Deep Learning Reconstruction at DUNE Far Detector

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for the DUNE Collaboration

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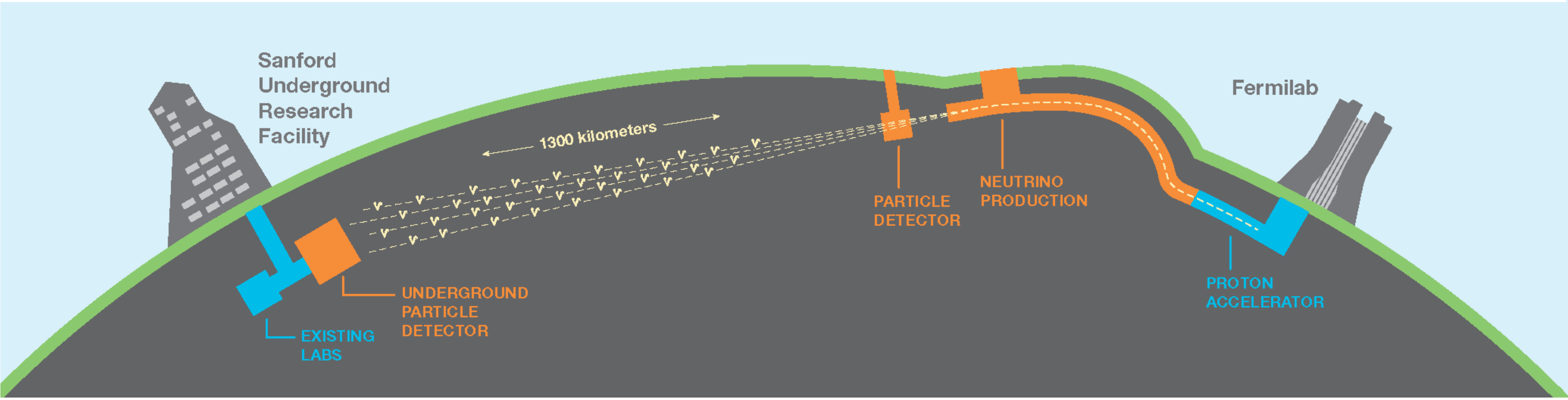
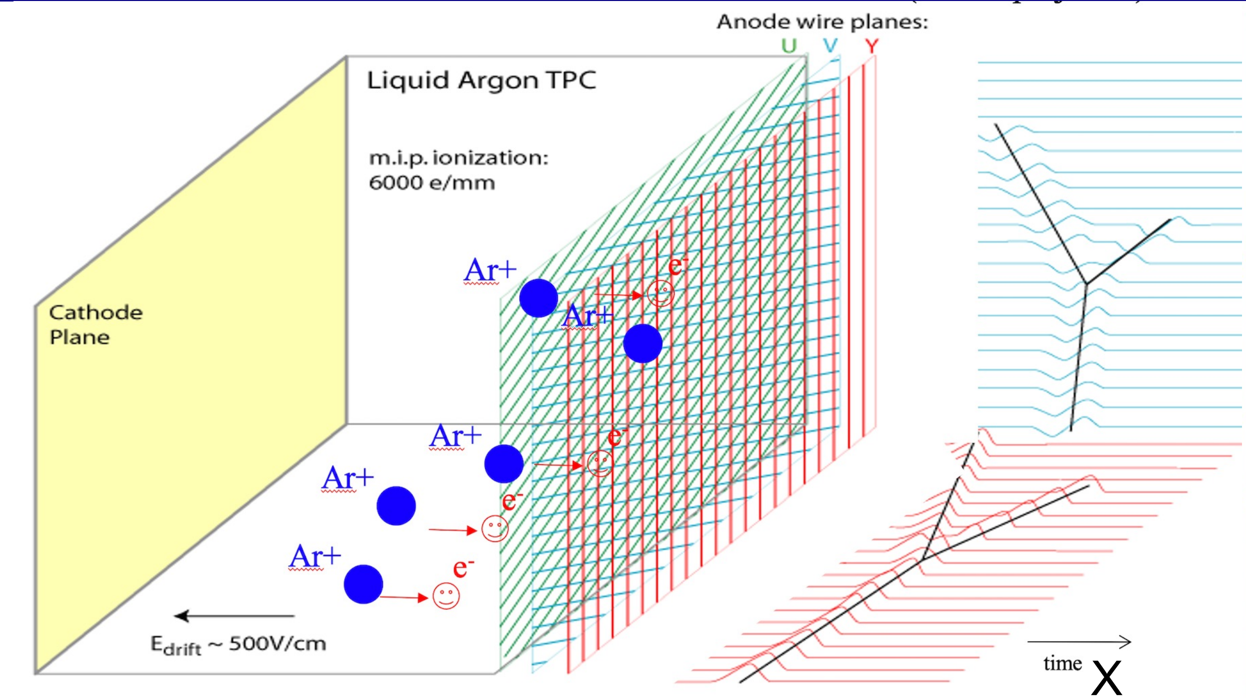
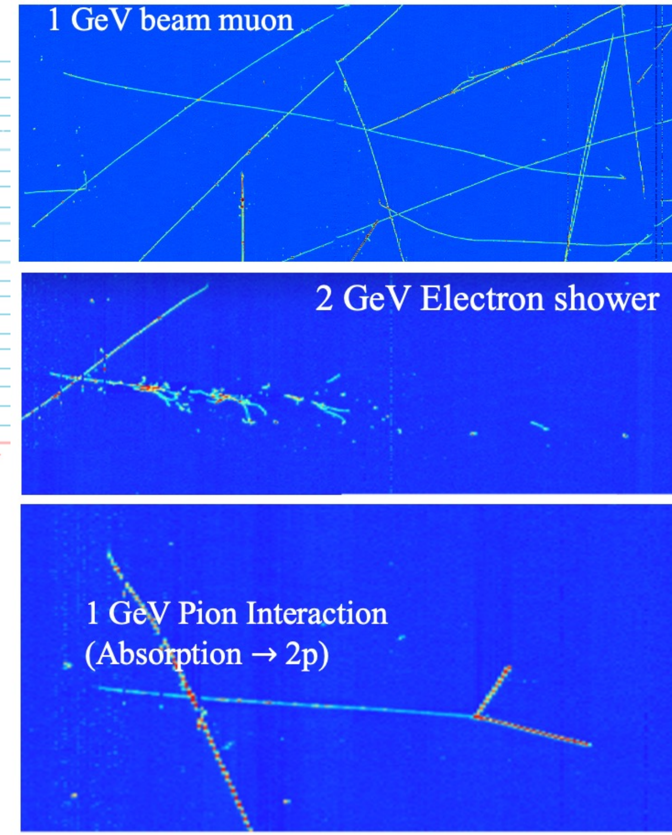
DUNE DEEP UNDERGROUND NEUTRINO EXPERIMENT



- New neutrino beam at Fermilab (1.2 MW, upgradeable to 2.4 MW), 1300 km baseline
- Four 17 kton Liquid Argon Time Projection Chamber (LArTPC) Far Detector modules at Sanford Underground Research Facility, South Dakota, 1.5 km underground
- Multiple technologies for the Near Detector (ND)
- ν_e appearance and ν_μ disappearance → Neutrino mass ordering and CP violation
- Large detector, deep underground, high intensity beam → Supernova burst neutrinos, atmospheric neutrinos, sterile neutrinos, nucleon decay, other BSM, etc

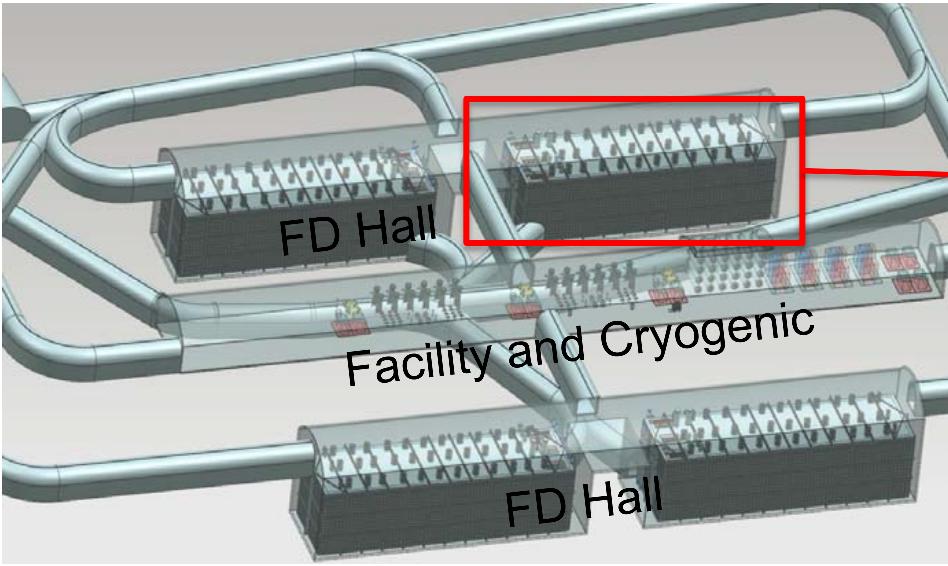
DUNE Far Detector (FD): Liquid Argon Time Projection Chamber (LArTPC)

