

Identifying Particles and Neutrino Final States with Convolutional Neural Networks in MicroBooNE

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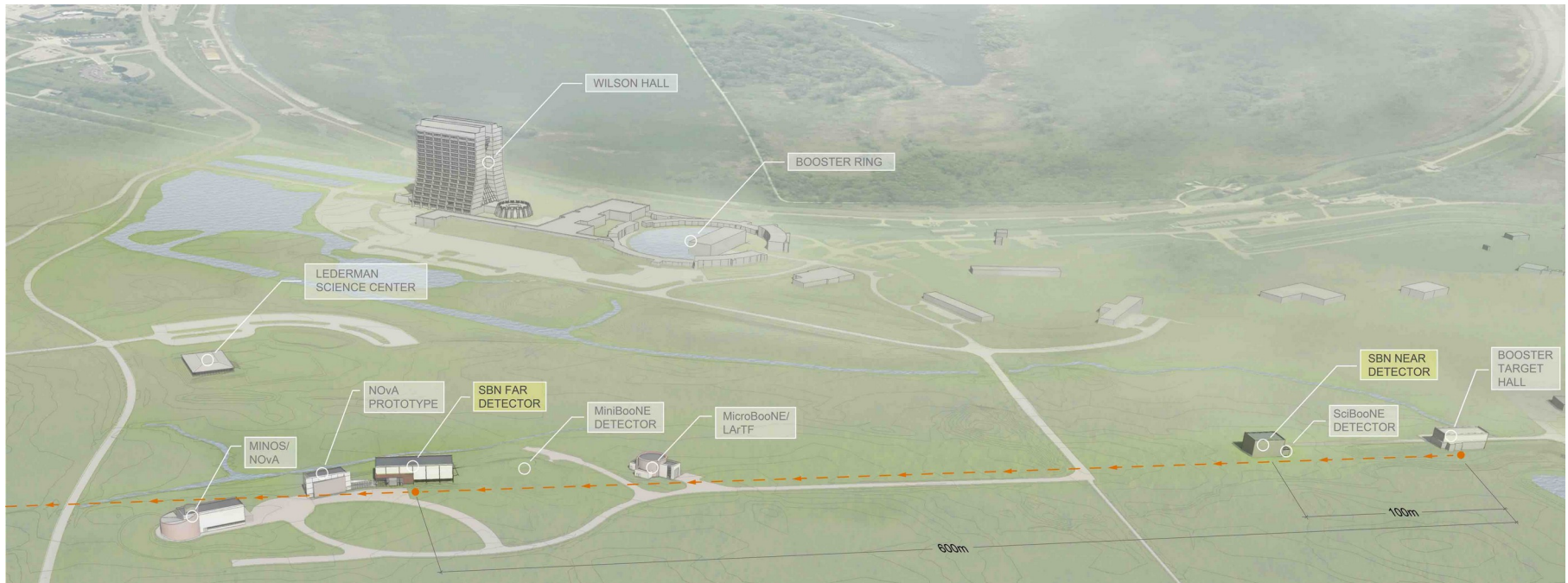


Overview

- A brief overview of:
 - The MicroBooNE detector
 - The motivation for new deep-learning-based reconstruction tools
 - LArMatch: a new U-NET CNN developed by Taritree Wongjirad to reconstruct 3D points from 2D LArTPC images
- Main focus: LArPID, a new CNN to classify 3D tracks and showers produced in the LArMatch-based MicroBooNE reconstruction
 - Development / training
 - Performance
 - Preliminary studies on interpreting the model
 - Utility in identifying neutrino final states in MicroBooNE
 - Initial results for an inclusive CC ν_e selection
- Applicability in other reconstruction frameworks and LArTPC detectors

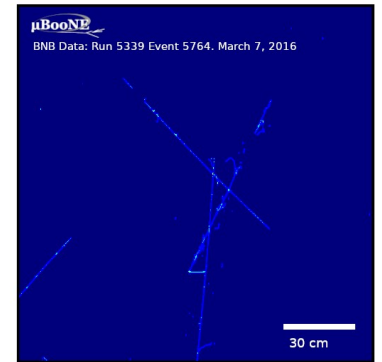
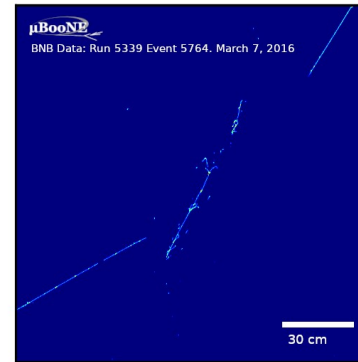
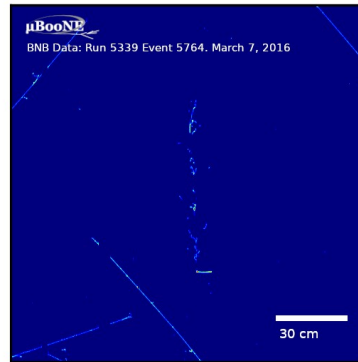
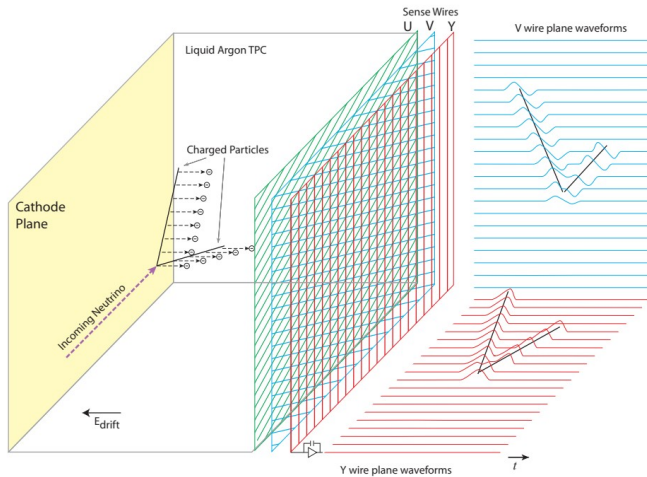
The MicroBooNE Detector

- A LArTPC located in the Booster Neutrino Beam at Fermilab
 - Designed with a primary aim of studying the MiniBooNE low-energy excess



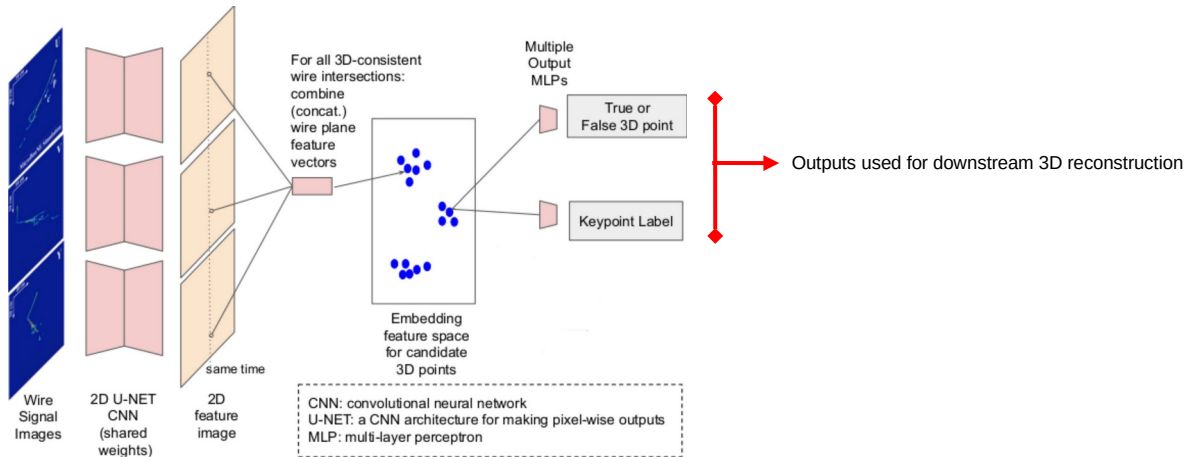
The MicroBooNE Detector

- A LArTPC located in the Booster Neutrino Beam at Fermilab
 - Provides the capability to image neutrino interactions with mm-scale precision
 - This allows for the use of powerful computer vision techniques to reconstruct neutrino interactions



