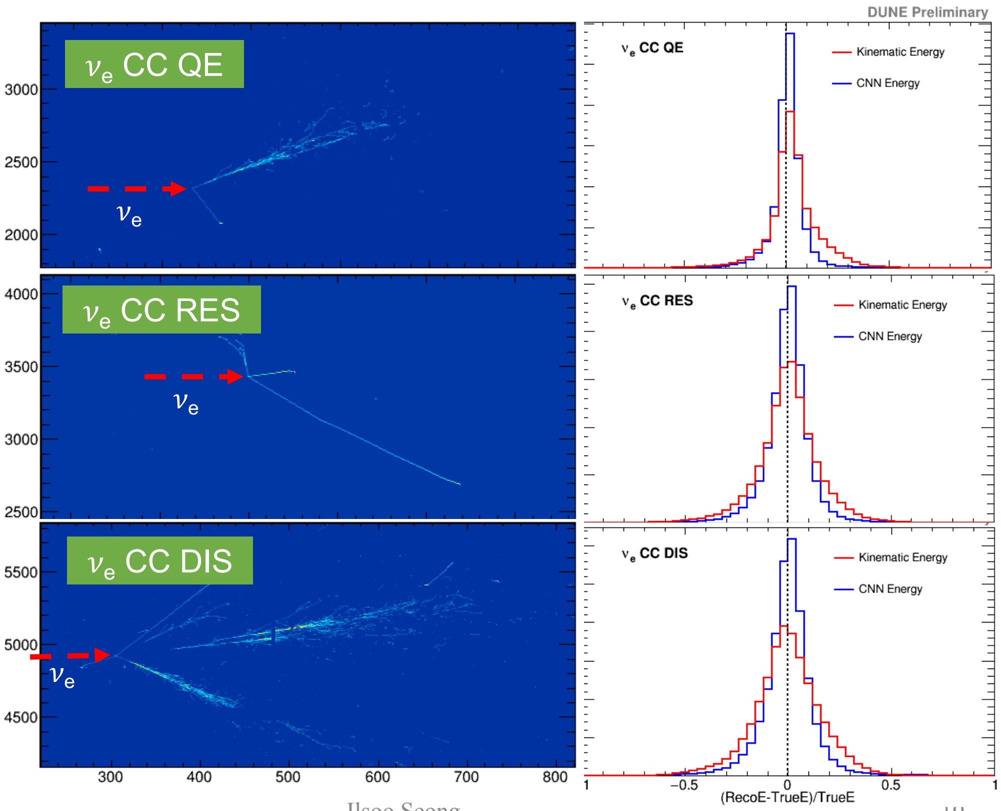






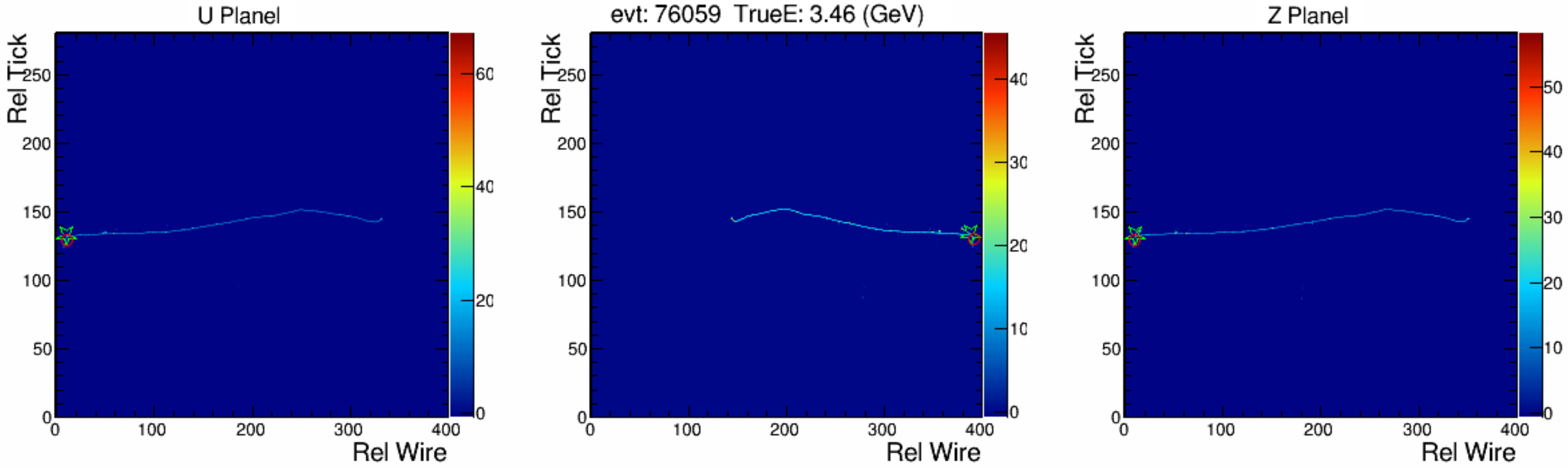
Energy Resolution with Different Interaction Modes