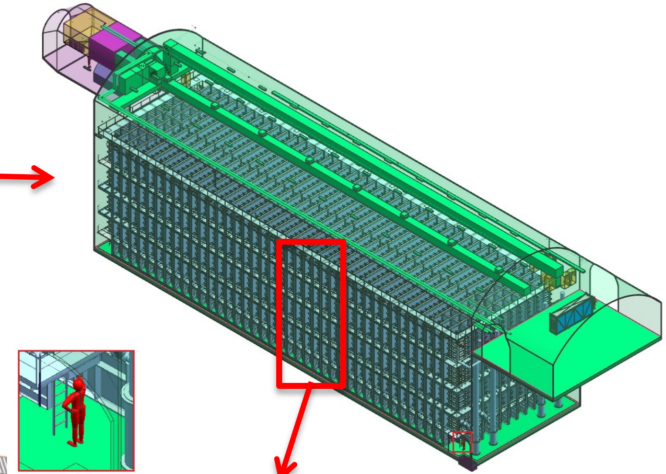


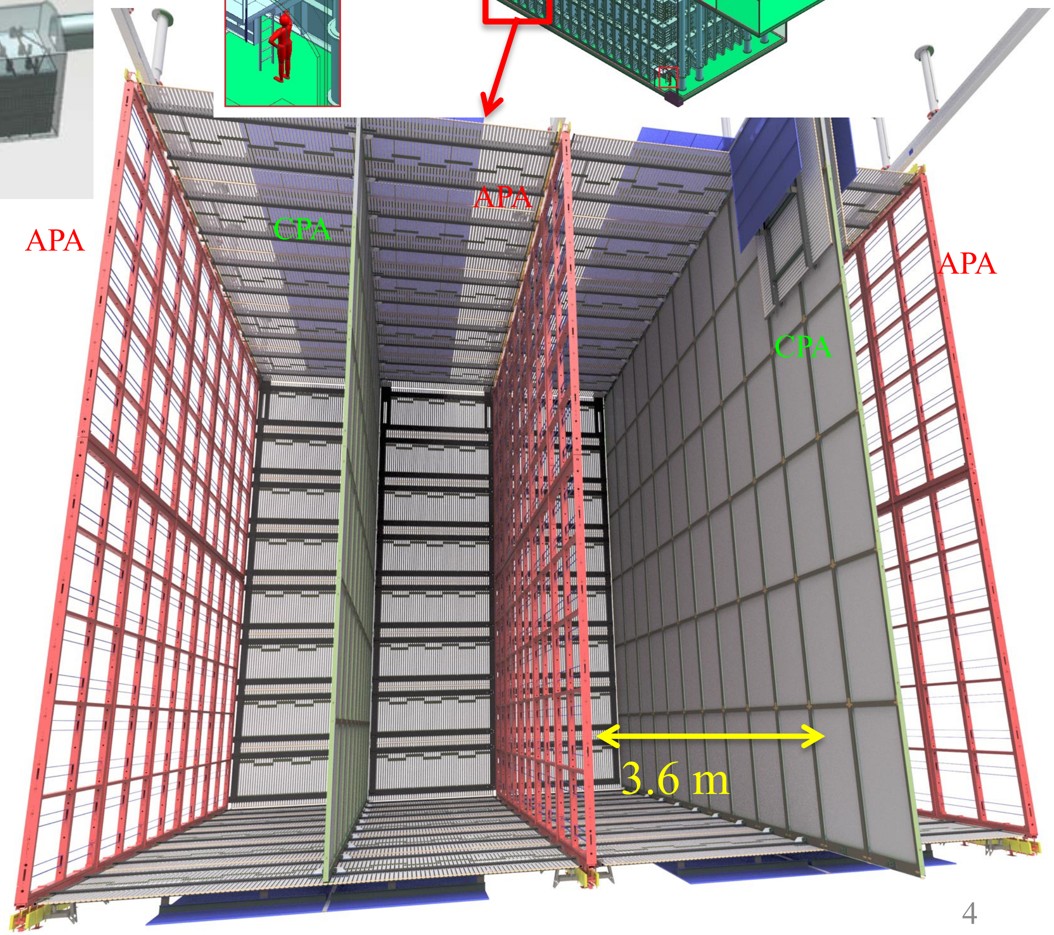


- High resolution 3D track reconstruction
  - Charged particle tracks ionize argon atoms
  - Ionized electrons drift to anode wires (~ms) for YZ-coordinate
  - Electron drift time projected for X-coordinate
- Argon scintillation light (~ns) detected by photon detectors, providing t_0
- Output: a 2-D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

Far Detector: Horizontal Drift (HD) LArTPC

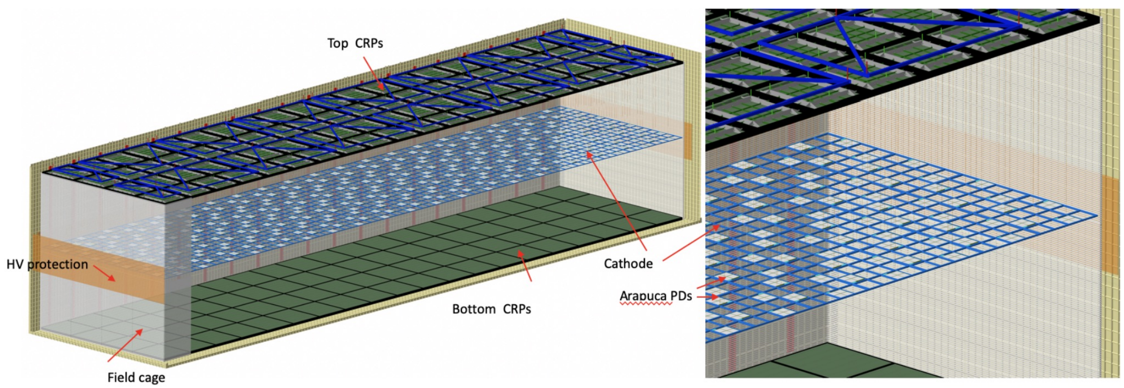


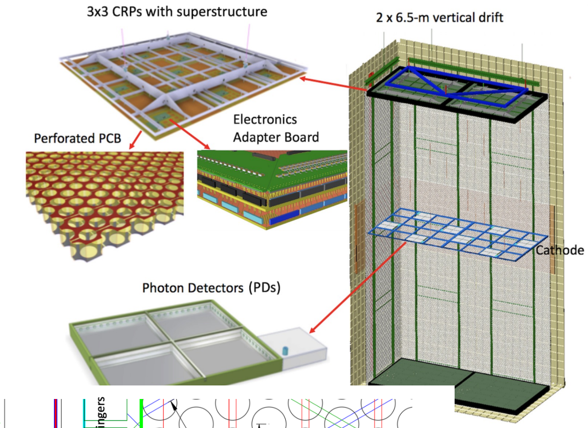


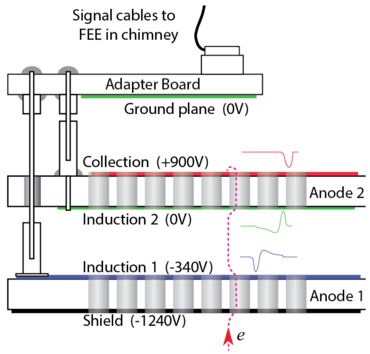


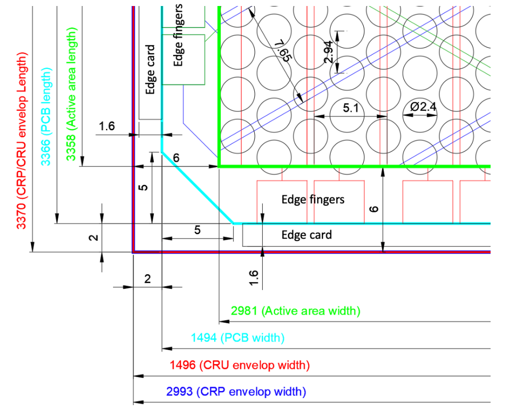
- Four 17-kt modules deployed in stages
- First module will be horizontal-drift:
  - 18m x 19m x 66m
  - 3 readout planes, two introduction and one collection
  - Drift distance: 3.6 m, wire pitch: 5 mm
  - 4 drift volumes