A New Deep-Learning-Based Reconstruction Framework

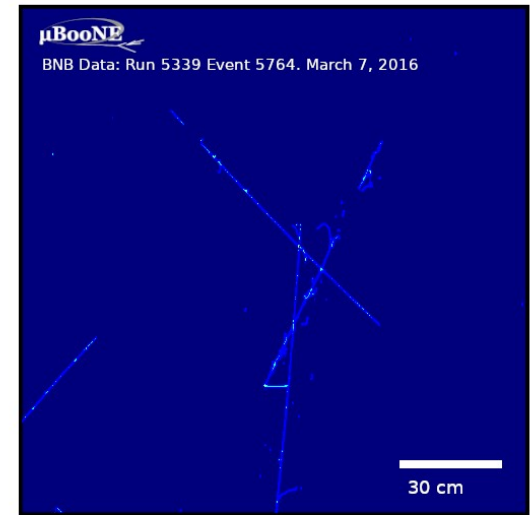
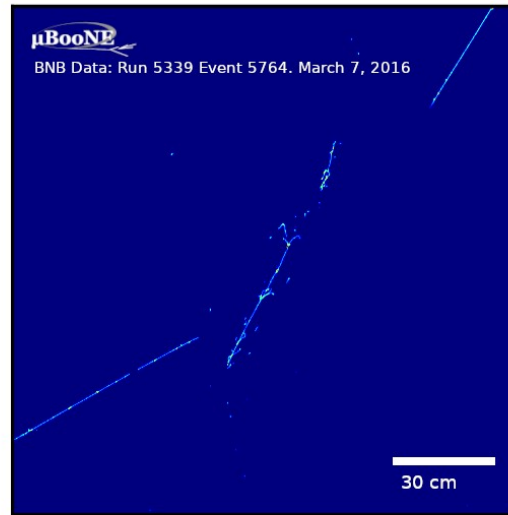
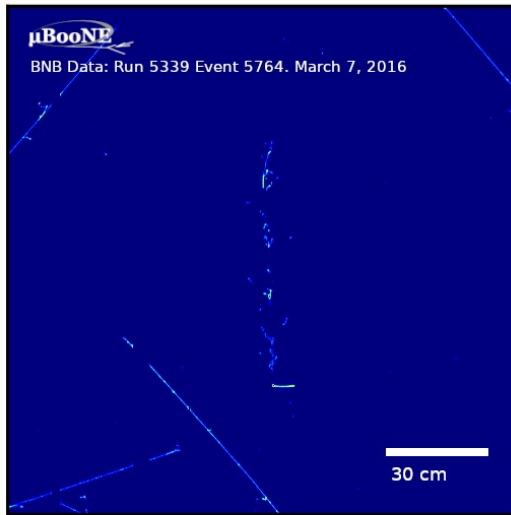
- A previous DL-based reconstruction directly searched (in 2D) for “v-shaped” 1e1p vertices from quasi-elastic CC ν_e events
 - P. Abratenko et al. (MicroBooNE), Phys. Rev. D **105**, 112003 (2022)
 - Designed to test hypothesis that MiniBooNE excess was produced by quasi-elastic CC ν_e interactions
- A new, more general reconstruction paradigm:
 - Use LArMatch, a U-NET CNN developed by Taritree Wongjirad, to find 3D energy-deposition points from 2D images



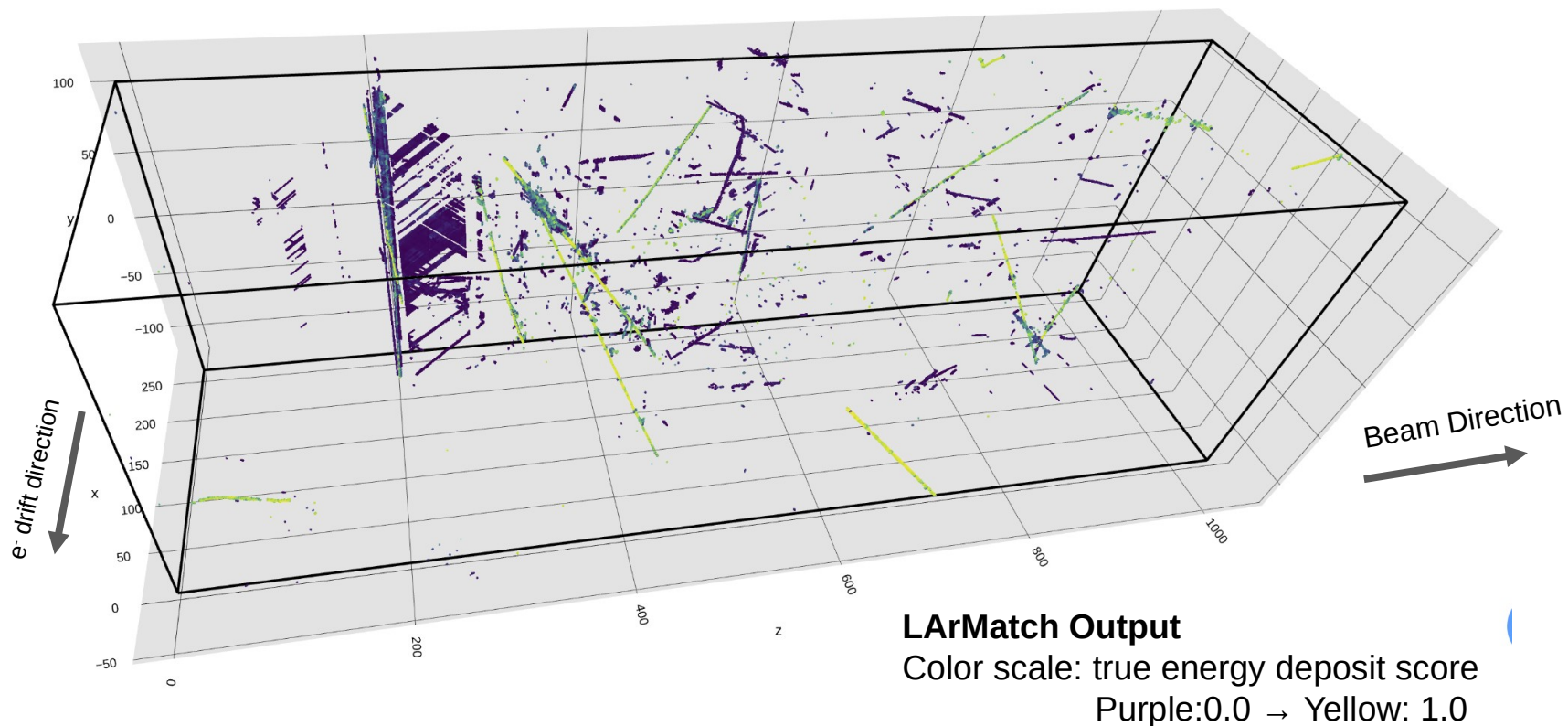
- Cluster tracks and showers (prongs) in 3D
- Use LArPID, a new CNN, to attach particle labels to 3D prongs by analyzing associated pixels in 2D images
 - Much more on this later

Reconstruction Example: LArMatch Input

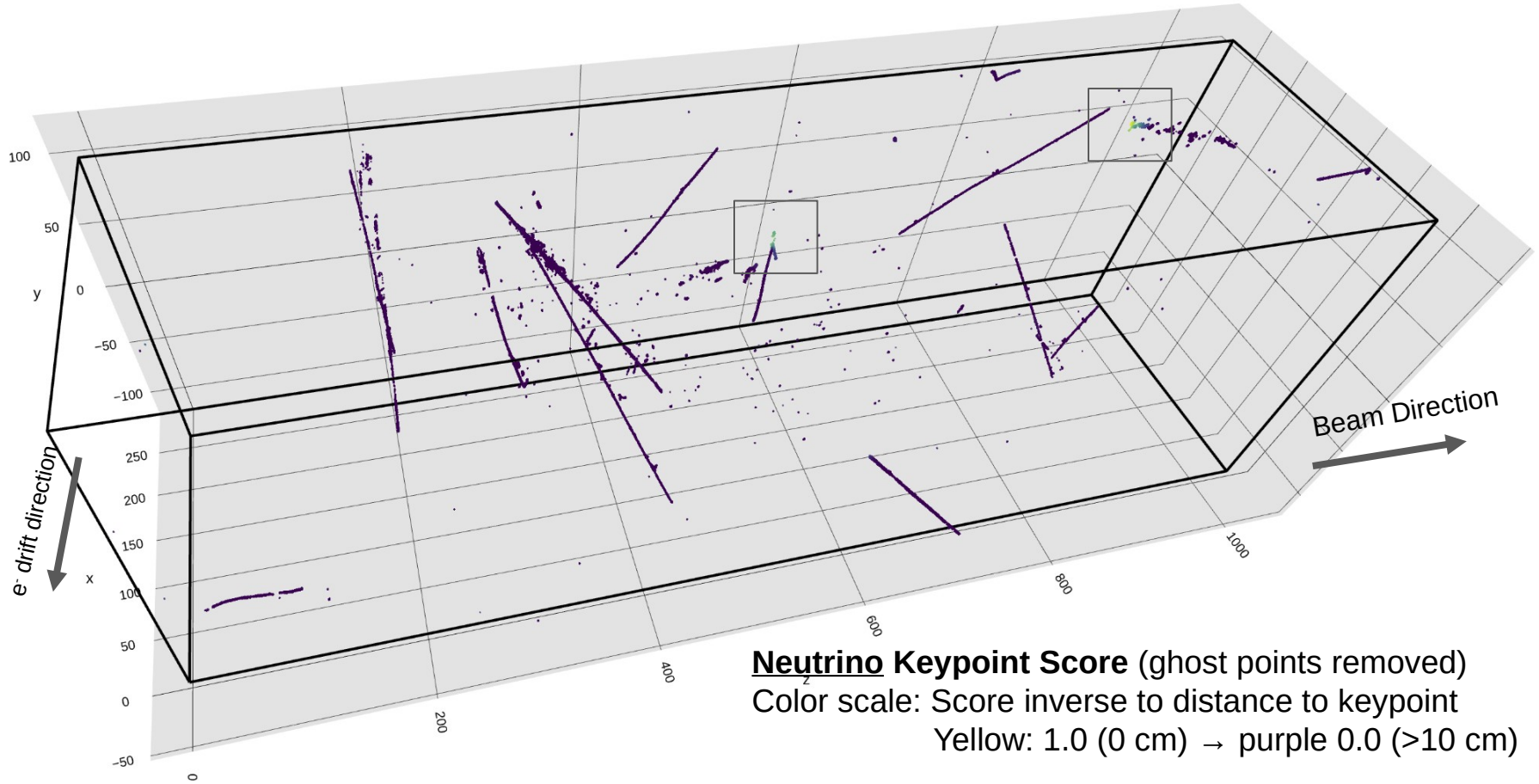
Zoomed in view of probable CC ν_e interaction from open data:



