Deep Learning at DUNE Far Detector

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for the DUNE Collaboration

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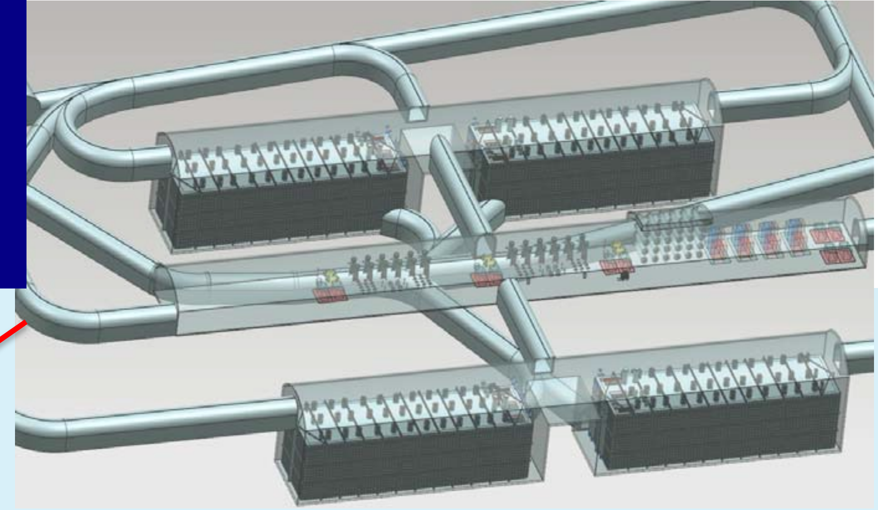
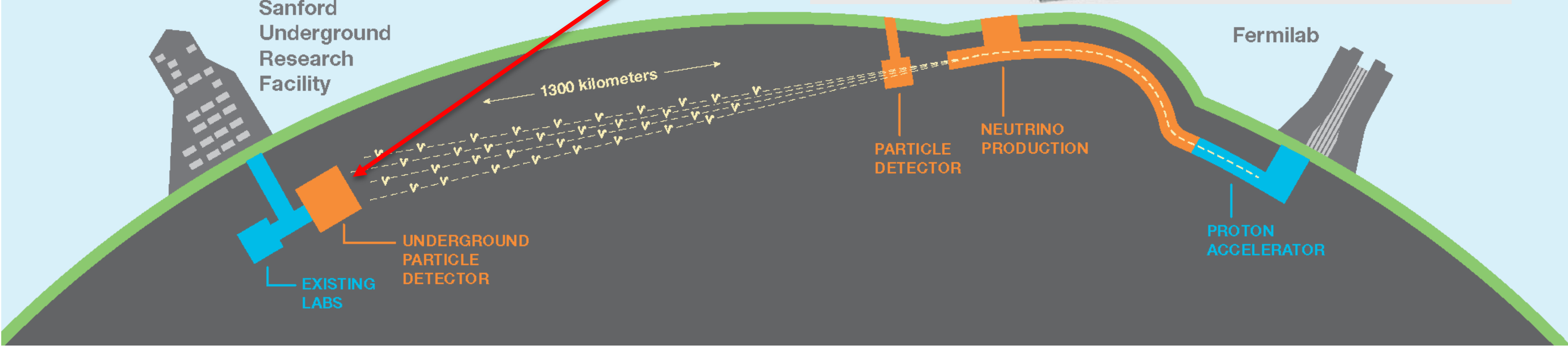
The DUNE Experiment

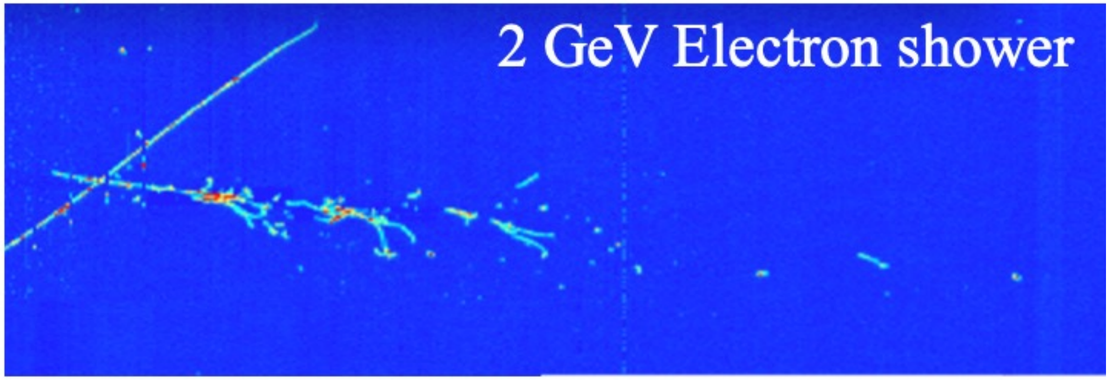


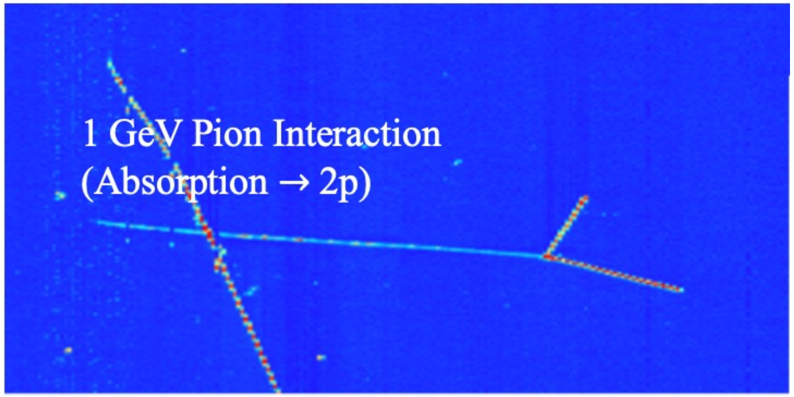


- New neutrino beam at Fermilab (1.2 MW, upgradeable to 2.4 MW), 1300 km baseline
- Utilize 17 kton Liquid Argon Time Projection Chamber (LArTPC) Far Detector modules at SURF: Horizontal-drift (HD), Vertical-drift (VD)
- Multiple technologies for the Near Detector (ND)
- Far Detector Prototypes at CERN: ProtoDUNE-HD (SP), ProtoDUNE-VD
- Neutrino oscillation and diverse non-beam neutrino and BSM projects