Far Detector: Vertical Drift (VD) LArTPC



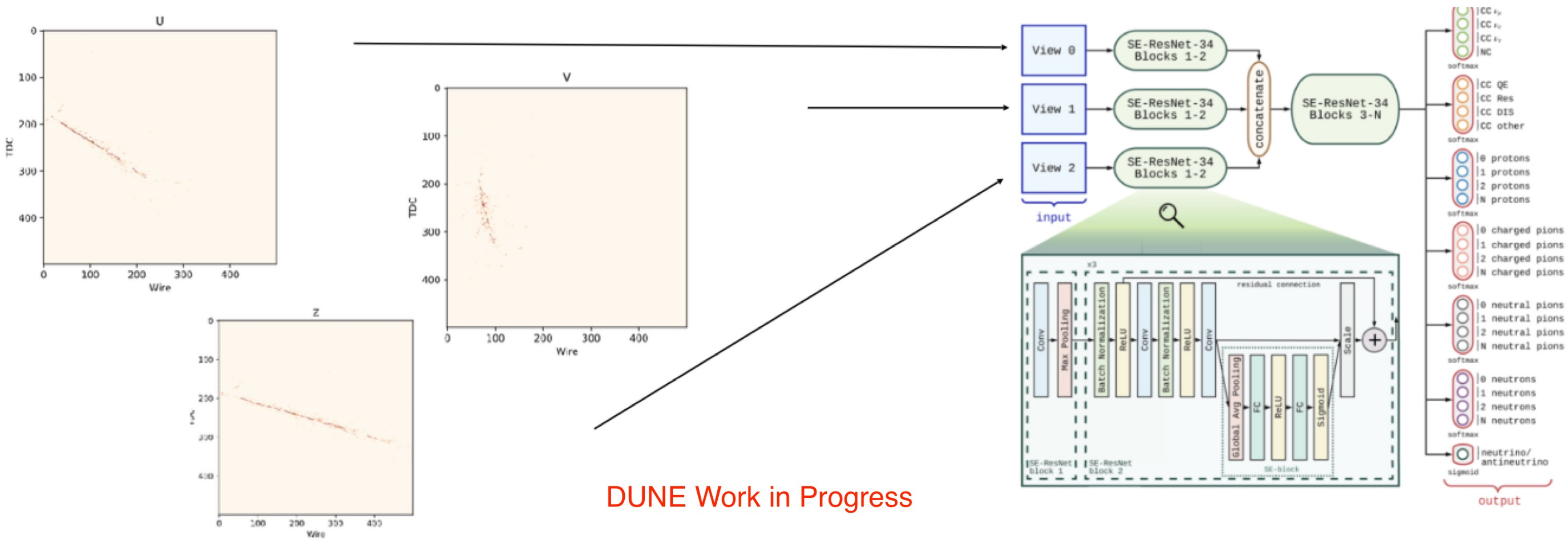






- For the 2nd DUNE FD module, has a vertical drift (VD) path in contrast to HD
- 2 drift volumes, cathode plane on the middle
- Anode: a stack of perforated PCBs with 3 layers of readout etched electrode strips in different orientations
- Modular design allows easy assembly and production. Wires → Strips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

Convolutional Neural Network (CNN) for Event Identification and Energy Reconstruction

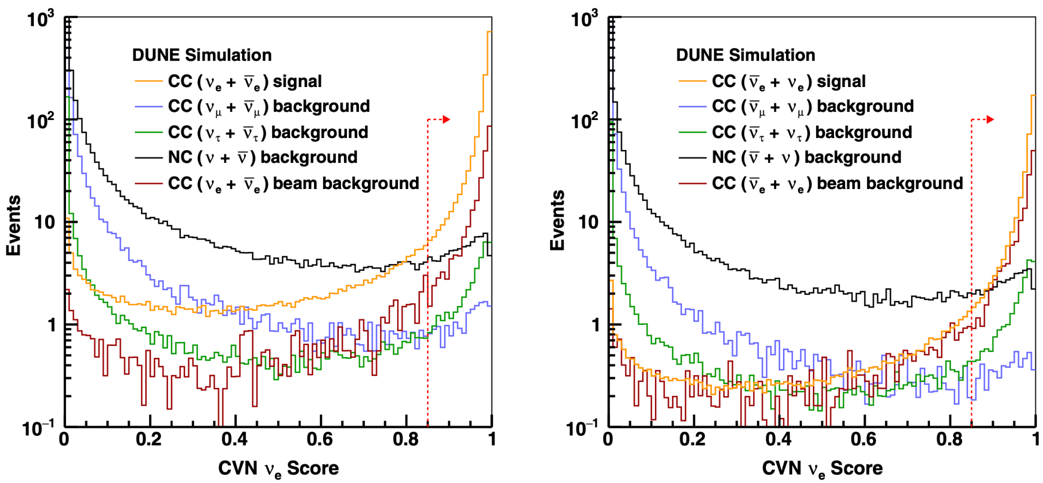


- DUNE's pixel map readout is ideal for image processing neural networks to reconstruct neutrino events.
- CNNs are deep neural networks take raw pixel values input, applying convolutional filters to reduce the number of parameters
- Uses the 3 x 2D readout images, one for each wire/strip-plane, directly as input to a ResNet CNN architecture
- CNN then merges information across the 3 planes and uses a fully connected layer at the end for neutrino flavor classification or energy regression

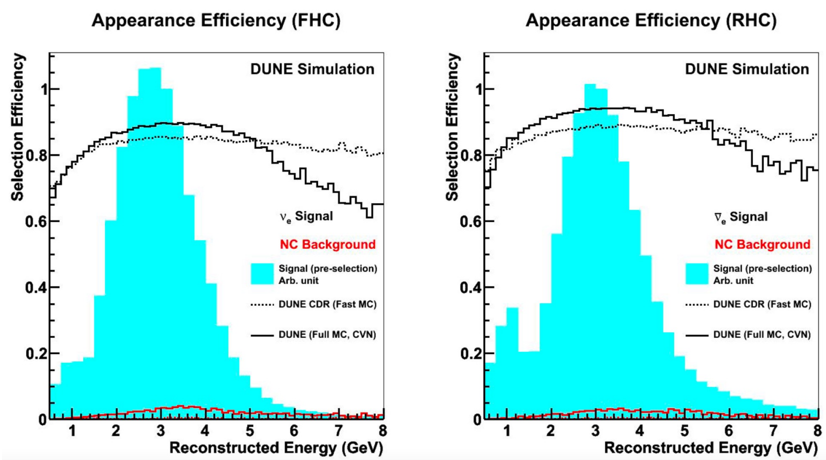
Event Classification CNN identifiers in DUNE FD HD

- 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_μCC, ν_eCC and NC events

Neutrino beam (FHC) Anti-Neutrino beam (FHC)

