# DUNE Energy Reconstruction: Kinematics-based and Deep-learning

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# Introduction

Neutrino Energy reconstruction at DUNE:

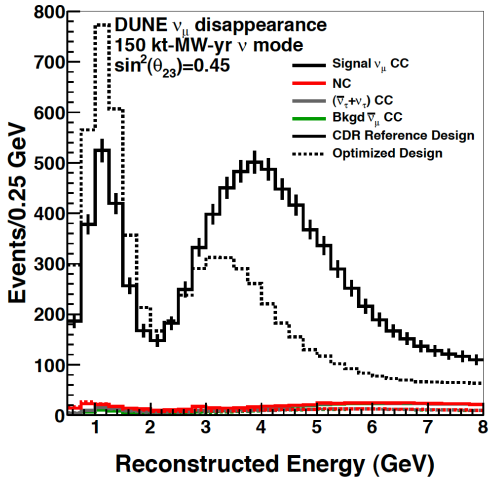
- Crucial because oscillations and differential cross-sections depend on it
- Challenging due to complexity in detector response and final state particle kinematics.

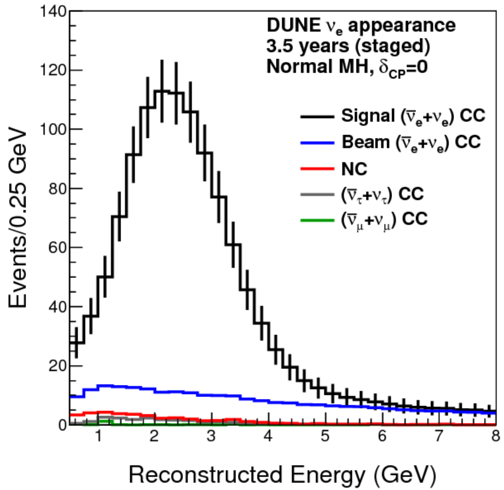
Two methods

- Kinematics-based Energy Reconstruction:

$$E(\nu) = E_{lep}^{cor} + E_{had}^{cor}$$

Regression Convolutional Neural Network (CNN) based Energy Reconstruction: deep learning with direct raw waveform inputs from U/V/Y planes



# Kinematics-based Energy Reconstruction

$$E(\nu) = E_{lep}^{cor} + E_{had}^{cor}$$

- $\nu_\mu$ CC energy: divide event into longest reconstructed track and hadronic energy.
- $\nu_e$ CC energy: divide event into reconstructed shower with highest charge and hadronic energy.
- Hadronic/Electron energy: electron lifetime (wire-by-wire) and recombination (constant) corrected calorimetric energy

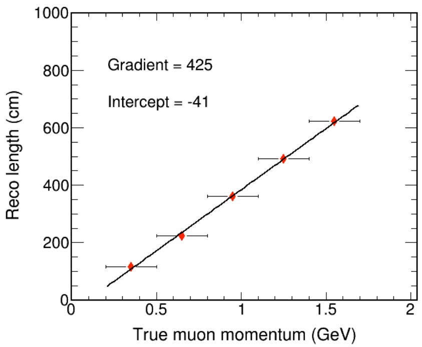
# $\nu_\mu$ CC energy: Muon Track Energy

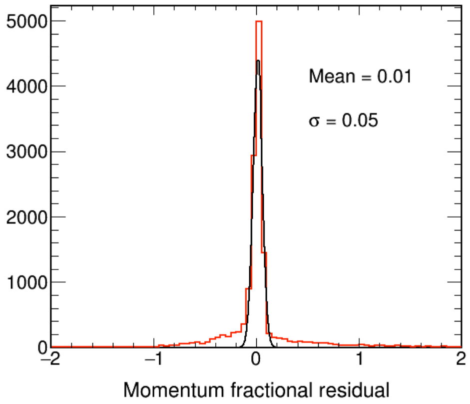
Longest track contained within detector, calculate momentum by range

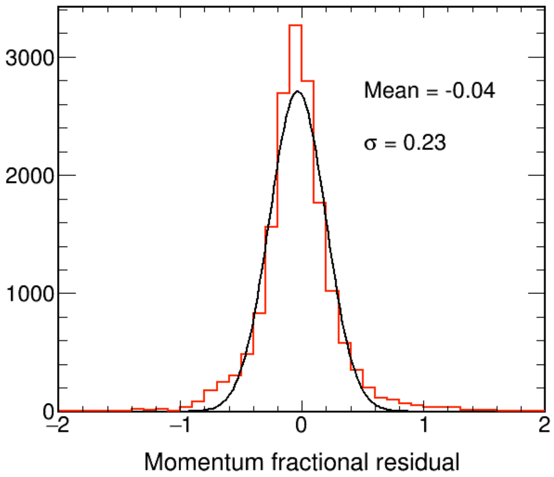
Using Monte Carlo, estimate reco track momentum as (range - intercept) / gradient.

Longest track exits detector, estimate its momentum from multi-Coulomb scattering (MCS).

Divide track into segments of equal length and fit a straight line to each segment. Scattering angle is angle between successive segments.

