Deep-learning Event Reconstruction in DUNE Far Detector

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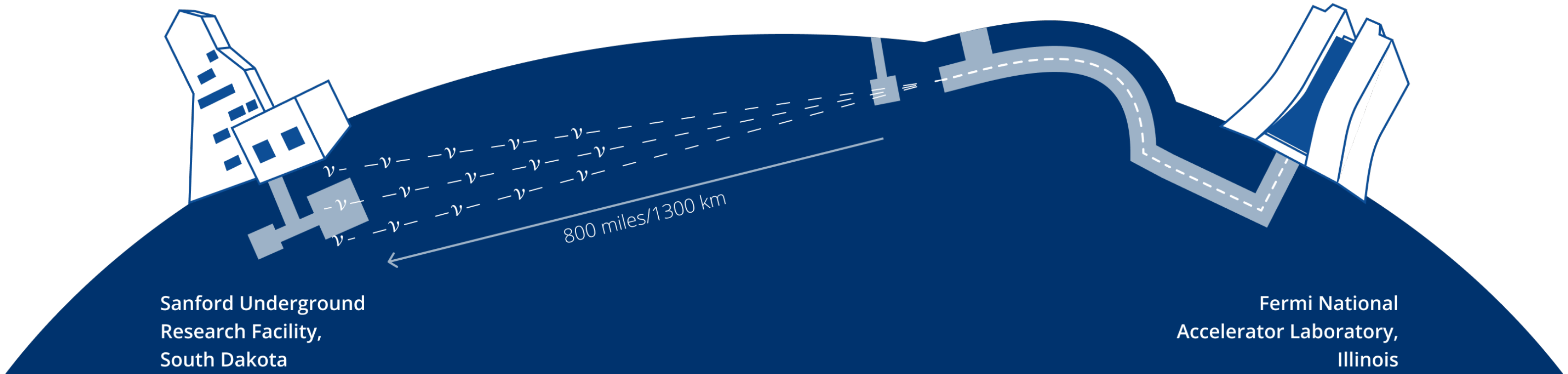
April 10th, 2024

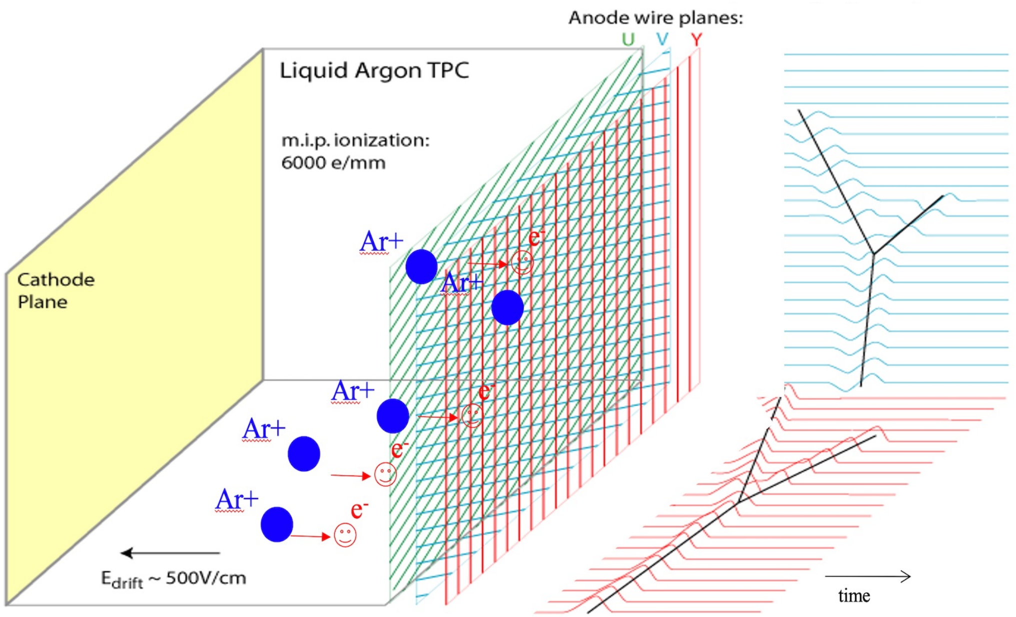
Background

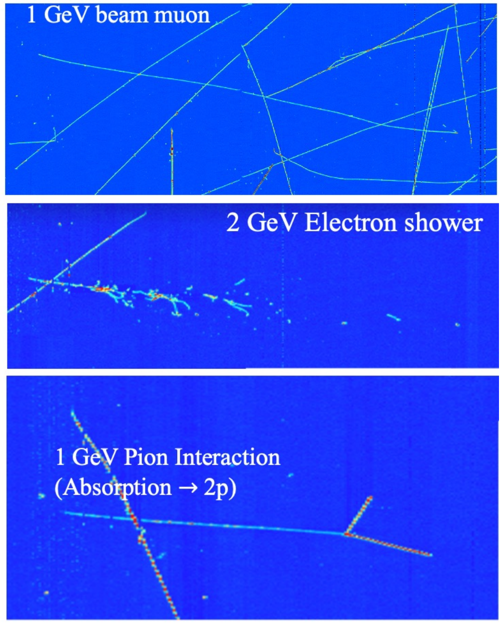
- The Deep Underground Neutrino Experiment (DUNE)
  - In the framework of three-active-neutrino mixing, the charge parity phase, the neutrino mass ordering, and the octant of θ_{23} remain unknown
- DUNE is a next-generation long-baseline neutrino oscillation experiment
  - Aims to address above questions by measuring the oscillation patterns of ν_μ/ν_e and $\bar{\nu}_\mu/\bar{\nu}_e$ over a range of energies spanning the first and second oscillation maxima



DUNE Far Detector (FD): LArTPC

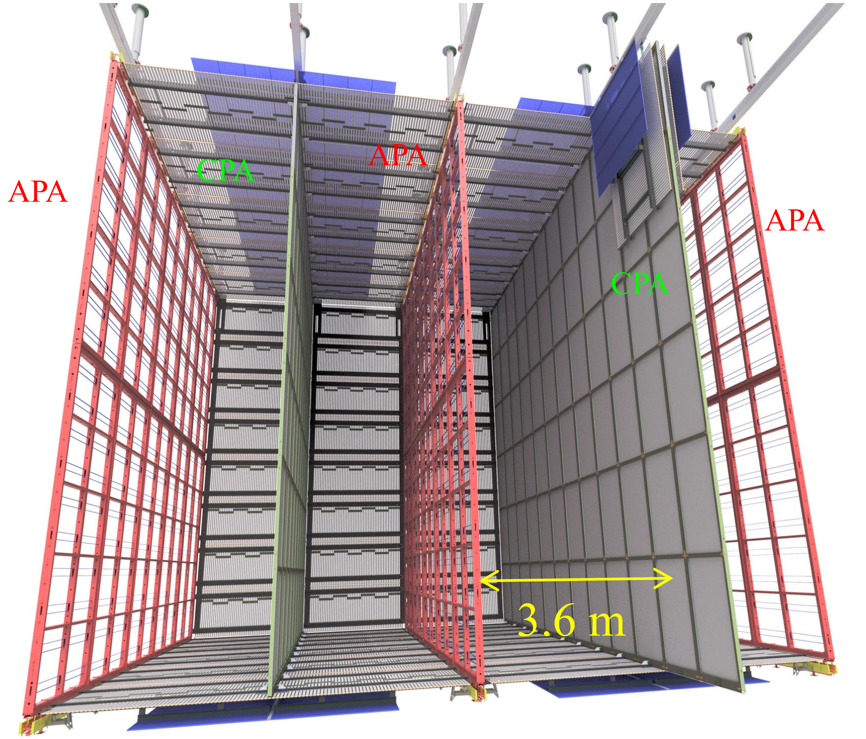
- High resolution 3D track reconstruction
  - Charged particle tracks ionize argon atoms
  - Ionized electrons drift to anode wires (~ms) for YZ-coordinate
  - Electron drift time projected for X-coordinate
- Argon scintillation light (~ns) detected by photon detectors, providing t_0
- Output: a 2-D pixelmap image for each readout plane