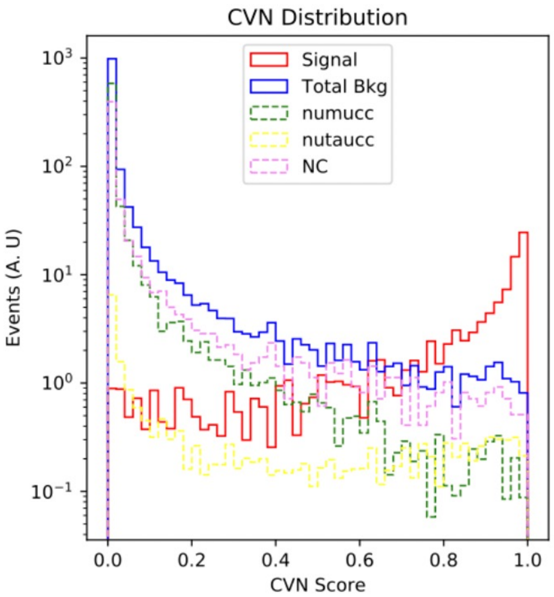


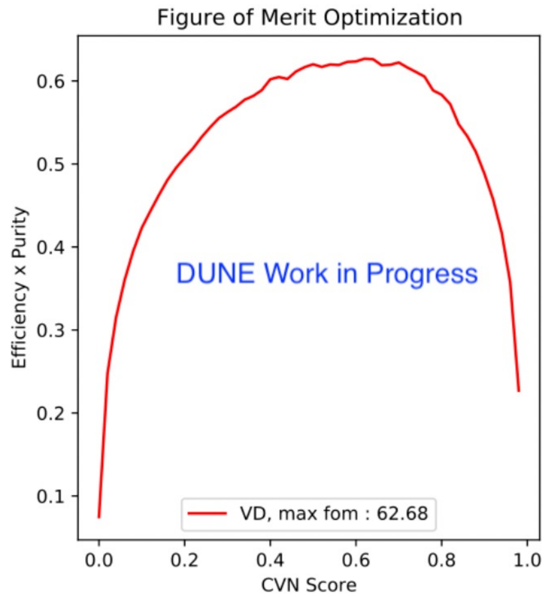
Phys.Rev.D 102 (2020) 9, 092003

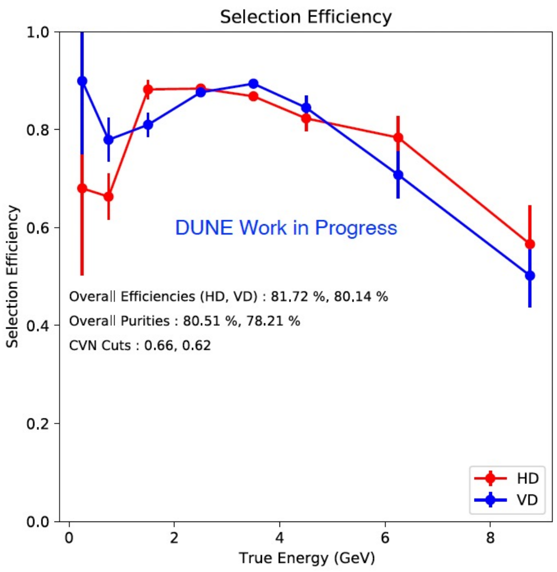


Performance is better than DUNE CDR assumptions

Event Classification CNN identifiers in DUNE FD VD





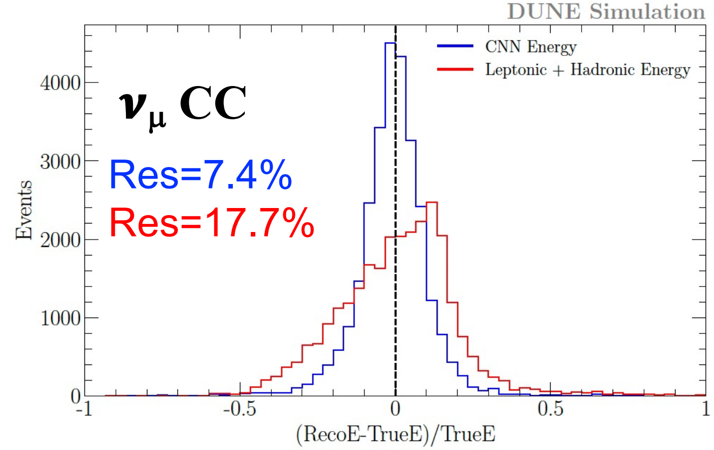


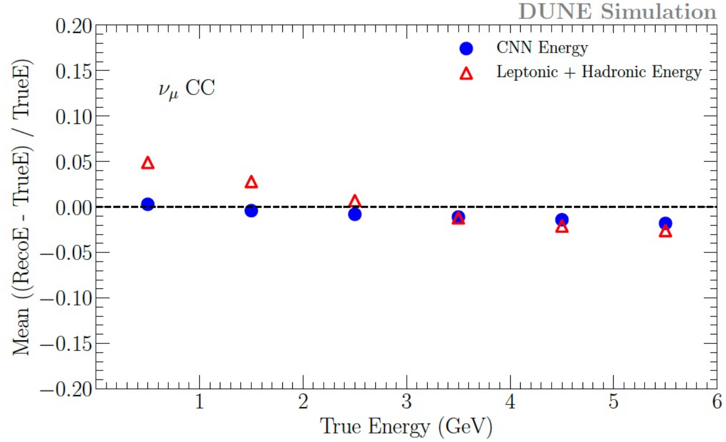
- Training on fraction of planned simulated sample shows very similar performance as for HD
- Efficiency to tag CC ~90% near peak DUNE flux (~2.5-3 GeV) with overall purity ~80%
- Used as input for new VD-based sensitivity studies (technical design report analysis), similar results as HD

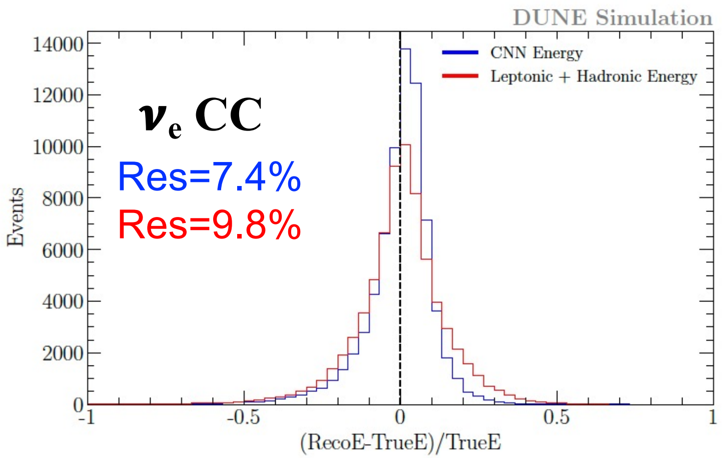
ν_e CC and ν_μ CC Event Energy

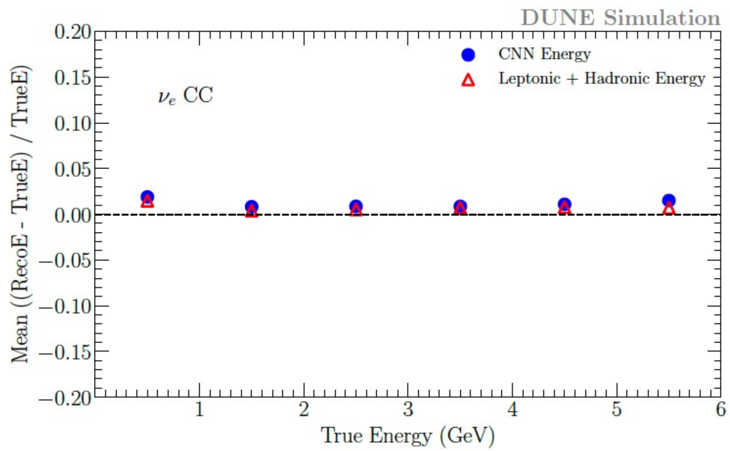
- CNN with linear output regression for event energy, optimizing resolution $(E_{reco}-E_{true})/E_{true}$
- Weighted events by energy to reduce energy dependent bias in training
- Better resolutions than leption+hadronic energy method, less energy dependent bias with energy-reweighted training