Reconstruction Example: LArMatch True Energy Deposit Output

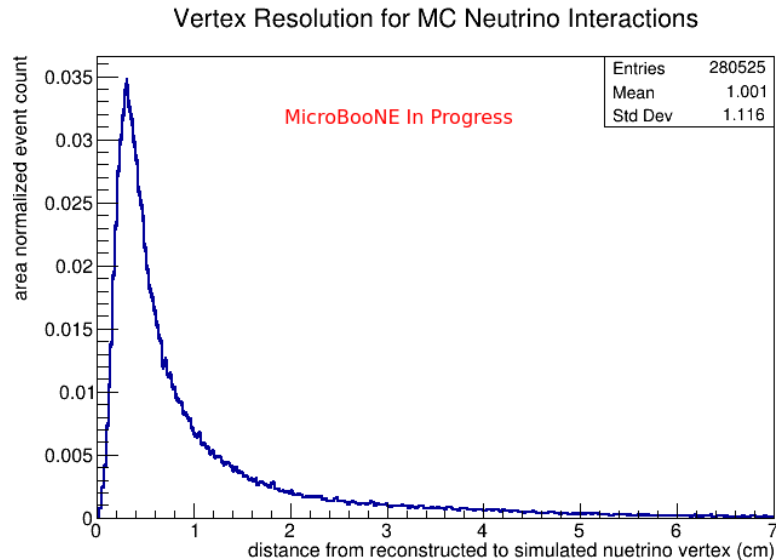


Reconstruction Example: LArMatch Neutrino Keypoint Score Output

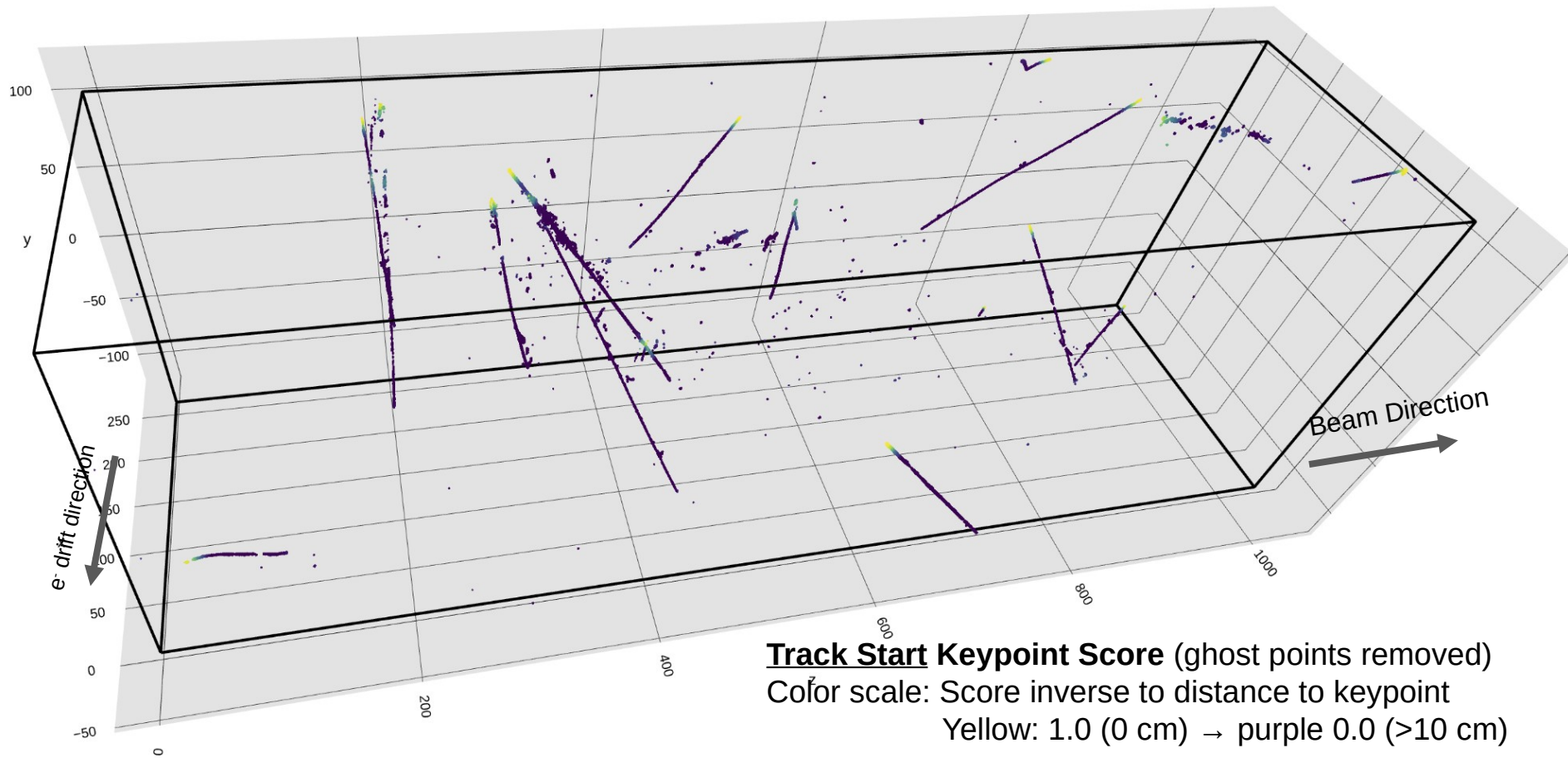


LArMatch Neutrino Vertex Resolution

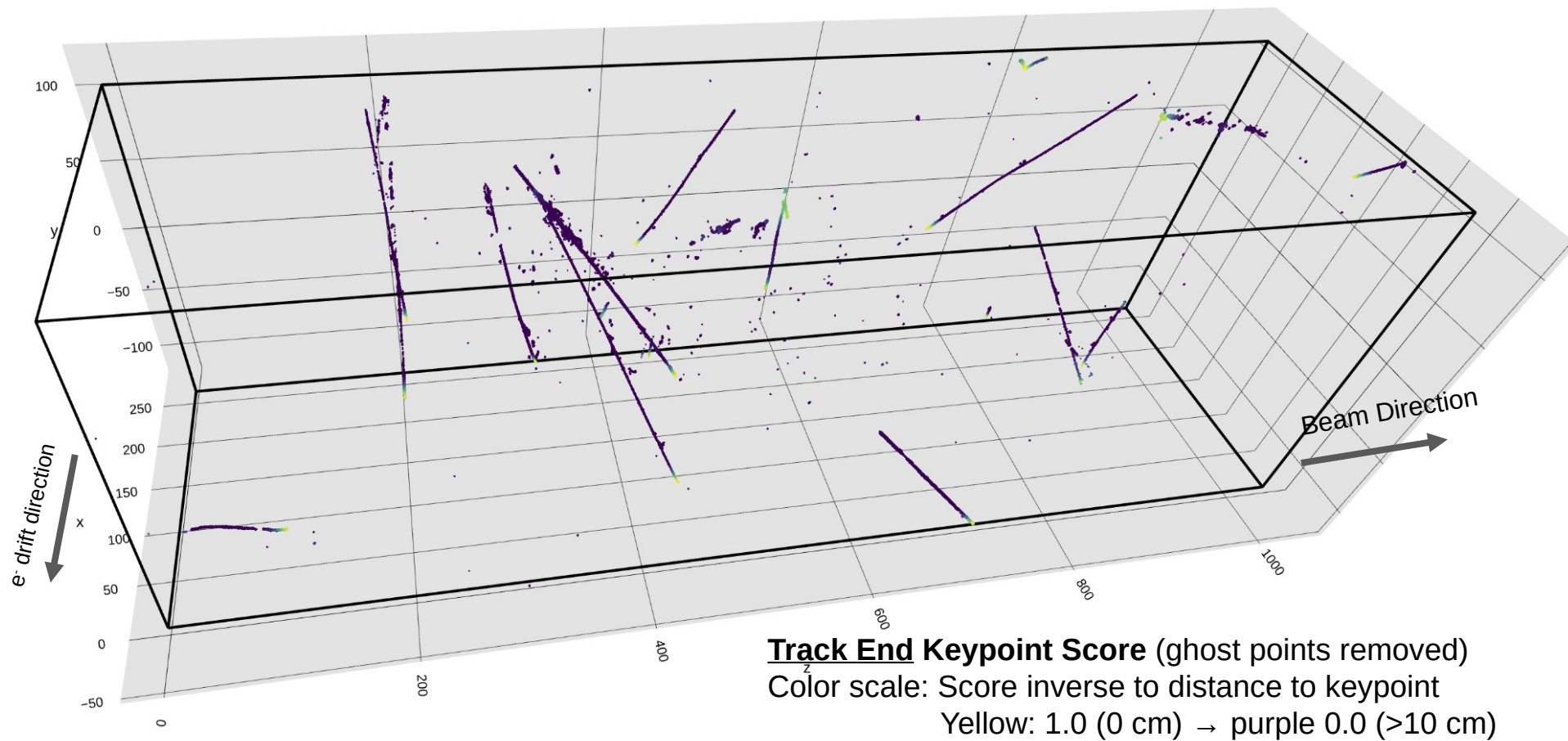
- In MC, 68% of reconstructed neutrino vertices are within 9.2mm of simulated interaction position
 - Wire spacing is 3mm, so this is within 3 wires, which is quite good