- 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)



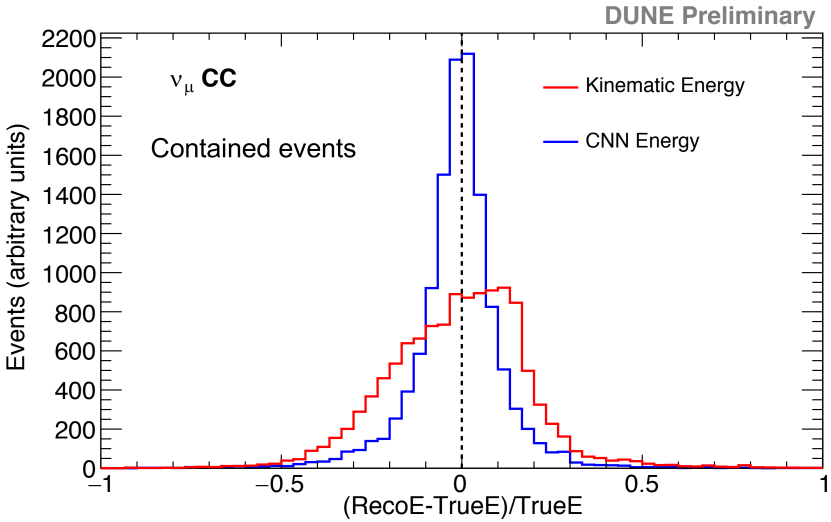
Low-resolution Pixel Map inputs for ν_μ Energy

- 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



ν_μ 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.



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

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

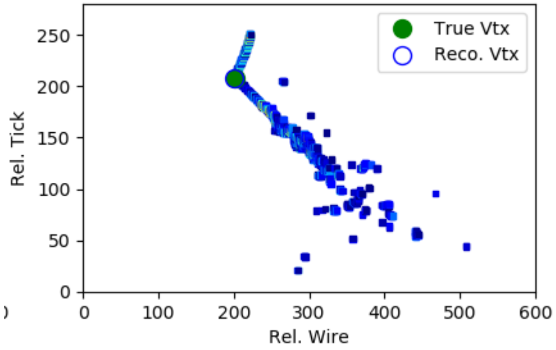
Use Pixel Map (280x**600**)
Find Vertex on Wire/Tick
for each plane

→

Crop image
Make Small Pixel Map
(24x40)

