Deep Learning Neutrino Event Reconstruction at DUNE

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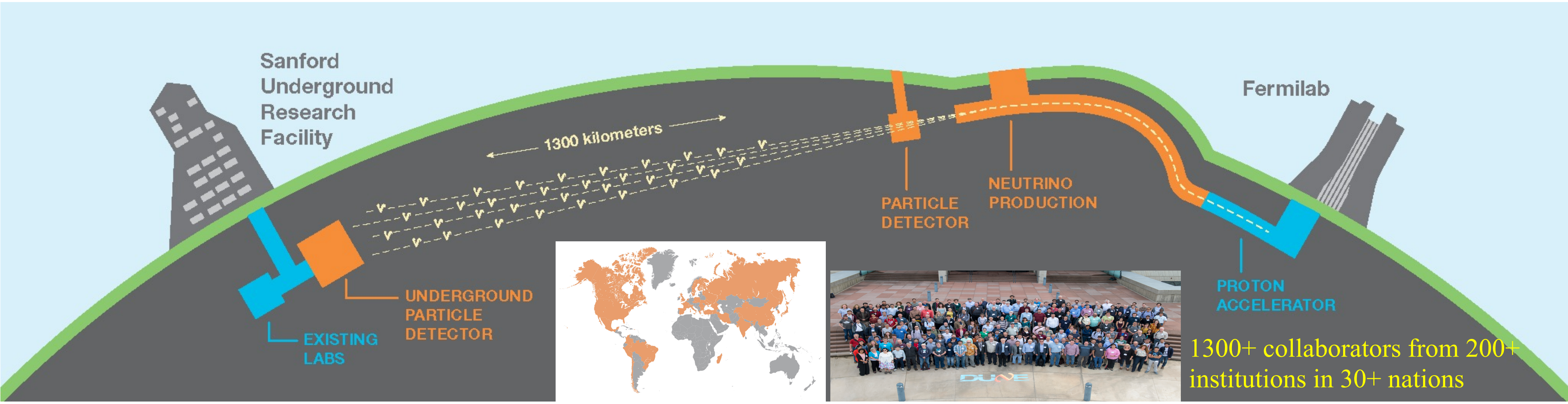
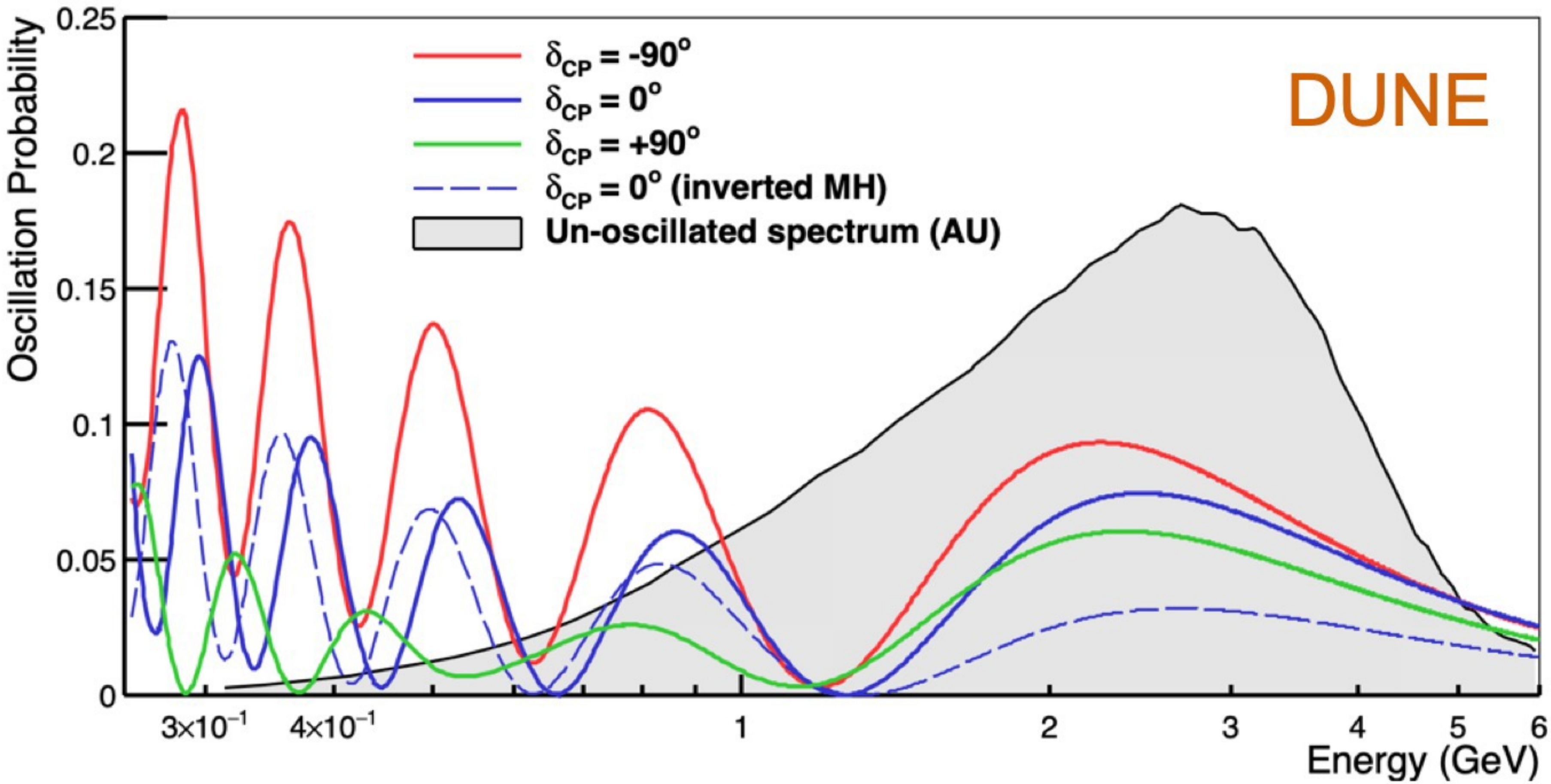
DUNE DEEP UNDERGROUND NEUTRINO EXPERIMENT



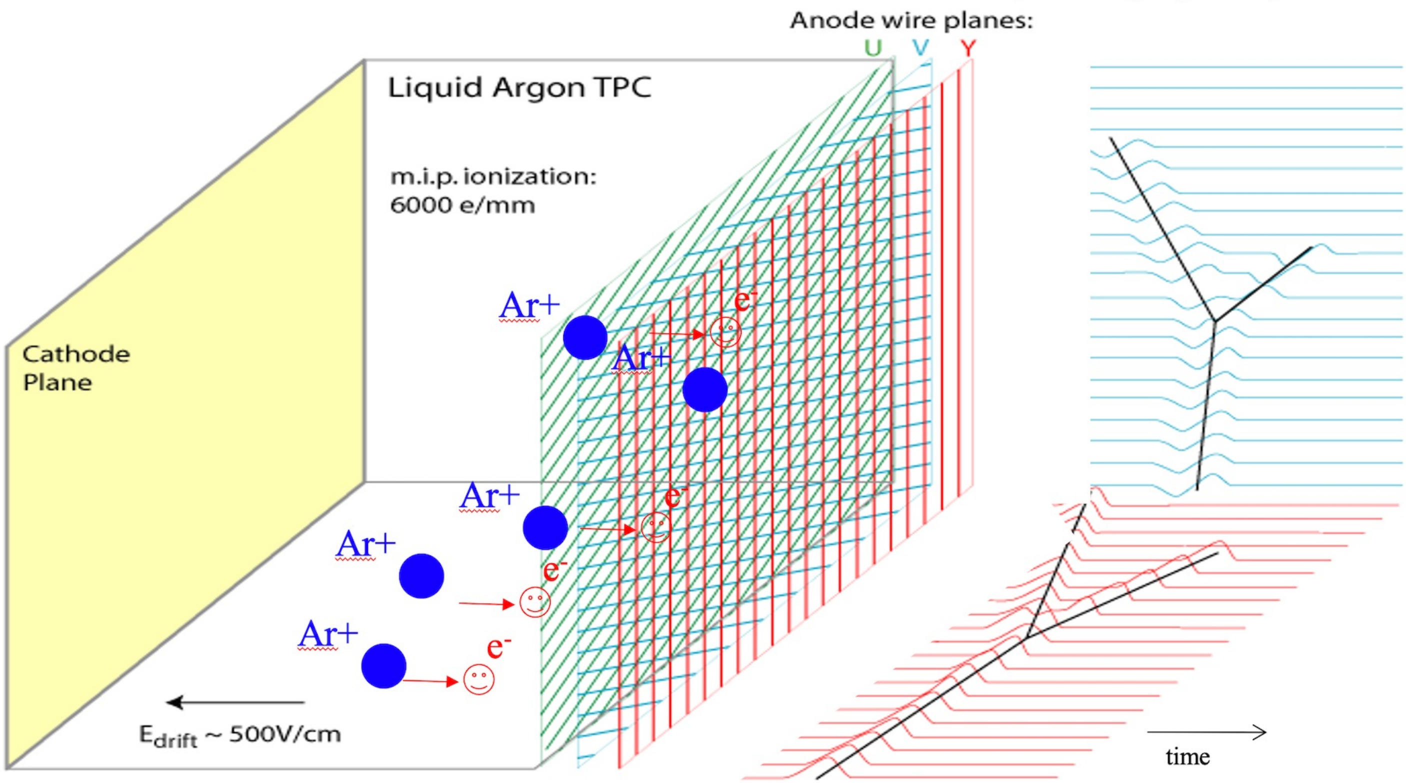
- New neutrino beam at Fermilab (1.2 MW@80 GeV protons, upgradeable to 2.4 MW), 1300 km baseline
- 70 kton Liquid Argon Time Projection Chamber (LArTPC) Far Detector at Sanford Underground Research Facility, South Dakota, 1.5 km underground
- Multiple technologies for the Near Detector (ND)
- ν_e appearance and ν_μ disappearance → Neutrino mass ordering and CP violation
- Large detector, deep underground, high intensity beam → Supernova burst neutrinos, atmospheric neutrinos, nucleon decay and other BSM, etc
- Excavation started in 2017, begin taking data in late 2020s

