Deep-Learning-Based Kinematic Reconstruction for DUNE

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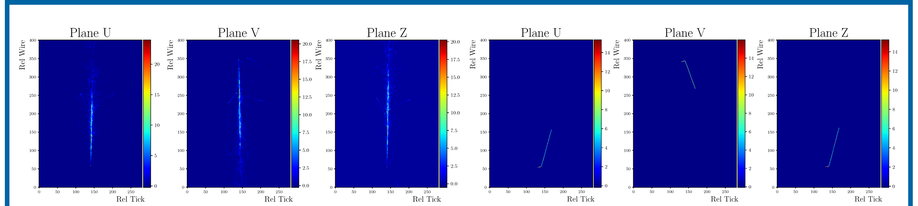
Problem Statement

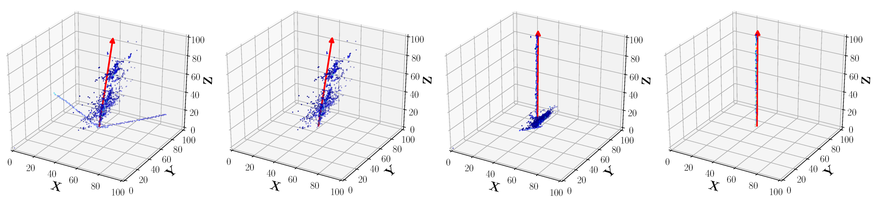
- The Deep Underground Neutrino Experiment (DUNE) is a next-generation long-baseline neutrino oscillation experiment.
- However, reconstruction of neutrino energy and final state particle momenta is challenging.
- We developed two CNN-based models to reconstruct the energy and direction of detected interactions at DUNE, showing considerable improvements compared to the traditional methods.

Data Samples



(a) 2D pixel maps of full-event ν_e CC

(b) 2D pixel maps of full-event ν_μ CC

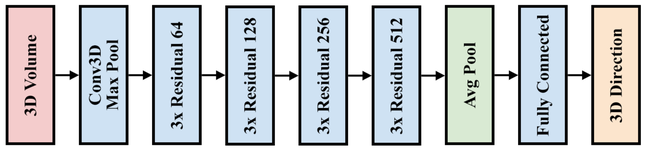


(c) 3D pixel maps of full-event (left) and prong-only (right) ν_e CC

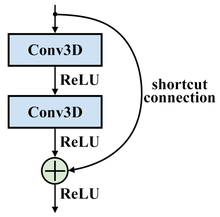
(d) 3D pixel maps of full-event (left) and prong-only (right) ν_μ CC

- The DUNE LArTPC far detector has 3 wire planes for readout, positioned at different angles from each other.
- For energy reconstruction, the three 2-D pixelmaps of each event are reconstructed by wire number and time ticks. The 400×280 pixels represent 400 wires by 1680 time ticks for ν_e, and 2800 wires by 6720 time ticks for ν_μ.
- For direction reconstruction, the 3-D pixelmaps are created by combining spatial and charge information from all 3 planes. These 3-D pixelmaps are 100×100×100 pixels which are 125×125×250 cm for ν_e and 500×500×1000 cm for ν_μ.

Direction Reconstruction



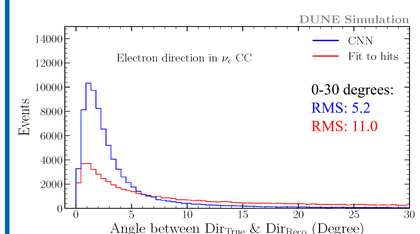
- For direction reconstruction, we designed a 3-D CNN to exploit the 3-D structure in the data.
- The direction regression is heavily dependent on the 3-D geometry in the data.



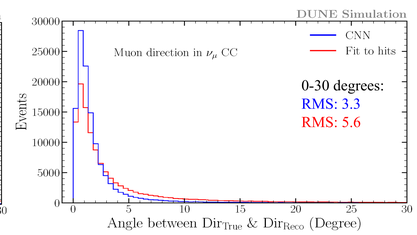
- We use cosine distance as the objective function for optimization. As the which hemisphere that directions are located in can be easily inferred from prior knowledge. We defined a relaxed cosine distance loss to evaluate the direction reconstruction performance:

$$L_{\text{dir}} = \frac{1}{n}\sum_{i=1}^{n} \min\left(1 + \frac{\vec{d}^{\,i}_{\text{True}} \cdot \vec{d}^{\,i}_{\text{Reco}}}{\left|\vec{d}^{\,i}_{\text{True}}\right|\left|\vec{d}^{\,i}_{\text{Reco}}\right|}, 1 - \frac{\vec{d}^{\,i}_{\text{True}} \cdot \vec{d}^{\,i}_{\text{Reco}}}{\left|\vec{d}^{\,i}_{\text{True}}\right|\left|\vec{d}^{\,i}_{\text{Reco}}\right|}\right)$$

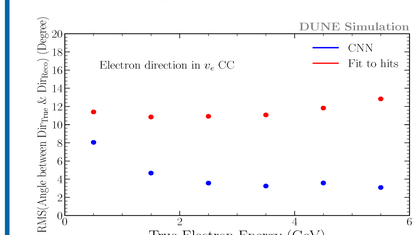
- Our 3-D model achieves resolution improvements of 65% for electron directions and 50% for muon directions.