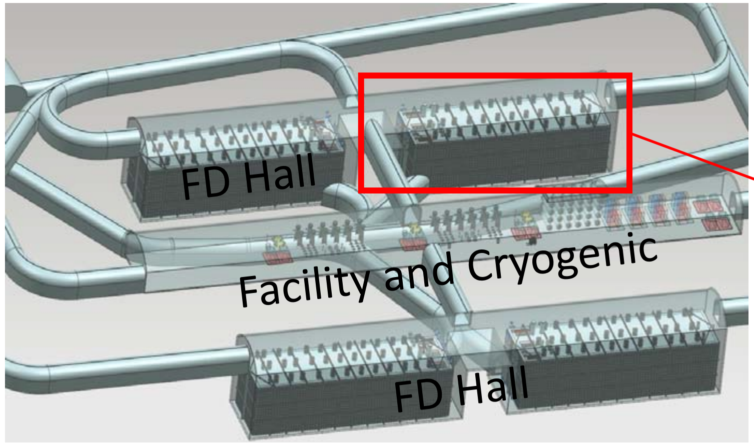


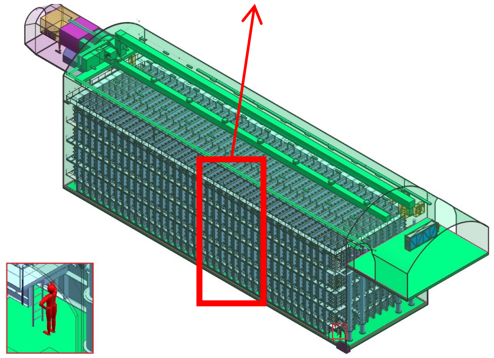


DUNE FD: Horizontal Drift (HD) LArTPC

- Four 17-kt modules deployed in stages
- 1st module will be horizontal-drift:
  - 18m x 19m x 66m
  - 3 readout planes, two introduction and one collection
  - Drift distance: 3.6 m, wire pitch: 5 mm
  - 4 drift volumes

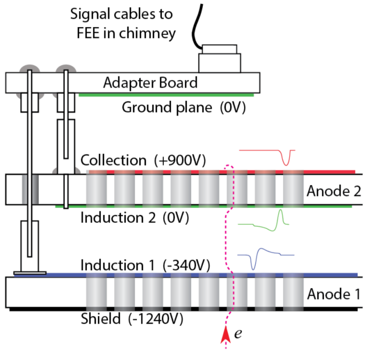


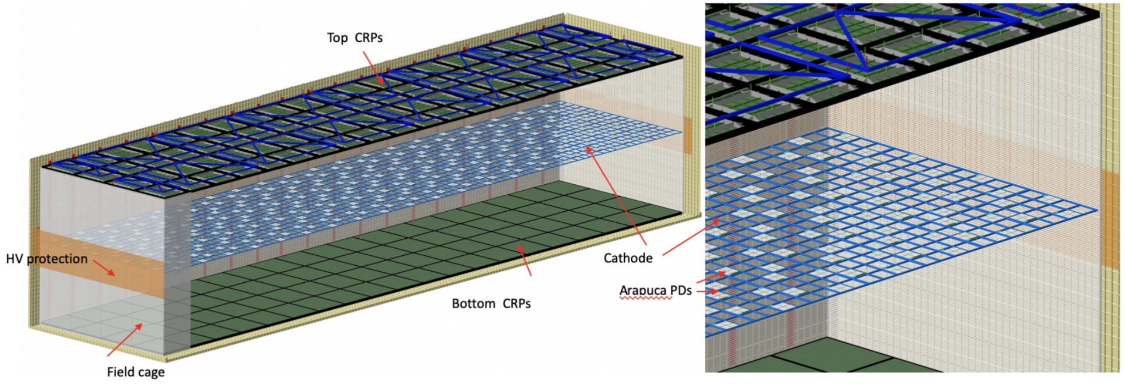


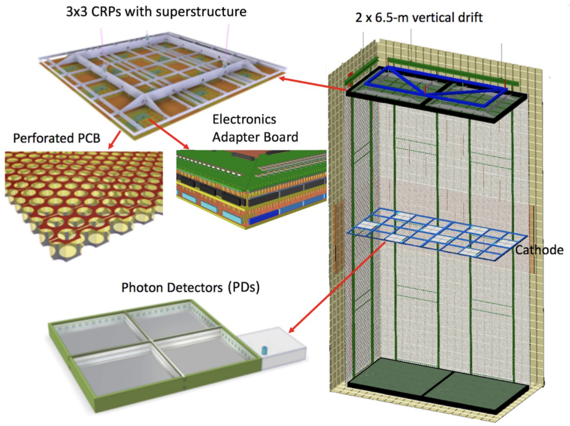


DUNE FD: Vertical Drift (VD) LArTPC

- 2nd DUNE FD module has a vertical drift (VD) path in contrast to HD
  - 2 drift volumes, cathode plane in the middle
  - Anode: a stack of perforated PCBs with 3 layers of readout etched electrode strips in different orientations
- Modular design allows easy assembly and production. Wires → Strips improves mechanical robustness

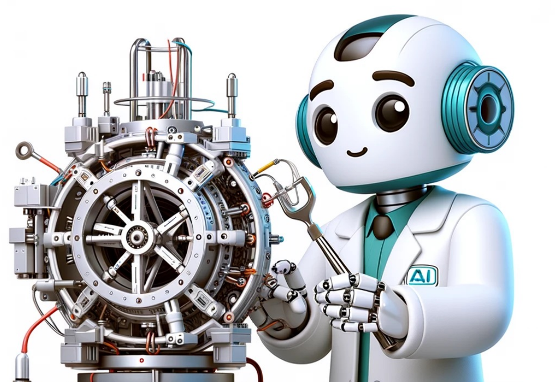






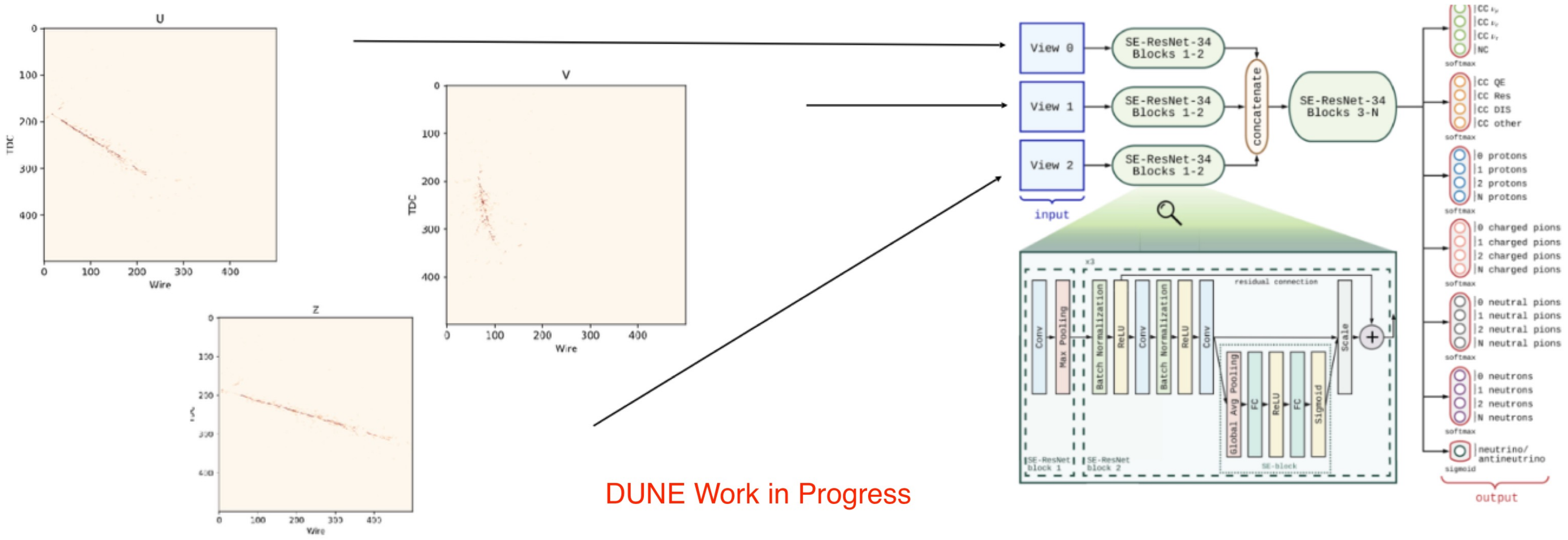
Motivations - AI Based Event Reconstruction Chain

- Traditionally, the reconstruction of neutrino events is expensive or inaccurate
  - Energies of electrons and hadrons are calculated from calorimetric energies and calibration factors
  - Directions of particles are reconstructed by fitting to detector hits
- A full AI based event reconstruction chain
  - The deep-learning based particle type, particle energy, vertices and momentum (energy + direction) reconstruction
- DUNE's pixel map readout is ideal for image processing neural networks to reconstruct neutrino events



Convolutional Neural Networks (CNNs) for Event Identification and Energy Reconstruction