Motivation: AI based reconstruction chain for DUNE

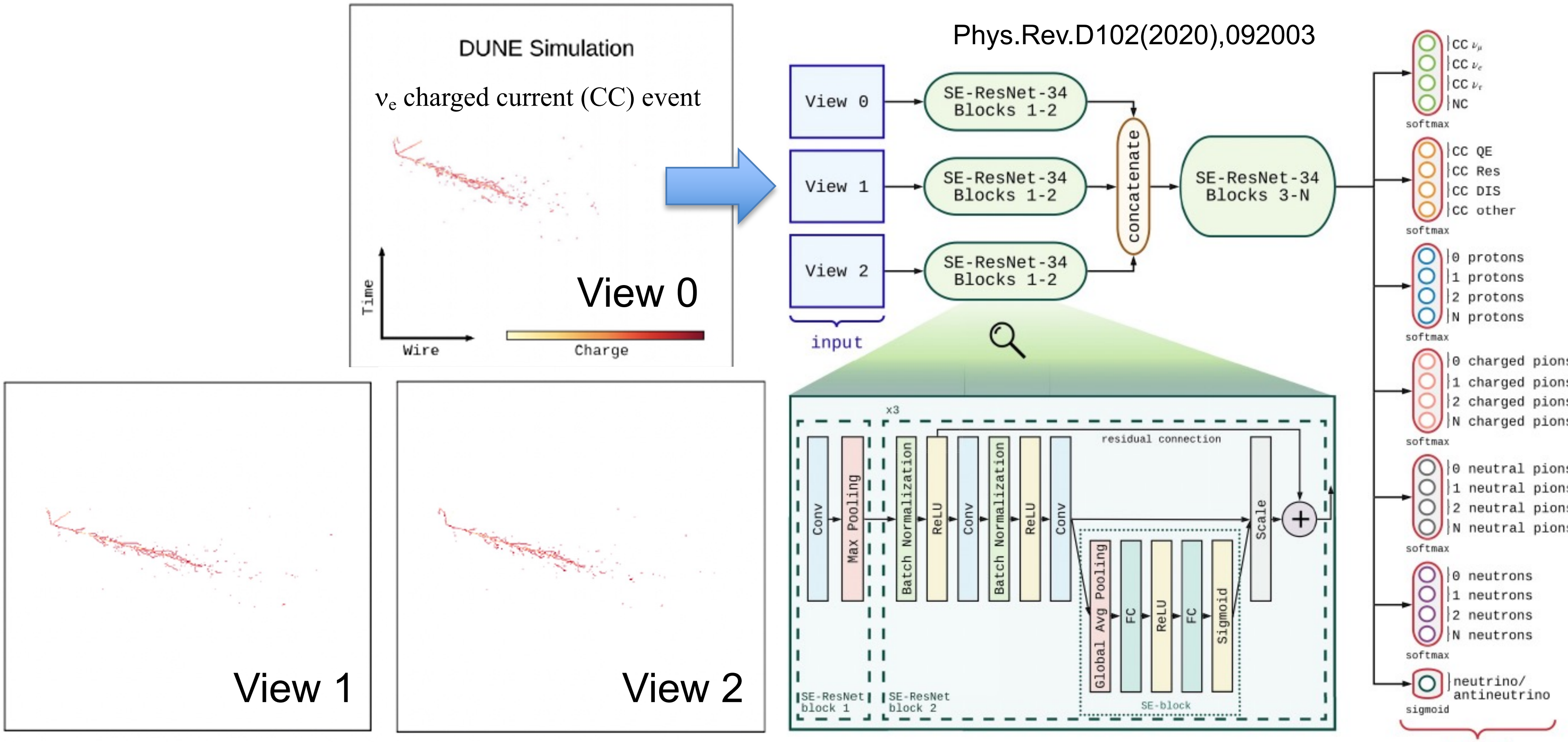
- DUNE's high-resolution LArTPC pixel map readout is ideal for image processing neural networks to reconstruct neutrino events
- Developing AI based Reconstruction Chain:
  - Energy, Direction, Vertex (regression, CNN)
  - Particle ID, Neutrino flavor ID (classification, CNN, Transformer)
  - Shower/Track Clustering (image segmentation, CNN, GNN)
- Goals: Performance, Robustness, Interpretability





Event display at ProtoDUNE-SP

Convolutional Neural Network (CNN) for classification and regression



Uses the 3 x 2D readout images, one for each wire/strip-plane, directly as input to a ResNet CNN architecture, then merges information across the 3 planes and uses a fully connected layer at the end for neutrino flavor classification or energy regression

- DUNE's high-resolution LArTPC images are challenging to process due to the large number of pixels
- CNNs are deep neural networks take raw pixel values input
- To reduce the number of parameters, CNNs apply convolutional filters to small regions of an image and then combine the features from these filters to produce the final decision
- Use the 3 x 2D readout images, one for each anode plane, as input to a ResNet CNN

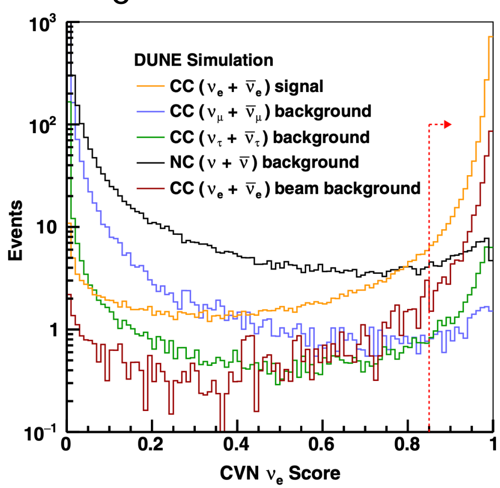
Event Classification CNN identifiers in DUNE FD HD

- Convolutional Neural Network (CNN)-based classifier ("CVN") to tag neutrino flavor, for both Horizontal-Drift FD (Phys. Rev. D 102, 092003, 2020) and Vertical-Drift FD (arXiv:2312.03130)
- Identify ν_μ charged current (CC), ν_e CC and neutral current (NC) events
- Basis for sensitivity projections

CVN for HD, ν_e CC identification, neutrino beam (FHC)

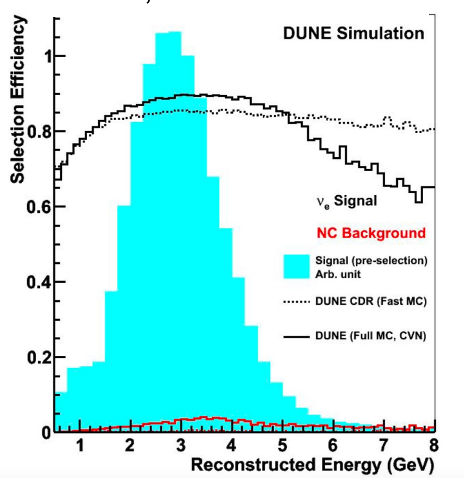
CVN for VD, ν_e CC identification, Neutrino beam (FHC)

ν_e score



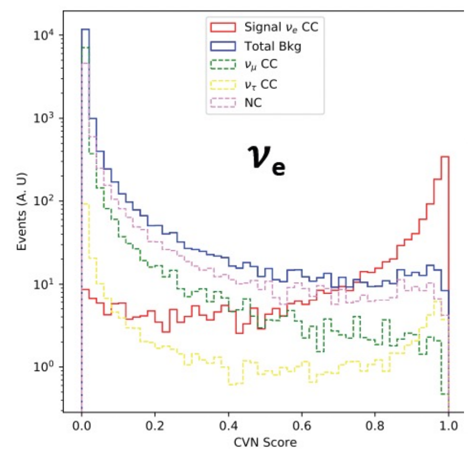
Phys.Rev.D 102 (2020) 9, 092003

ν_e selection efficiencies in HD, TDR vs. CDR



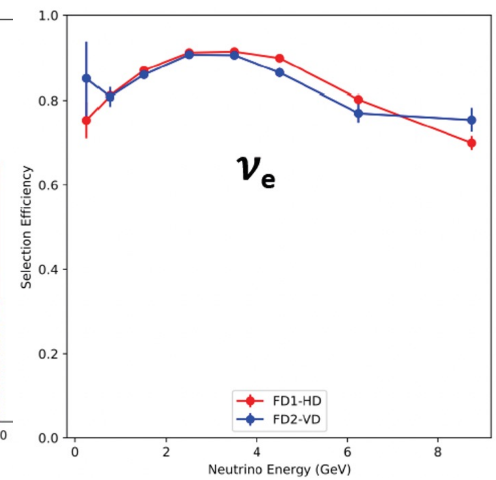
Performance is better than DUNE CDR assumptions