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# $\nu_e$ CC energy: Electron Shower Energy

Electron shower energy: Calorimetric energy calibrated with Monte Carlo

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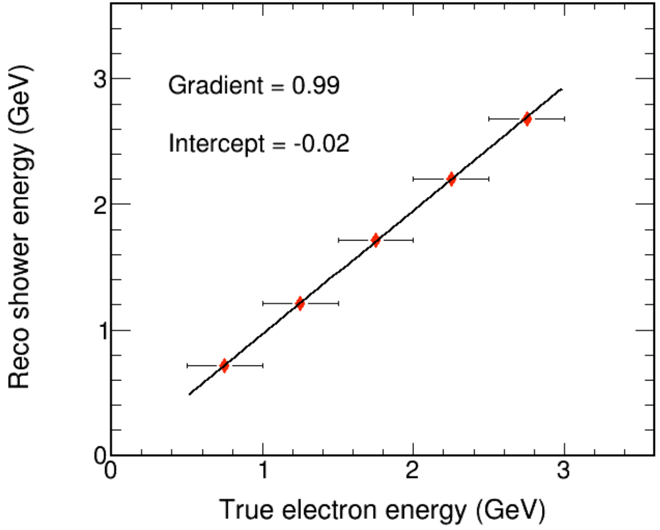
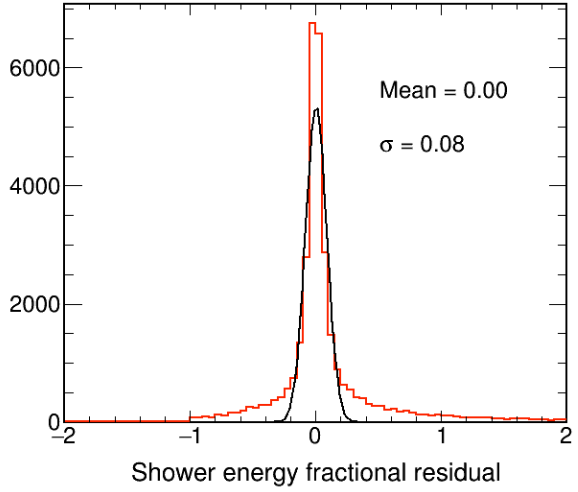
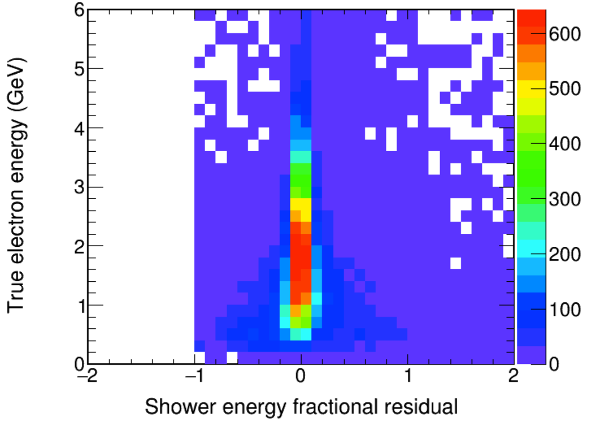


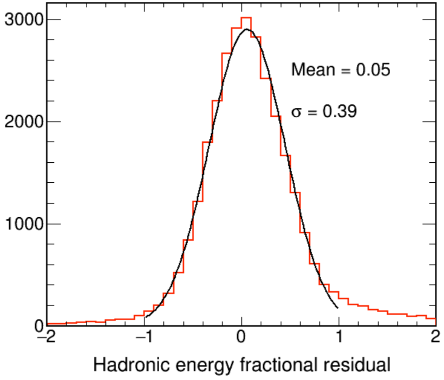



# Hadronic Energy

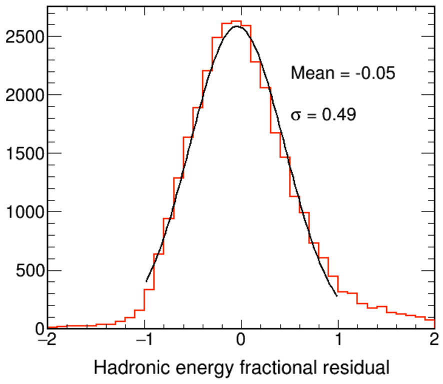
- Estimate the hadronic energy from reconstructed hits that are not in the muon track or electron shower. Make calibration using Monte Carlo.

- Reco hadronic energy tends to be too low since neutral particles are not reconstructed in the DUNE far detector. On average 40% of the energy is invisible due to neutron scattering etc, and there are fluctuations in this from event to event, and this limits energy resolution.

Hadronic Energy in Numu CC




Hadronic Energy in Nue CC

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# Kinematics-based $\nu_\mu$CC and $\nu_e$CC Total Energy