Neutrino oscillation in DUNE



- On-axis wideband beam covering main oscillation features at 1295 km
- High performance detector and reconstruction to measure signal and control beam backgrounds

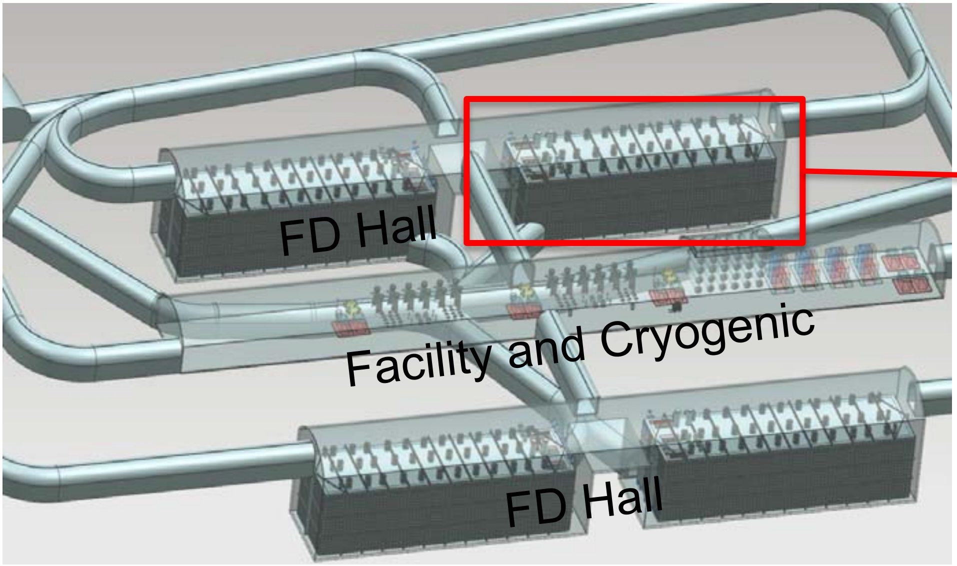
Far Detectors: Liquid Argon Time Projection Chamber (LArTPC)

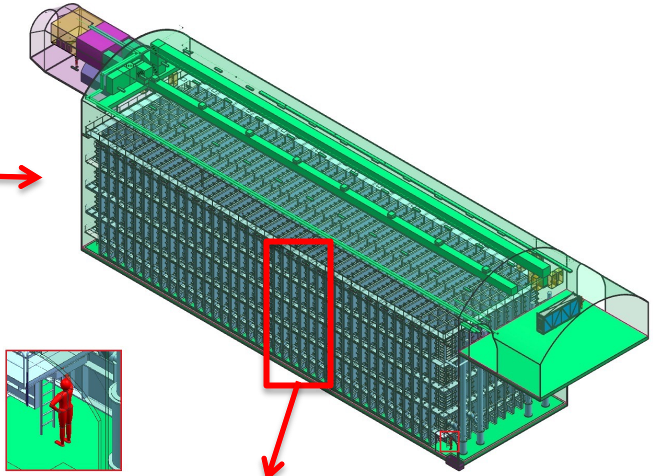


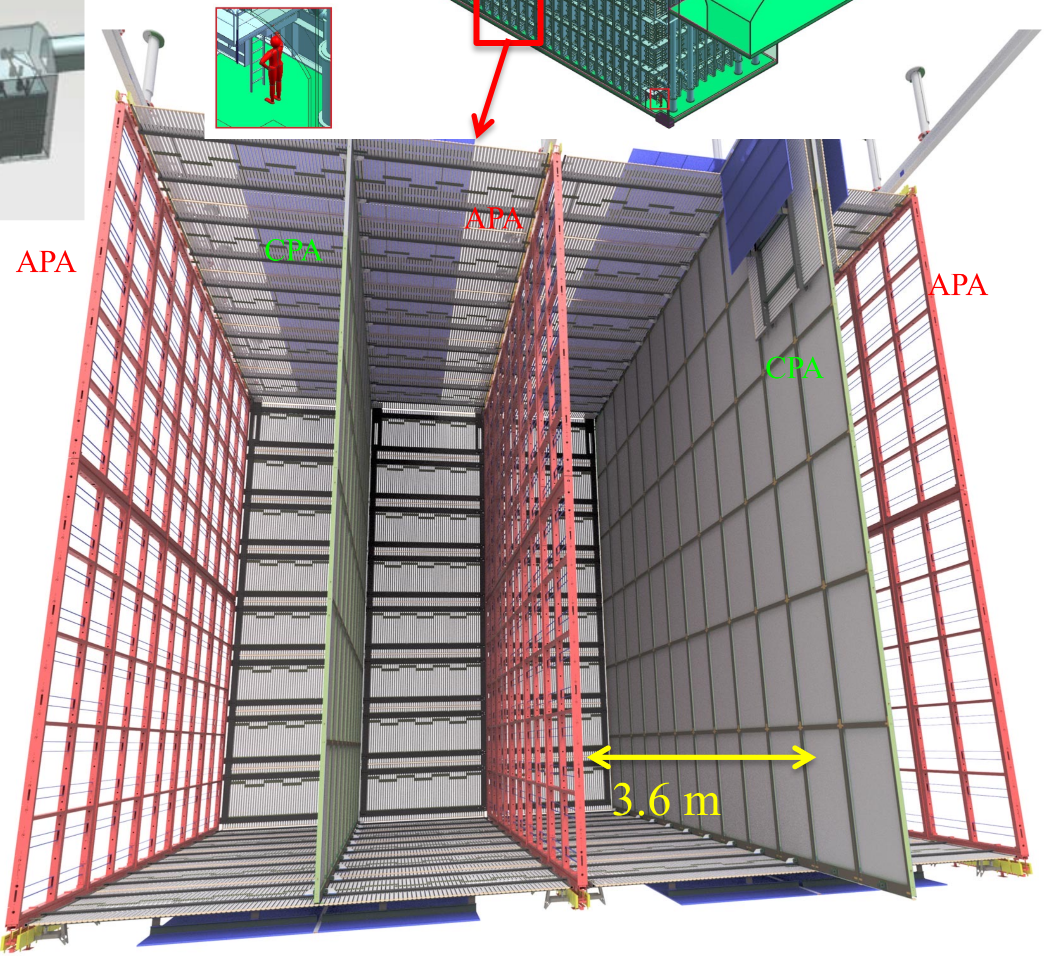
Event display in LArTPC (MicroBooNE MC)

- High resolution 3D track reconstruction
  - Charged particle tracks ionize argon atoms
  - Ionized electrons drift to anode wires (~ms) for XY-coordinate
  - Electron drift time projected for Z-coordinate
  - Ionizing electrons drift long distances, impurity atoms attract electrons → liquid argon purity is essential to signal detection
- Argon scintillation light (~ns) detected by photon detectors, providing t_0

Far Detectors: Liquid Argon Time Projection Chamber (LArTPC)



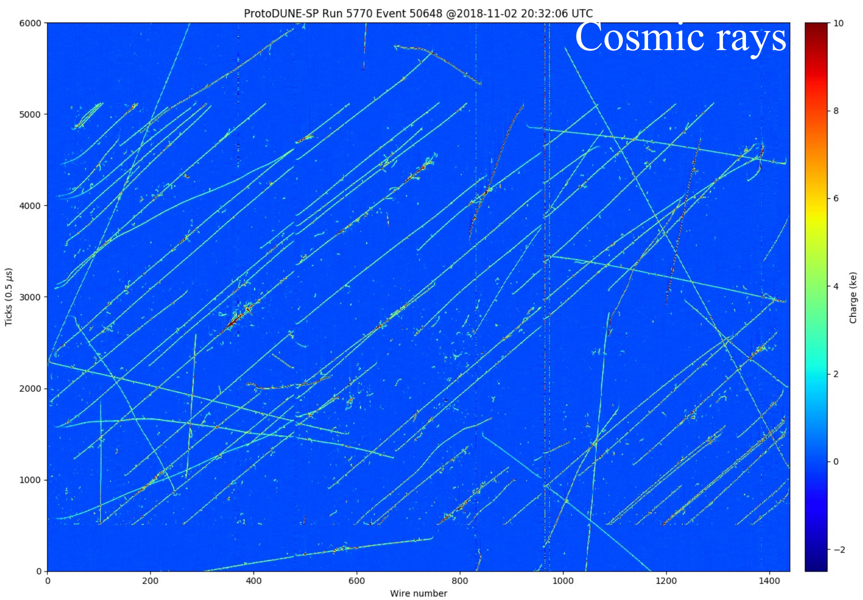


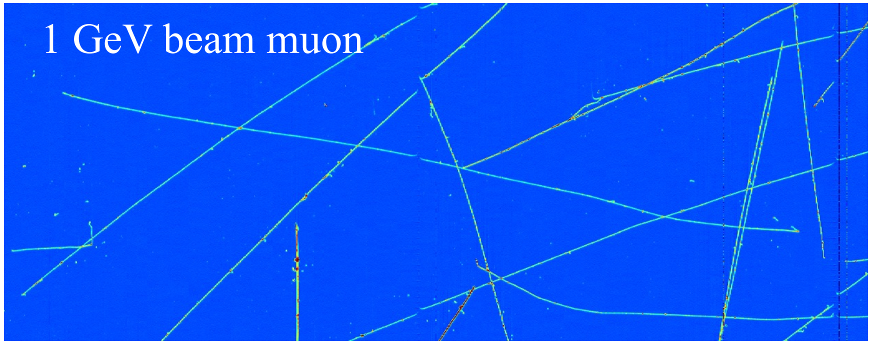


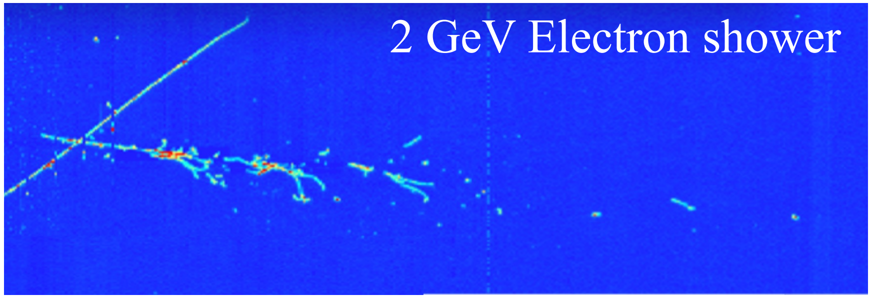
- Four 17-kt modules deployed in stages
- Single Phase LArTPC: all wire planes immersed in liquid argon
- First module will be single phase:
  - 18m x 19m x 66m
  - Drift distance: 3.6 m, wire pitch: 5 mm