ν_e score



VD TDR, arXiv:2312.03130

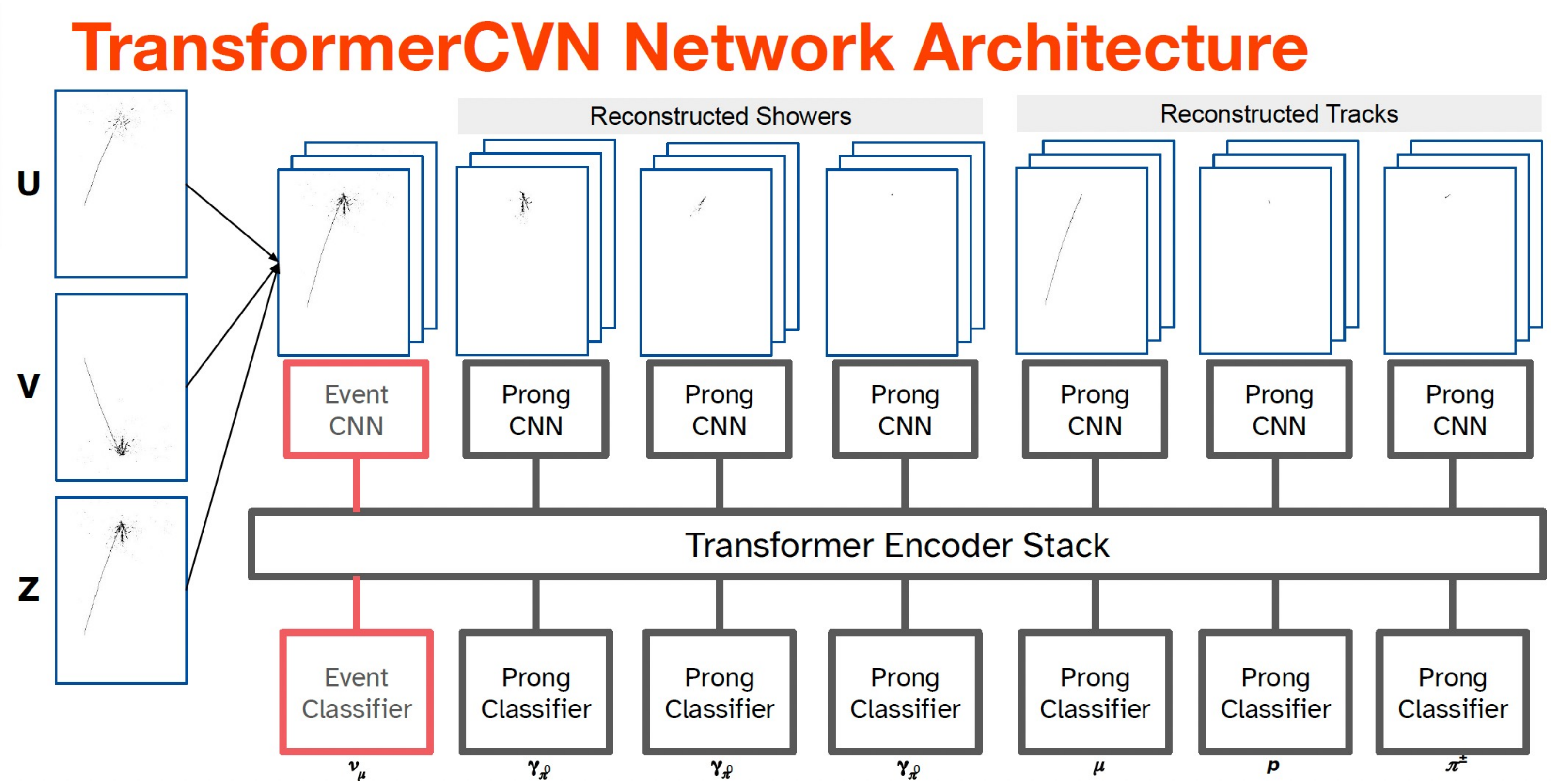
ν_e selection efficiencies in HD and VD



VD CVN has similar efficiency as HD

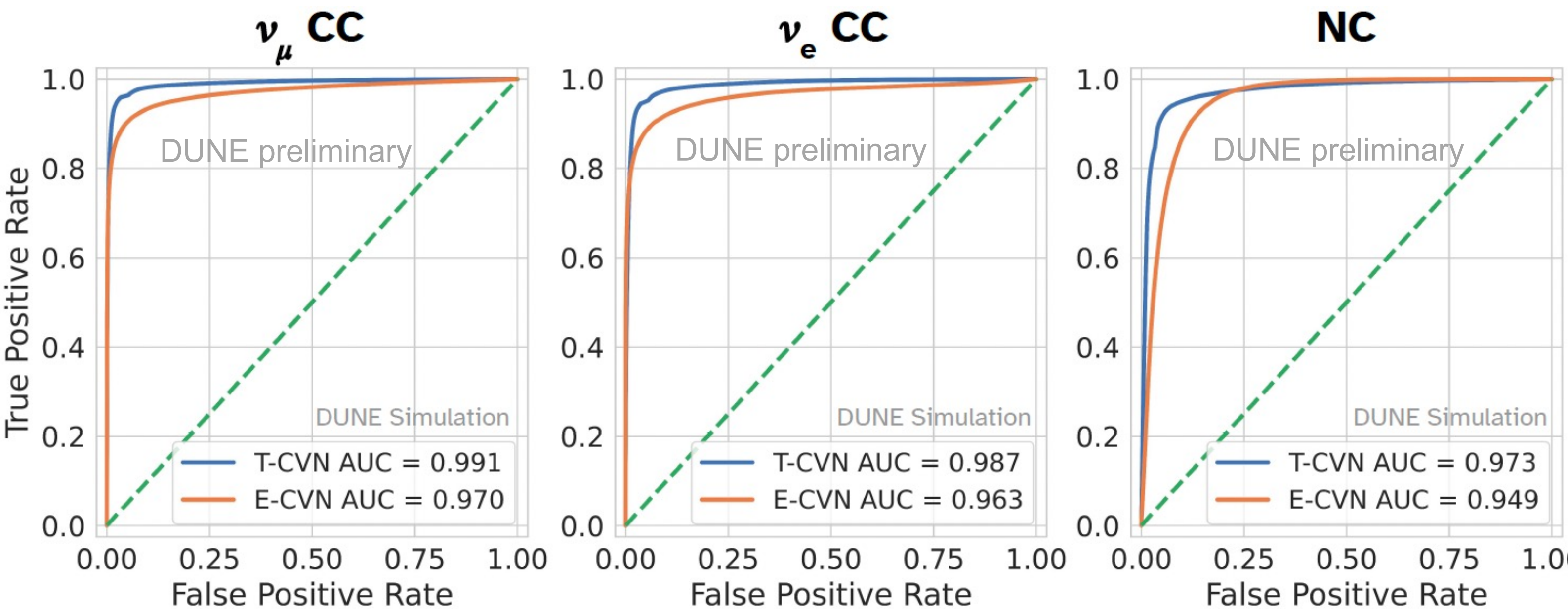
Transformer CNN for Event and Particle Identification

- Transformer: attention based network, foundation of ChatGPT, ideal for training on variable-length collection of object such as prongs (shower/track reconstructed by Pandora)
- Uses both event and prong images as inputs, identifies neutrino flavor and each particle simultaneously.
- Attention mechanisms automatically focus training and evaluation on image regions important to the final decision, significantly reducing the computing burden and enhancing training performance
- Attention mechanisms also provides interpretability, making deep learning more than just a "black box"