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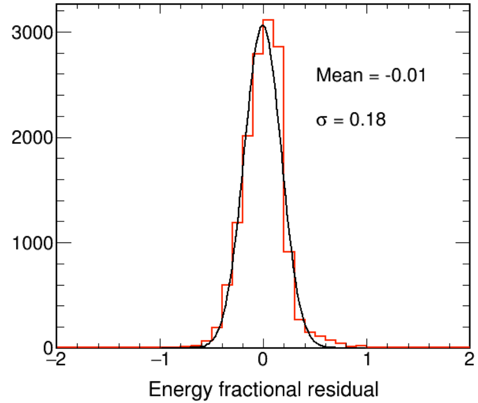
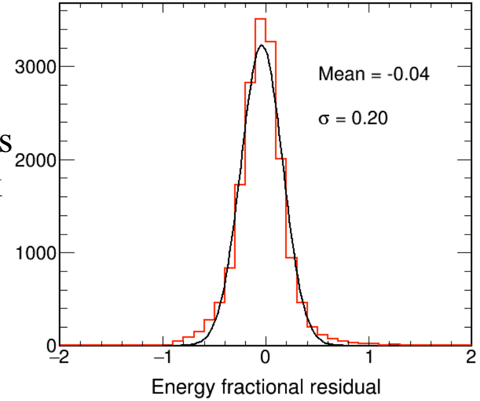
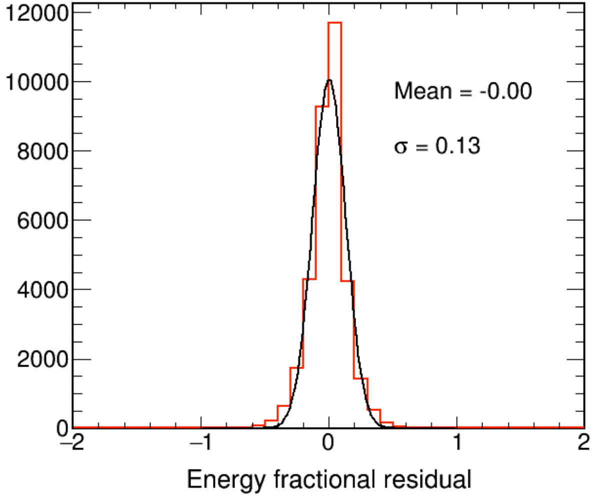
True $\nu_\mu$CC events with contained track




True $\nu_\mu$ CC events with exiting track




True $\nu_e$ CC energy resolution

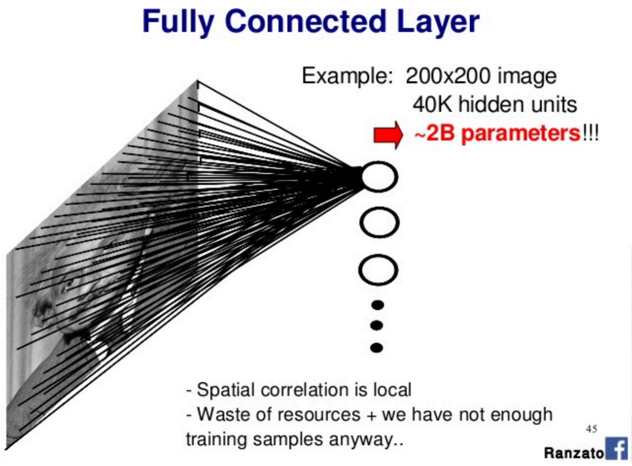



Fiducial cuts based on true vertex, at least one track/shower required

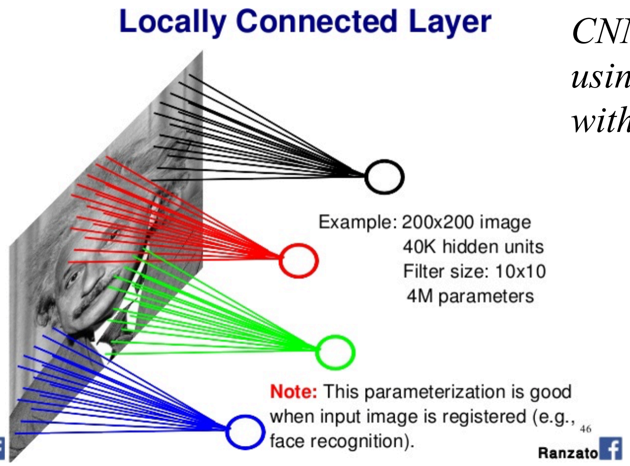
| | $\nu_\mu$ CC | $\nu_e$ CC |
|---|---|---|
| Longest reco track (contained) | 5 | - |
| Longest reco track (exiting) | 20 | - |
| Reco shower with highest charge | - | 8 |
| Hadronic energy | 39 | 49 |

# Regression Convolutional Neural Network for $\nu_e$ CC Energy

- Kinematics-based method complicated by event topology, invisible energy and identities (mass) of hadrons, shower/track reconstruction quality etc.
- Convolutional Neural Networks (CNNs) with raw pixel inputs have demonstrated success in **Classification** problems such as event identification
- Developed **Regression** CNN based method for $\nu_e$ CC energy reconstruction at DUNE
- Can also be extended to solve other regression problems in HEP