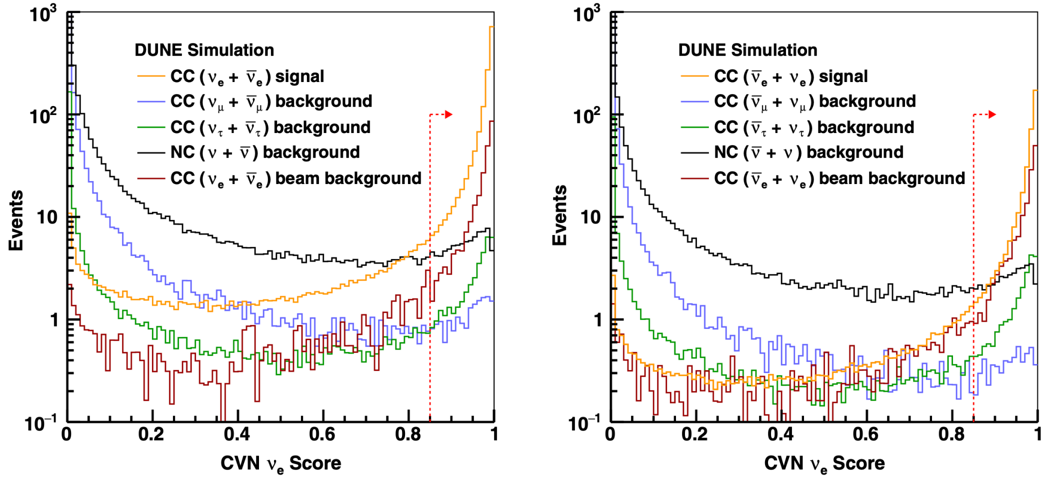
- CNNs are deep neural networks taking raw pixel values as the input and applying convolutional filters across the pixelmaps/images
  - Uses the 3 x 2D readout images, one for each wire/strip-plane, directly as input to a ResNet architecture
- CNNs then merge information across the 3 planes and use fully connected layers at the end for neutrino flavor classification or energy regression



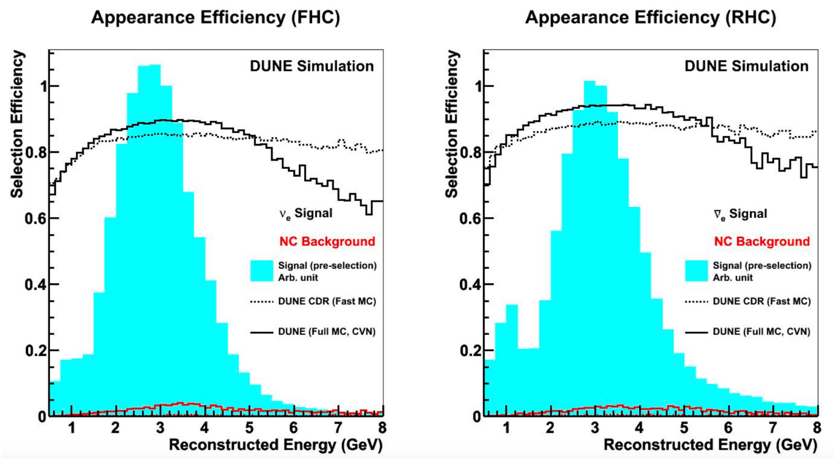
DUNE Work in Progress

Event Classification CNN identifiers in DUNE FD HD

- Convolutional Neural Network (CNN)-based classifier ("CVN") to tag neutrino flavor, main PID for HD Technical Design Report (TDR) analysis and basis for sensitivity projections [Phys. Rev. D 102, 092003, 2020]
- Identify ν_μ CC, ν_e CC and NC events



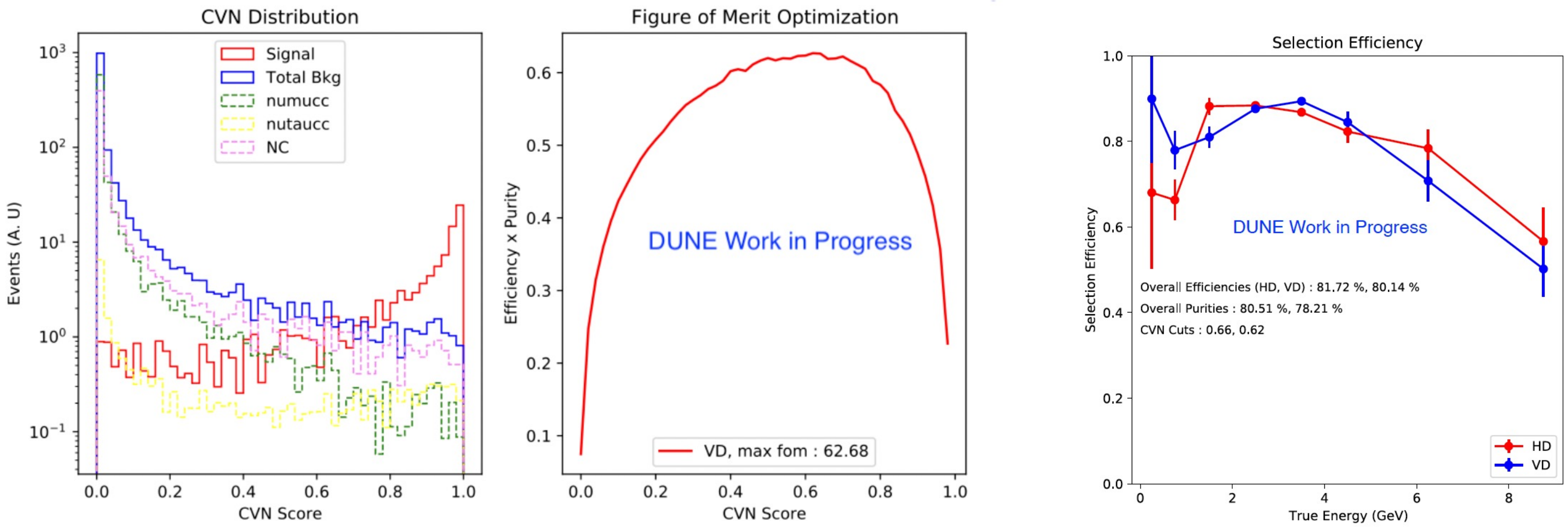
Phys.Rev.D 102 (2020) 9, 092003



Performance is better than DUNE CDR assumptions

Event Classification CNN identifiers in DUNE FD VD

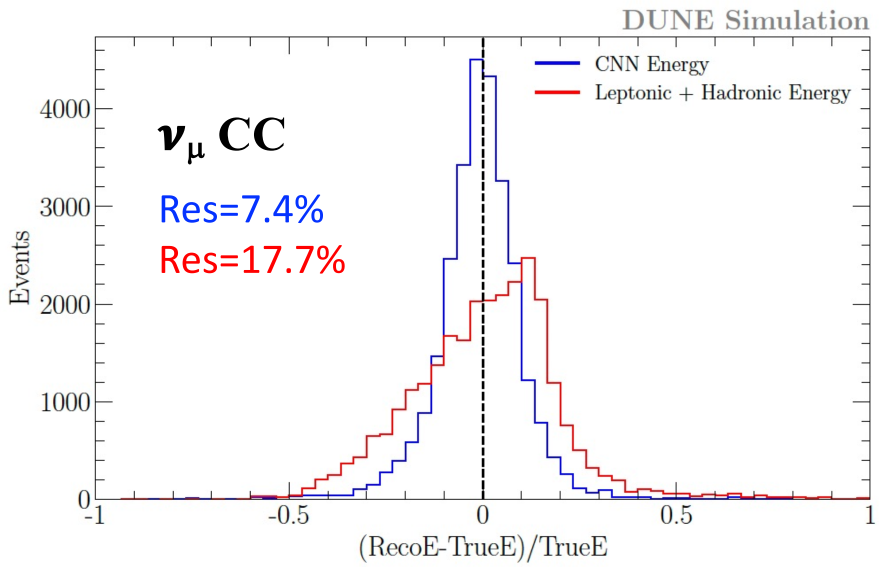
- Training on a fraction of planned simulated samples shows very similar performance as for HD
- Efficiency to tag CC ~90% near peak DUNE flux (~2.5-3 GeV) with overall purity ~80%
- Used as input for new VD-based sensitivity studies (technical design report analysis), similar results as HD