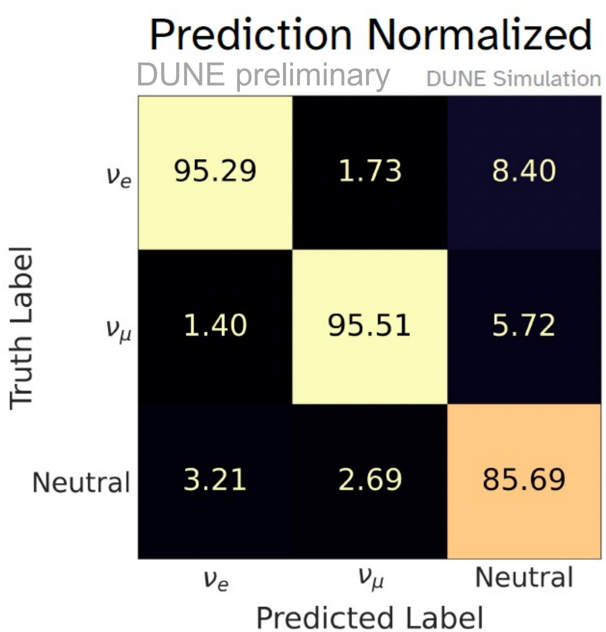


Event ROC Curves

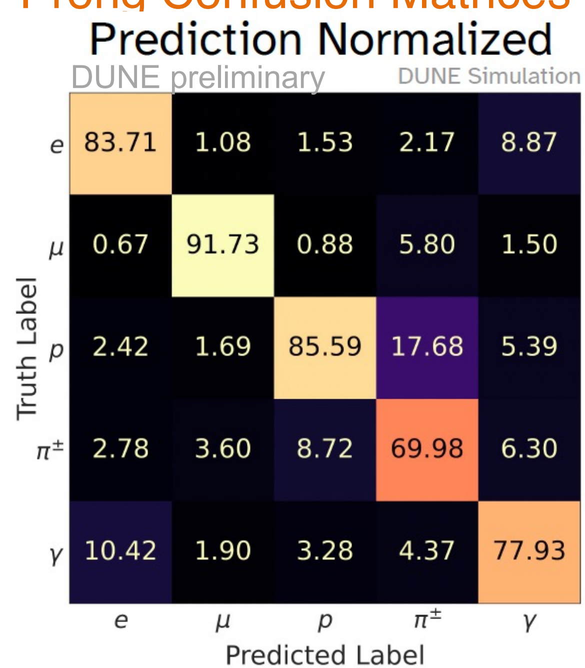
T-CVN = Transformer CNN, E-CVN = CVN



Event Confusion Matrices

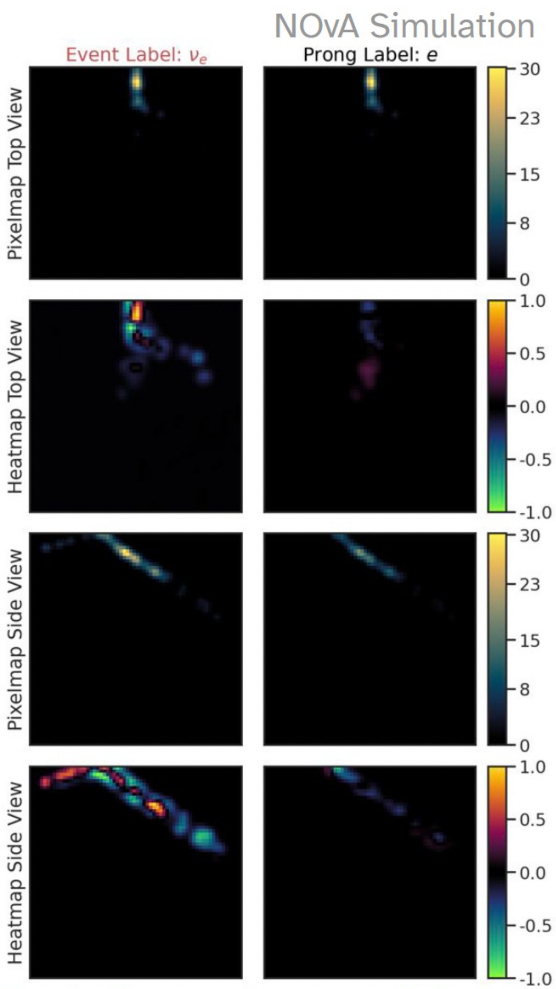


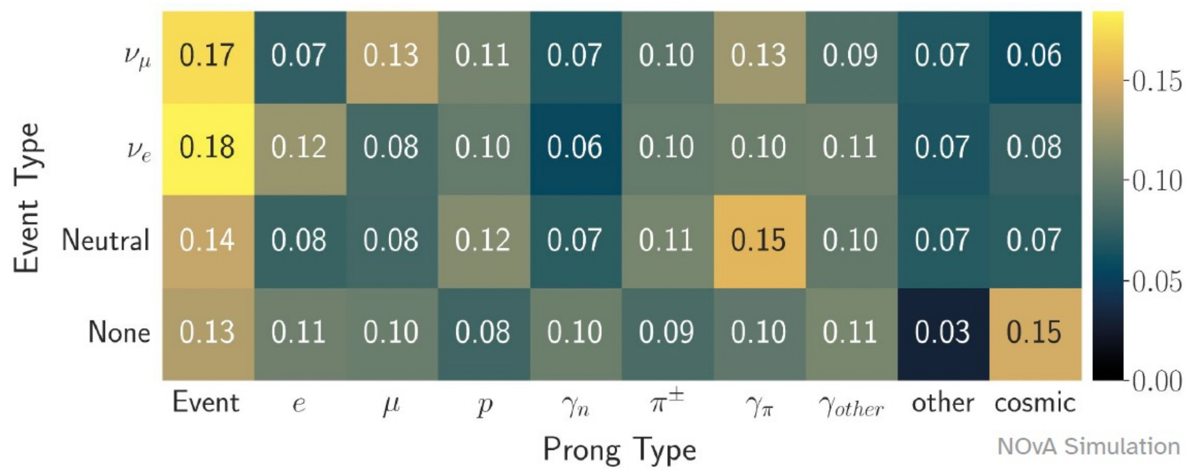
Prong Confusion Matrices



Interpretability

- Attention scores indicate importance of different elements to the network output → diagnose neural network and explain decision
- Identify image regions that are important to the final decision; analyze correlations between inputs and outputs, as well as among outputs





- e, μ important for corresponding CC events.
- p and π^0 important for NC.

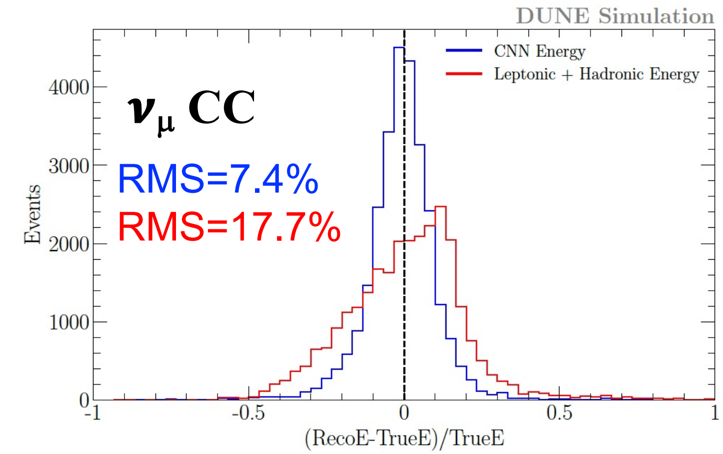
Red: more likely to predict the given flavor/particle type with more energy in that location.
Blue: less likely to predict if there is more activity (anti-correlation).

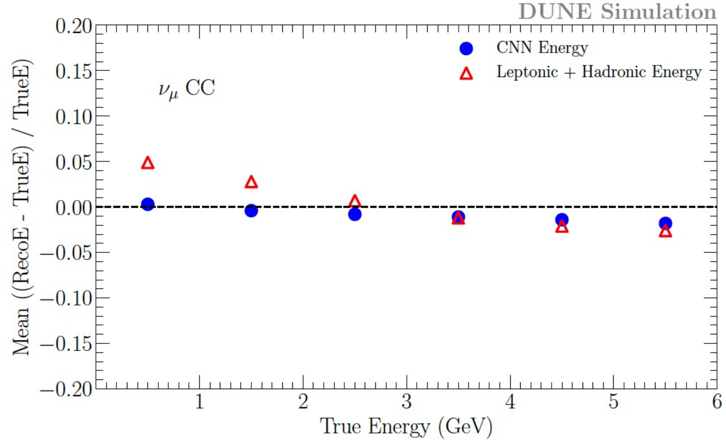
Note: These interpretability studies come from NOvA (arxiv2303.06201), have not been conducted yet for DUNE simulation.

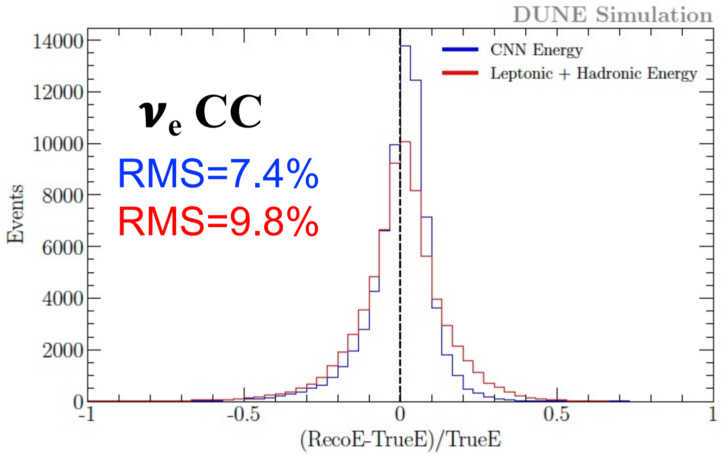
ν_e CC and ν_μ CC Event Energy

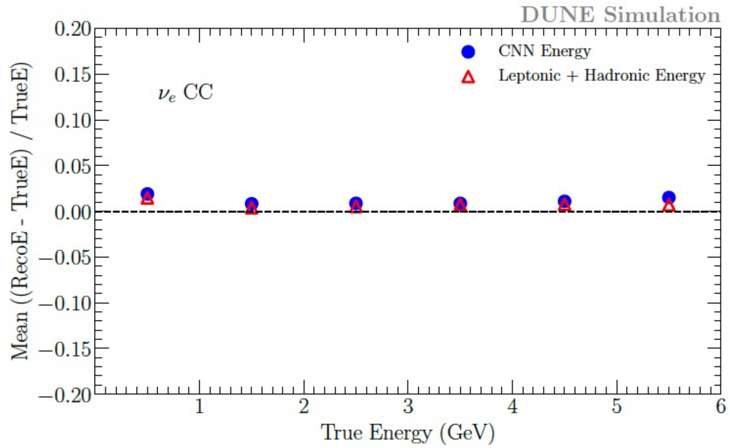
- CNN with linear output regression for event energy, optimizing resolution $(E_{reco} - E_{true})/E_{true}$
- Weighted events by energy to reduce energy dependent bias in training
- Better resolutions than leption+hadronic energy method, less energy dependent bias with energy-reweighted training