arXiv:2012.06181



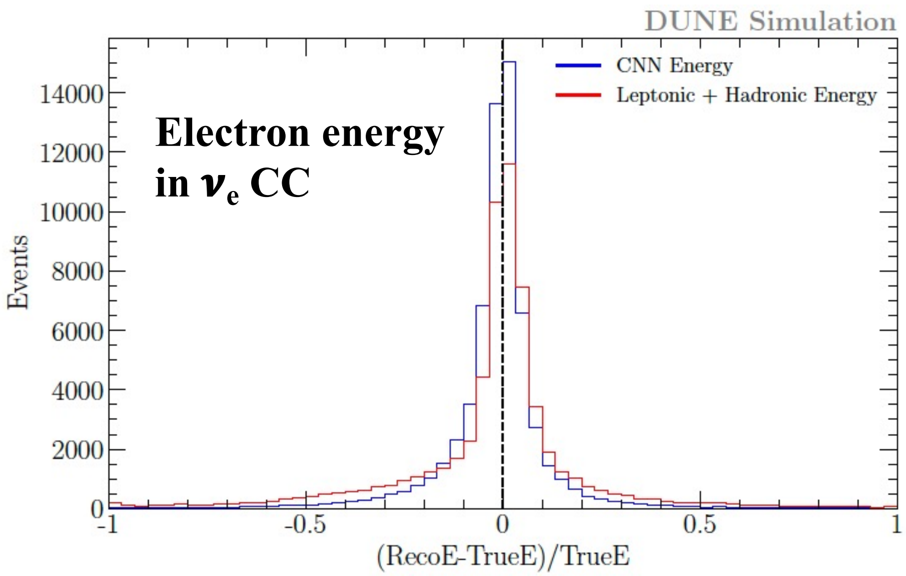


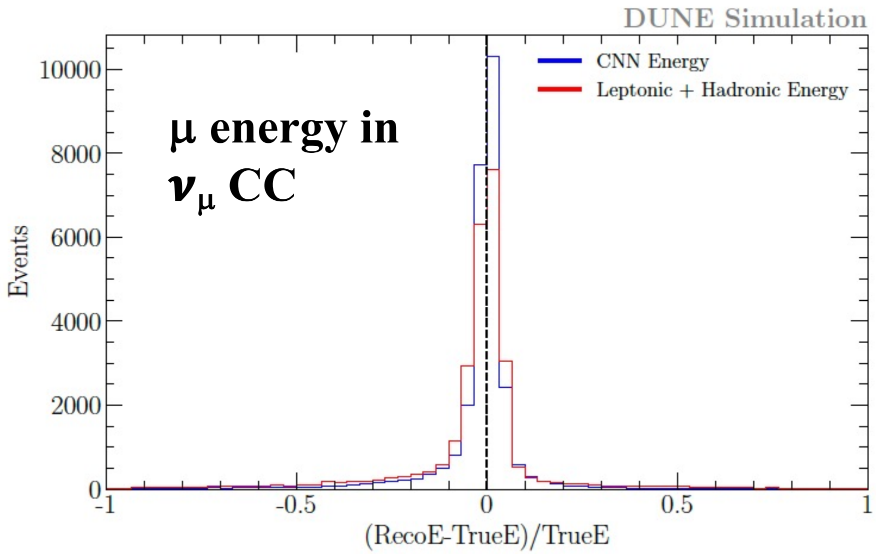




Particle Energy Reconstruction

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

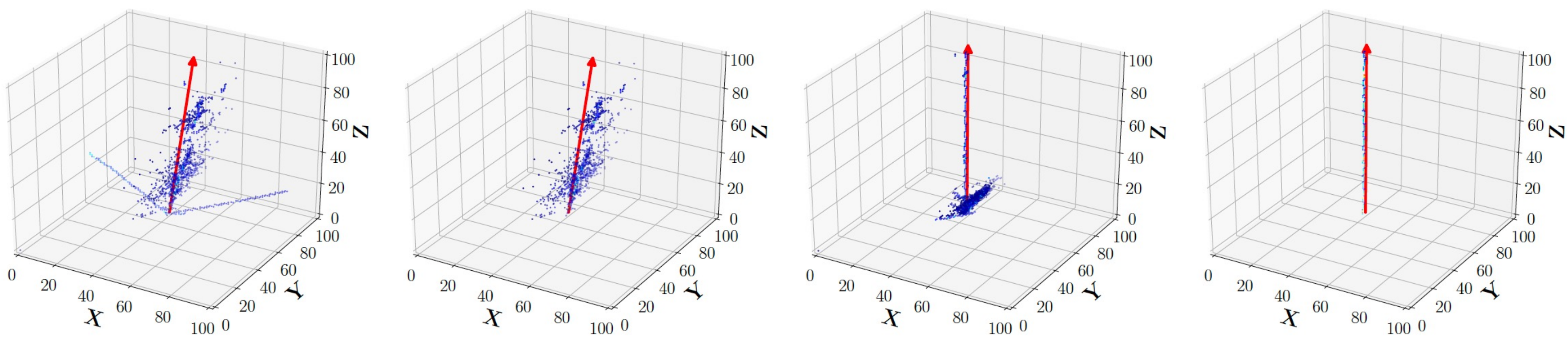




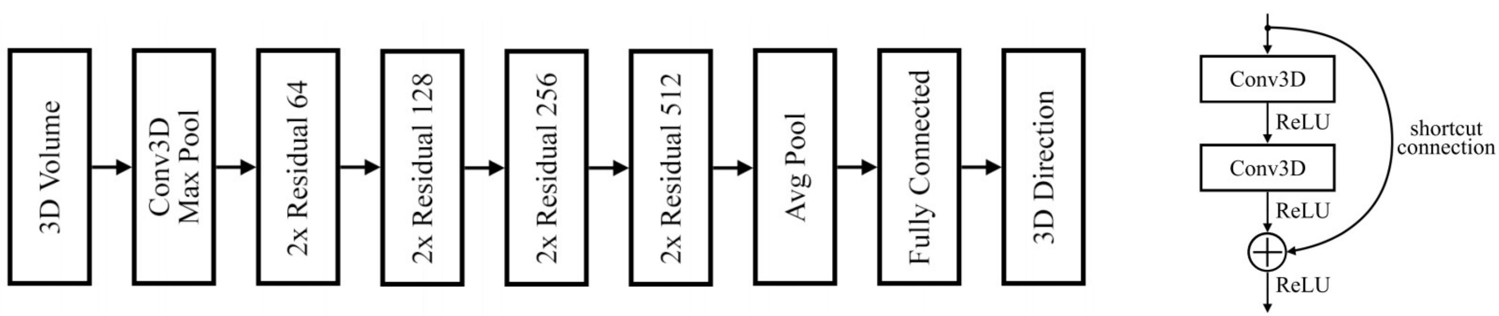
3-D Particle Direction Reconstruction

- 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

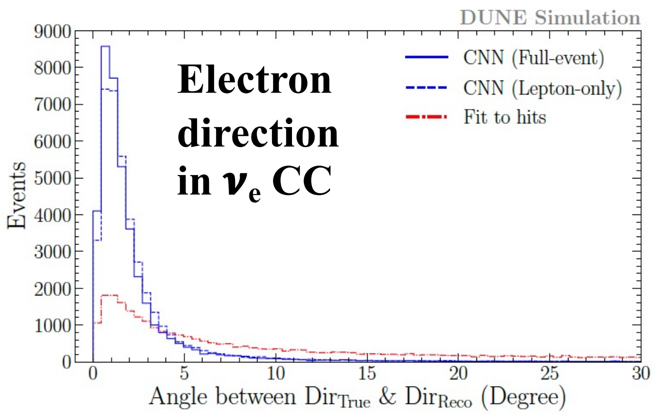


(a) Direction Regression (b) Residual block

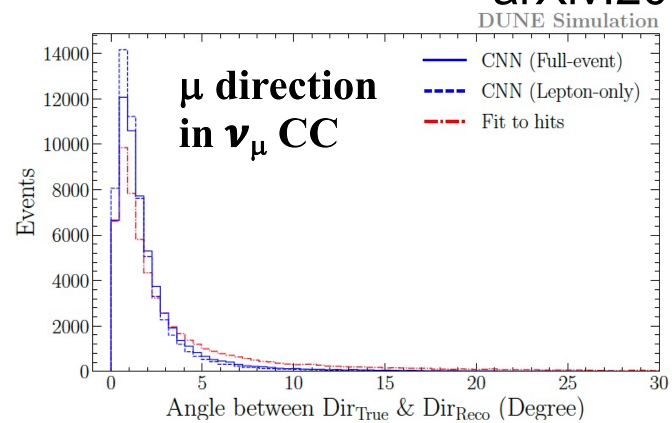
Particle Direction Reconstruction

- 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

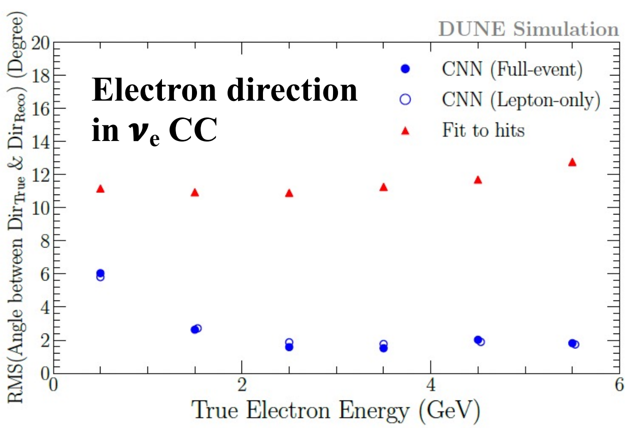
arXiv:2012.06181



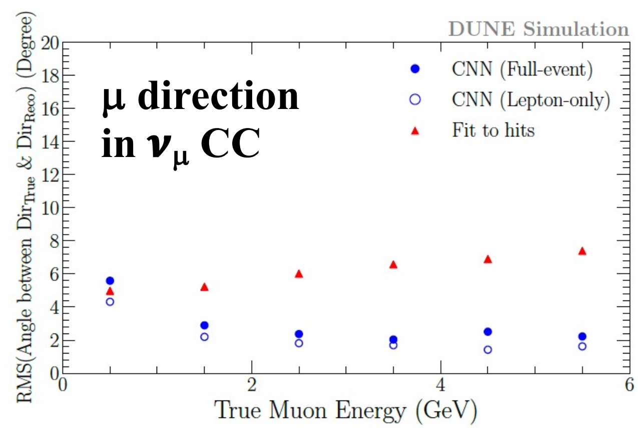
(a) Angular resolution for ν_e CC



(b) Angular resolution for ν_μ CC



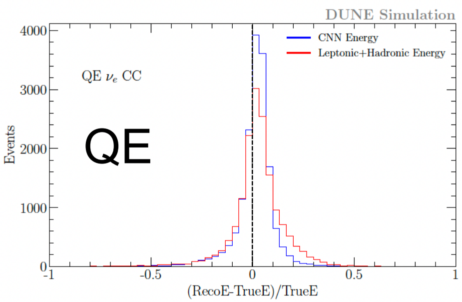
(c) Energy dependency for ν_e CC



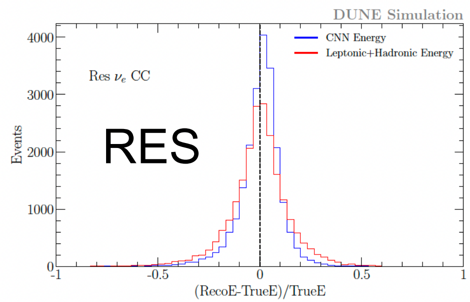
(d) Energy dependency for ν_μ CC

Neural Network Robustness Tests

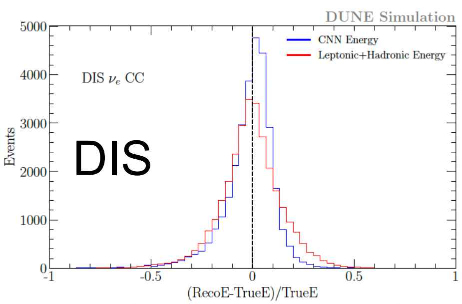
- CNNs show robustness against neutrino interaction modes