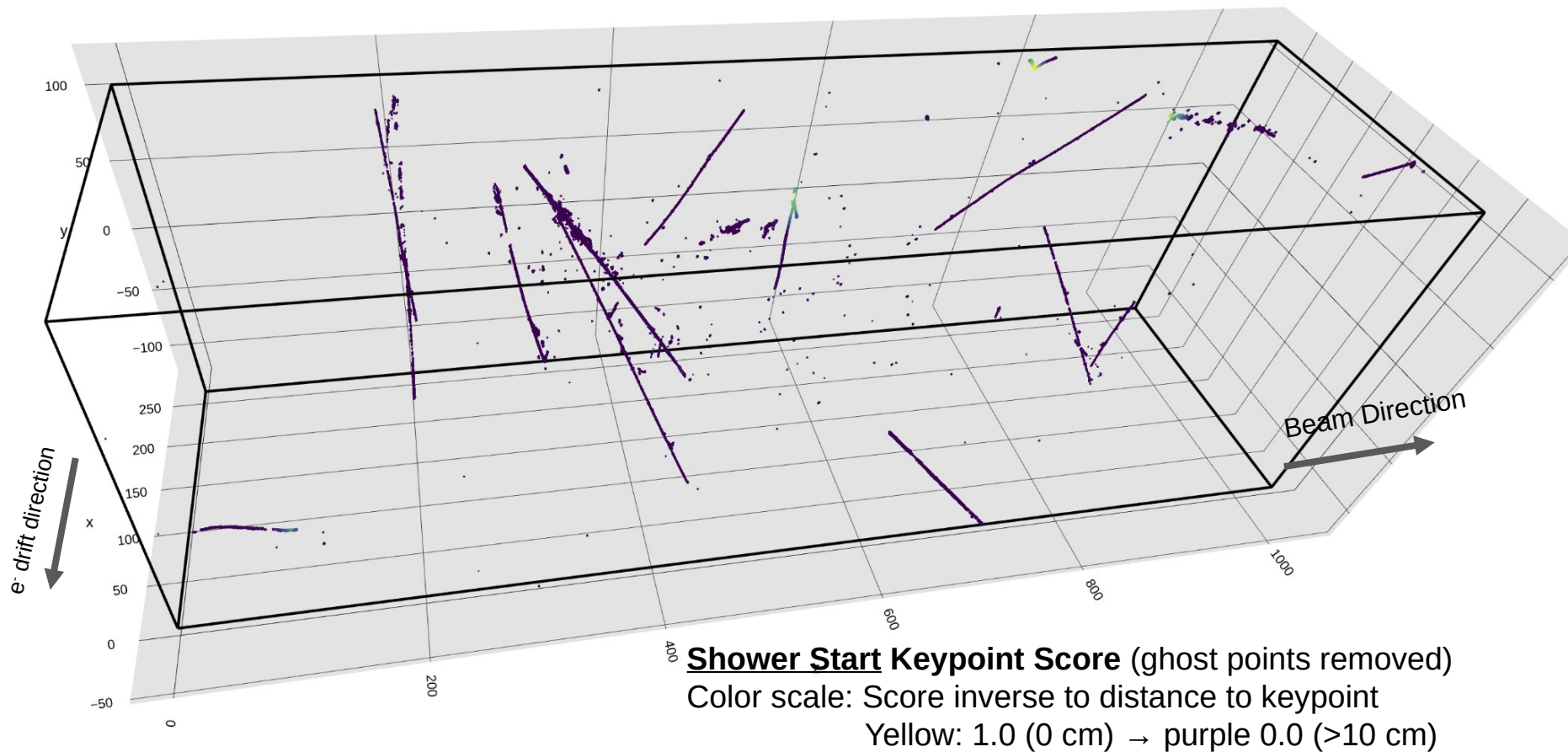
Reconstruction Example: LArMatch Track Start Score Output



Reconstruction Example: LArMatch Track End Score Output

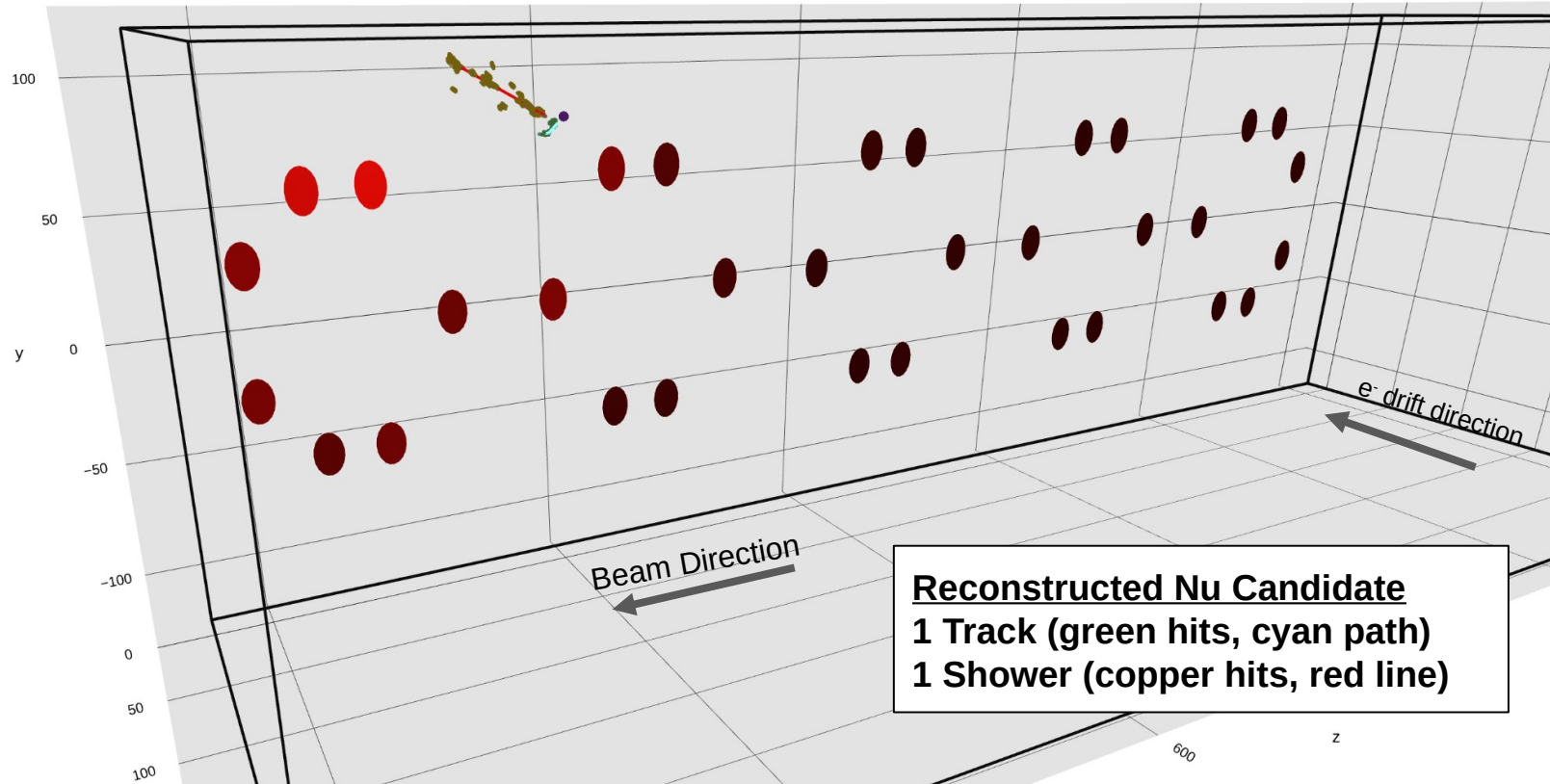


Reconstruction Example: LArMatch Shower Start Score Output



Reconstruction Example: Vertexing & Track/Shower Clustering

Shower trunk obscured in both U and V plane → leads to missing shower trunk in 3d hits, but seen by 2D CNN in Y plane

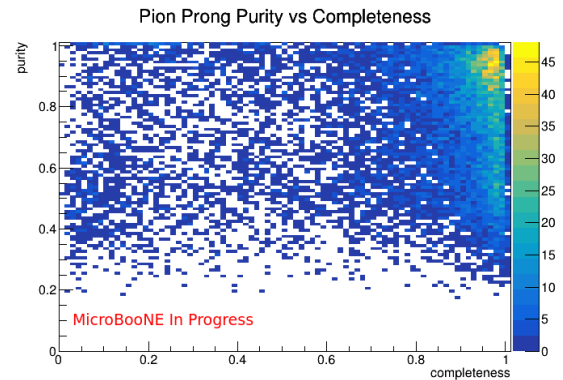
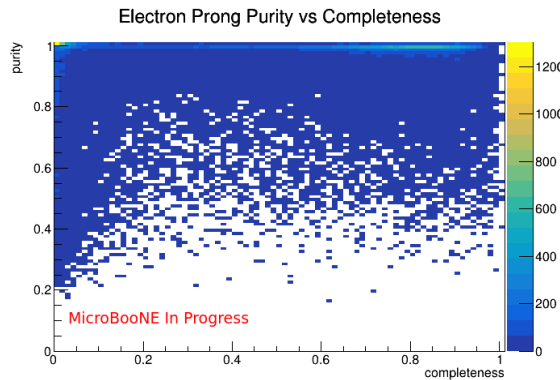
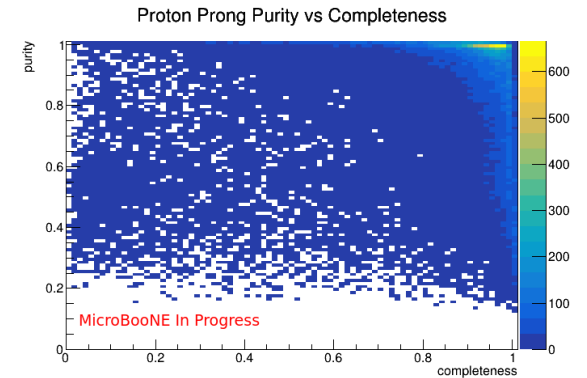
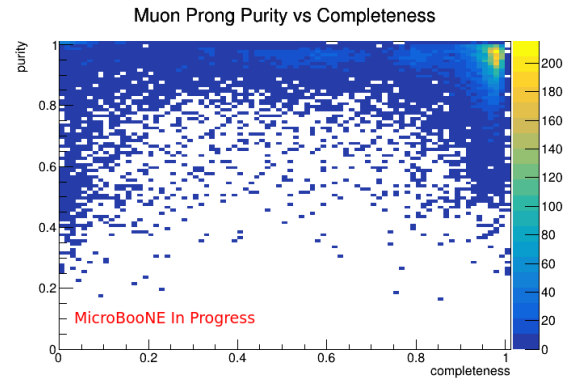
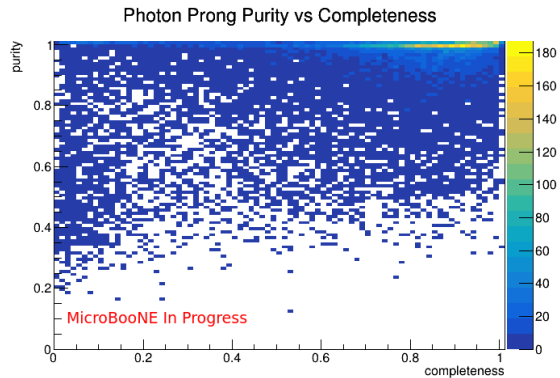


