

DUNE Far Detector Event Reconstruction with Pandora

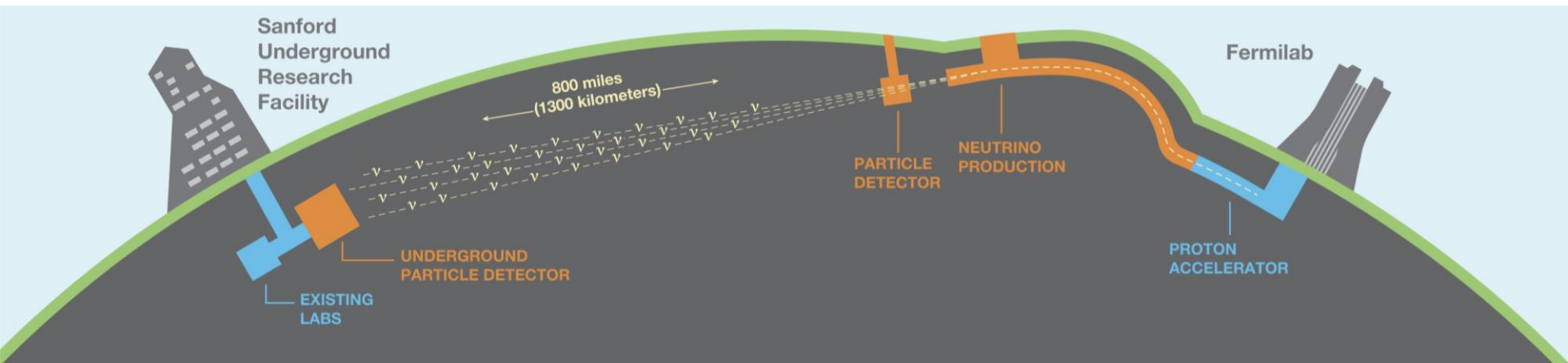
Andy Chappell for the DUNE Collaboration

20/07/2024

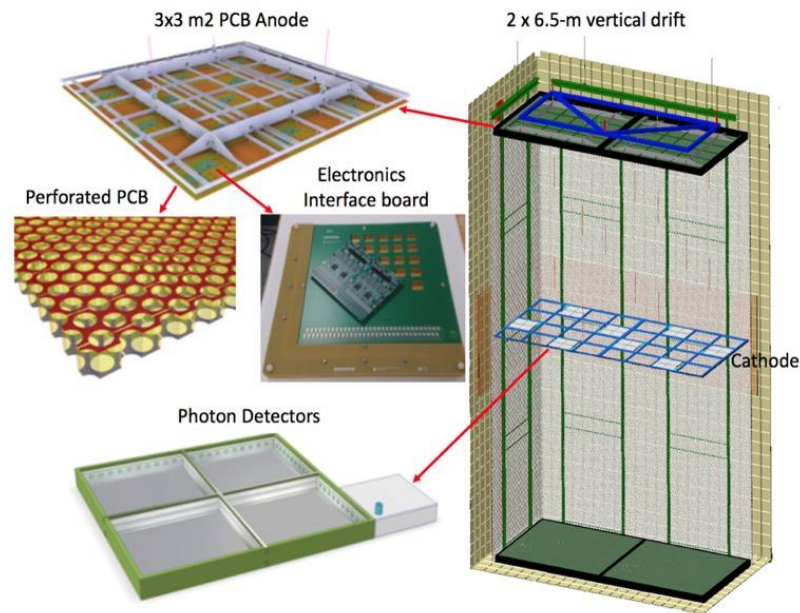
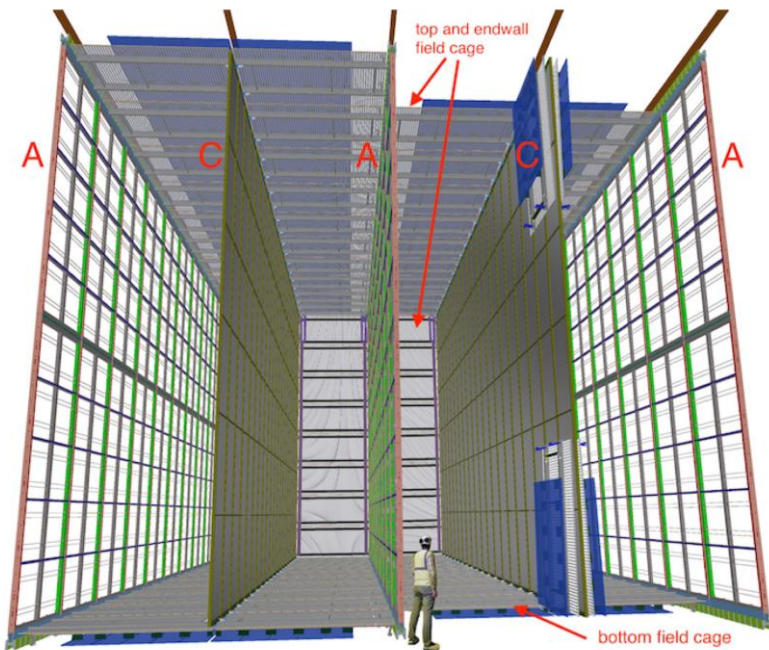
ICHEP 2024