arXiv:2012.06181



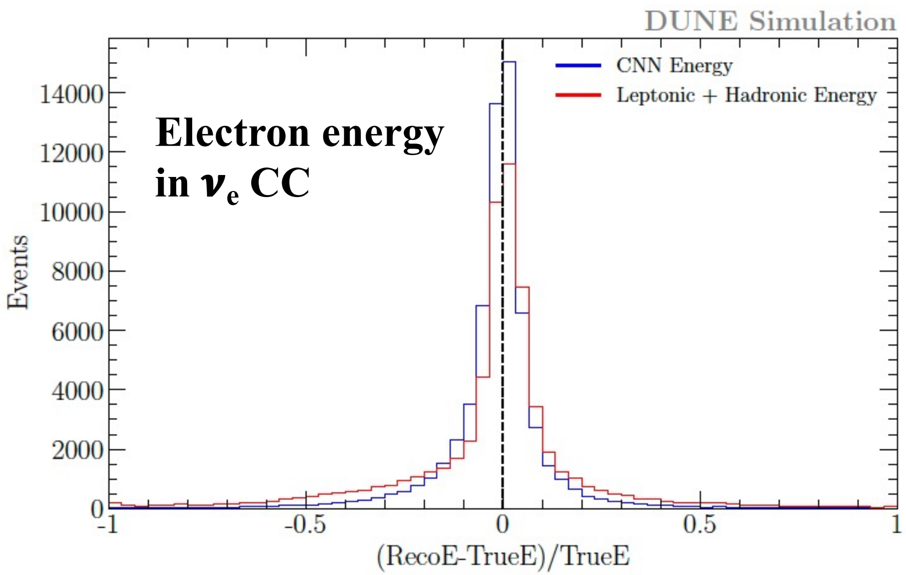


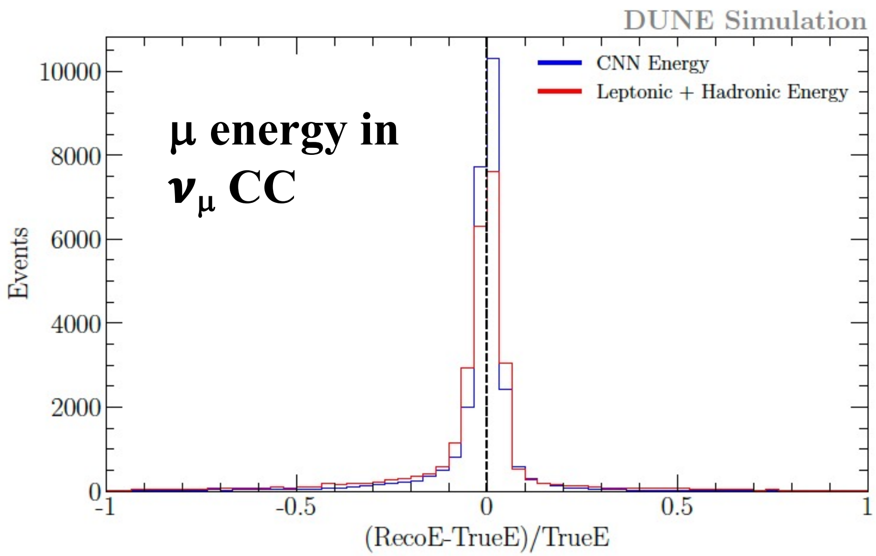




Particle Energy Reconstruction

- Regression CNNs for final state particle energies
- Trained on clustered lepton shower/track pixelmaps produced by Pandora

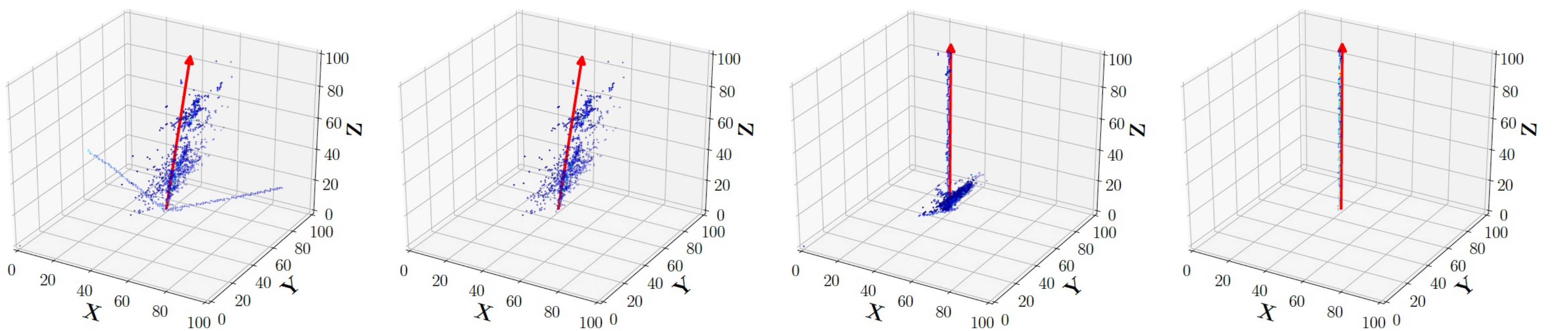




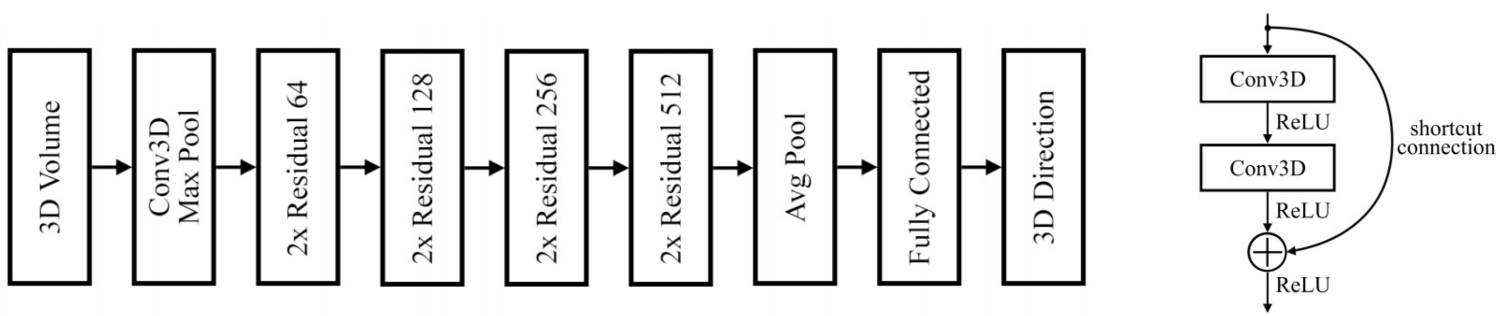
3-D Particle Direction Reconstruction

- Direction regression heavily dependent on 3-D geometry
- Designed a 3-D CNN to reconstruct particle directions.
- 3-D image constructed from the 3x2D detector images
- Train direction CNNs on full-event pixelmaps or clustered lepton shower/track pixelmaps

arXiv:2012.06181



(a) Full-event ν_e CC (b) Lepton-only ν_e CC (c) Full-event ν_μ CC (d) Lepton-only ν_μ CC

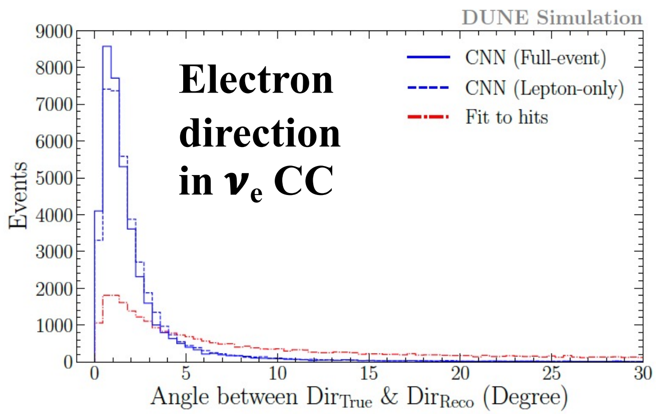


(a) Direction Regression (b) Residual block

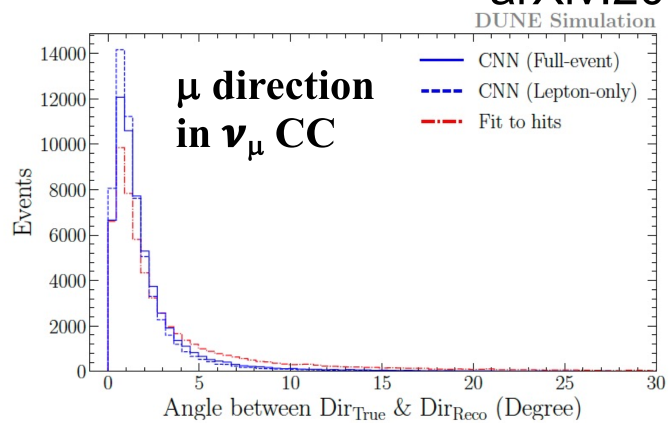
Particle Direction Reconstruction

- 3D CNNs beat traditional fit-to-hits method (PCA) with better electron and muon resolutions in all energy regions
- 3D CNN trained with full-event pixelmaps shows comparable performance to that trained with clustered lepton shower/track pixelmaps → extract particle kinematics without clustering/tracking