Traditional artificial neural network

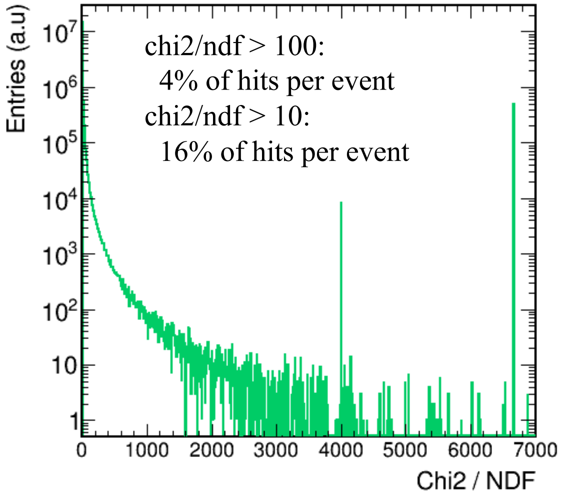



Convolutional neural network

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

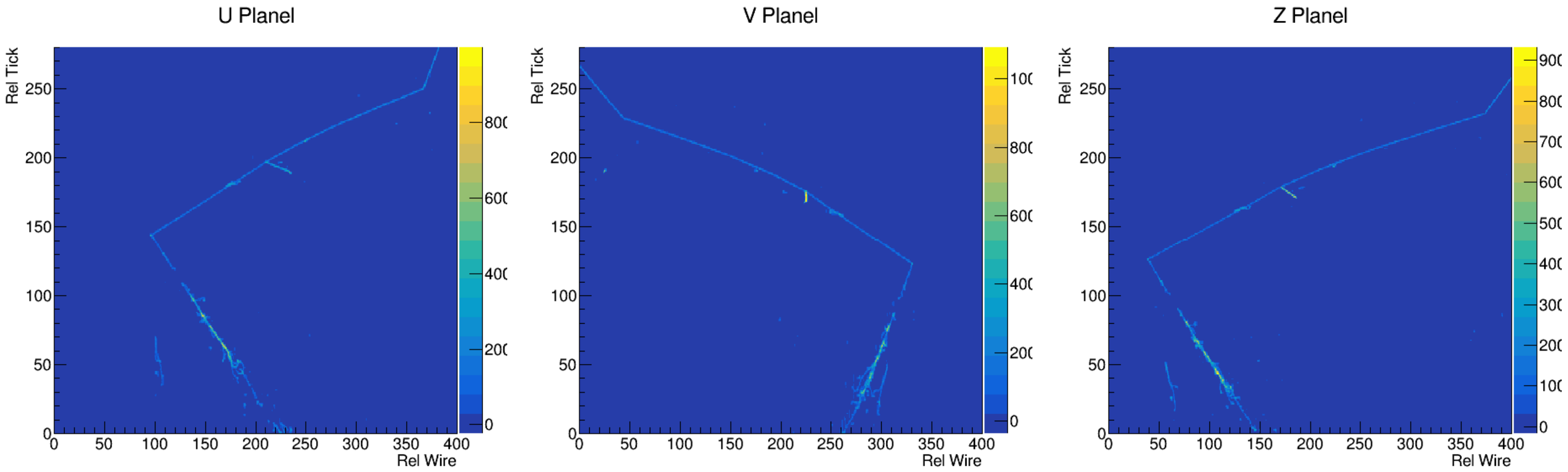
# Charge Information: Direct waveform inputs

- We use ADC counts and TDC units from Wire instead of using the reconstructed hits
- The hits from “gaus hit” sometimes fail to correctly reconstruct hits
- Goodness of Fit shows that minimum 4% of hits per event correspond to such hits

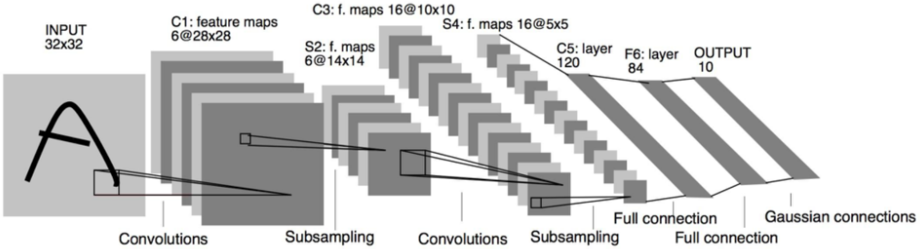


# Pixel Map inputs

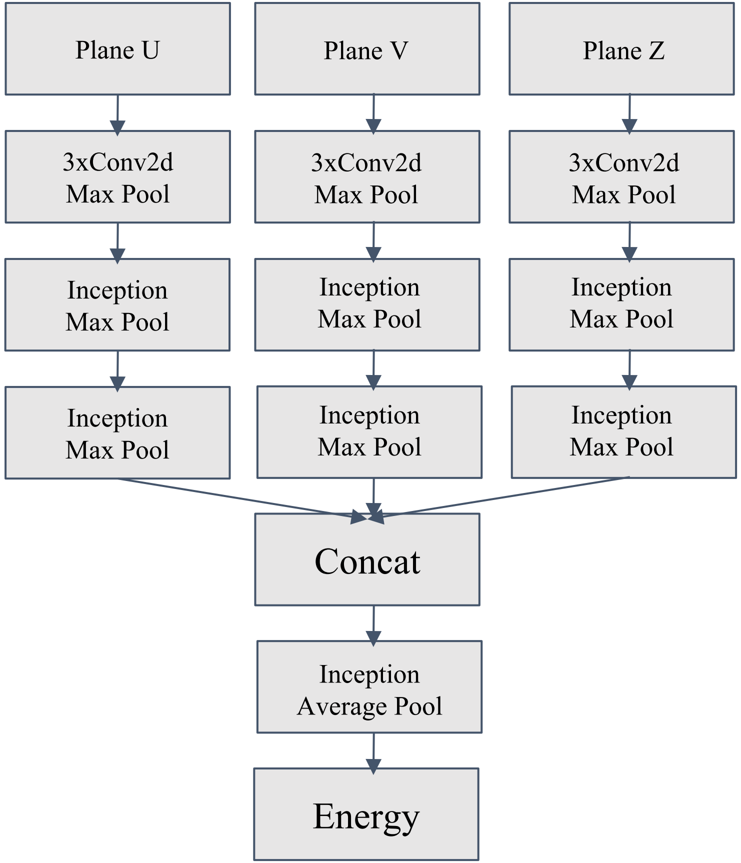
- Three input pixel maps: U-T, V-T, and Z-T
- Pixel map size has been chosen to contain 90% of hits on average
- Coarsed TDC ticks to make same physical dimensions of the x- and y-axis of the pixel map
- Pixel map size: 280x400 (actual covered space: 1680 ticks x 400 wires) → 6 ticks are merged