The Deep Underground Neutrino Experiment

- Long baseline oscillation experiment
- Most intense neutrino beam in the world (at up to 2.4 MW)
- Wide-band energy
- Near detector at Fermilab
- LArTPC far detector technology 1.5 km underground at SURF
- Broad physics program (accelerator ν , astrophysical and low energy ν , BSM)



The horizontal and vertical drift detectors

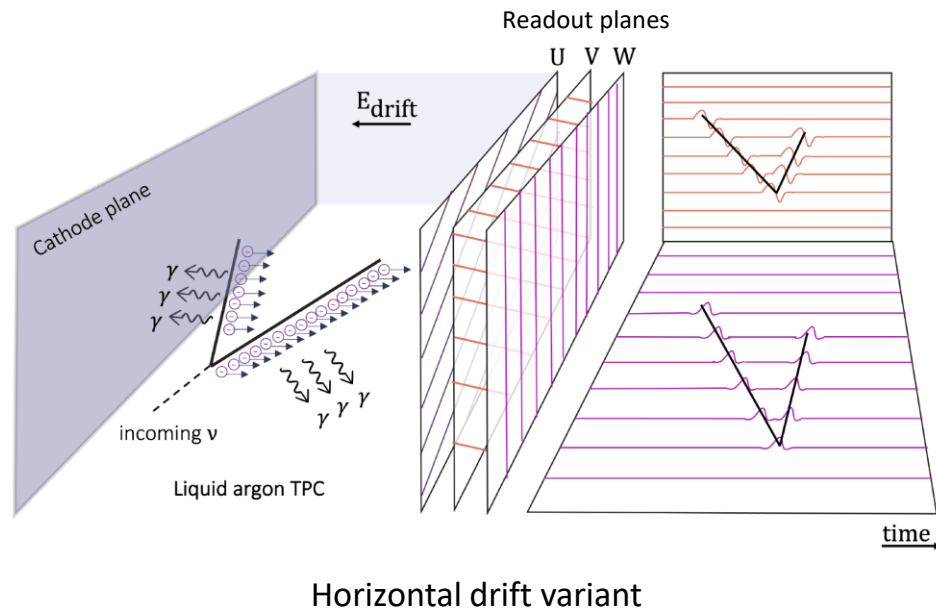


- Modular wire-based charge readout
- 4 drift volumes defined by 5 arrays of anode and cathode planes

- Modular PCB-based charge readout
- 2 drift volumes defined by a cathode plane, and 2 PCB-based anode planes