- GENIE versions have small effects in CNNs



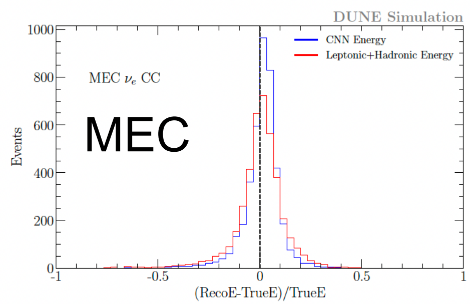
(a) ν_e CC energy QE



(b) ν_e CC energy Res

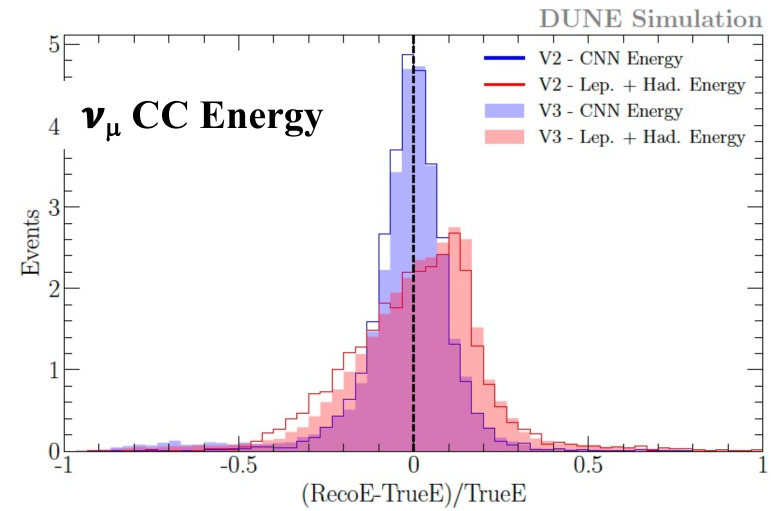


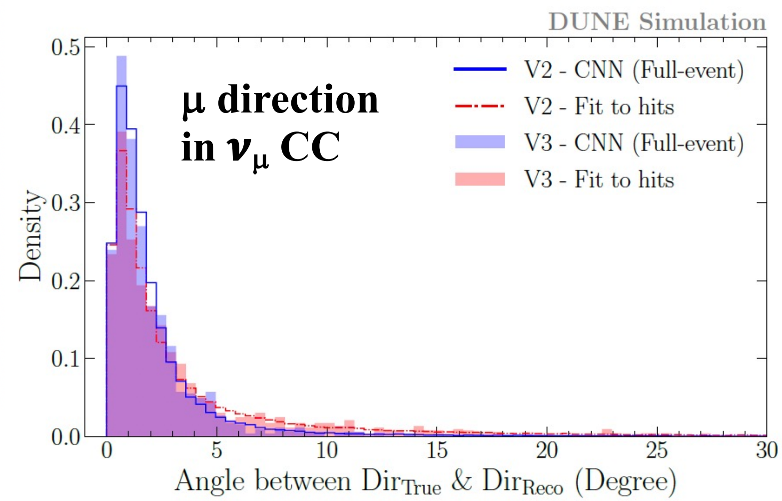
(c) ν_e CC energy DIS



(d) ν_e CC energy MEC

Nue Event Energy vs. interaction modes

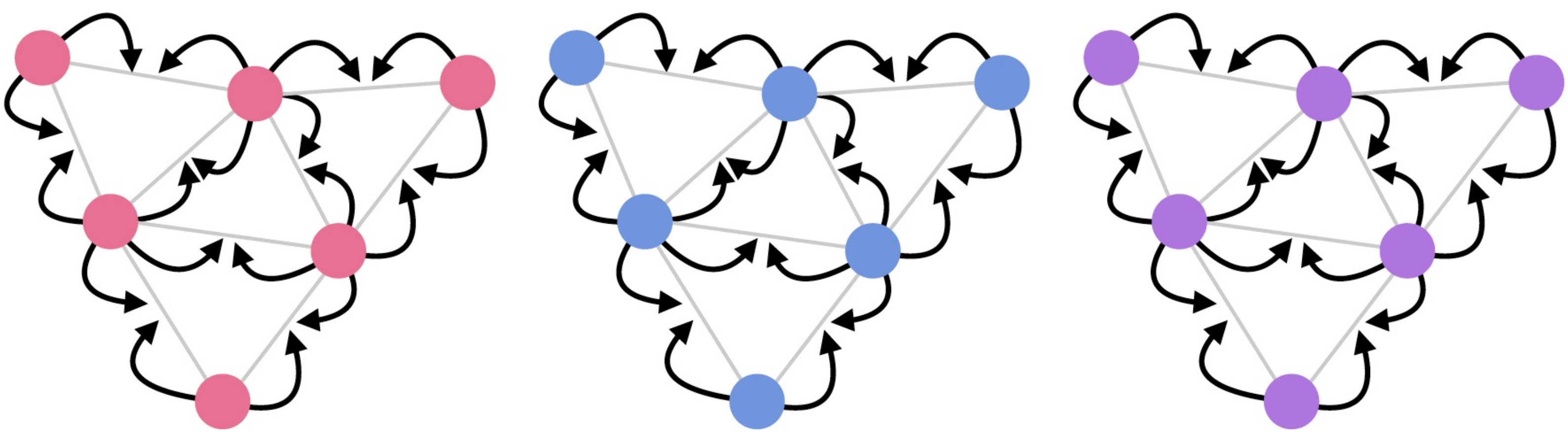




GENIE version 2 vs 3

Graph Neural Networks (GNN)

- Graph Neural Networks (GNN)
  - Define input data as a graph represented by nodes and edges
  - Nodes are generalised as quantised objects with some arbitrary set of features.
  - Edges describe the relationships between nodes.
  - Perform convolutions on nodes and edges rather than the entire pixel map in CNN → Speed up NN training
  - Output is user-defined: Classification and regression



Graph Neural Network 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

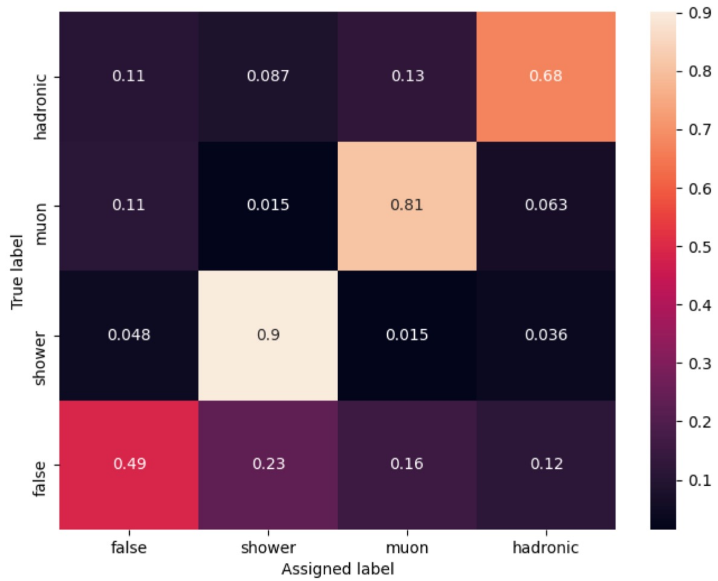


Figure 4. Confusion matrix showing the overlap of true and reconstructed edge labels.