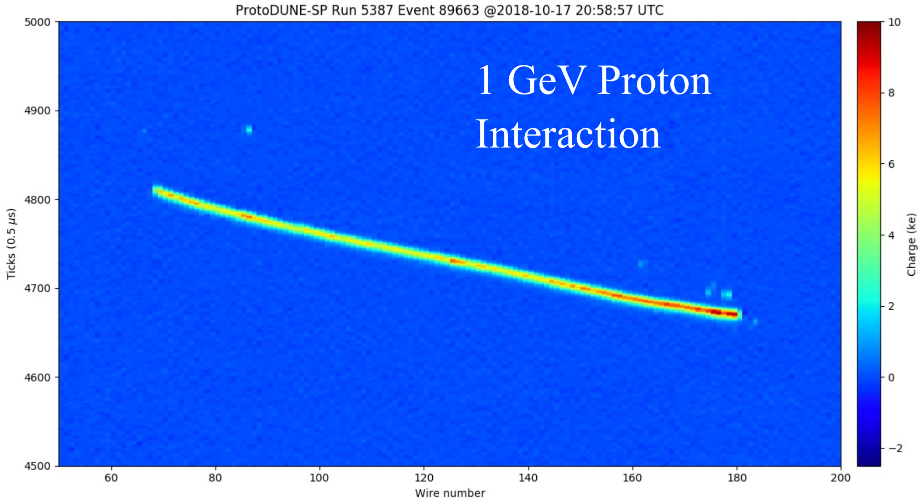
Event Displays in ProtoDUNE-SP Data

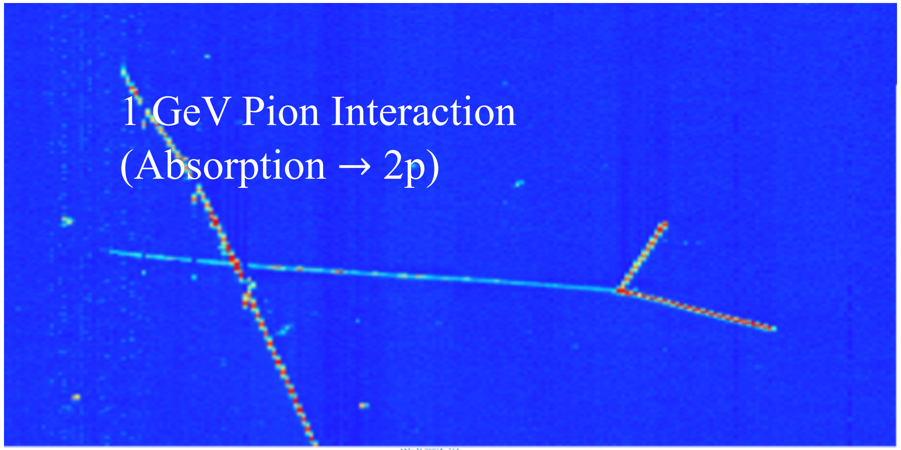
- ProtoDUNE-SP: single phase DUNE prototype detectors at CERN, 770-ton LAr
- Resolution and data quality excellent → Liquid argon has high purity, Electronic noise under control





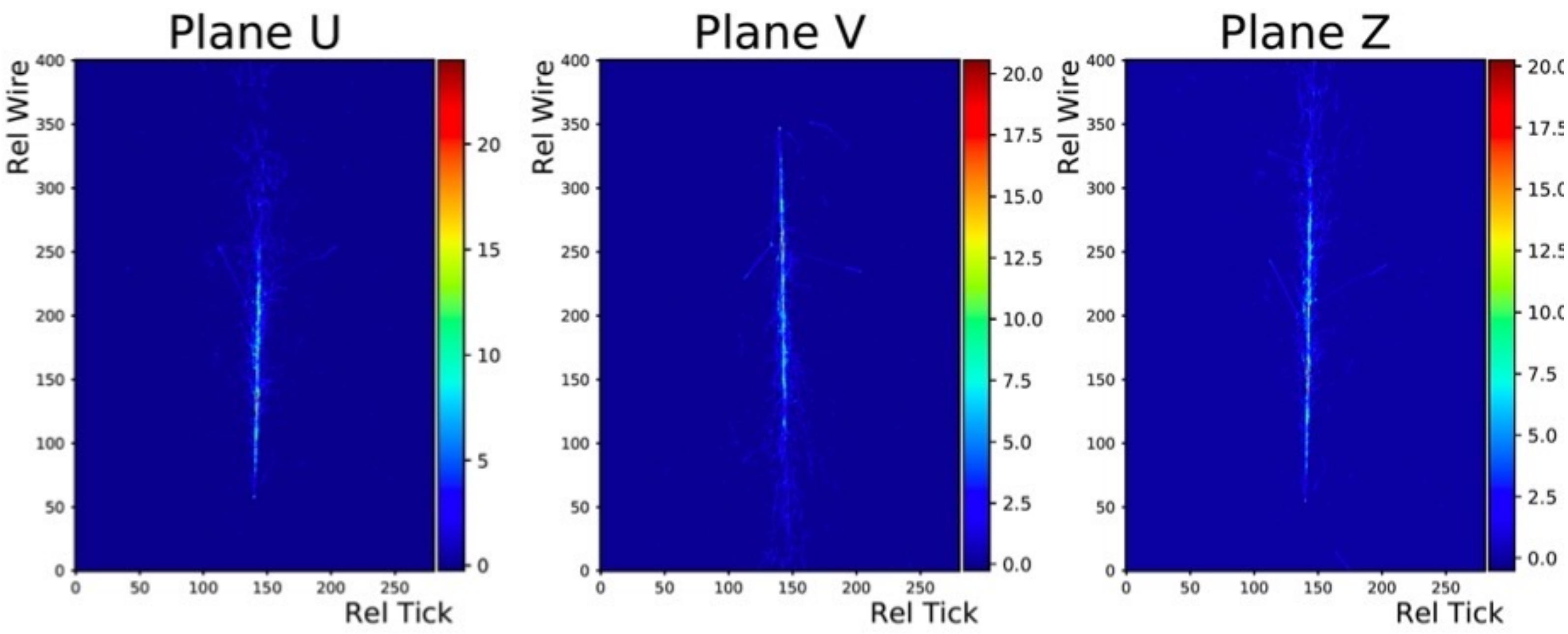






Convolutional Neural Network for Classification and Regression

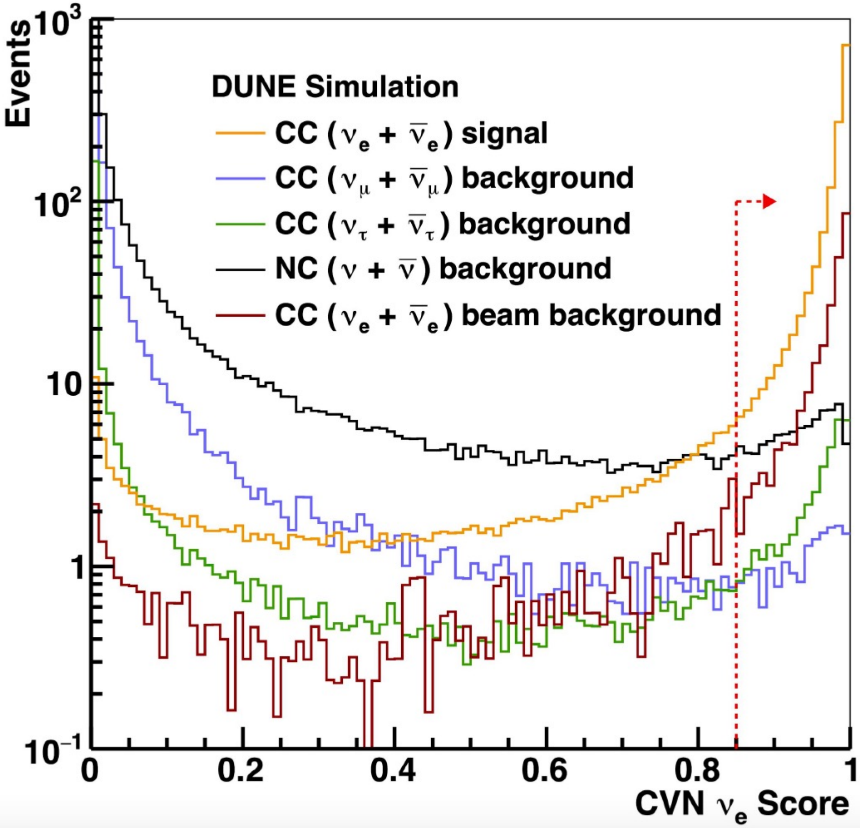
- LArTPC pixel maps for each event are either 3 x 2D images
- CNNs are neural networks specialized to taking images, using a set of translationally invariant filters
- Therefore, reconstructing DUNE events with CNNs is ideal application of deep learning techniques
- CNNs can be used for:
  - Classification: Particle and event identification
  - Regression: fitting for particle energy, event energy, or event vertex