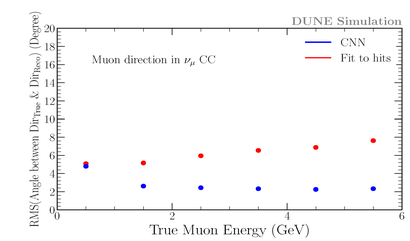
(a) Angular resolution for ν_e CC



(b) Angular resolution for ν_μ CC



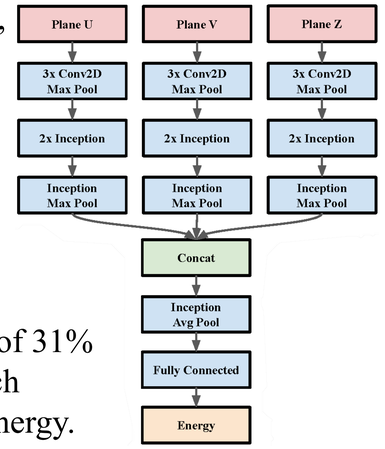
(c) Energy dependency for ν_e CC

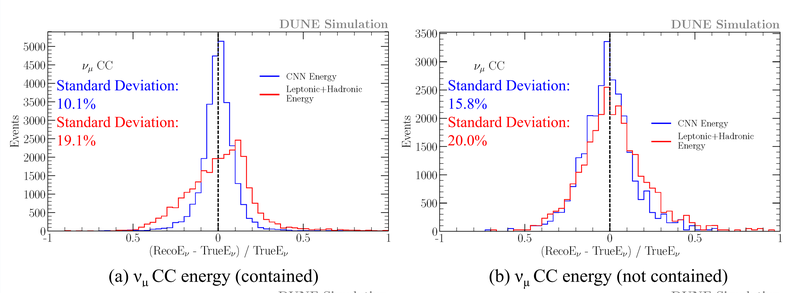


(c) Energy dependency for ν_μ CC

Energy Reconstruction

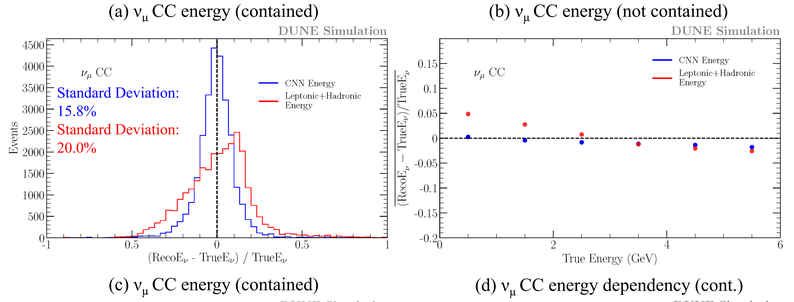
- For energy reconstruction, we built a 2-D CNN that consists three towers, one per image plane.
- We use the MAPE as the loss function during the optimization.
- Our 2-D model achieves resolution improvements of 31% for ν_μ CC energy and much smaller RMS for lepton energy.





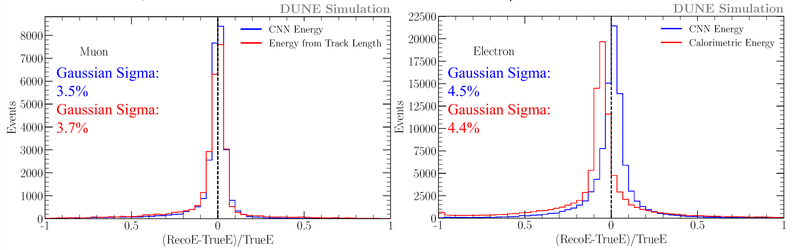
(a) ν_μ CC energy (contained)

(b) ν_μ CC energy (not contained)



(c) ν_μ CC energy (contained)

(d) ν_μ CC energy dependency (cont.)



(e) Muon prong energy (contained)

(f) Electron prong energy

(c) and (d) trained with reweighted energy spectrum to address energy dependent biases