# CNN Architecture



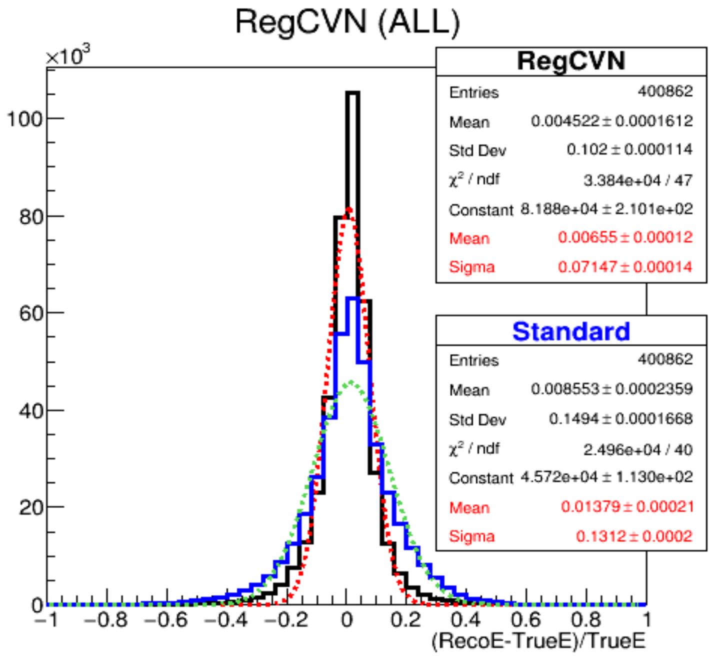

- Architecture based on the NOvA Regression CNN energy estimator (Pierre Baldi, Jianming Bian, Lars Hertel, Lingge Li, arXiv:1811.04557)
- Loss: $L(\mathbf{W}, \{\mathbf{x}_i, y_i\}_{i=1}^{n}) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{f_{\mathbf{W}}(\mathbf{x}_i) - y_i}{y_i}\right|$
- One linear output unit
- No regularization applied
- Hyperparameter optimization software SHERPA used



# NueCC Energy Resolution

RegCVN: regression CNN energy
Standard: kinematics-based energy

- Training with 1M events, without energy dependent weight
- Applied the model into the Nue MCC10
- Fiducial cuts based on true vertex, at least one track/shower required
- Fit with Gaussian in (-1,1)
- Sigma of RegCVN: 7.1% , Std. : 13.1%

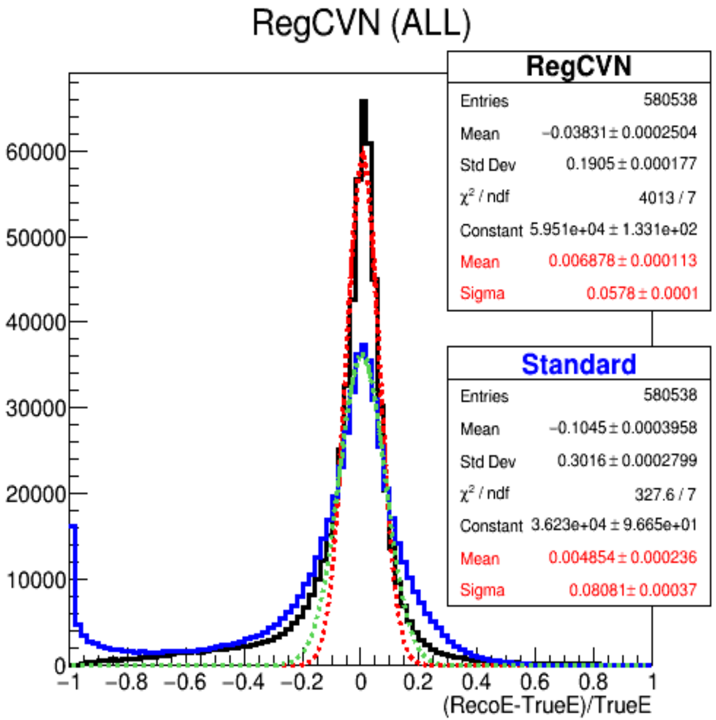



Fiducial cuts based on true vertex,
At least one track/shower required

# NueCC Energy Resolution

RegCVN: regression CNN energy
Standard: kinematics-based energy

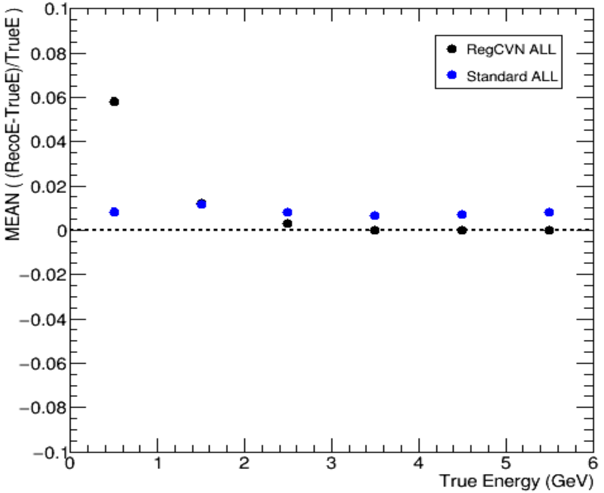
- Fiducial cuts: true vertex → reco hits location
- Regression CNN could solve uncontained energy
- Fit with Gaussian close to peaks
- Sigma of RegCVN: 5.8% , Std. : 8.0%