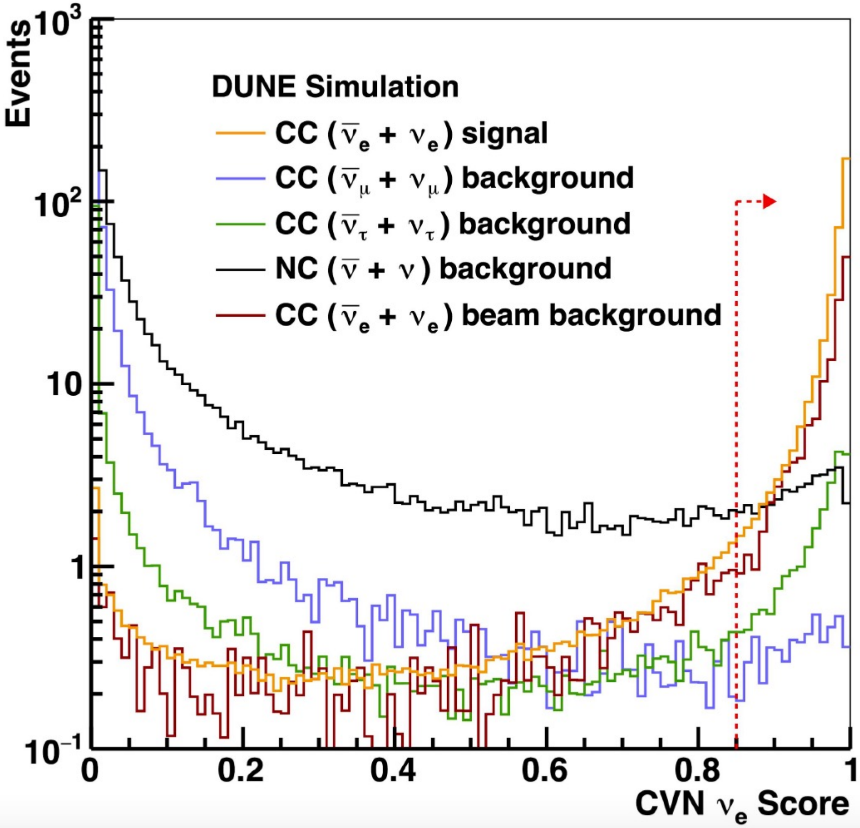


3 x 2-D images for a ν_e CC event in DUNE FD simulation: Wire ID vs Time Tick for U,V and Z wire planes

Event Classification CNN identifiers in DUNE

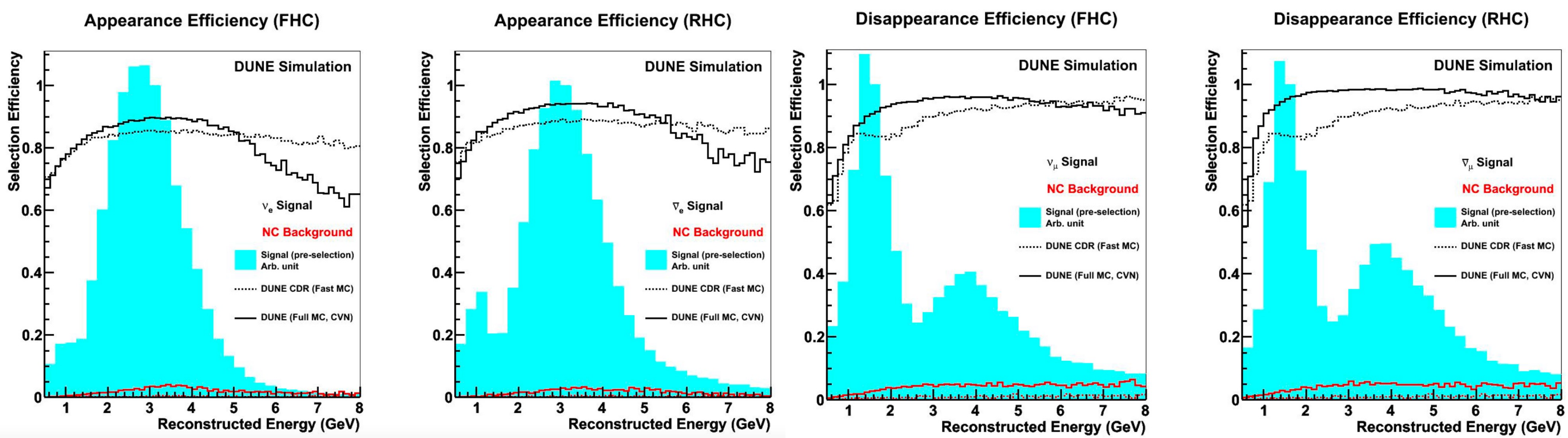
- Classification Convolutional Neural Network has been implemented at DUNE for event identification (CVN)
- Identify ν_μCC, ν_eCC and NC events





Event Classification CNN identifiers in DUNE

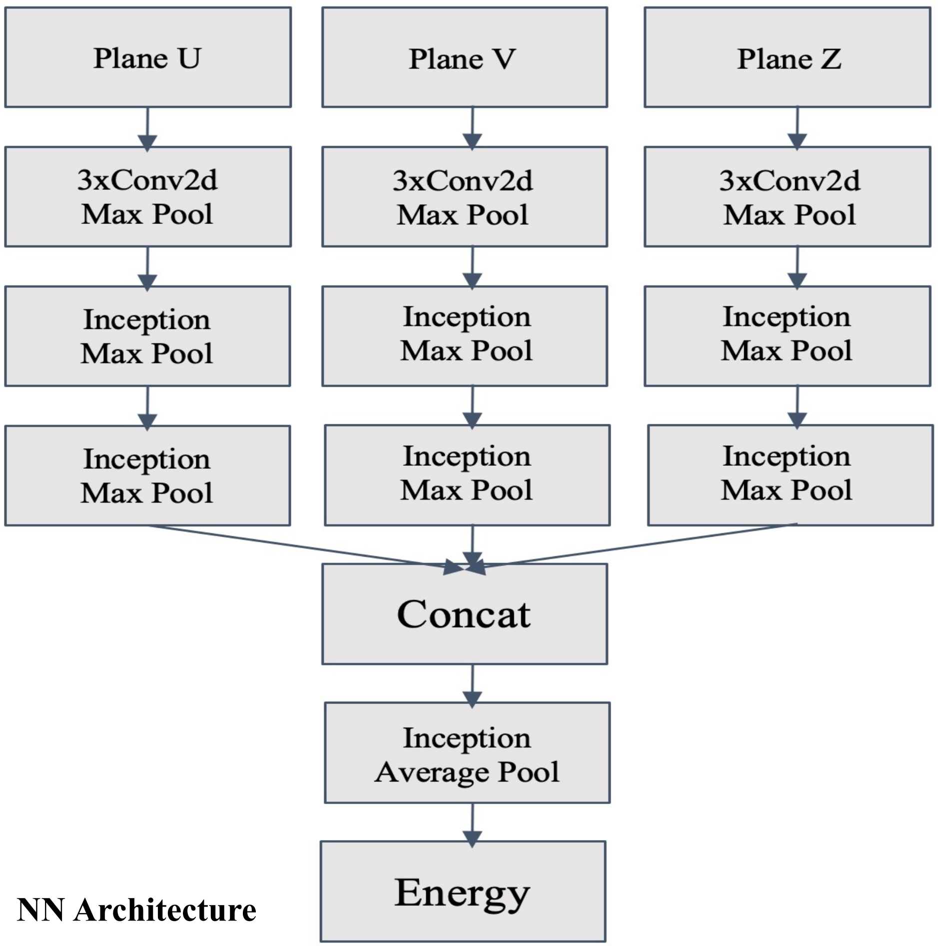
- Performance is better than DUNE CDR assumptions
- Paper published: Phys.Rev.D 102 (2020) 9, 092003



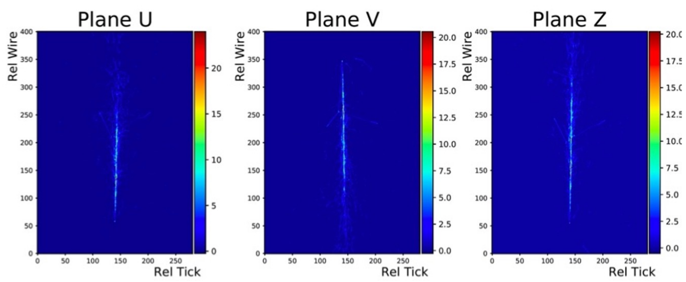
Regression Convolutional Neural Network for Energy Reconstruction in DUNE

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

Loss function



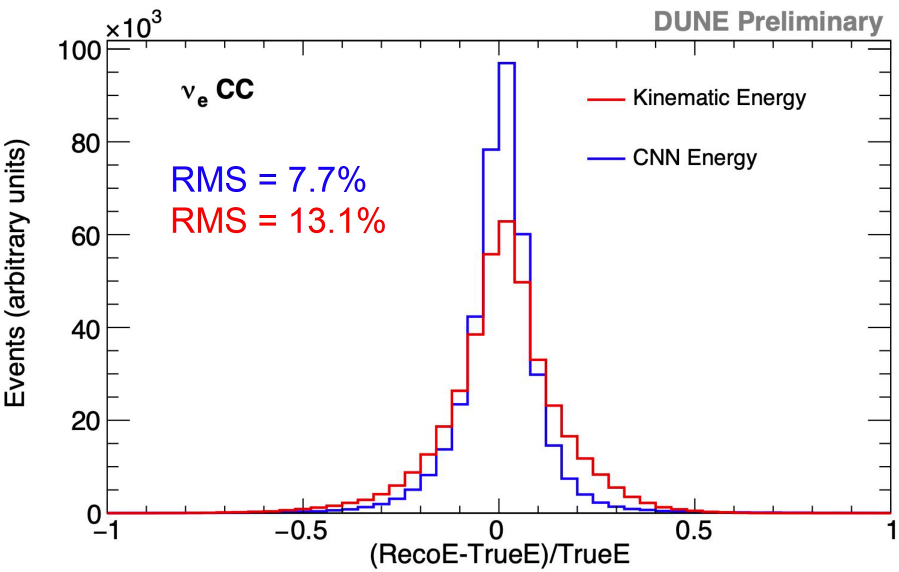
NN Architecture

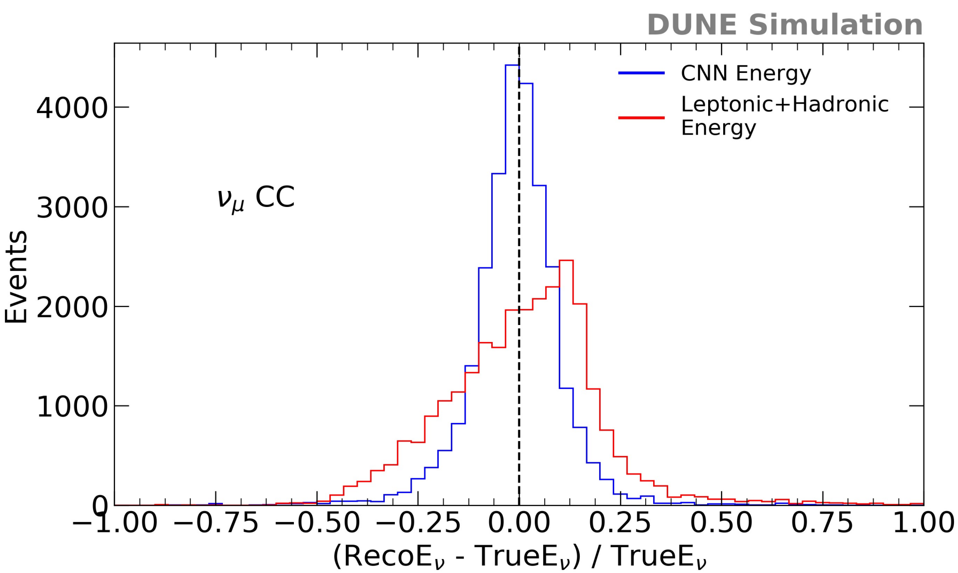


- Provides appropriate surrogate to optimize energy resolution $E_{reco} - E_{true}/E_{true}$
- Linear output unit for energy
- Optimize energy resolution and reduce impacts from outliers.
- Use hyperparameter optimization software SHERPA
- Weighted events by energy to reduce energy dependent bias