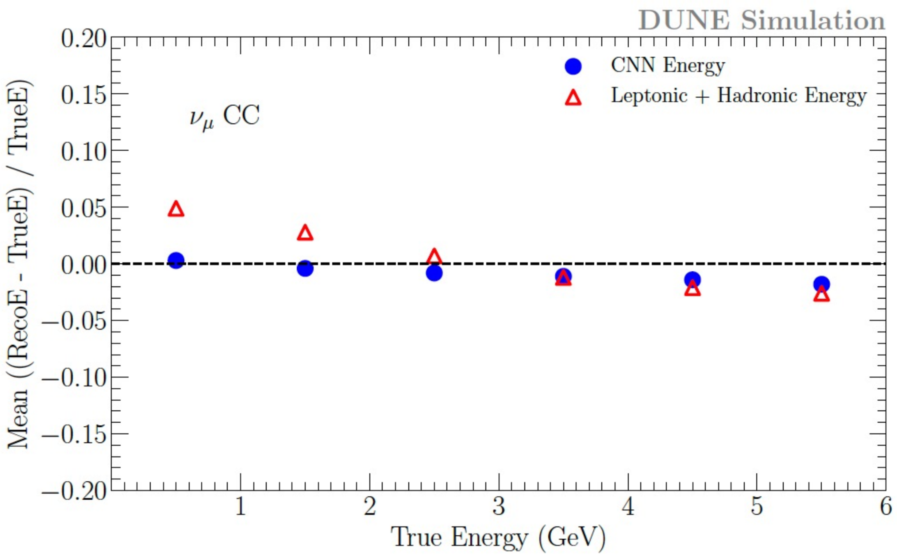


ν_e CC and ν_μ CC Event Energy in DUNE FD HD

- Regression CNN for event energy, optimizing resolution $(E_{reco}-E_{true})/E_{true}$
- Reweighted events to reduce energy dependent bias in training
- Better resolutions than lepton+hadronic energy method, less energy dependent bias with energy-reweighted training

arXiv:2012.06181





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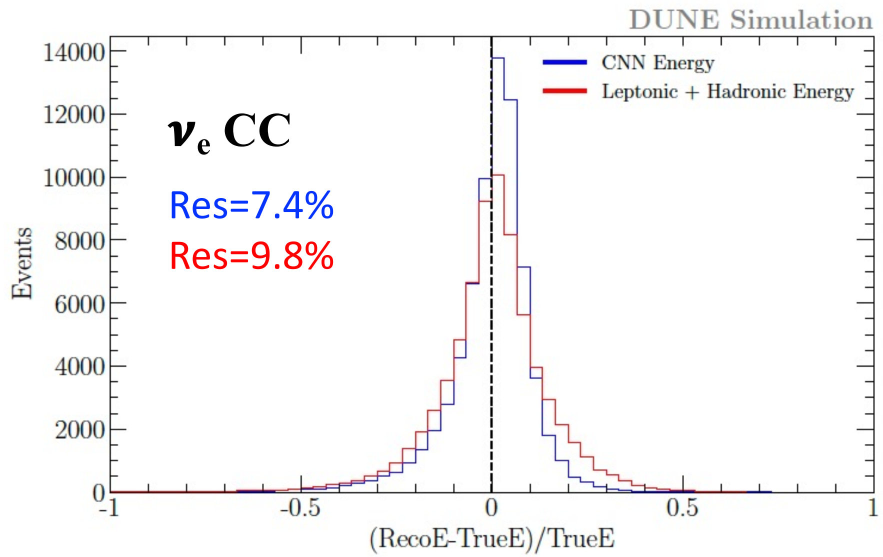
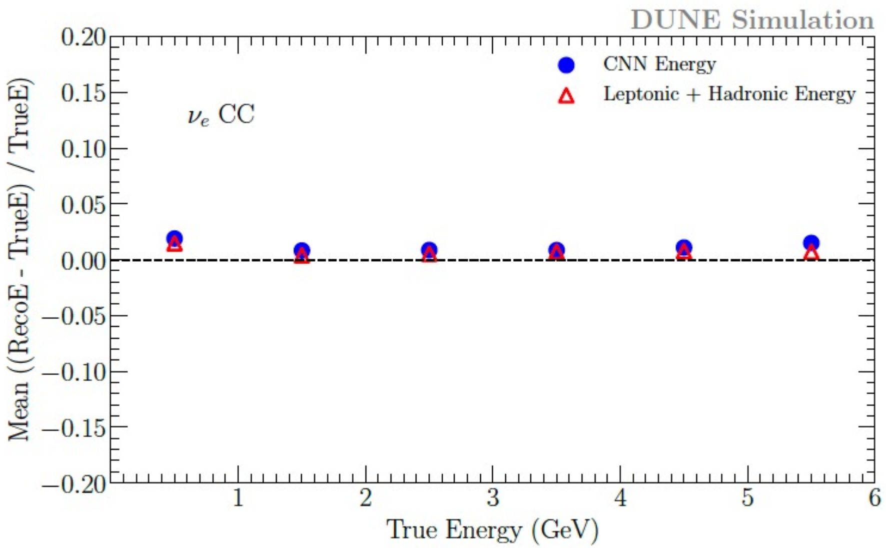
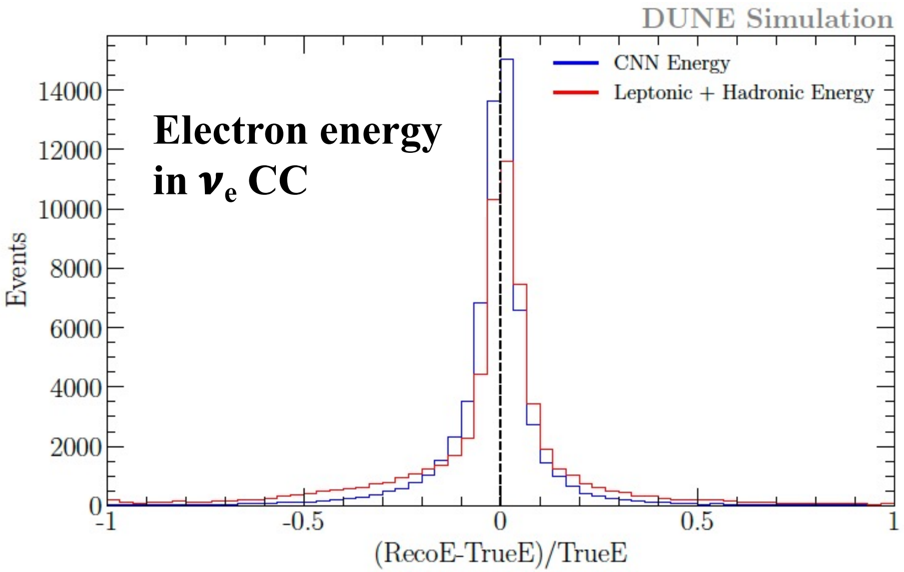
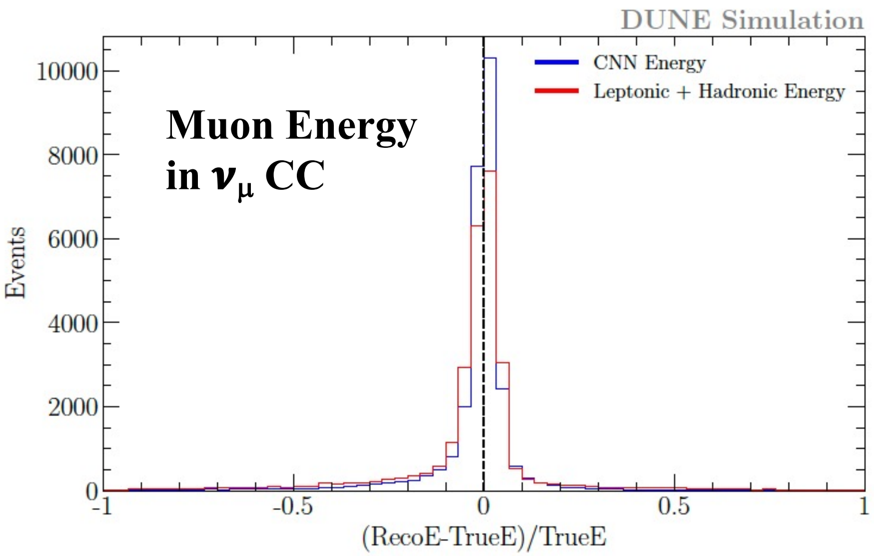