The LArPID Network

- A CNN to classify reconstructed 3D tracks and showers
 - Similar to work by NOvA: [PhysRevD.100.073005](https://arxiv.org/abs/1907.07305)
- Does particle identification (PID)
 - Outputs five score indicating how likely that the input is a muon, pion, proton, photon, or electron
- Outputs reconstruction quality metrics
 - Completeness prediction: fraction of true particle reconstructed in input track/shower
 - Purity prediction: fraction of reconstructed track/shower that was created from true particle

LArPID: Training Sample

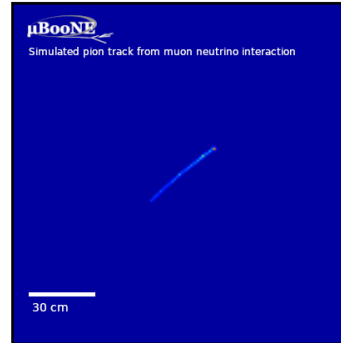
- Trained on reconstructed tracks and showers attached to LArMatch-identified neutrino vertices from MicroBooNE neutrino Monte Carlo simulations



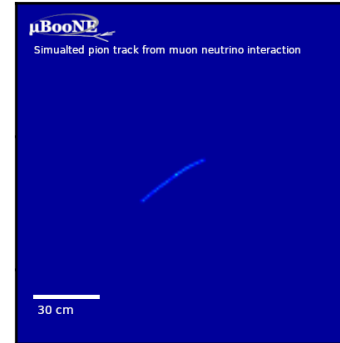
LArPID: Image Preprocessing

- In 2D images, select all pixels included in 3D prong hits
- Crop to 512 x 512 window. Center prong in image if it fits, otherwise crop around prong end point (if it's a track) or start point (if it's a shower)
- Normalize pixel values (subtract mean, divide by standard deviation)
- Provide full event images (with cosmics removed) along with prong images

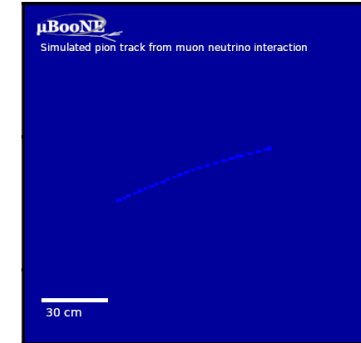
plane 0 prong



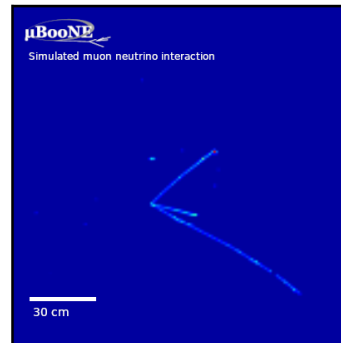
plane 1 prong



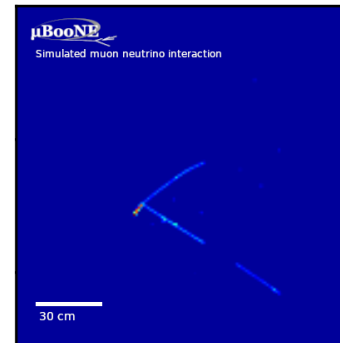
plane 2 prong



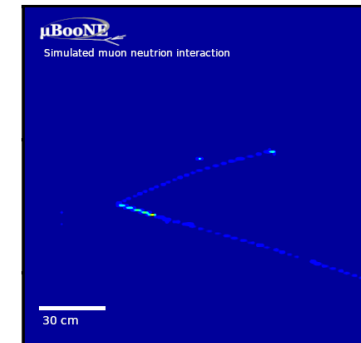
plane 0 all



plane 1 all

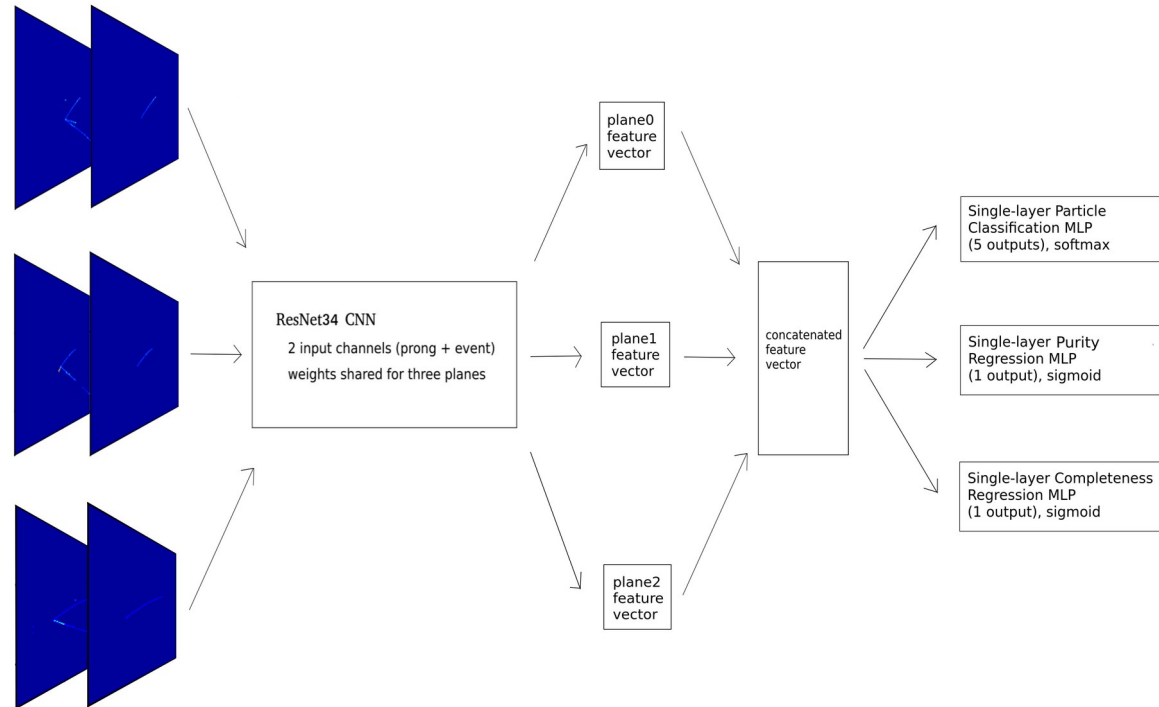


plane 2 all



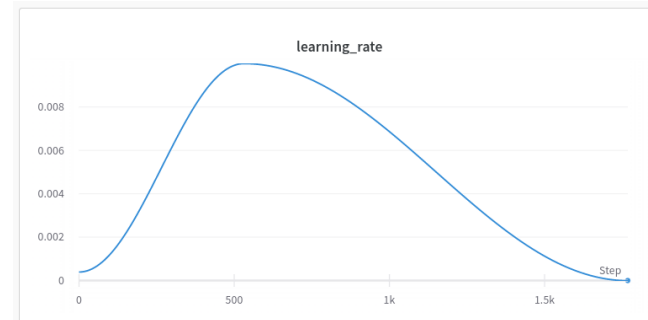
LArPID: Network Architecture

- Use tried and tested ResNet architecture ([arXiv:1512.03385](https://arxiv.org/abs/1512.03385))
- Limit CNN depth to 34 layers due to computational constraints