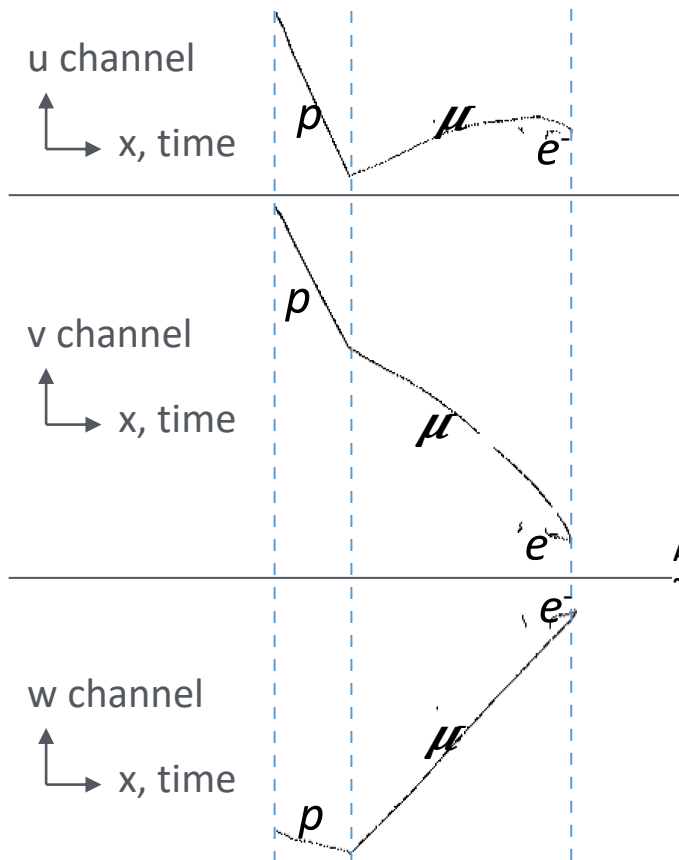
LArTPC operation

- Fully active interaction medium
- Charged particles ionize argon atoms to produce drift electrons (and scintillation light) along the particle trajectory
- Electrons drift in the electric field
- Three anode readout planes record the deposited charge using wires of different orientations
 - We describe the gaussian fits of the peaks in the resultant waveforms form as “hits”
- Light collected by Photon Detection System

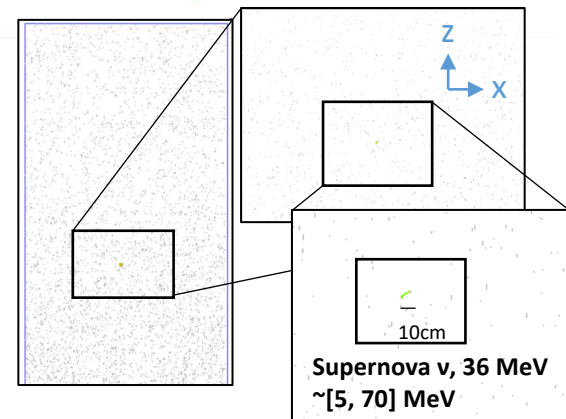
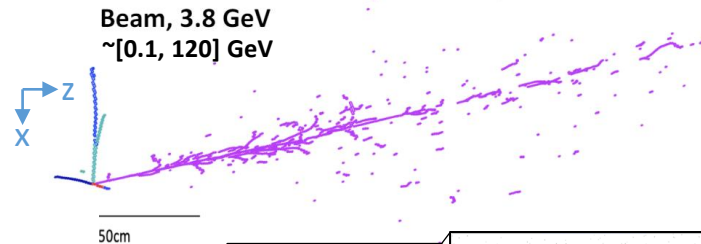
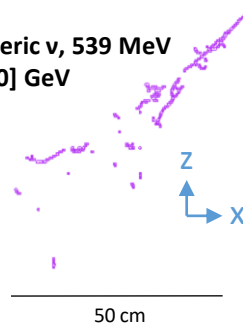


Inputs to pattern recognition

- Projection of a ν_μ CC quasielastic interaction onto readout planes (left)
- 2D hits represented by readout channel and common drift time coordinate

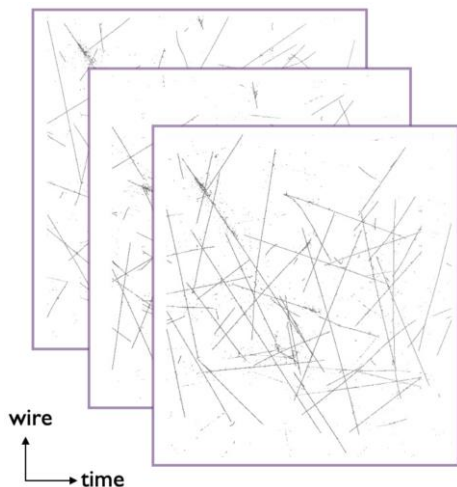


Atmospheric ν , 539 MeV
 $\sim[0.1, 100]$ GeV



Pandora's multialgorithm approach

- Many small steps from 2D input hits to 3D particle hierarchy
- Mix **hand-engineered algorithms** and **machine learning techniques**
 - Use physics and detector knowledge
 - Use modern machine learning