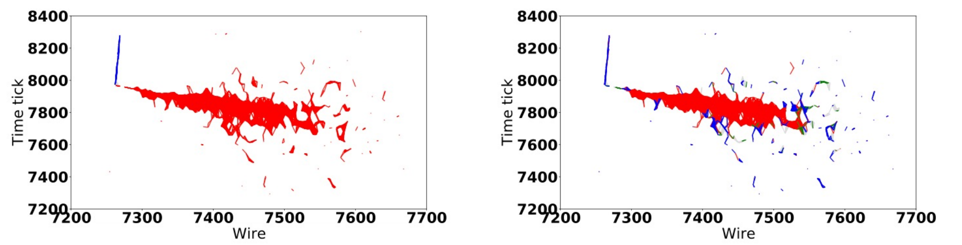
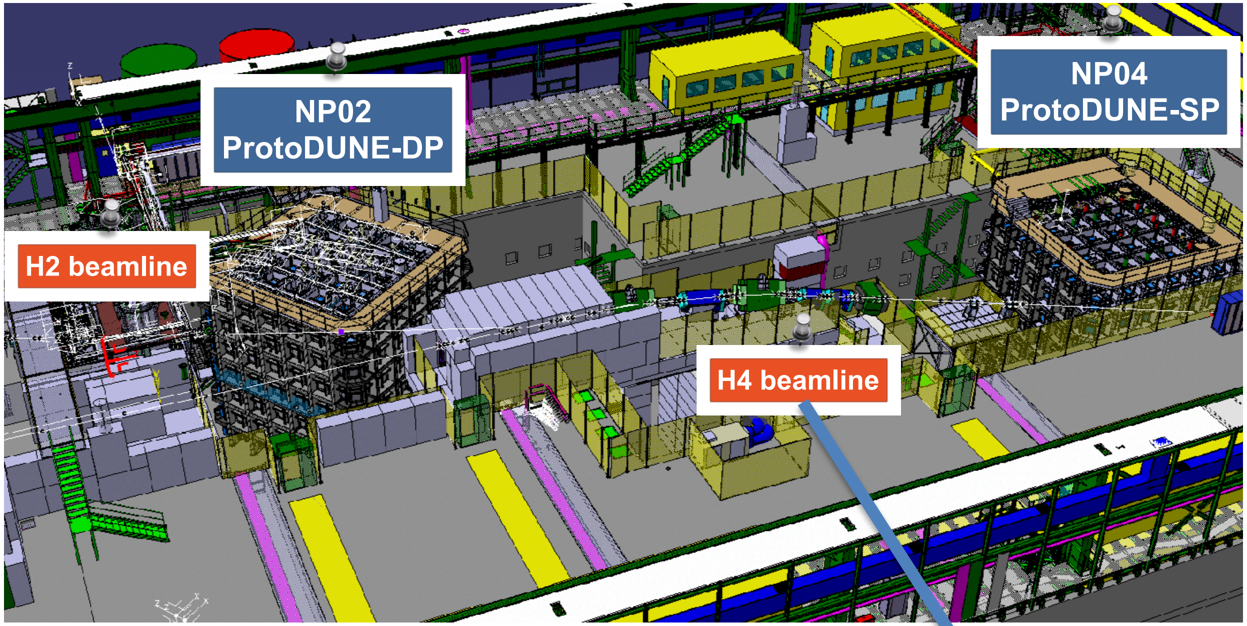
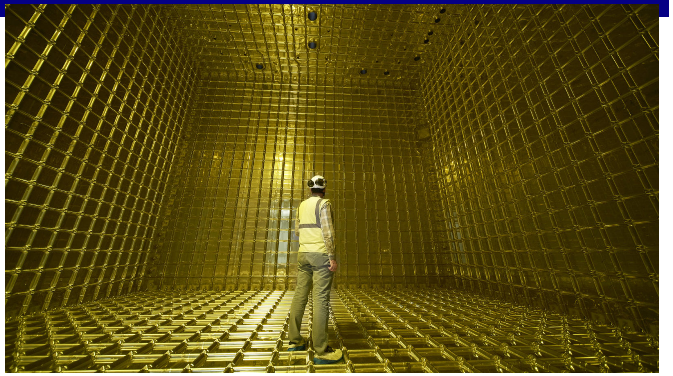


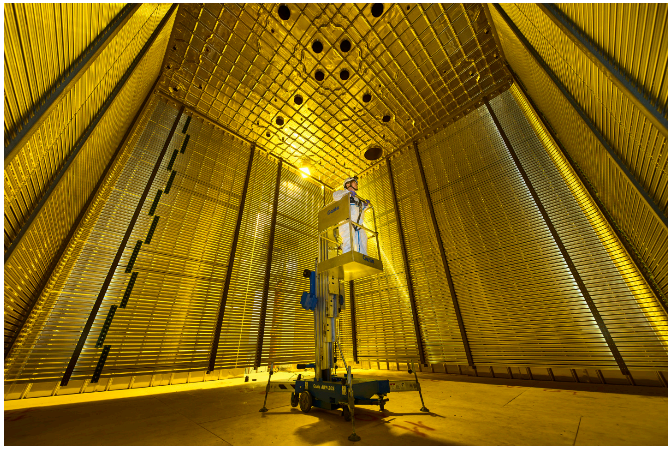
Figure 2. Example graph of a ν_e interaction (left: ground truth, right: model output). Shower-like edges are drawn in red, hadronic edges are drawn in blue, muonic edges are drawn in green and false edges are drawn in grey.

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

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



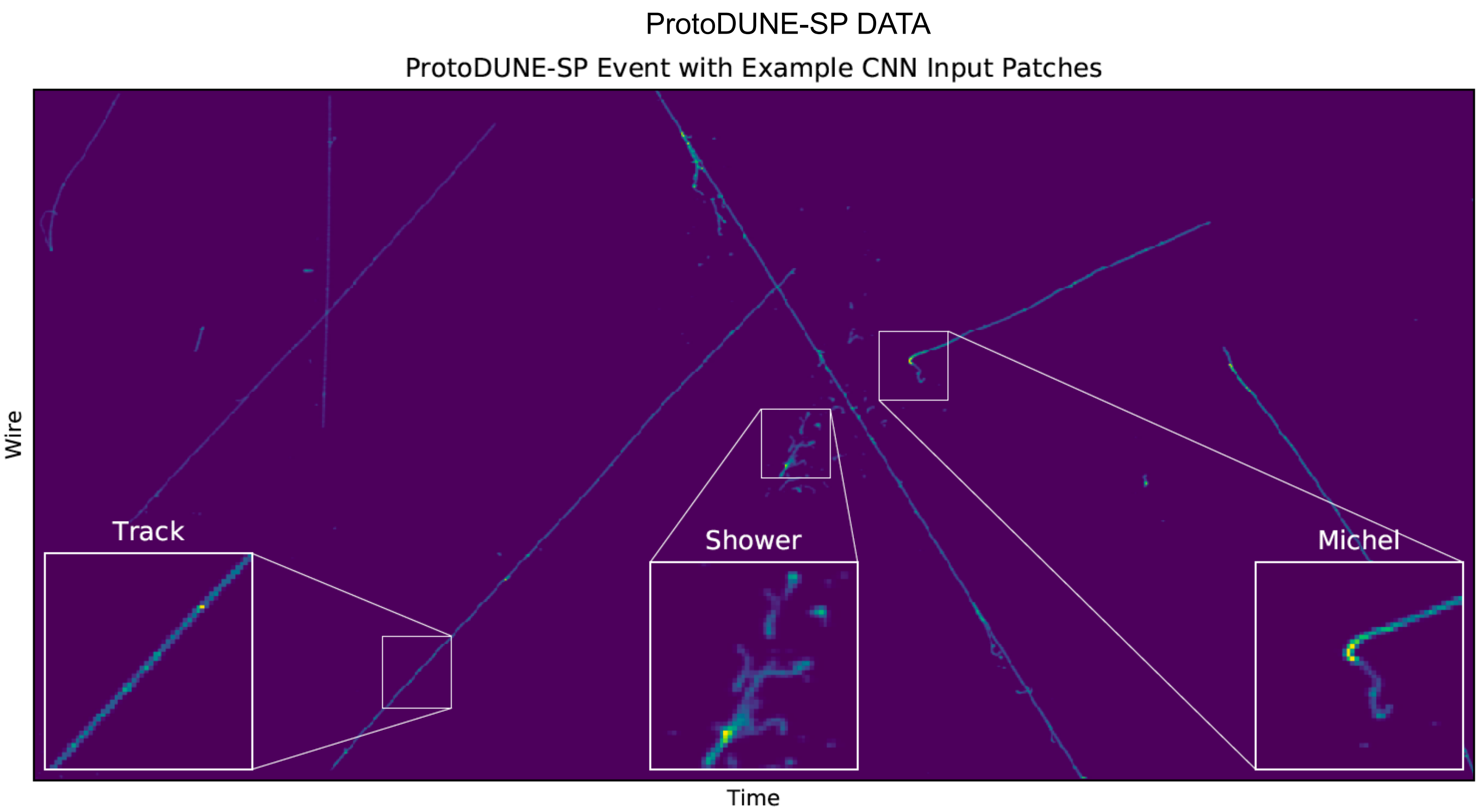




- ProtoDUNE-HD (SP in Phase I) and VD are two large DUNE prototype detectors at CERN Neutrino Platform EHN1
- 770 tons LAr mass each
- Expose to test beams, momentum-dependent beam composition contains e, $K^{\pm}$, μ, p, $\pi^{\pm}$
- Also take cosmic ray data
- ProtoDUNE Phase I completed, preparing for Phase 2 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