ν_e CC and ν_μ CC Event Energy

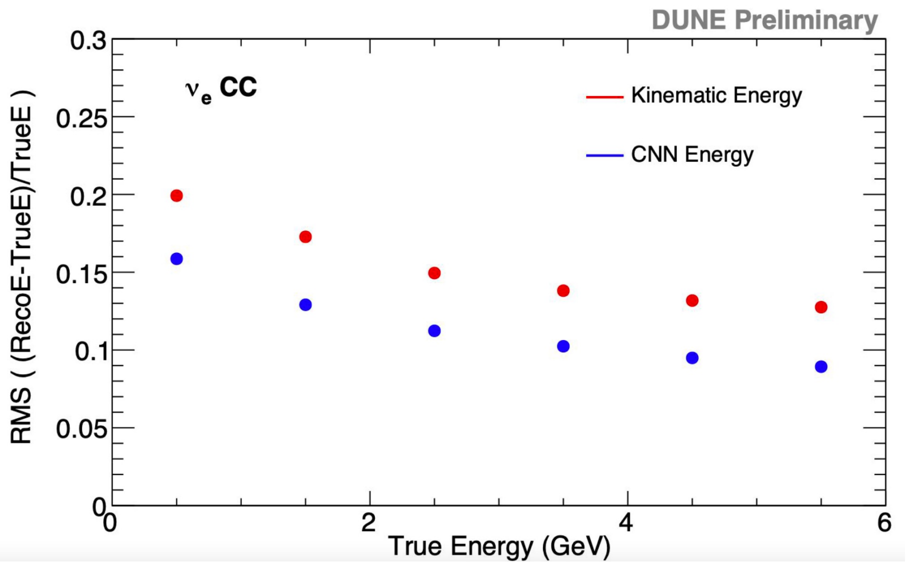
- Regression CNNs outperform kinematic energy based energy reconstruction ($E(\nu) = E_{lep}^{cor} + E_{had}^{cor}$)

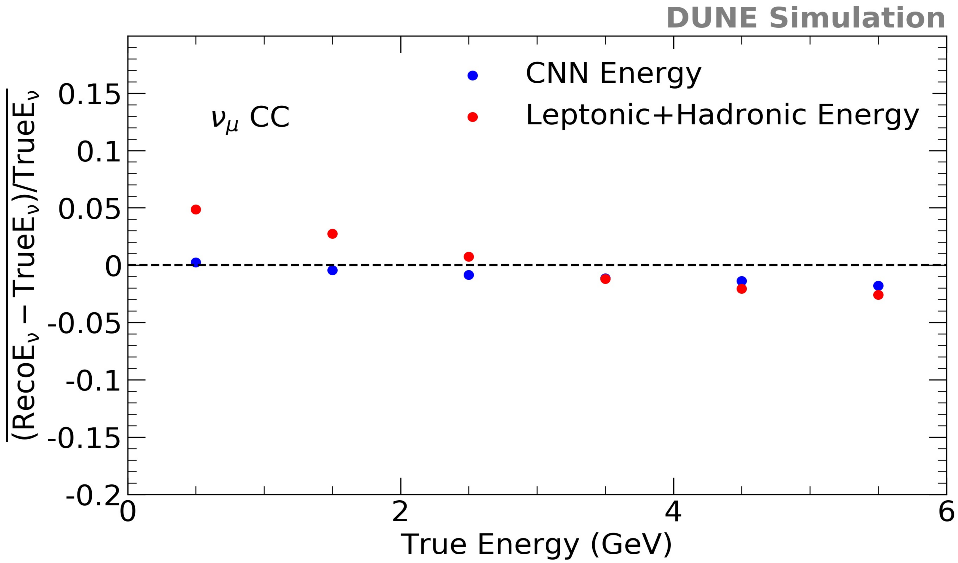




ν_e CC and ν_μ CC Event Energy

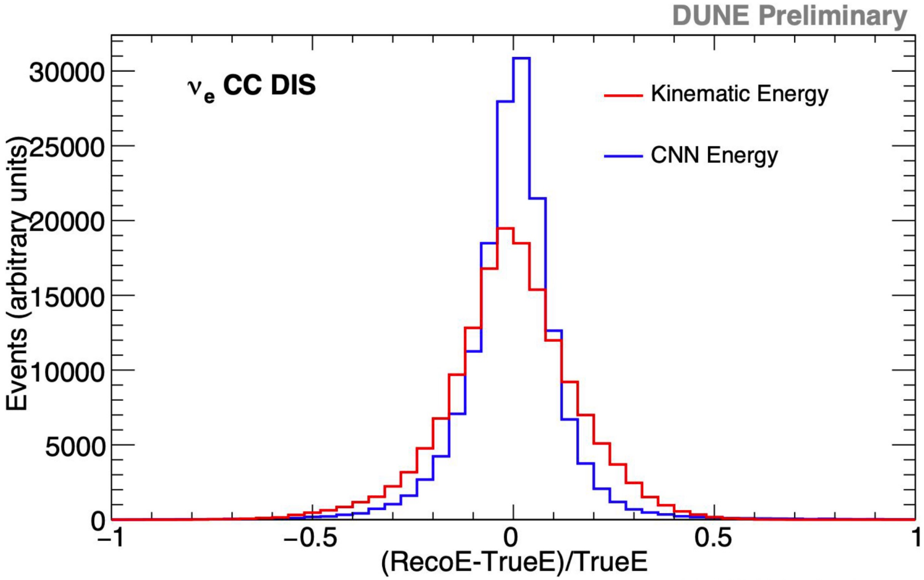
- Regression CNNs outperform kinematic energy based energy reconstruction ($E(\nu) = E_{lep}^{cor} + E_{had}^{cor}$)
- Better resolutions in all energy regions
- Less energy dependent bias

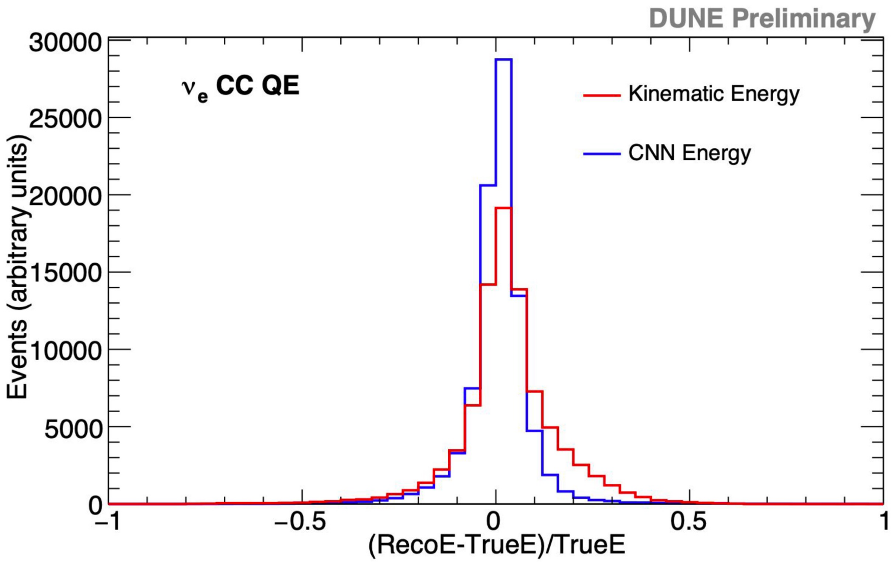


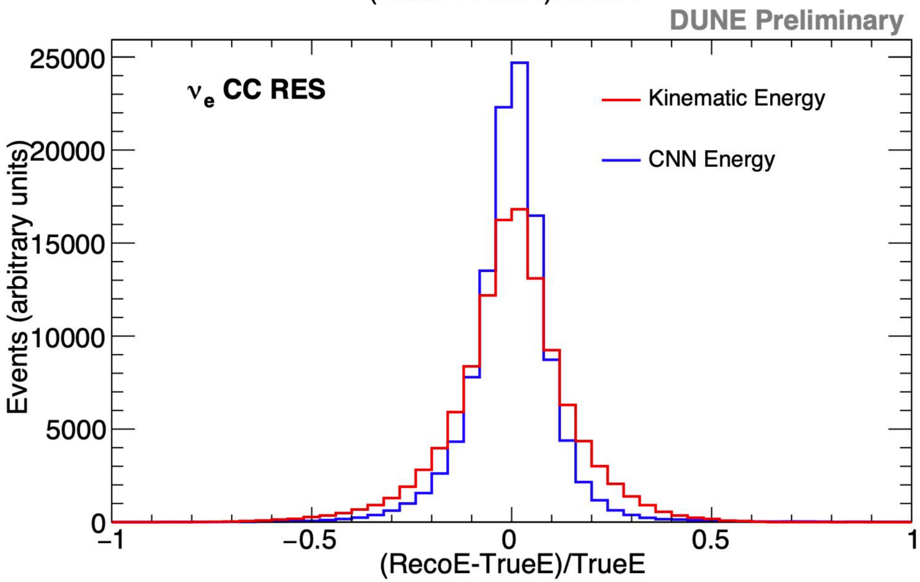


ν_e CC and ν_μ CC Event Energy

- CNNs are also robust against neutrino interaction modes, because of high number of degrees of freedom to fit to different types of interaction