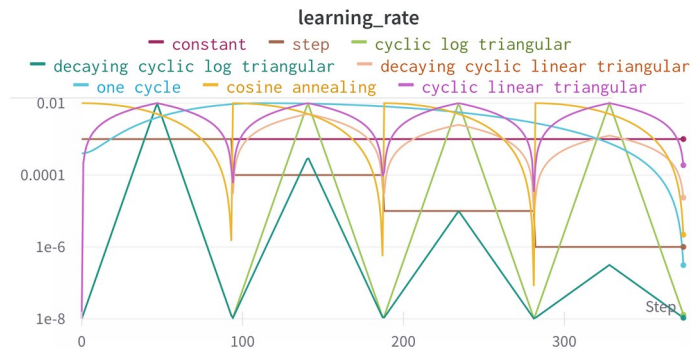
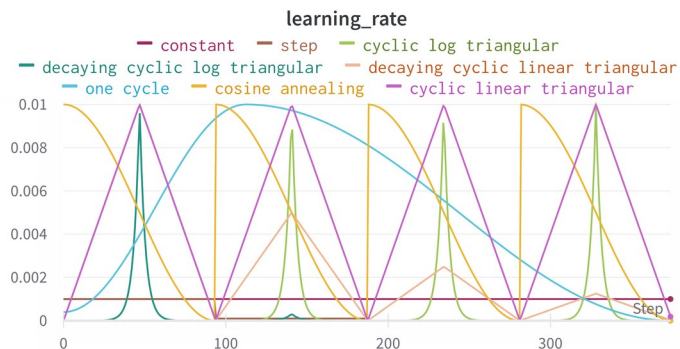
LArPID: Training

- Use learned weights to combine losses from three tasks ([arXiv:1705.07115](https://arxiv.org/abs/1705.07115))
 - Loss = $\exp(-s_{cr})L_{cr} + \exp(-s_{pr})L_{pr} + 2\exp(-s_{pc})L_{pc} + s_{cr} + s_{pr} + s_{pc}$
 - L_{cr} = mean square error **completeness regression** loss
 - L_{pr} = mean square error **purity regression** loss
 - L_{pc} = cross entropy **particle classification** loss
- Training sample: on the order of 100k prongs (tracks/showers) of each particle type (electrons, photons, muons, pions, and protons)
 - Weight L_{pc} contributions to account for class imbalance
- Validation sample:
 - 10k prongs, 2k per particle type
- Training
 - Data augmentation: randomly flip input images
 - Trained for 20 epochs with a variable learning rate scheduler:



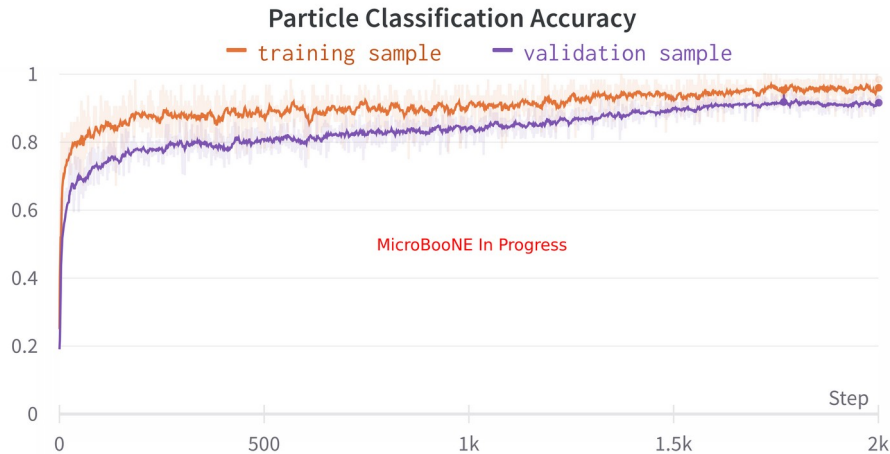
LArPID: Training/Development Lessons Learned

- Model wouldn't learn with batch normalization, used instance normalization instead
 - I suspect this has to do with the sparsity of LArTPC images, and the difficulty this presents in calculating representative running averages in batch normalization layers
- Using learned loss weights in multi-task loss provides better performance than adding loss functions with hard-coded weights, regardless of choice of weight values
- Adding completeness and purity regression tasks neither hurt nor helped particle classification performance
- Including small, low-purity tracks/showers in training did not make model's performance on larger, better reconstructed particles any worse
- Increasing depth of final classification/regression MLPs made it much more difficult for the model to learn and did not provide any boost in performance
- The “single cycle cosine annealing” learning rate scheduler is a good choice for this task, outperformed other learning rate choices:



LArPID: Particle Classification Results

- Results shown with true prong purity > 0.6 cut for accurate labels
- Overall validation accuracy: 91.1%

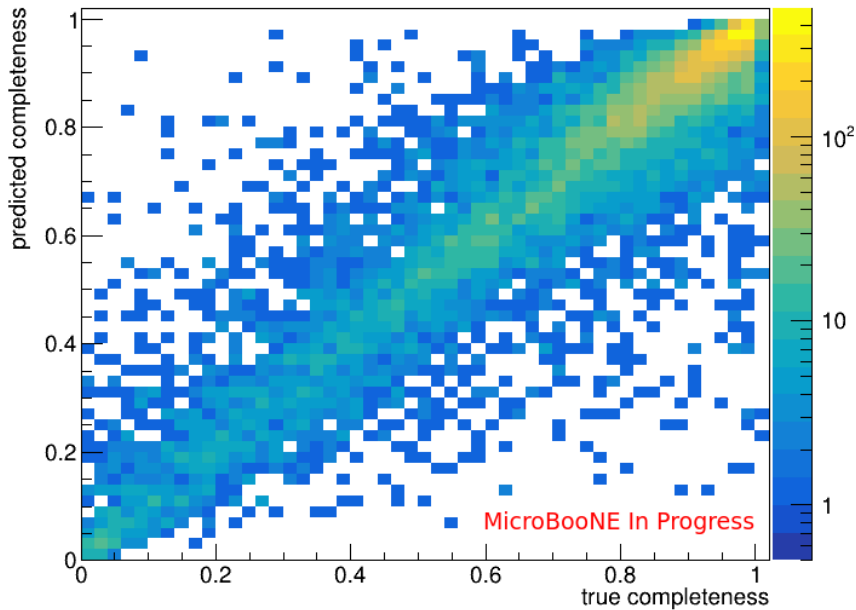


Validation Sample Accuracy Statistics

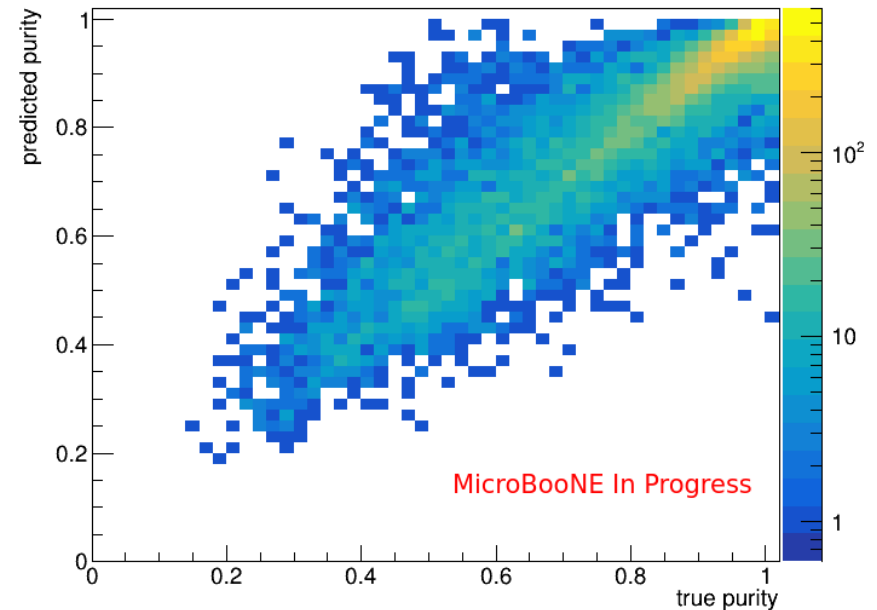
	True electrons	True photons	True muons	True pions	True protons
Fraction classified as electrons	83.5%	4.8%	0.1%	0.4%	0.1%
Fraction classified as photons	13.3%	94.7%	0.1%	0.2%	0.2%
Fraction classified as muons	0.4%	0%	93.6%	12.1%	0.2%
Fraction classified as pions	2.7%	0.4%	6.1%	85.9%	1.4%
Fraction classified as protons	0.2%	0.2%	0.2%	1.5%	98.2%

LArPID: Completeness and Purity Results

Predicted vs. True Completeness, Validation Sample

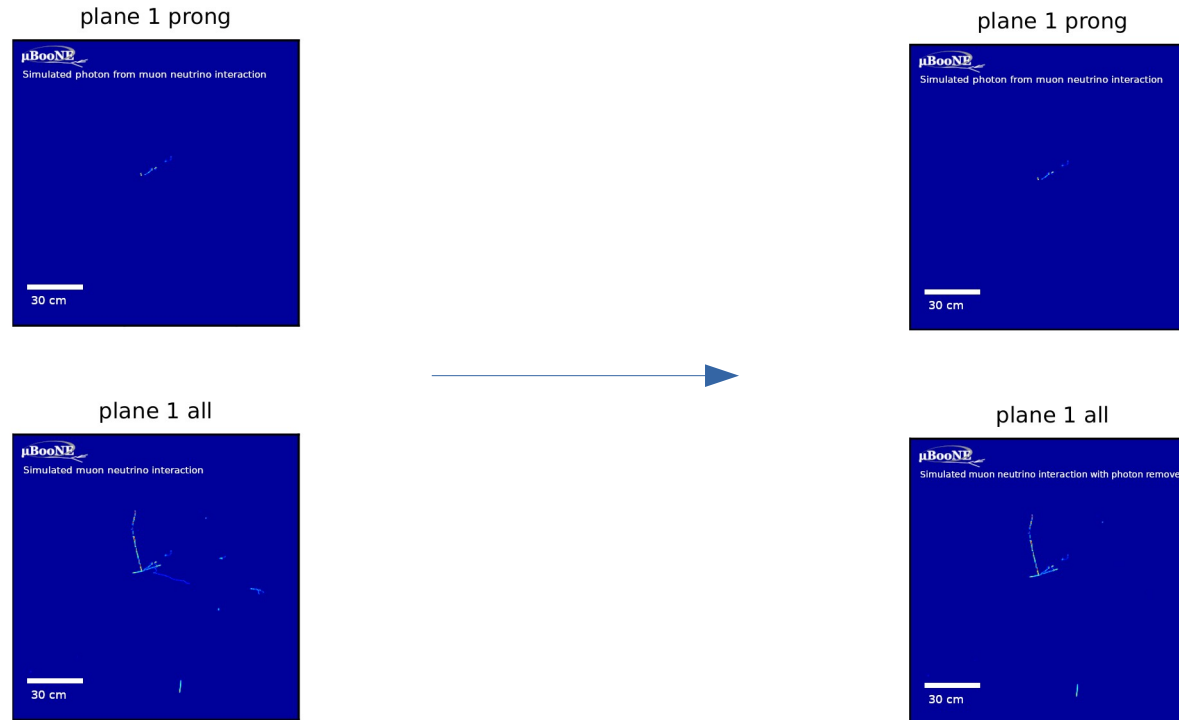


Predicted vs. True Purity, Validation Sample



LArPID: Interpreting the Model

- In progress: image manipulation studies designed to understand what information the model is using to make decisions