Final-state Particle Energy Reconstruction

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

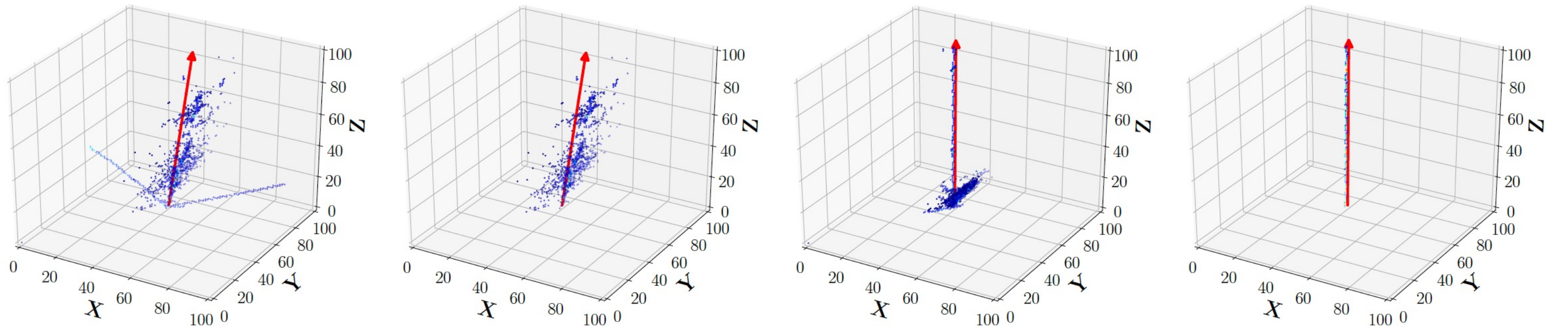




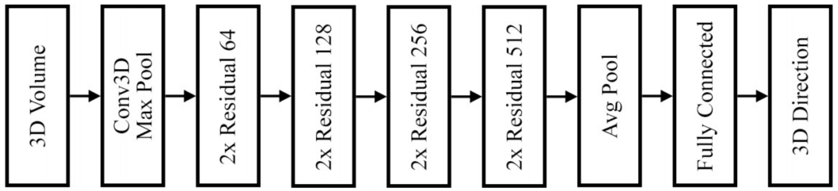
3D Particle Direction Reconstruction

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

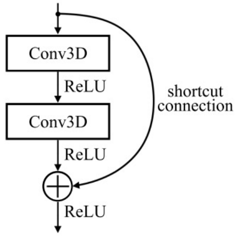
arXiv:2012.06181



(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

3D 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

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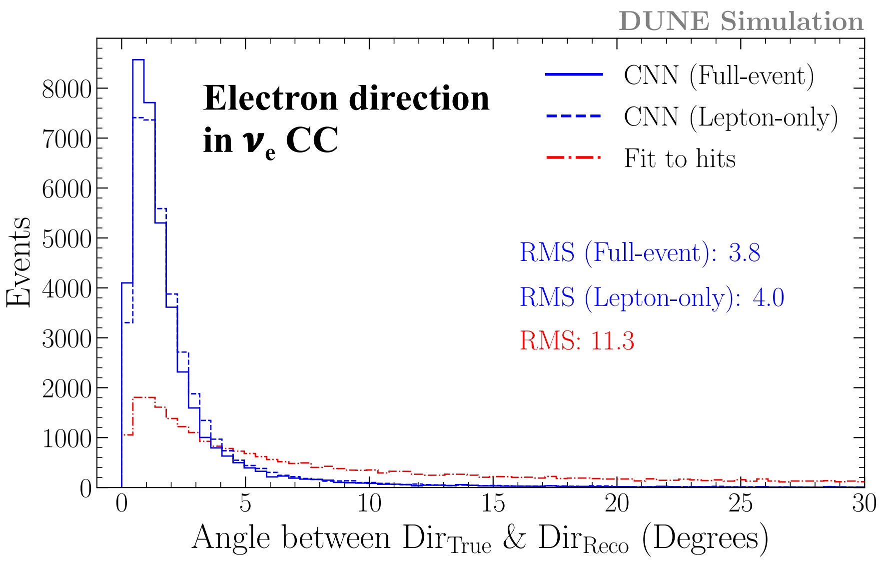

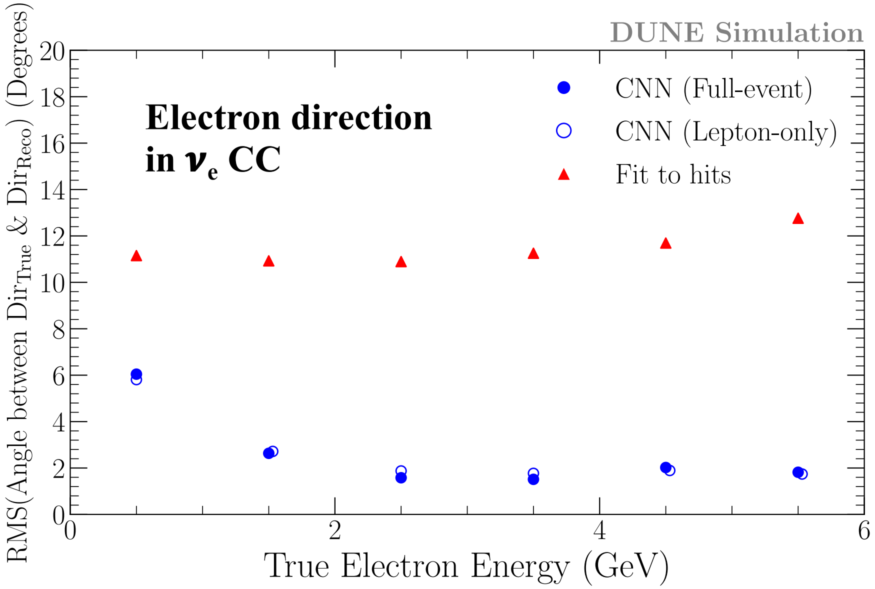

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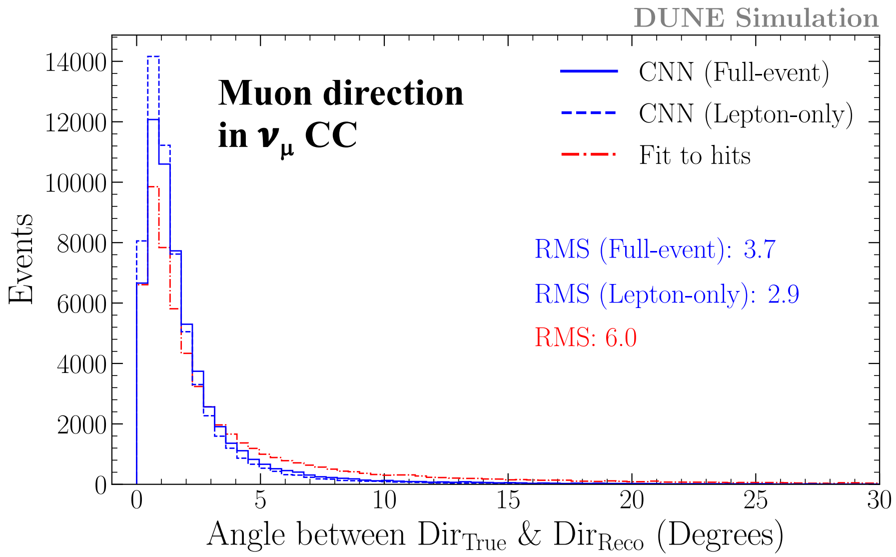
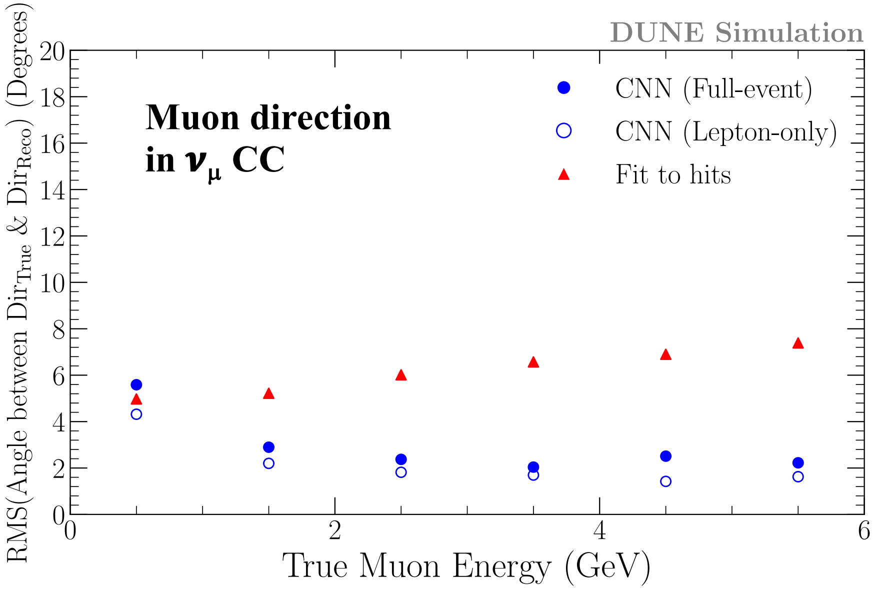
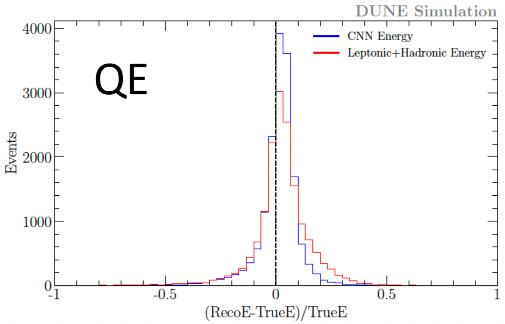