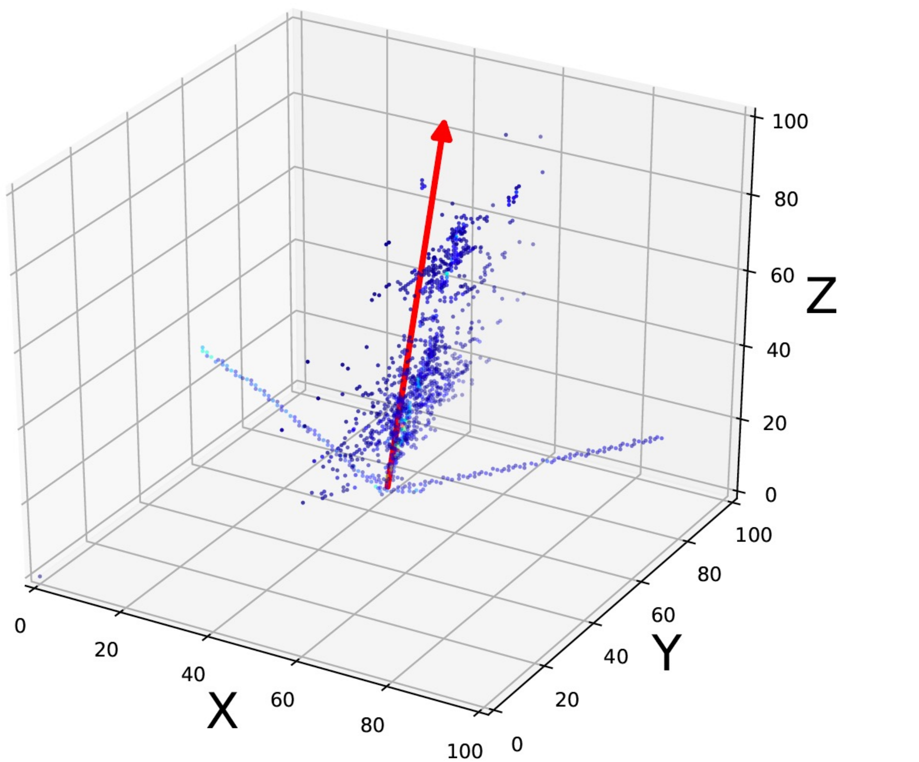






Particle Direction Reconstruction

- Direction regression heavily dependent on 3-D geometry
- So we designed a 3-D CNN to reconstruct particle directions.
- 3-D image constructed from the 3x2D detector images

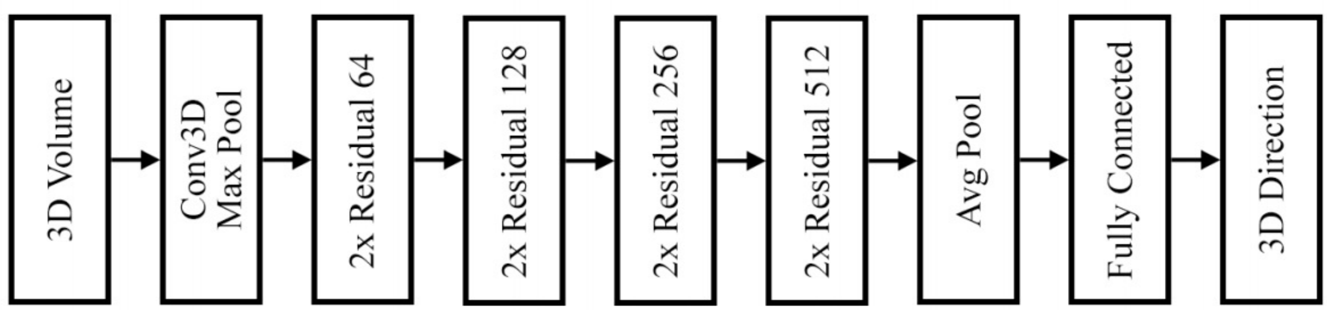


Particle Direction Reconstruction

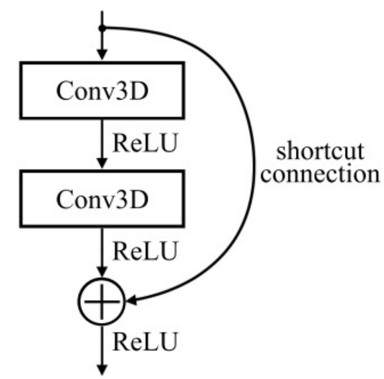
- To distinguishes between exactly opposite directions, we defined relaxed cosine distance loss for better performance:

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

- Architecture model built on a series of residual blocks and a linear layer to output 3-D direction vectors. A cosine distance metric used for training



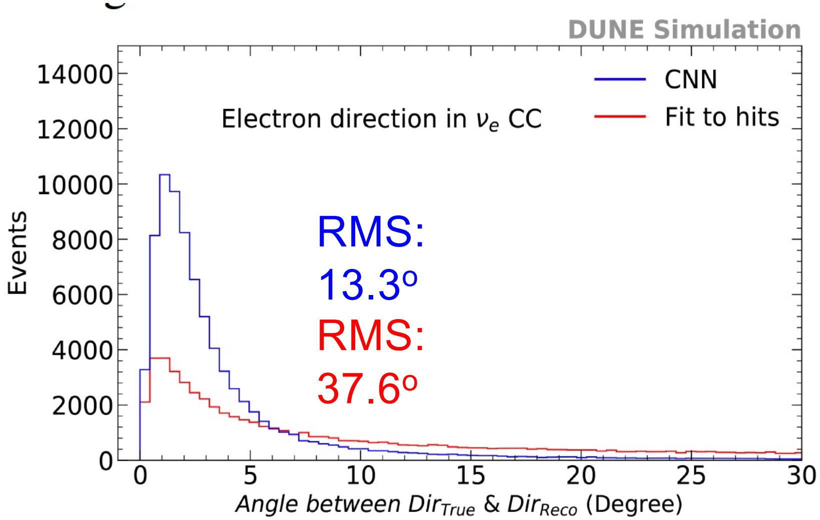
(a) Direction Regression

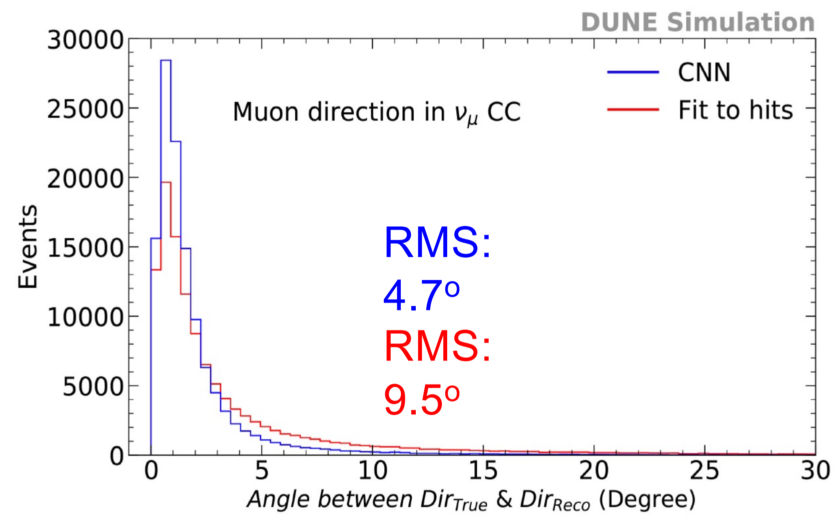


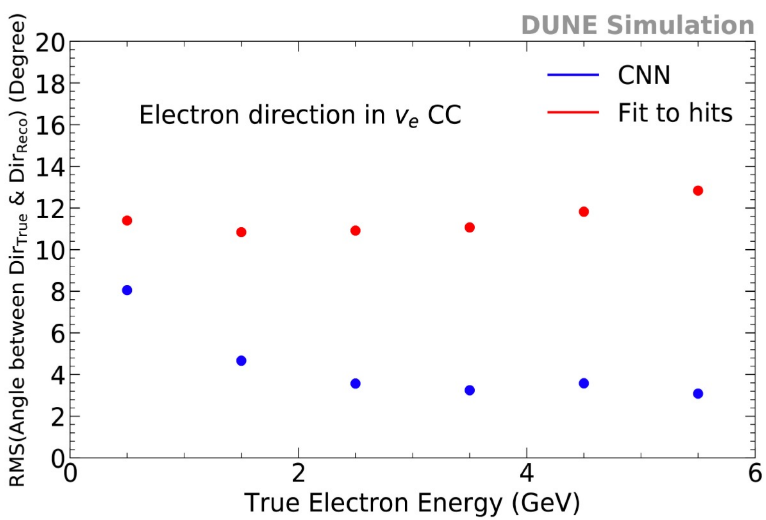
(b) Residual block

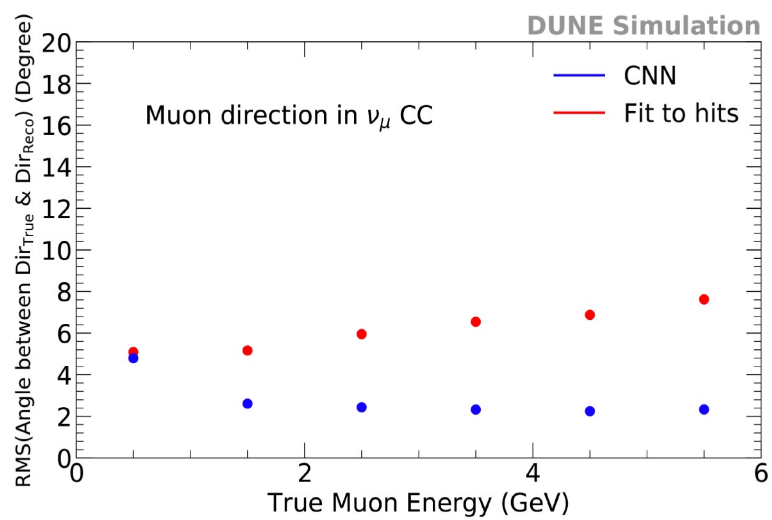
Particle Direction Reconstruction

- Regression CNNs beat traditional fit-to-hits method with better electron and muon resolutions in all energy regions