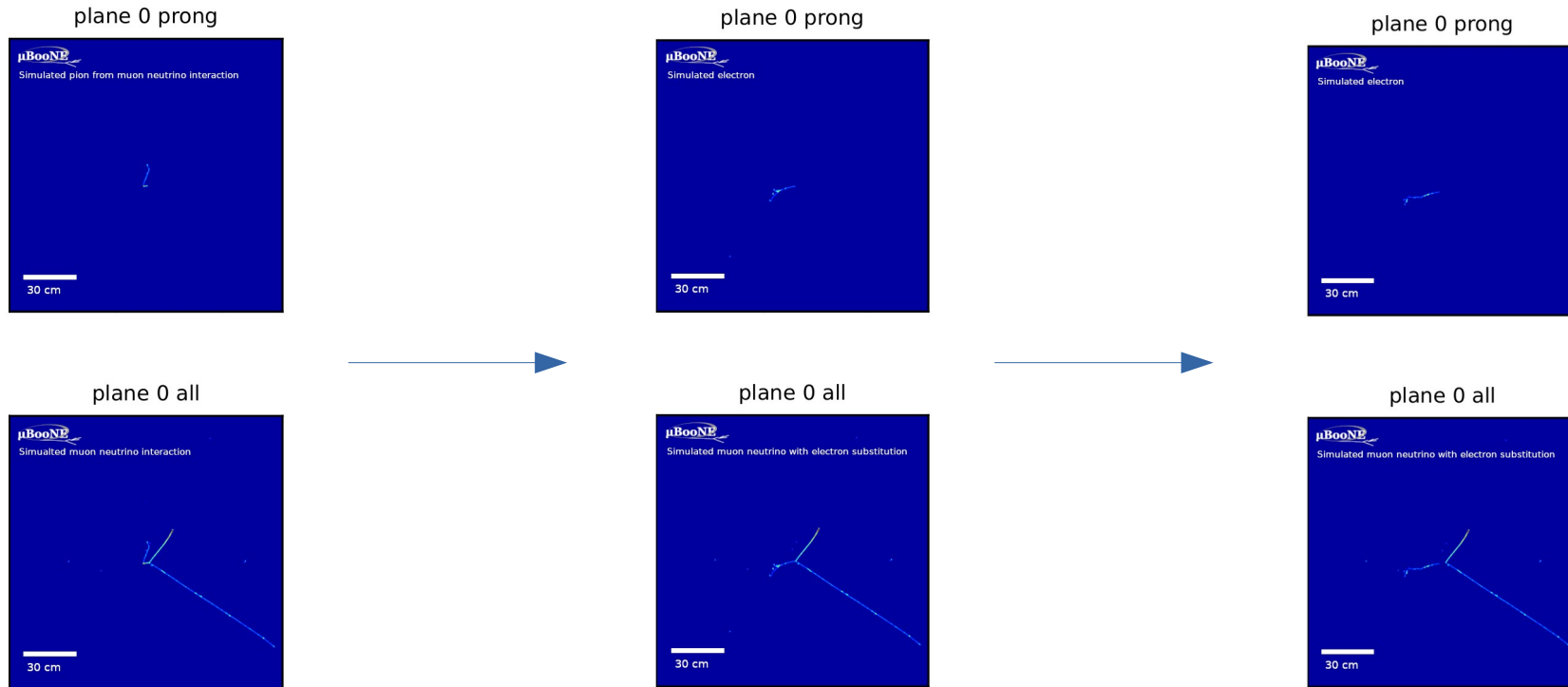


electron score = -3.63, photon score = -0.03

electron score = -1.53, photon score = -0.25

LArPID: Interpreting the Model

- In progress: image manipulation studies designed to understand what information the model is using to make decisions



electron score = 0, photon score = -7.02,
pion score = -6.02

electron score = -0.01, photon score = -5.03,
pion score = -8.63

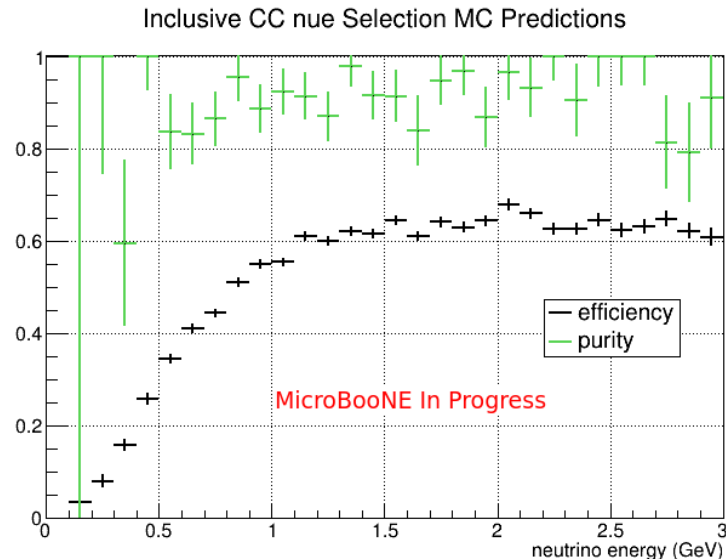
electron score = -7.87, photon score = 0,
pion score = -12.84

An Inclusive CC ν_e Selection with New DL-Based Reconstruction

- Will show that new DL-based reconstruction utilizing LArMatch and LArPID networks are competitive in selecting CC ν_e events in MicroBooNE
 - Great potential to improve the sensitivity of future MicroBooNE analyses
- Selection simply utilizes:
 - Basic reconstruction quality cuts
 - Neutrino vertex found by LArMatch, doesn't overlap with tagged cosmic activity
 - Cuts on LArPID particle scores
 - No muon tracks
 - One forward-going electron shower identified with high confidence (high electron score, low photon and pion scores)

Preliminary Inclusive CC ν_e MC Selection Results

- Backgrounds included: cosmic, CC numu, NC numu, and NC nue
- Selection purity above 80%, efficiency rises above 60% around 1 GeV
- **Caveat:** MC samples used to calculate purity and efficiency numbers were also used in prong CNN training (additional MC simulation not available in time)
 - Large training sample, not much over-fitting
- Selection is preliminary, performance will increase as selection criteria are refined

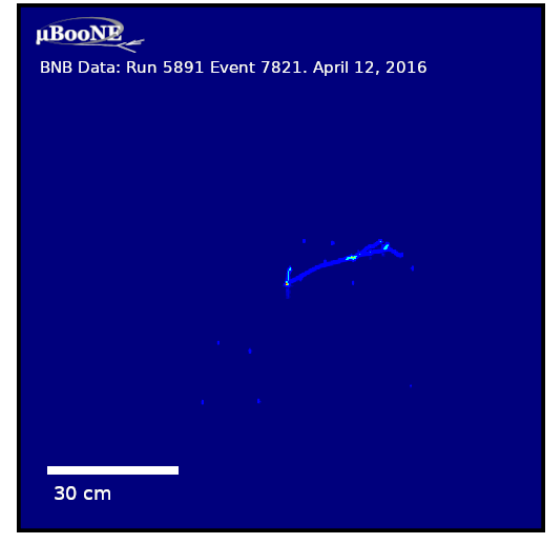
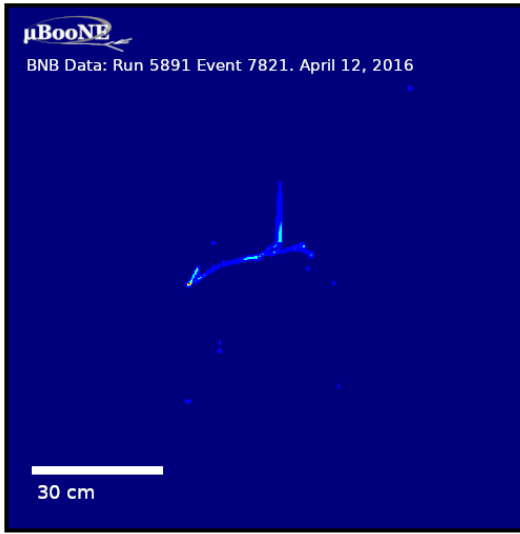
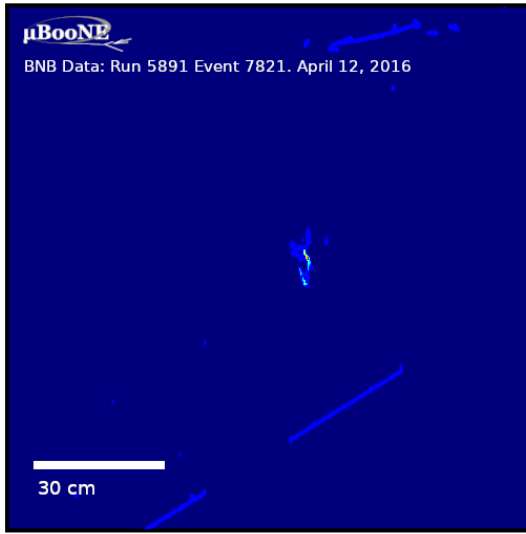