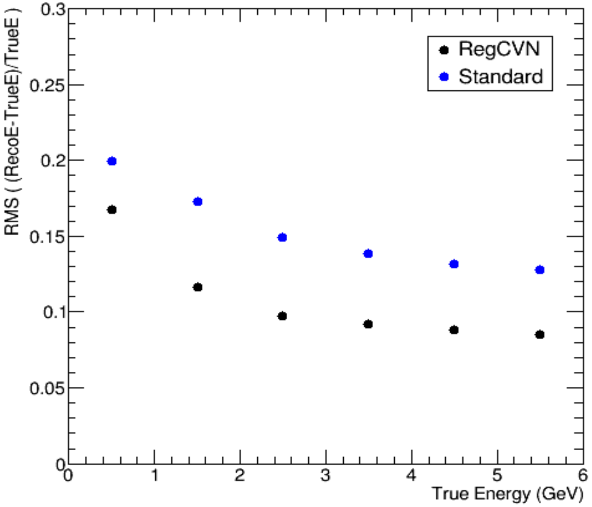


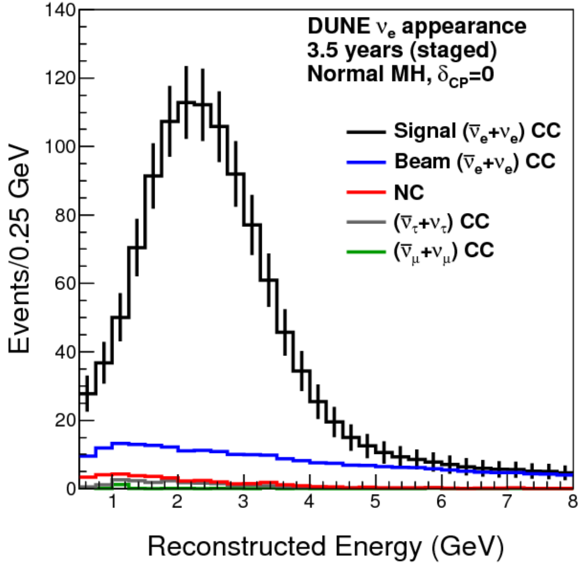

Fiducial cuts based on reco hits location,
At least one track/shower required

# Energy Resolution vs True Energy

- Mean and RMS of energy resolution
- RegCVN shows less bias than and smaller RMS
- Still need improvement in the low energy region → weighted training




RegCVN: regression CNN energy
Standard: kinematics-based energy

# Weighted Training

- Network over-estimates for low energies.
- Bias due to low statistics in low energy neutrino in training data.
- Best solution: Use flat flux energy spectrum to enrich low energy neutrinos in the training.
- Since flat flux sample currently not available, re-weight individual events to give low energy events larger impacts in the training

# Weighted Training

Re-weigh samples in the loss function:

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

If the weights are highly imbalanced, this can impact the efficiency of the stochastic gradient descent.

Instead, sample $(x_i, y_i)$ with probability: $p_i = \frac{\sqrt{\omega_i}}{\sum_j^N \sqrt{\omega_i}}$

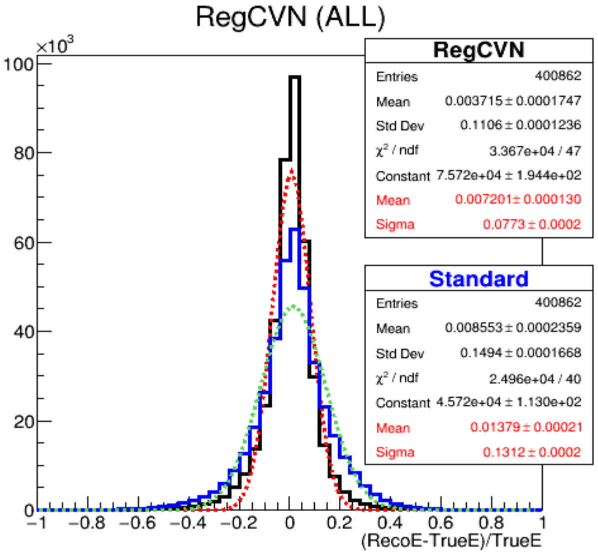
Use a loss function with weights:

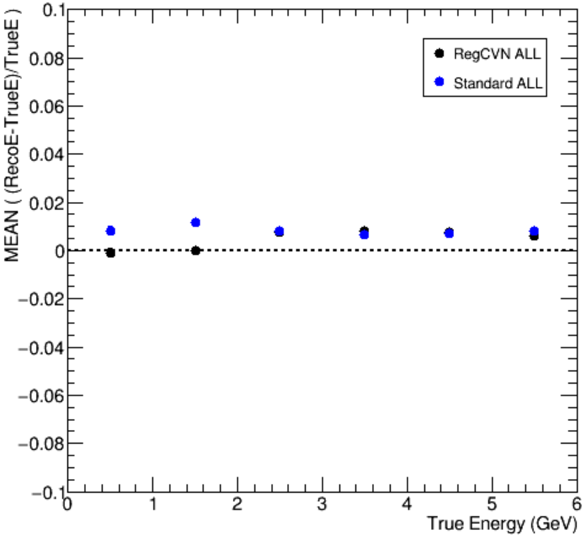
$$L(\mathbf{W}, \{(\mathbf{x}_i, y_i)\}_{i=1}^n) = \frac{1}{\sum_j^n \sqrt{\omega_j}} \sum_i^n \sqrt{\omega_i} L(\mathbf{W}, \mathbf{x}_i, y_i)$$