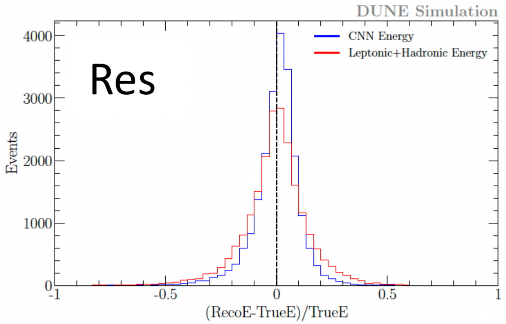


Neural Network Robustness Tests

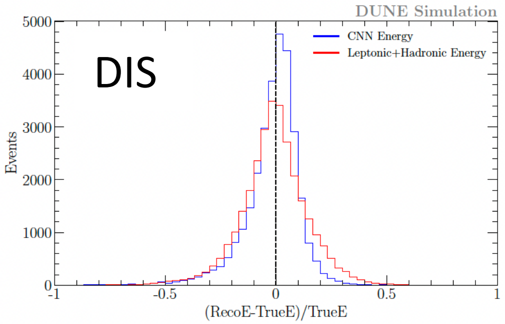
- CNNs show robustness against neutrino interaction modes
- Different GENIE versions have small effects on CNNs



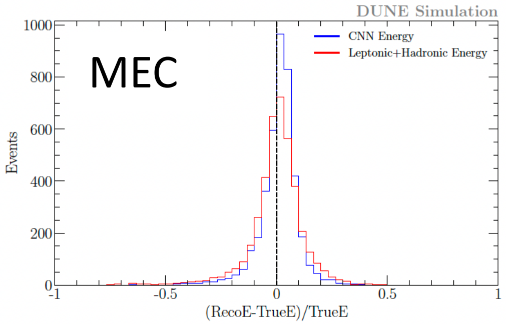
(a) ν_e CC energy QE



(b) ν_e CC energy Res

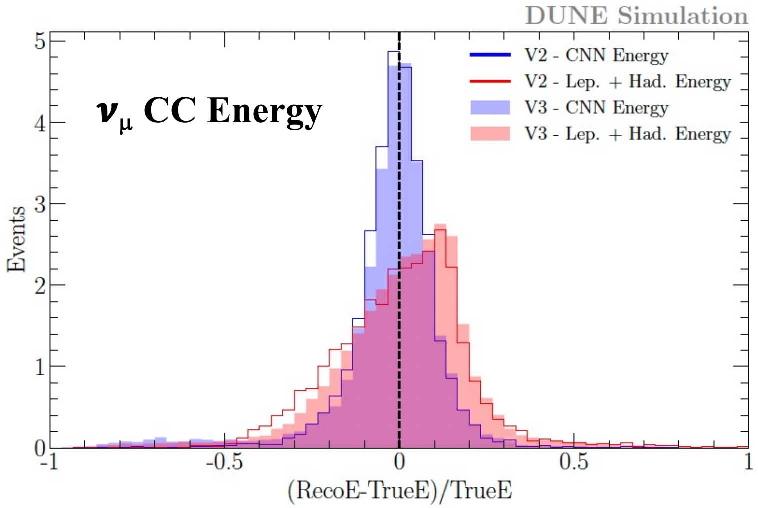


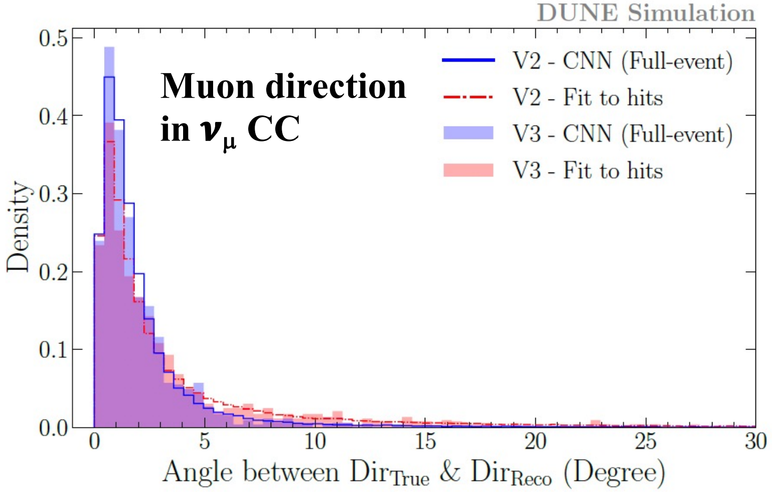
(c) ν_e CC energy DIS



(d) ν_e CC energy MEC

$\boldsymbol{\nu_\mu}$ Event Energy vs. Interaction Modes

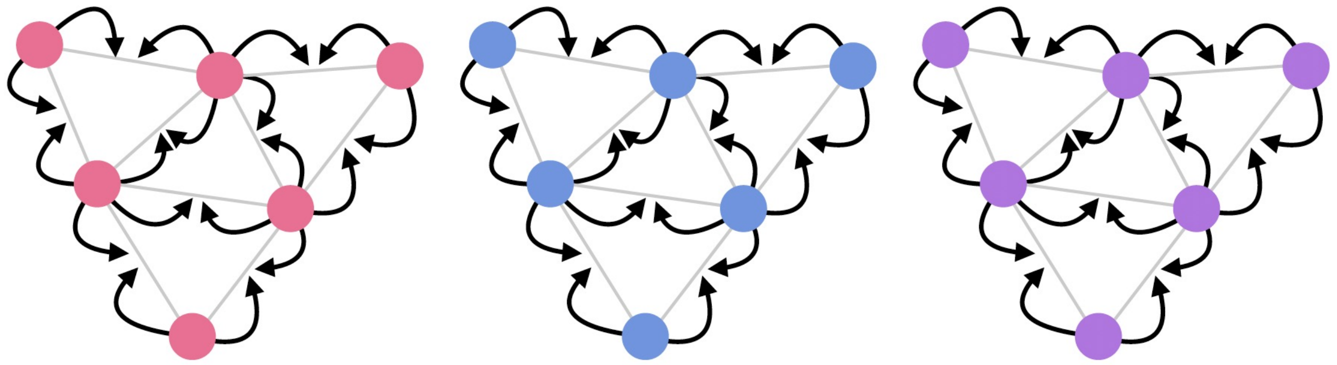




GENIE version 2 vs 3

Graph Neural Networks (GNN)

- Define input data as a graph represented by nodes and edges
  - Nodes are generalised as quantised objects with arbitrary set of features
  - Edges describe the relationships between nodes
- Perform convolutions on nodes and edges rather than the entire pixelmap in CNN → speed up the training
- Output is user-defined: classification and regression



GNN for Object Reconstruction in LArTPC (ExtExa.TrkX project)

- Successfully reconstruct LArTPC showers/tracks with GNN in ExtExa.TrkX project (a collaboration developing GNN reconstruction for HEP)
- Implementing under DUNE context

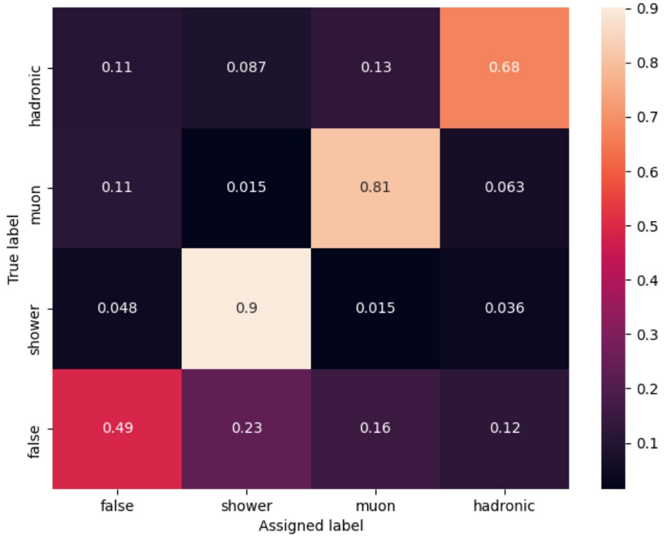


Figure 4. Confusion matrix showing the overlap of true and reconstructed edge labels.