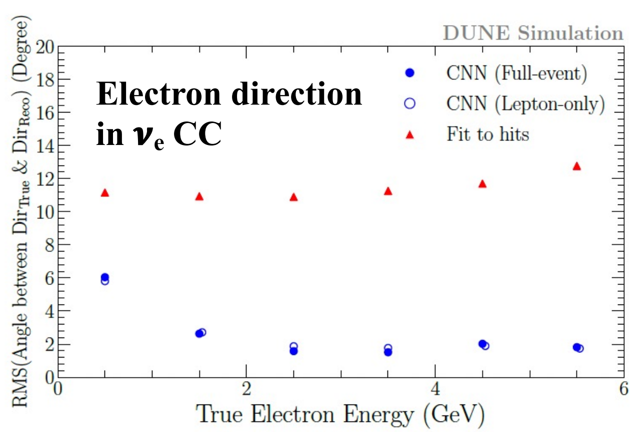
arXiv:2012.06181



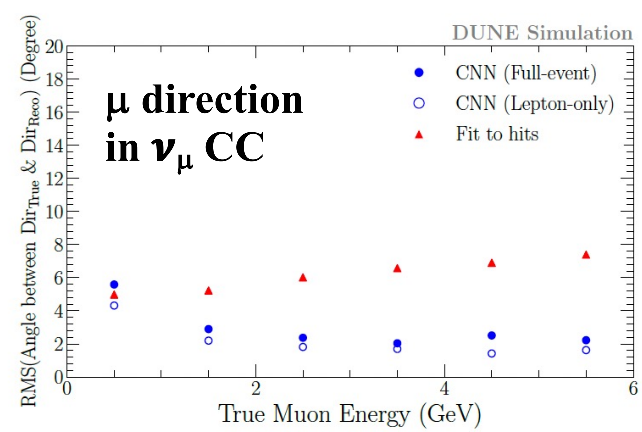
(a) Angular resolution for ν_e CC



(b) Angular resolution for ν_μ CC



(c) Energy dependency for ν_e CC

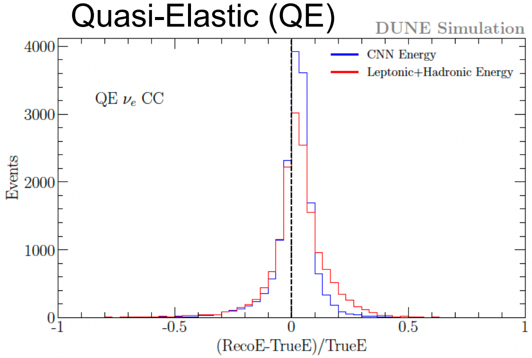


(d) Energy dependency for ν_μ CC

Neural Network Robustness Tests

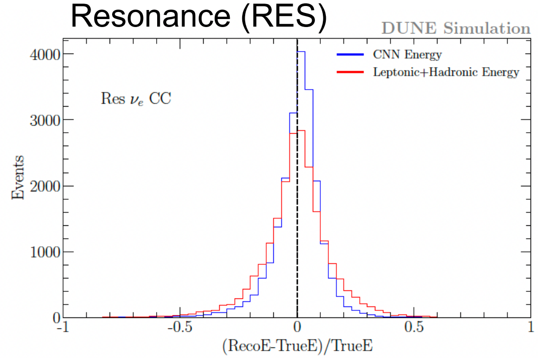
- CNNs show robustness against neutrino interaction modes
- GENIE versions have small effects in CNNs
- Robustness studies still on going

Quasi-Elastic (QE)



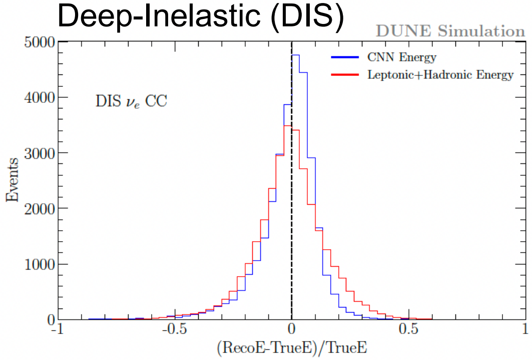
(a) ν_e CC energy QE

Resonance (RES)



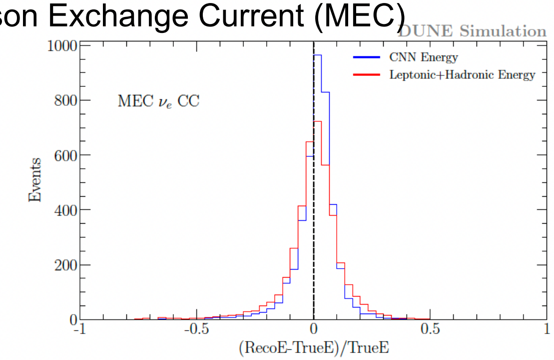
(b) ν_e CC energy Res

Deep-Inelastic (DIS)



(c) ν_e CC energy DIS

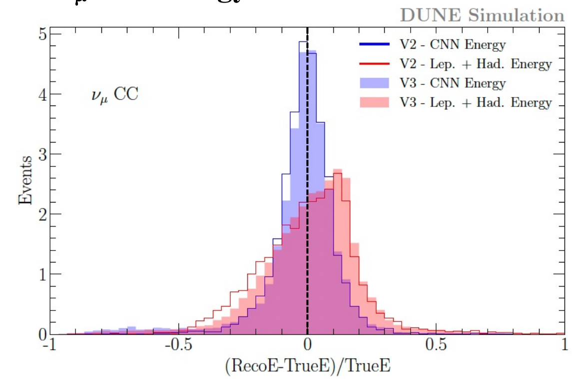
Meson Exchange Current (MEC)