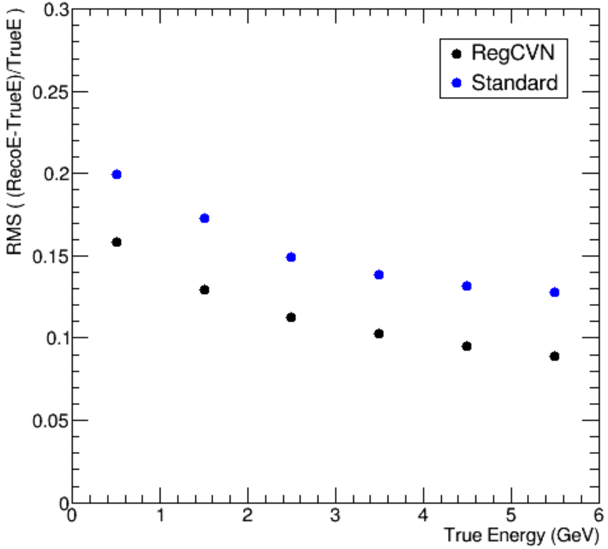
# Result of Weighted Training

- Similar energy resolution: 7.7%
- With weighted training

RegCVN: regression CNN energy
Standard: kinematics-based energy



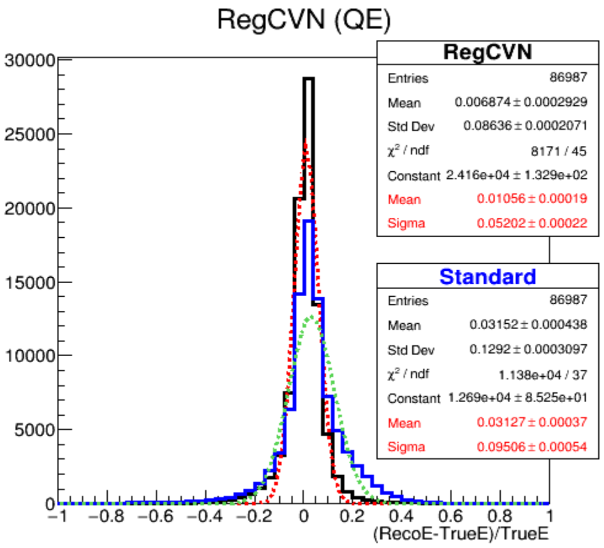



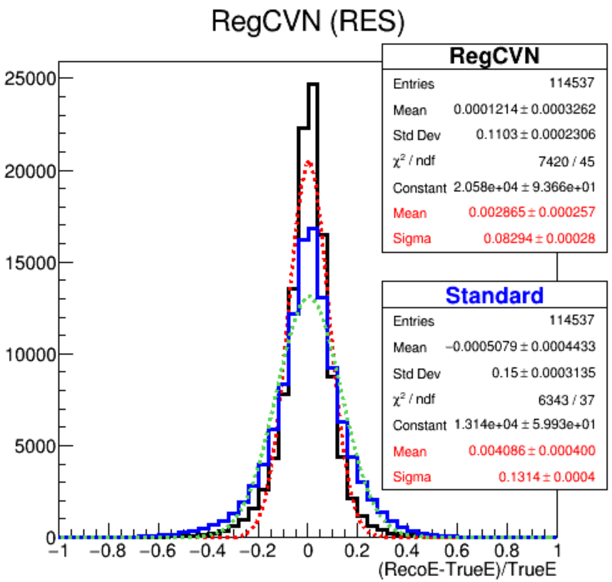



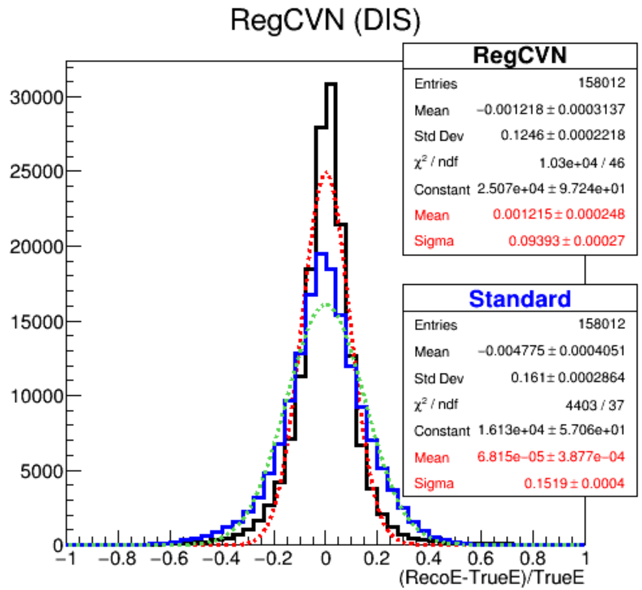

Fiducial cuts based on true vertex,
At least one track/shower required

# Energy resolution for different interaction modes

Regression CNN: Reconstructed to true energy ratio not sensitive to interaction modes, resolutions 5.1% (QE), 8.3% (RES) and 9.1% (DIS)