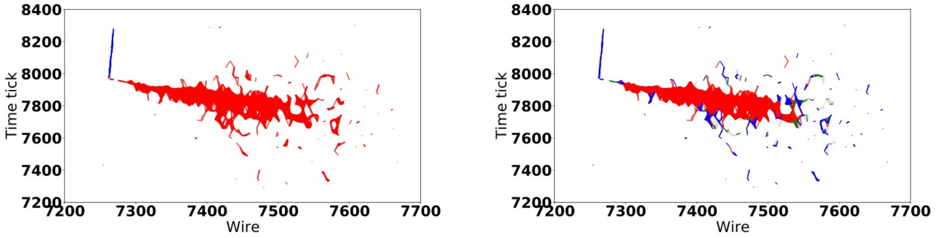
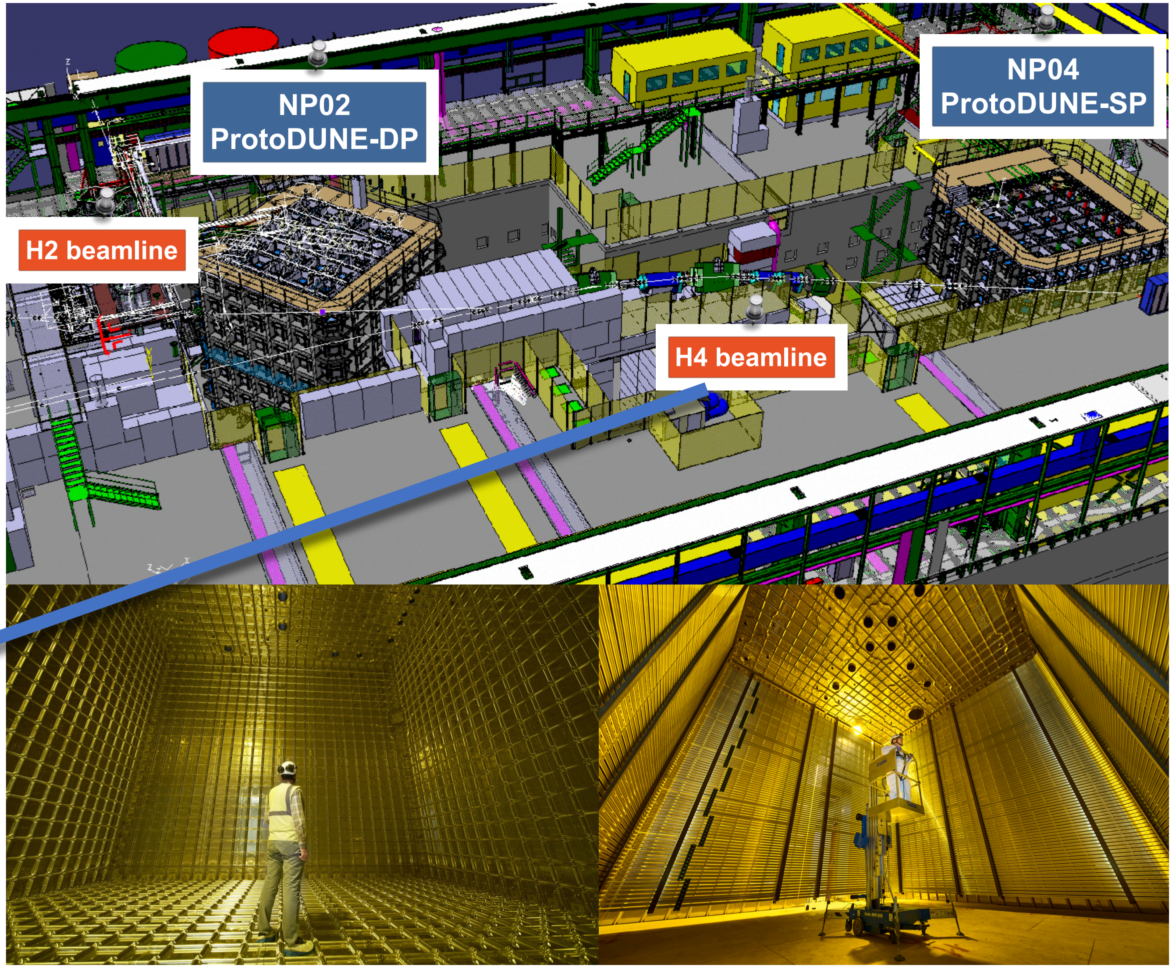


Figure 2. Example graph of a ν_e interaction (left: ground truth, right: model output). Shower-like edges are drawn in red, hadronic edges are drawn in blue, muonic edges are drawn in green and false edges are drawn in grey.

Jeremy Hewes, Adam Aurisano etc., EPJ Web of Conferences 251, 03054 (2021)

ProtoDUNE HD (SP) and VD at EHN1 (CERN)

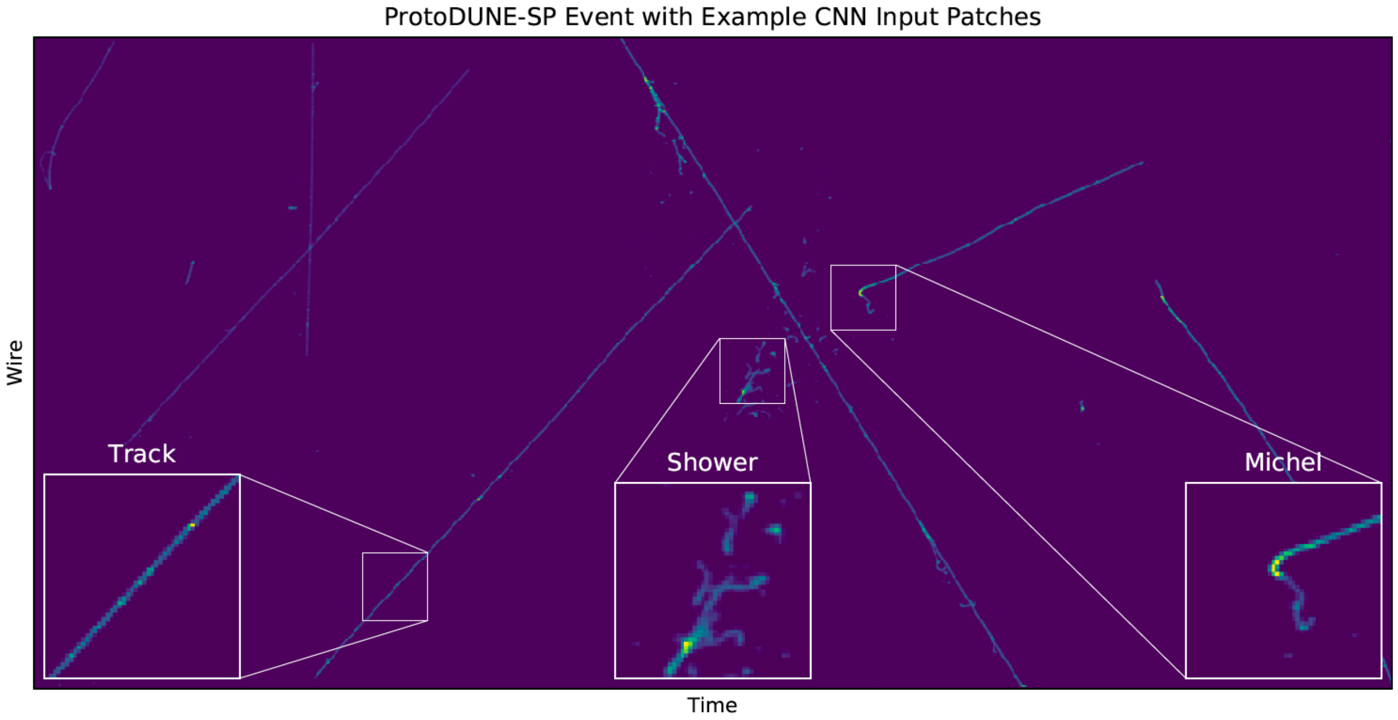
- ProtoDUNE-HD (SP in Phase I) and VD are two large DUNE prototype detectors at CERN Neutrino Platform EHN1
  - 770 tons LAr mass each
  - Expose to test beams, momentum-dependent beam composition contains e, $K^{\pm}$, μ, p, $\pi^{\pm}$
  - Also take cosmic ray data
- Phase I completed, preparing for Phase II running of ProtoDUNE HD and VD



- H4-VLE beam line [Phys. Rev. Accel. Beams 22, 061003 (2019)]
- New tertiary, low-mom beam line; 2 secondary targets
- W for lower momenta (0-3 GeV/c); Cu for higher momenta (4-7 GeV/c)
- TOF and Cherenkov counters for PID

CNN for Shower/Track Separation in ProtoDUNE

- Use CNN to classify energy deposits (hits) from Shower, Track and Michel electrons
  - 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
- Can be used in clustering, PID, etc



ProtoDUNE-SP DATA

Shower/Track CNN architecture

- The inputs are 48-pixel images centered on the reconstructed hit object to be classified
- A single convolutional layer is used to extract feature maps from the images
- These are processed by two dense (fully connected) layers before being split into two branches which classify the images
- Output is the type of hit: from shower? Track? Michel electron?