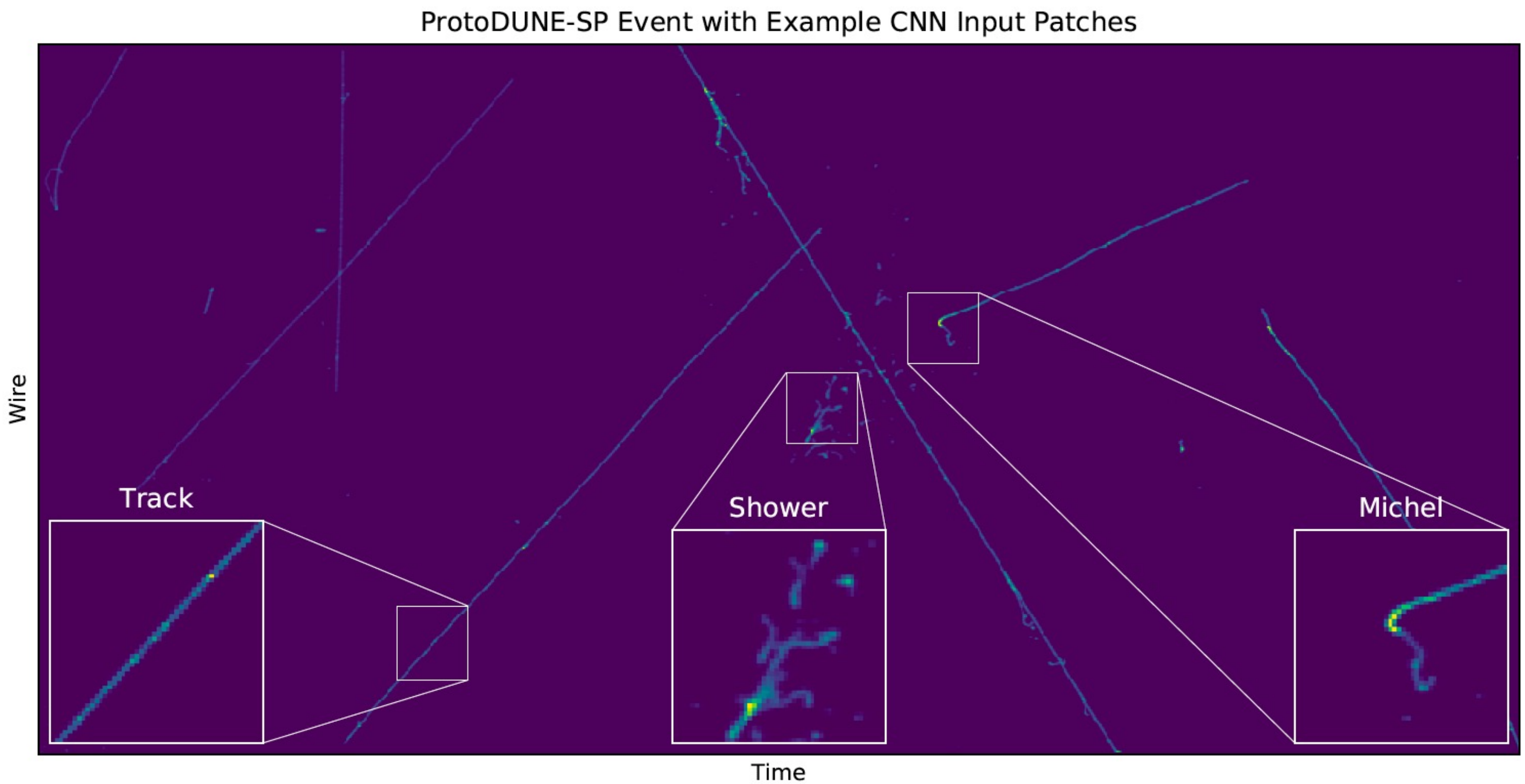








CNN for Shower/Track Separation in ProtoDUNE-SP

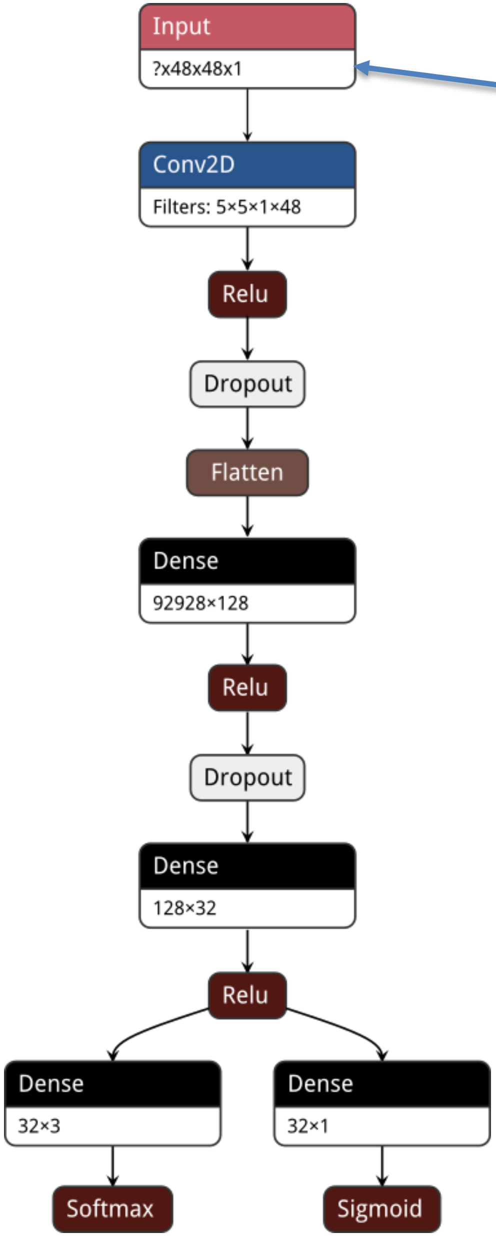


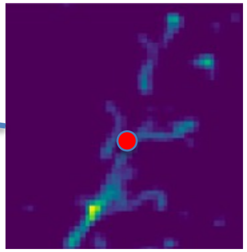
Use CNN to classify energy deposits (hits) from Shower, Track and Michel electrons