Testing the CC ν_e Selection on Data

- We ran our new selection on a small MicroBooNE open data set
- New probable CC ν_e events were found!
 - Event displays for four low-energy probable CC ν_e events not identified in other reconstruction frameworks are shown on the following slides

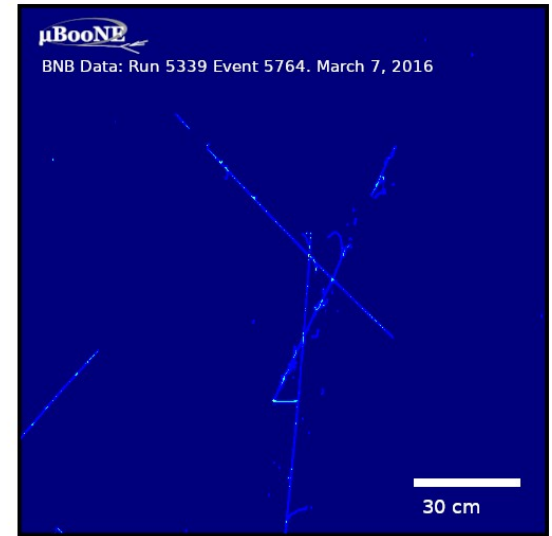
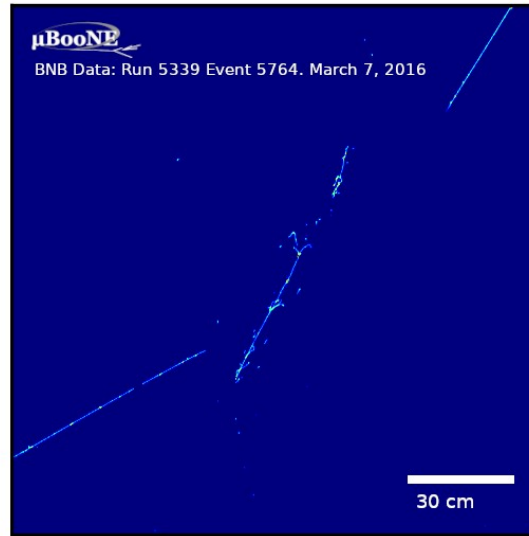
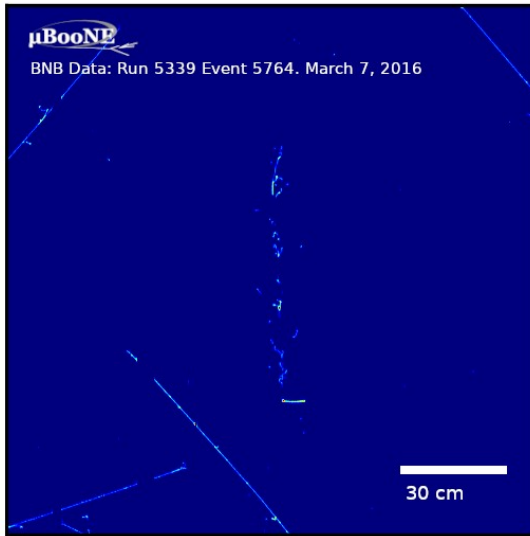
New Low-Energy Event Found by CC ν_e Selection

Reconstructed neutrino energy: 197.3 MeV



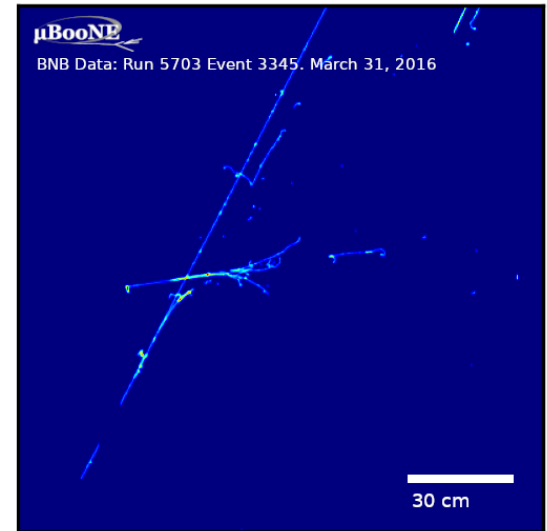
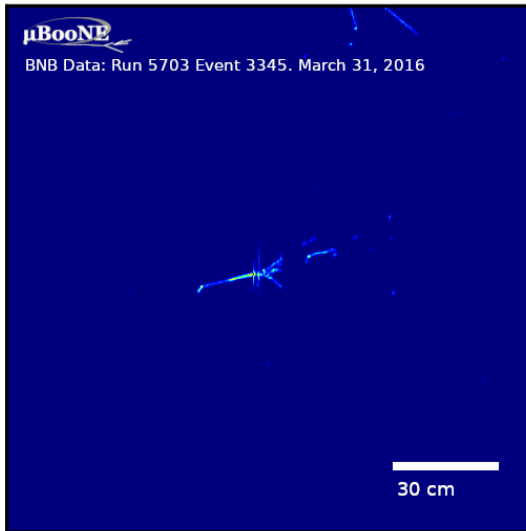
New Low-Energy Event Found by CC ν_e Selection

Reconstructed neutrino energy: 305.6 MeV



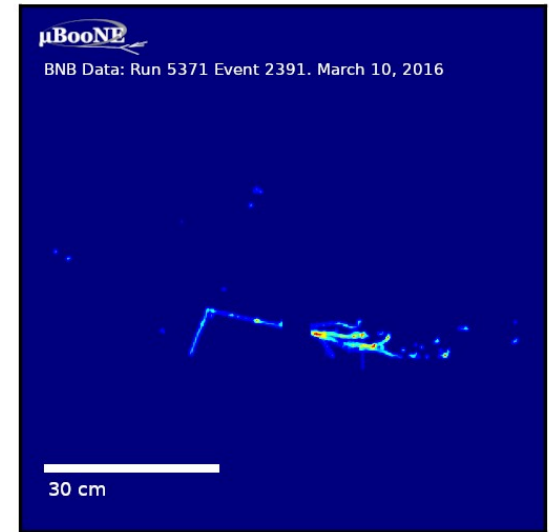
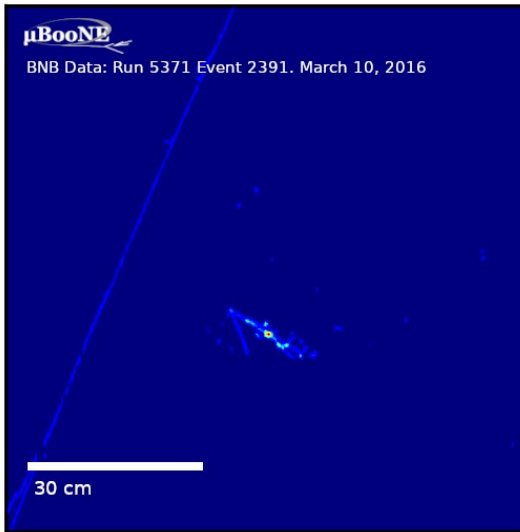
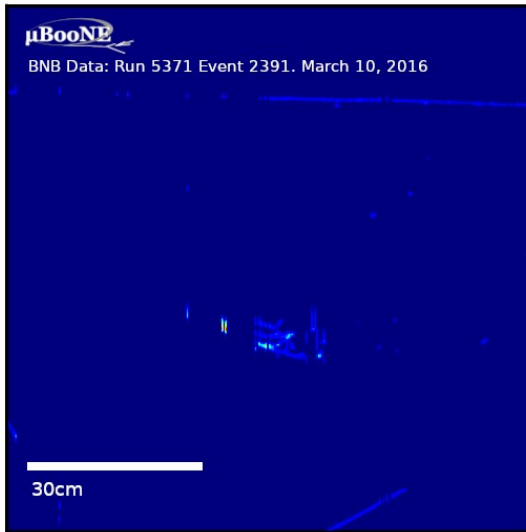
New Low-Energy Event Found by CC ν_e Selection

Reconstructed neutrino energy: 318.6 MeV



New Low-Energy Event Found by CC ν_e Selection

Reconstructed neutrino energy: 411.8 MeV



Conclusions

- New DL-based MicroBooNE reconstruction framework with LArMatch and LArPID in place
 - Good neutrino vertex resolution, track/shower clustering, and particle identification
 - Allows for competitive CC ν_e selection that can find new events in open data
 - Further improvements expected!
 - Great potential to improve the sensitivity of future MicroBooNE analyses
- Applicability in other reconstruction frameworks and LArTPC experiments
 - Work ongoing to implement LArMatch in SBN
 - Should be easy to retrain LArPID network for other reconstruction frameworks used by MicroBooNE, SBN (ICARUS and SBND), and DUNE
 - Currently collaborating with Wanwei Wu and Donna Naples at the University of Pittsburgh to implement LArPID in the Pandora reconstruction framework (used in all of these LArTPC experiments)