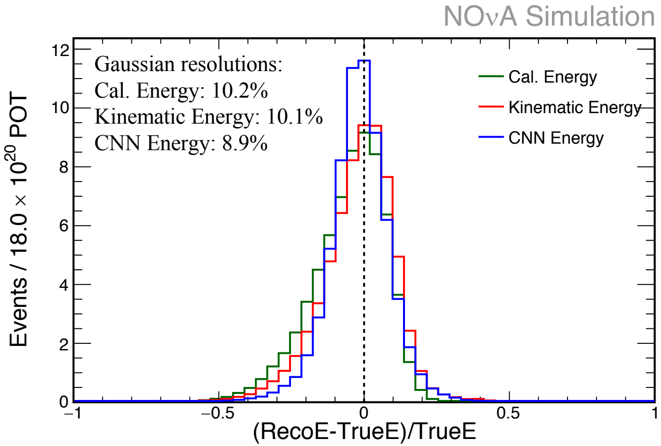

Weighted training
Fiducial cuts based on true vertex,
At least one track/shower required

RegCVN: regression CNN energy
Standard: kinematics-based energy

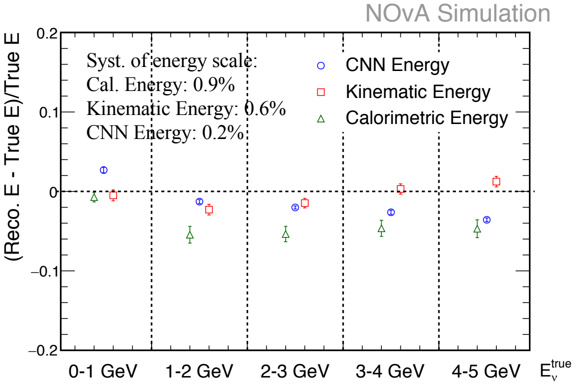
# Systematic uncertainties in Regression CNN $\nu_e$ CC Energy Reconstruction at NOvA

- Regression CNN systematic uncertainties from neutrino interactions evaluated by GENIE parameter reweighting at NOvA
- The regression CNN shows smallest systematic uncertainties from the simulation of neutrino interactions
- Varying calibration by 5% changes output $\nu_e$ CC Energy by 4.5%
- At DUNE, will use similar method and ProtoDUNE data to estimate systematic errors

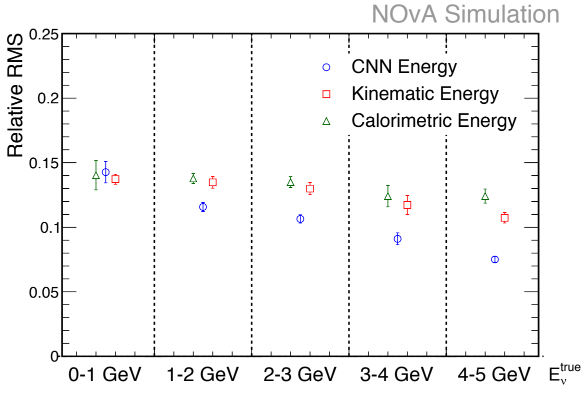
Electron Neutrino Energy




Reco. $E_{\nu e}$ Energy Scale vs. True $E_{\nu e}$




Reco. $E_{\nu e}$ Resolution vs. True $E_{\nu e}$




Error bars represent systematic uncertainties evaluated by GENIE reweighing

# Summary

Kinematics-based energy:

- Implemented a complete first version of neutrino energy reconstruction in DUNE far detector
- Energy resolutions - $\nu_\mu$ CC: 20%, $\nu_e$ CC: 13%
- Shower/track resolutions - Electron: 8%, muon: 5% (contained),20% (uncontained)

Regression CNN Energy:

- $\nu_e$ CC energy reconstruction implemented in DUNE software, working on $\nu_\mu$ CC energy
- Promising $\nu_e$ CC energy resolution of 7%
- Energy scale shows small dependence on true energy (with weighted training) and and interaction modes.
- Developing regression CNN based shower/track energy reconstruction

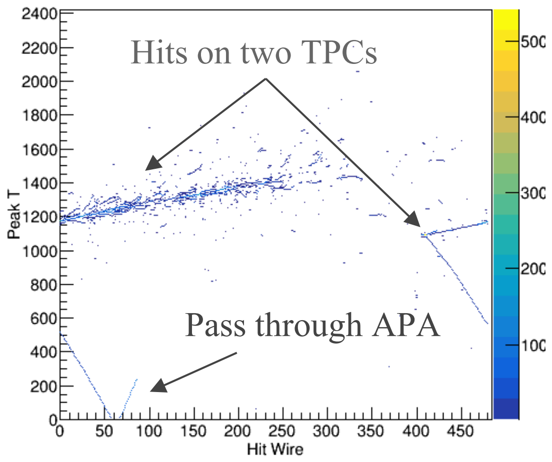
Systematic uncertainty studies underway, will use protoDUNE data

# Backup

# Fiducial cuts with reco hits and Global Wire

- Select Nue CC MC events: No hits near the edge of the FD
- Global Wire
  - modified the GlobalWire algorithm in the “BlurredClusteringAlg” module
  - It shows a clean and continuous event in the one image.

Local Wire using “gaus hit”




Global Wire