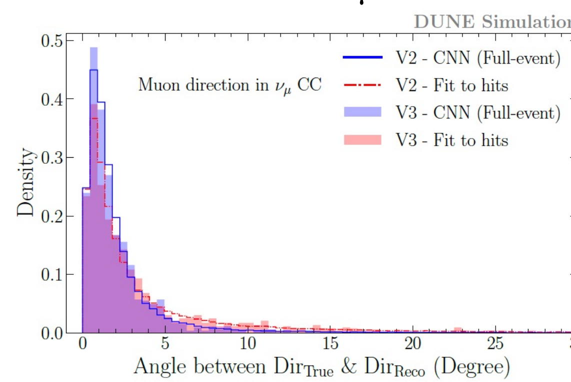
(d) ν_e CC energy MEC

ν_e Event Energy vs. interaction modes

ν_μ CC Energy

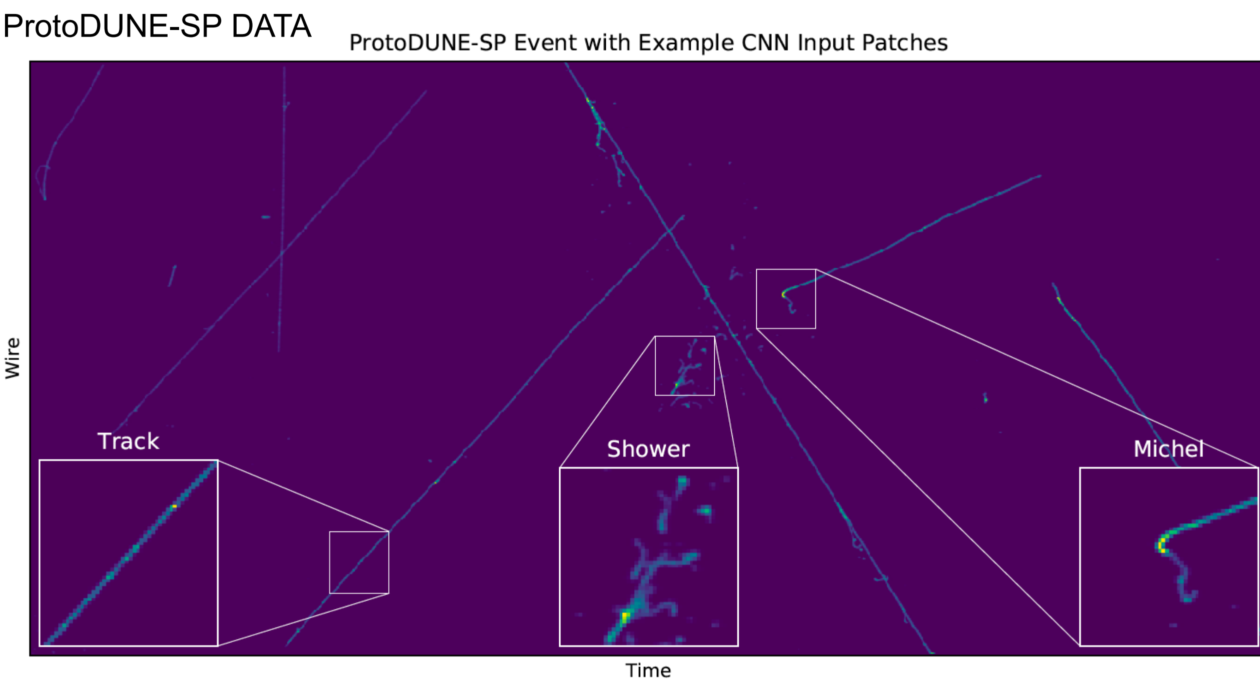


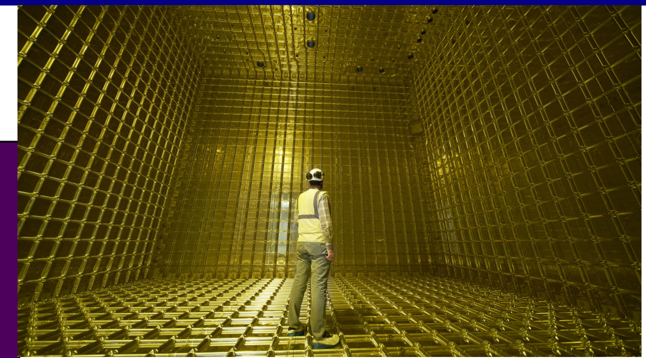
μ direction in ν_μ CC

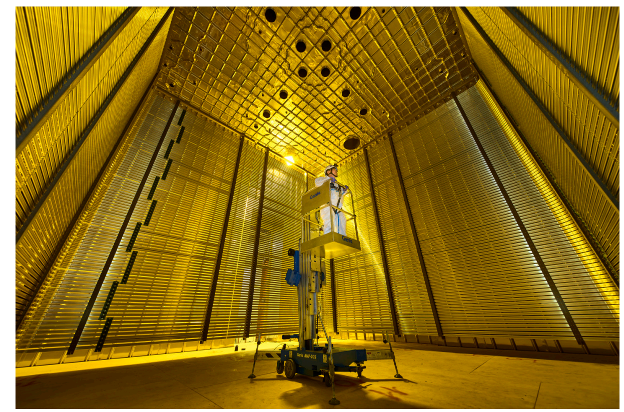


GENIE version 2.12.10 vs 3.0.4

CNN for Shower/Track Separation in ProtoDUNE



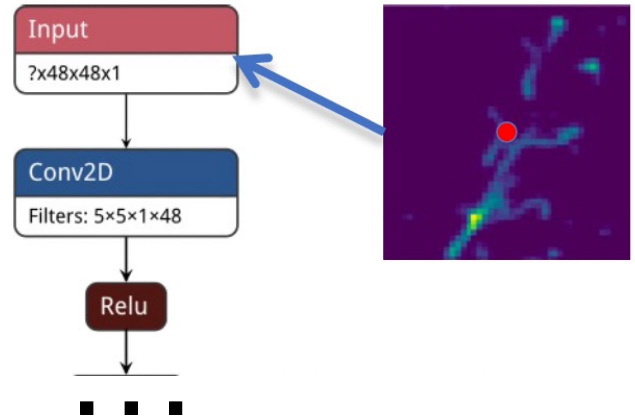




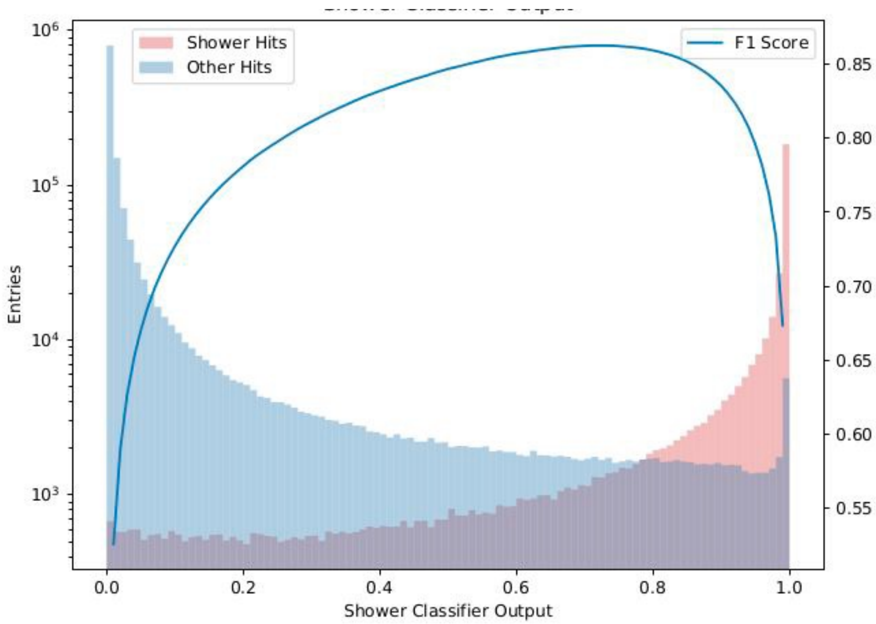
- ProtoDUNE-HD (SP in Phase I) and VD are two large DUNE prototype detectors at CERN
- ProtoDUNE-SP has collected test beam and cosmic ray data
- Use CNN to classify hits (pixels on LArTPC image) from Shower, Track and Michel electrons in ProtoDUNE-SP
  - Showers: Energy deposit pattern caused by electron, gamma, etc
  - Tracks: Energy deposit pattern caused by muon, pion, etc
  - Michel electrons: Low energy electron from muon decays
- Hit classification used in clustering and PID

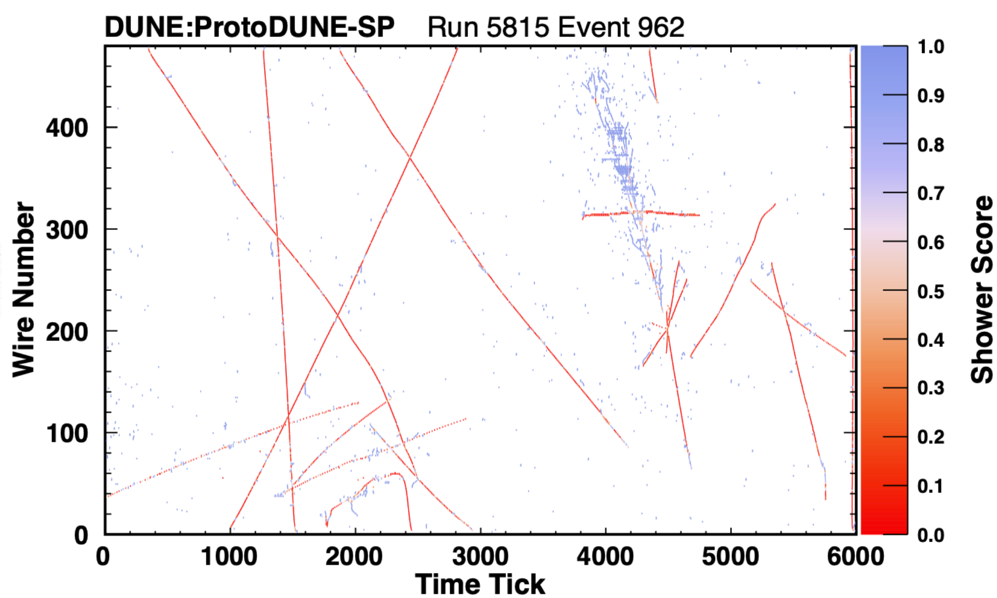
CNN for Shower/Track Separation in ProtoDUNE