→

Reconstruct Vertex on
X/Y/Z



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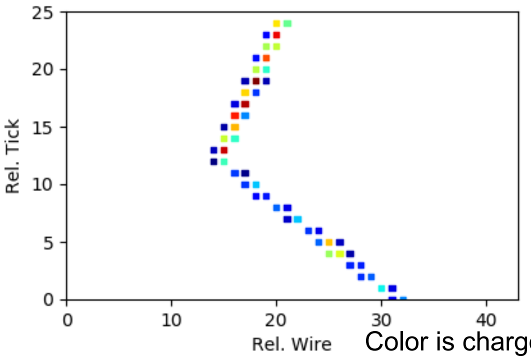
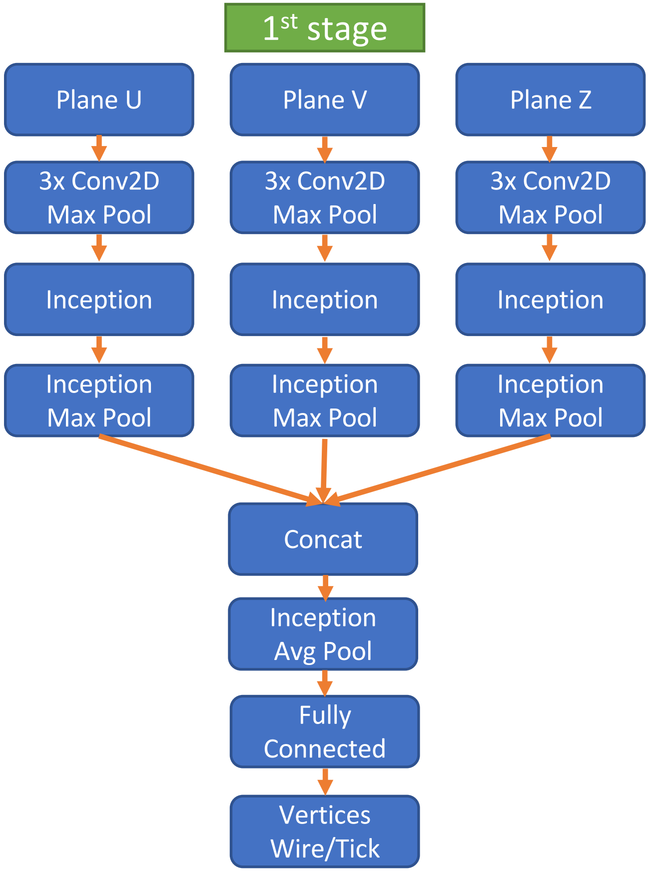
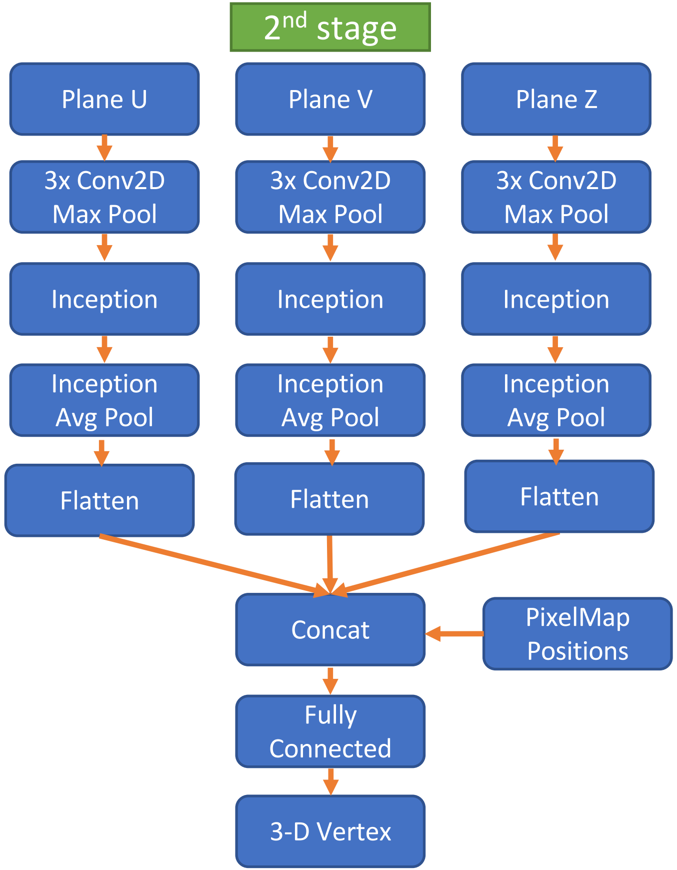


Color is charge

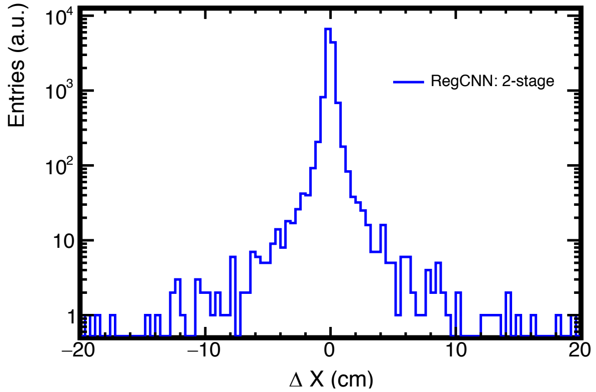
Vertex Regression CNN Architectures

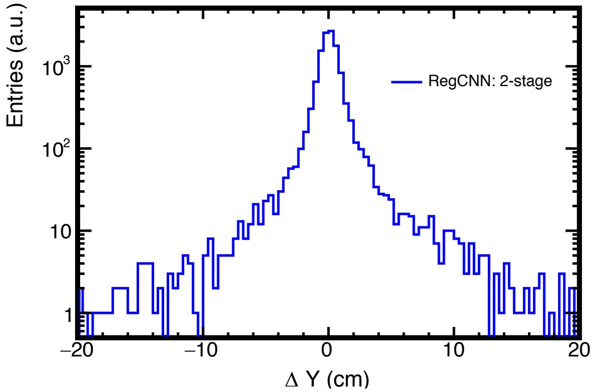


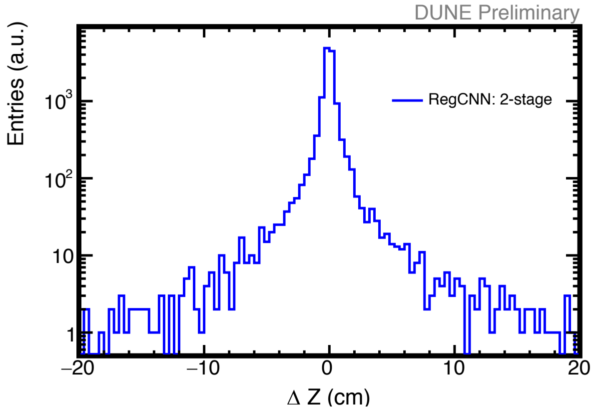


Reconstructed 3-D Vertex

- 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
- 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!