- 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

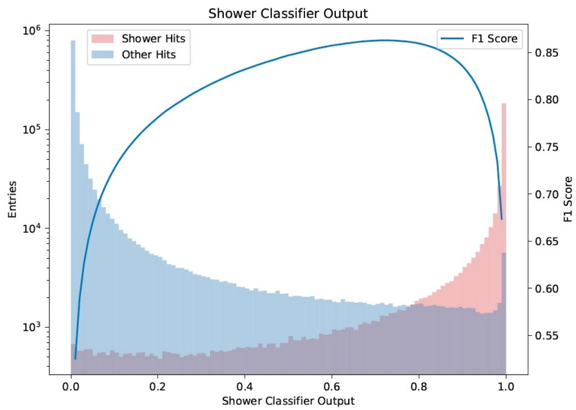
CNN architecture

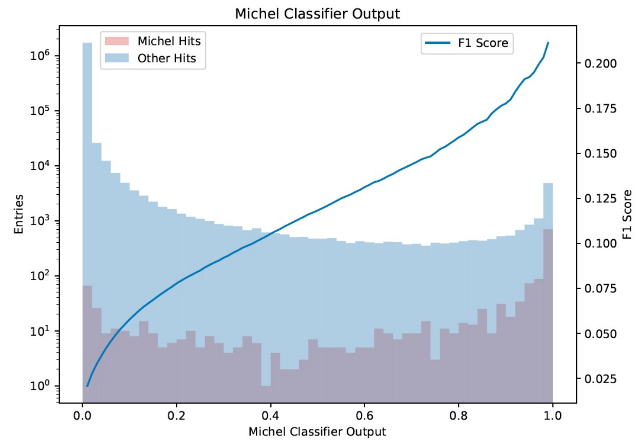


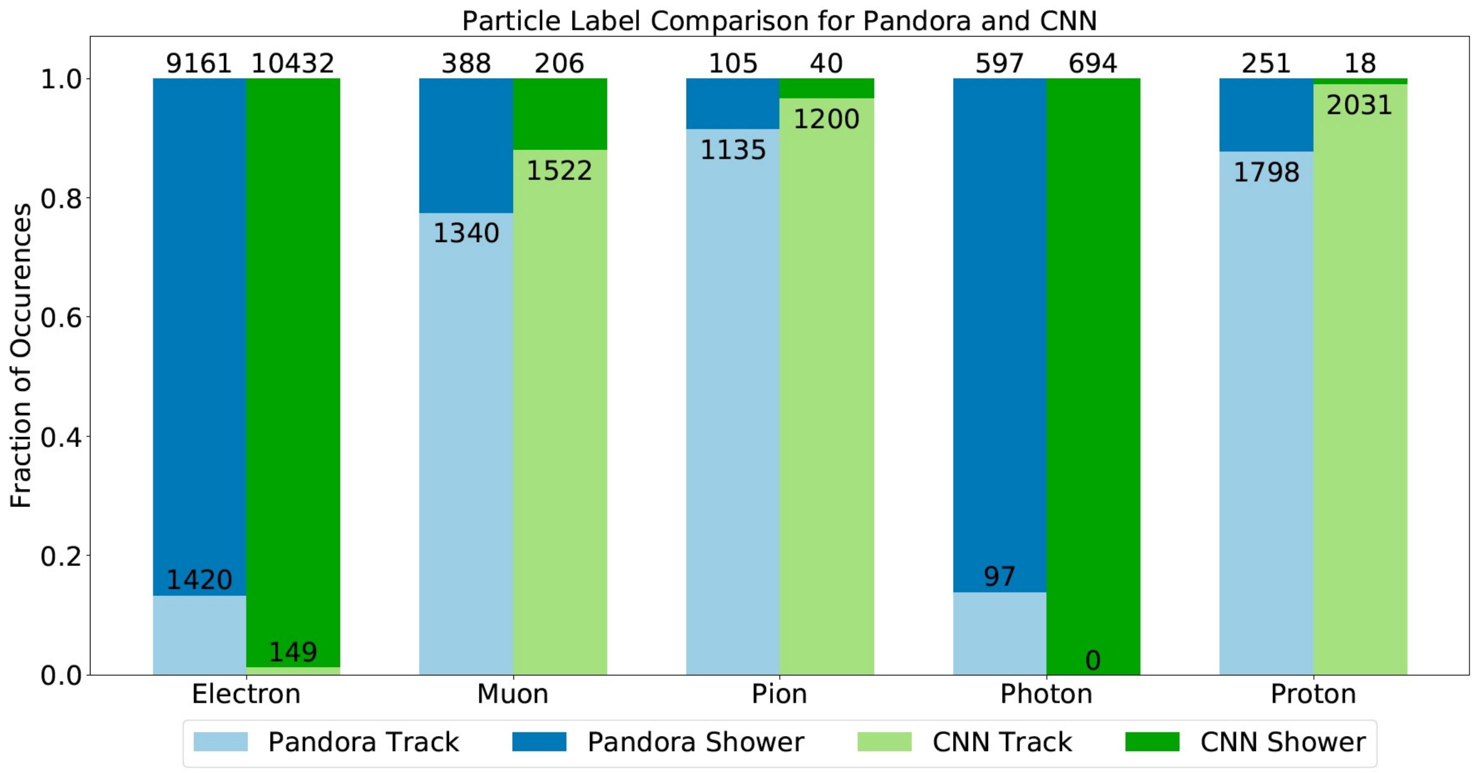


- The inputs are 48 pixel images centered on the reconstructed hit object to be classified
- A single convolutional layer is used to extract feature maps from the images
- These are processed by two dense (fully connected) layers before being split into two branches which classify the images
- The question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

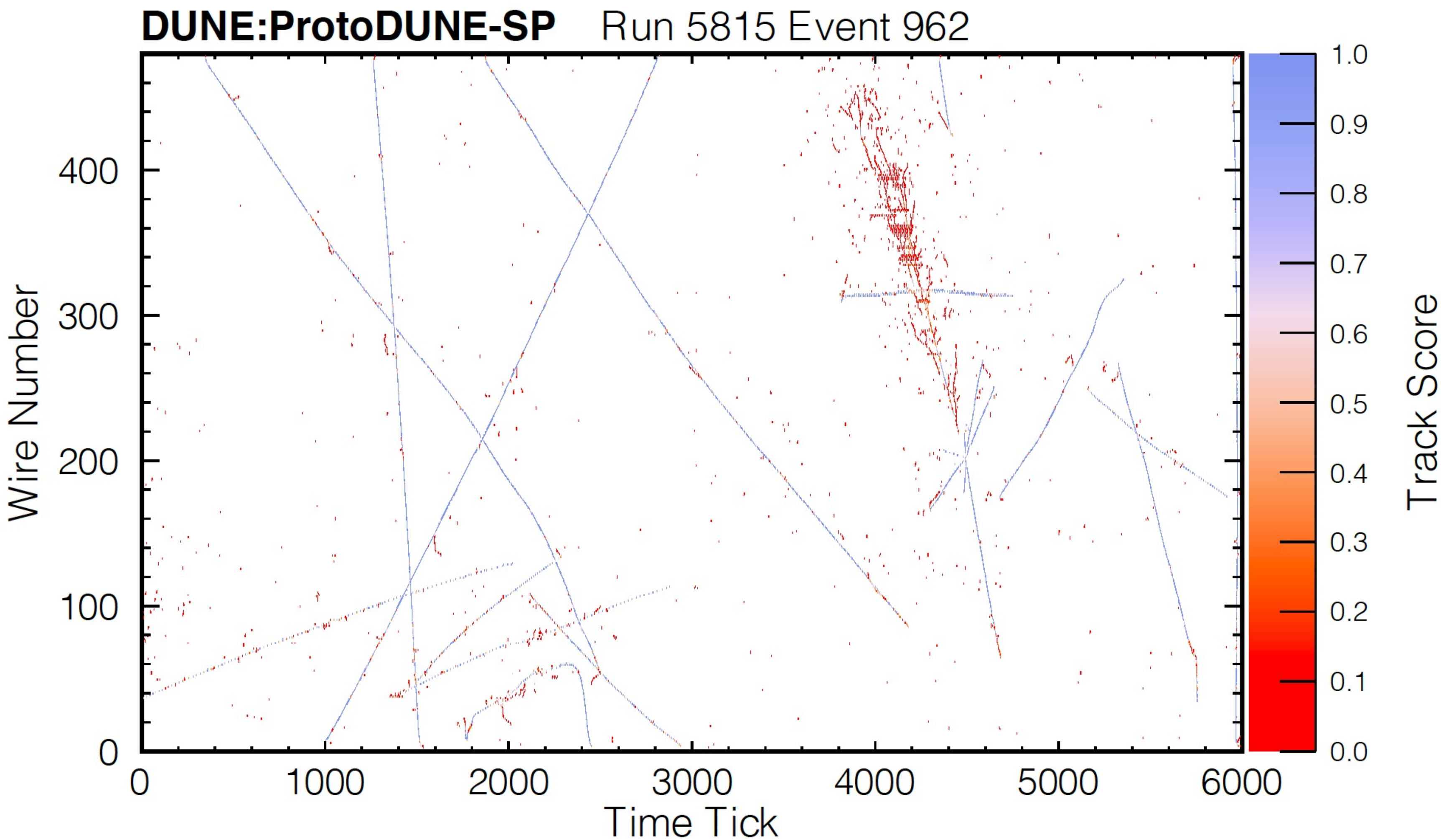
Performance of Shower/Track CNN in MC



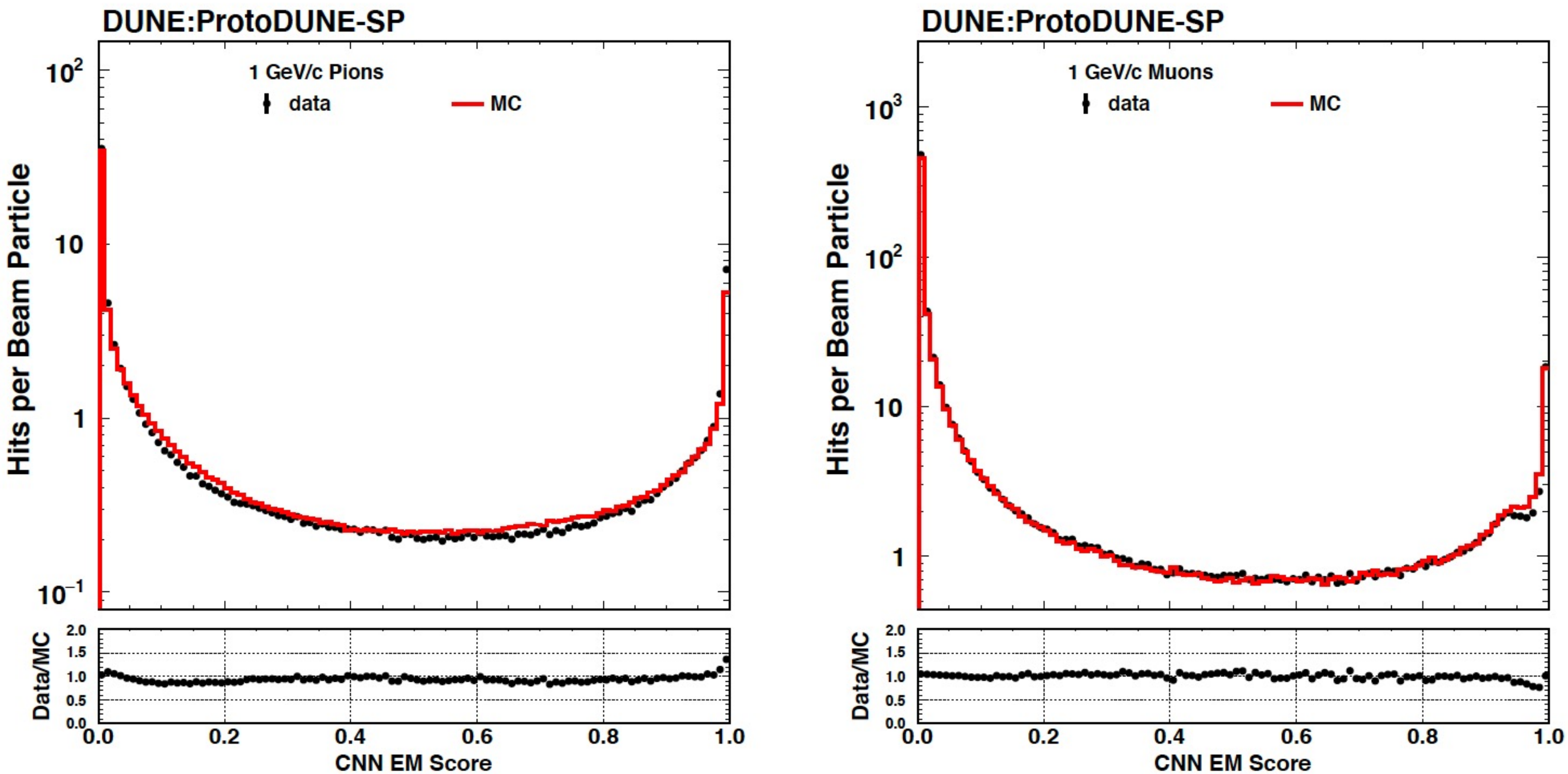




Performance of Shower/Track CNN in Data



Performance of Shower/Track CNN in Data



(a) pion (b) muon

Shower classifier scores for different particle species in the ProtoDUNE-SP beam. The error bars on the data are statistical.

Other Methods Being Developed at DUNE

- Sparse CNNs for Semantic Segmentation
  - Takes advantage of sparseness of hits in 3D pixelmaps
  - Has shown promise for identifying individual pixels as part of tracks or showers
- Graph Neural Networks (GNN)
  - Breaks up hits into "graph" comprised as connected nodes with information such as geometry and energy composition
  - Feeds these graphs to a NN which labels individual nodes
  - Has shown promise in ProtoDUNE

Speed up training for sparse pixelmap

Thank you!