- The inputs are 48-pixel images centered on the reconstructed hit to be classified
- Output is the classification of hit: from shower? Track? Michel electron?
- Successful identify hits and cluster shower/track



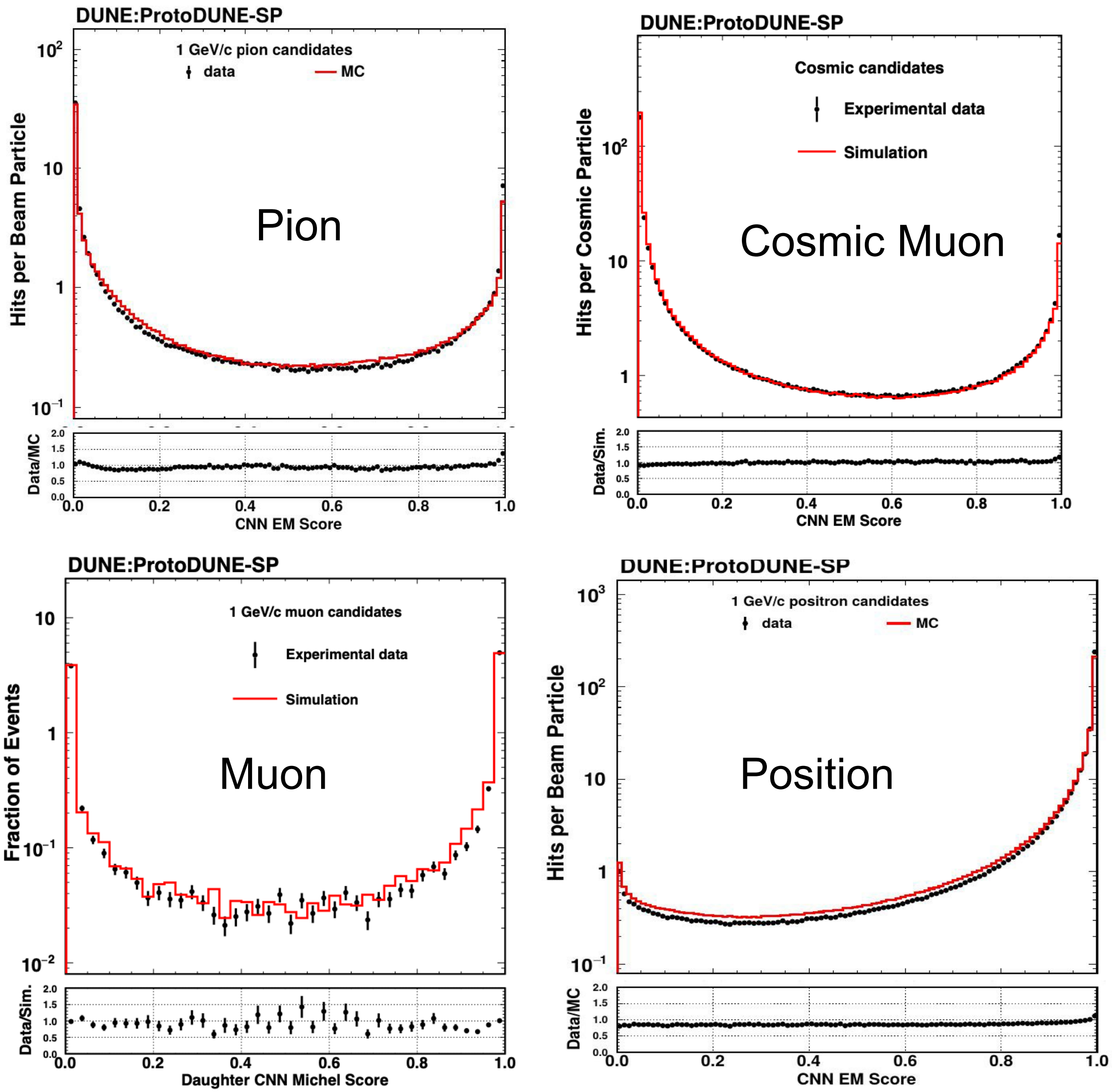
Shower Classifier Scores for each hit





Eur.Phys.J.C 82 (2022) 10, 903

Performance of CNN in ProtoDUNE Data



Hit level EM/Michel shower scores

- Test shower classifier scores for different particle species in the ProtoDUNE-SP
- Reasonable DATA/MC agreement

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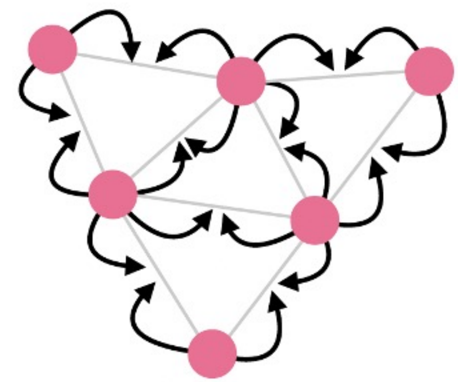
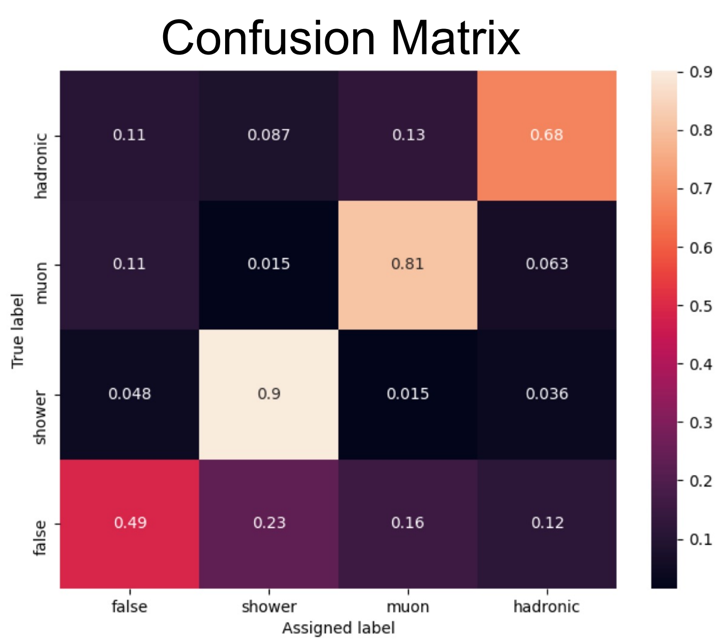
Graph Neural Network for Object Reconstruction in LArTPC (ExtExa.TrkX project)

- Graph Neural Networks (GNN): define input data as a graph represented by nodes and edges, convolutions on nodes and edges rather than the entire pixel to speed up training
- Successfully cluster LArTPC showers/tracks with GNN in ExtExa.TrkX project (a collaboration developing GNN reconstruction for HEP)
- Implementing under DUNE context





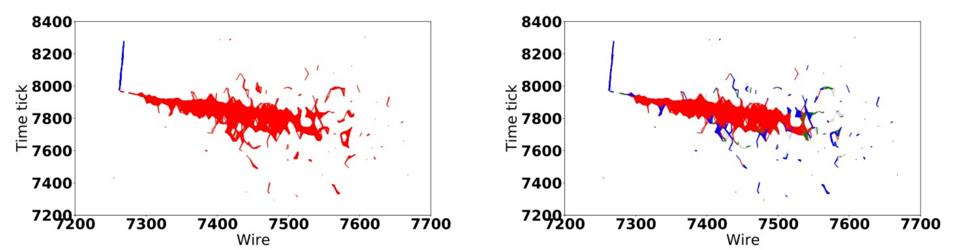


Figure 2. Example graph of a ν_e interaction (left: ground truth, right: model output). Shower-like edges are drawn in red, hadronic edges are drawn in blue, muonic edges are drawn in green and false edges are drawn in grey.

V Hewes, A. Aurisano etc,, EPJ Web of Conferences 251, 03054 (2021), arXiv:2403.11872

Summary

- Systematically developed most elements of the reconstruction chain for DUNE far detectors using deep-learning methods.
  - neutrino flavor ID, particle ID, neutrino energy reconstruction, particle energy reconstruction, particle direction reconstruction and shower/track clustering …
- Achieve very good selection efficiency and resolution
- Introduced Transformer/Attention to enhance performance and interpretability in Deep-Learning reconstruction
- Developing GNN, sparse neural networks and other new technologies to reduce computational burden
- Performing robustness tests with ProtoDUNE data and alterative simulation models

Thank you!