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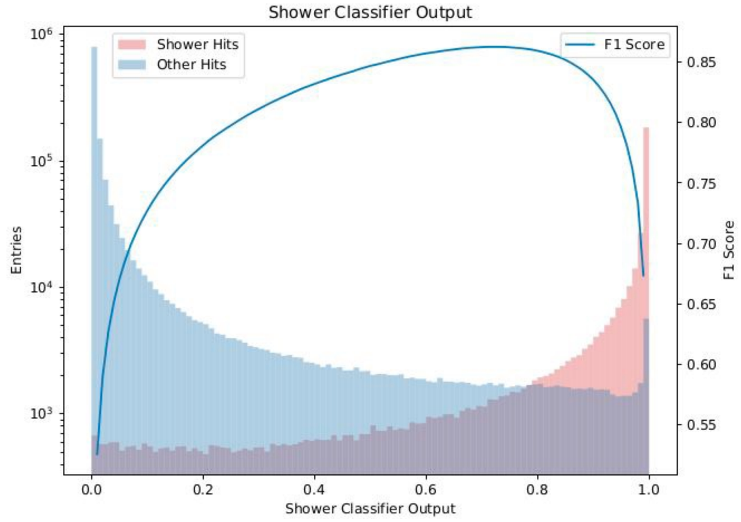

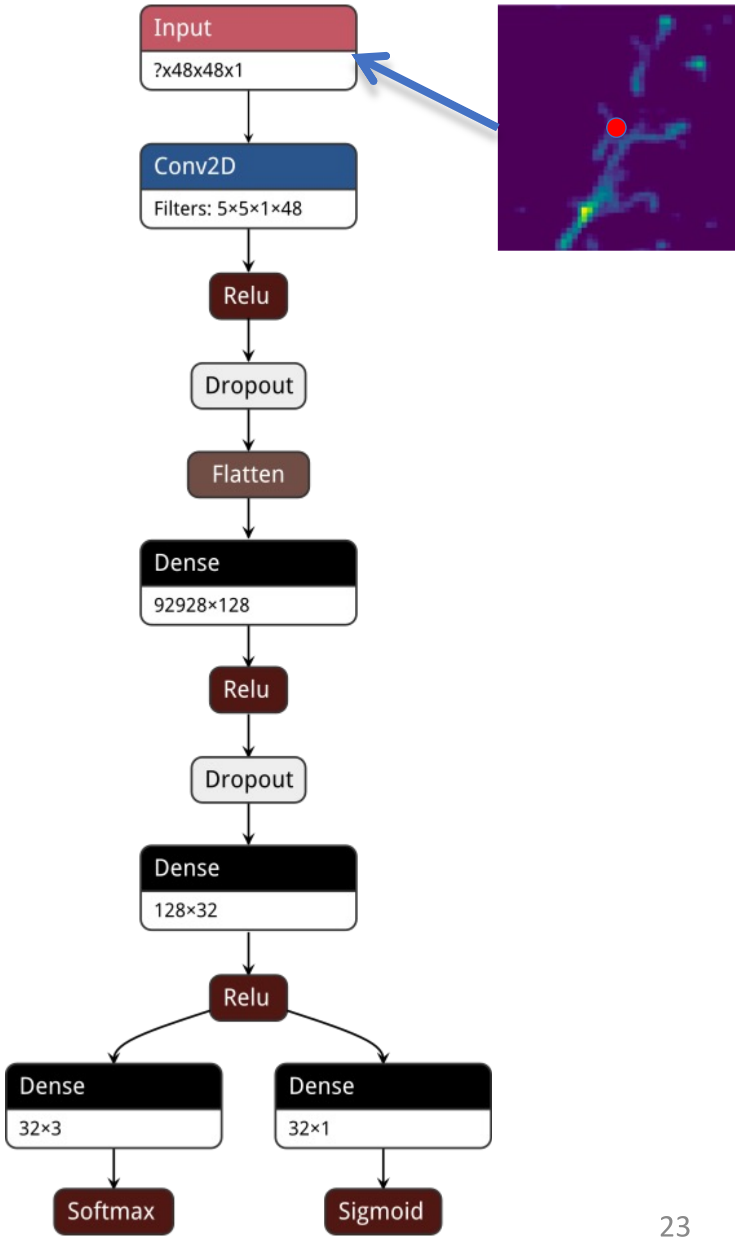

Performance of CNN in ProtoDUNE Data

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

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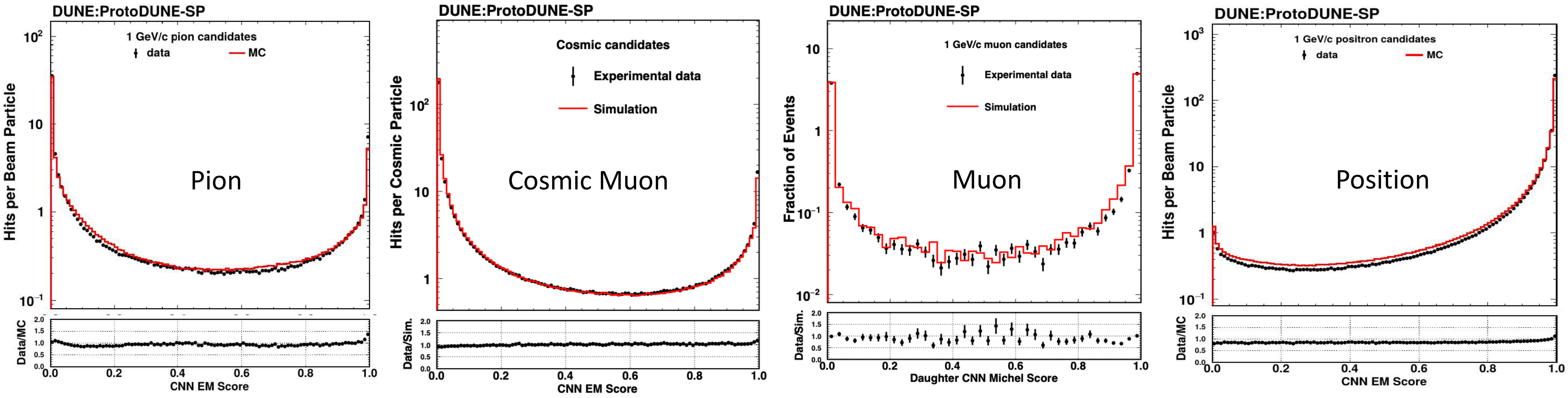

Hit level EM/Michel shower scores

Summary

- Systematically developed event ID, particle ID, event energy, particle energy, particle direction reconstruction and shower/track clustering with deep-learning methods for DUNE far detectors
- Achieved very good selection efficiency and resolution
- Developed Graph Neural Networks and sparse neural networks to reduce computational burden
- Performed robustness tests with ProtoDUNE data and alterative simulation models

Future Directions

- Fast Simulation – Deep Generative Models (DGMs)
  - Generation of simulated detector response is crucial to data analysis in neutrino physics but computationally very expensive
  - DGMs are a promising approach to learning such a response function
- DGMs developed for particle physics calorimeters
  - Generative Adversarial Networks (GAN), Variational Auto-Encoders (VAE), Normalizing Flows (NF), etc.
  - DGMs are also promising for fast simulation in neutrino physics

Thank you!

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UCI DEEP UNDERGROUND NEUTRINO EXPERIMENT Fermilab