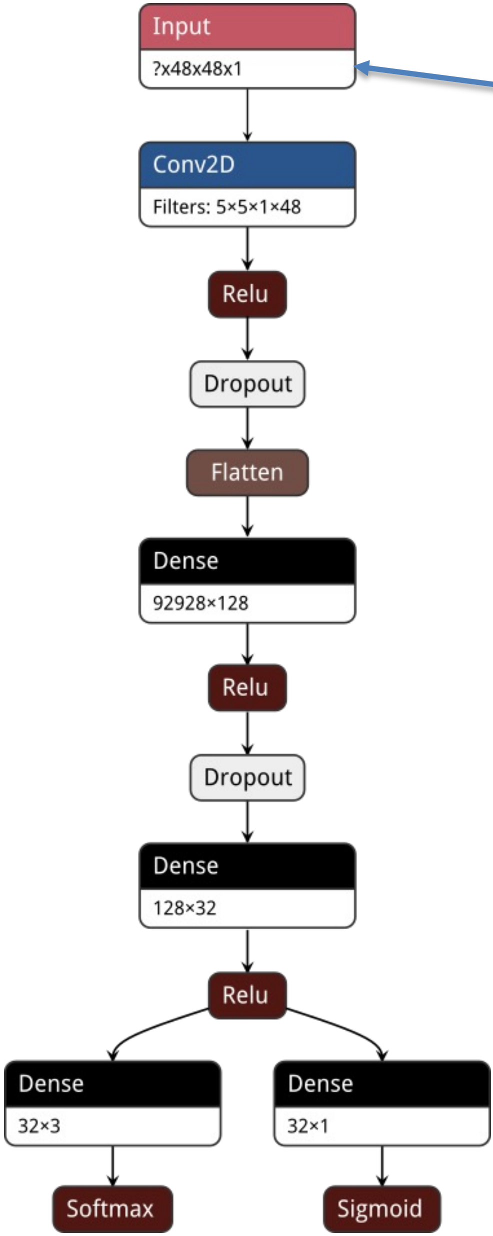


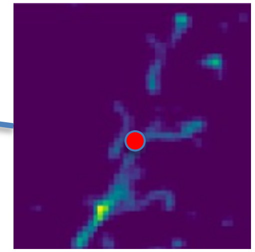
Use CNN to classify energy deposits (hits) from Shower, Track and Michel electrons

- 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

Shower/Track CNN architecture





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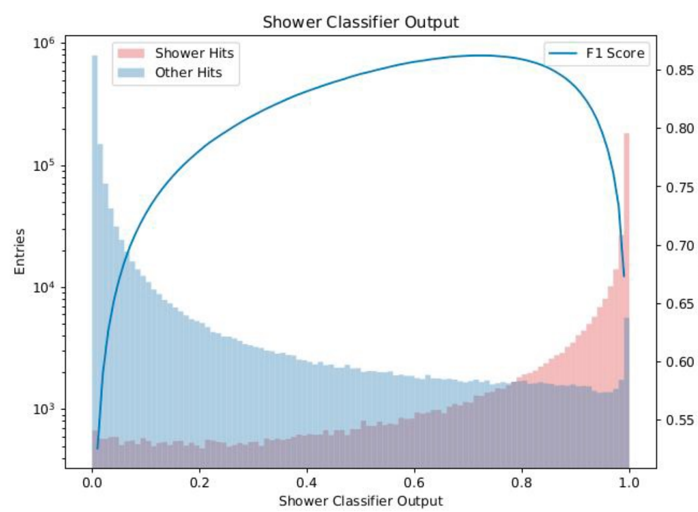
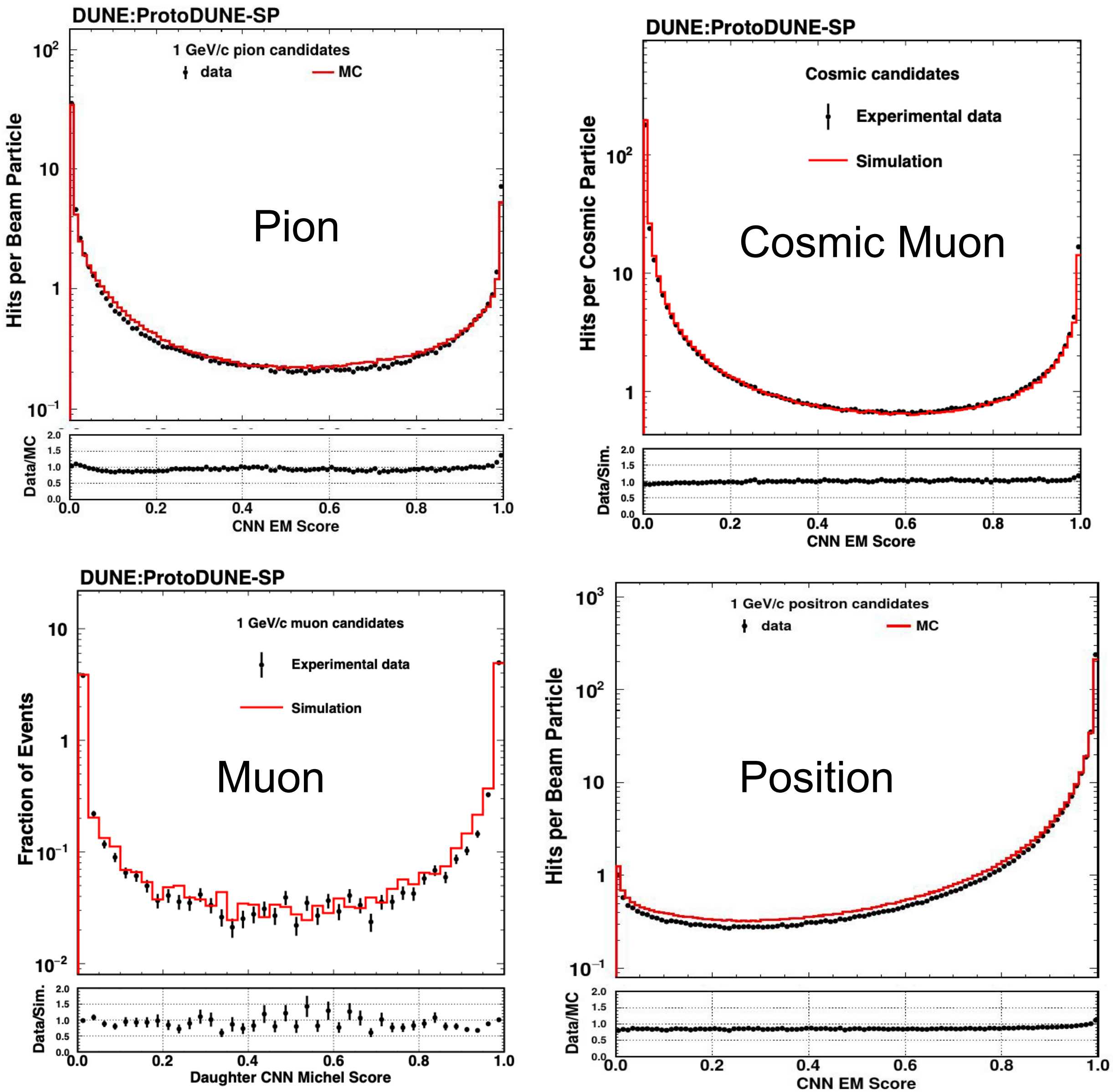
- The inputs are 48 pixel images centered on the reconstructed hit object to be classified
- A single convolutional layer is used to extract feature maps from the images
- These are processed by two dense (fully connected) layers before being split into two branches which classify the images
- Output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



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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Summary

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

감사합니다 *Thank you!*