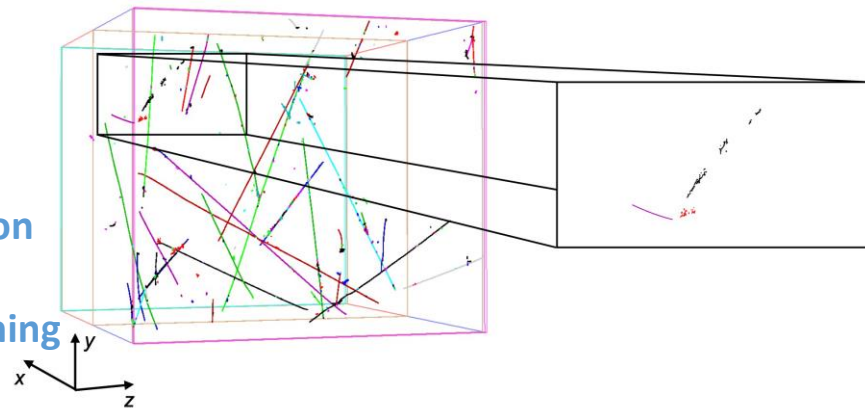
Vertex finding

2D pattern recognition

3D Inter-plane matching

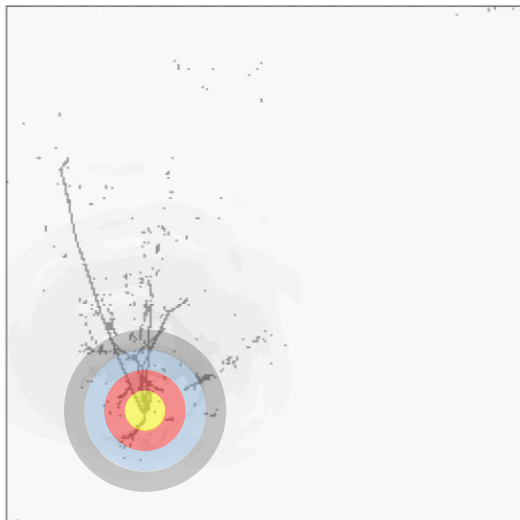
Track/Shower characterization

Particle hierarchy building

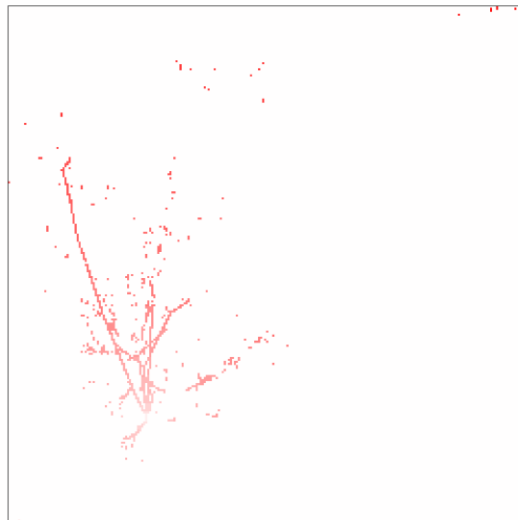


Vertexing concept

In training hits are assigned a class according to distance from true vertex



Network trained to learn those distances from input images

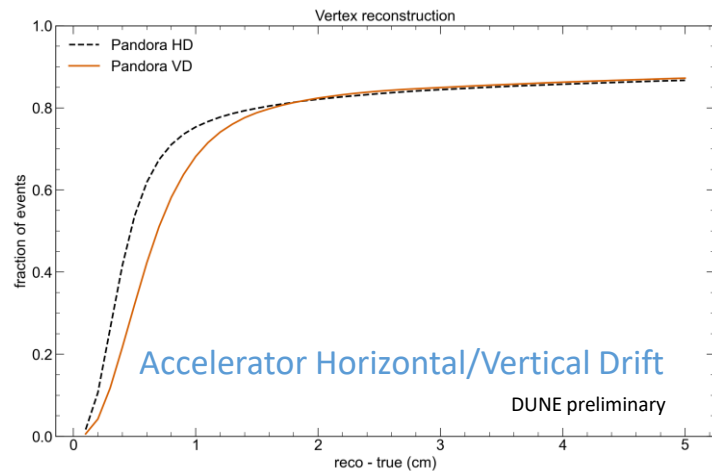
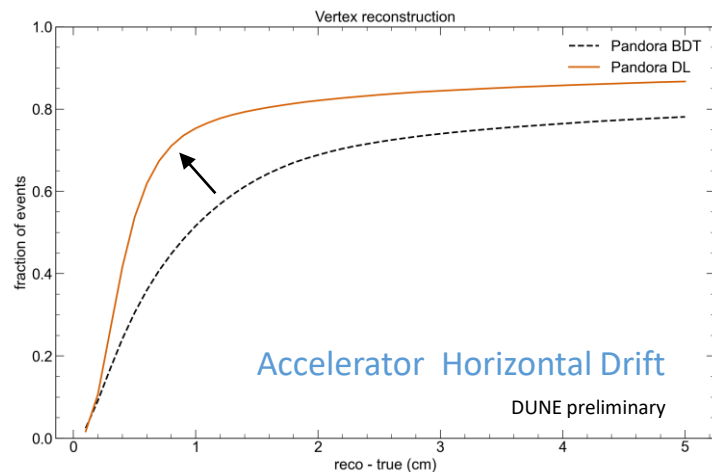
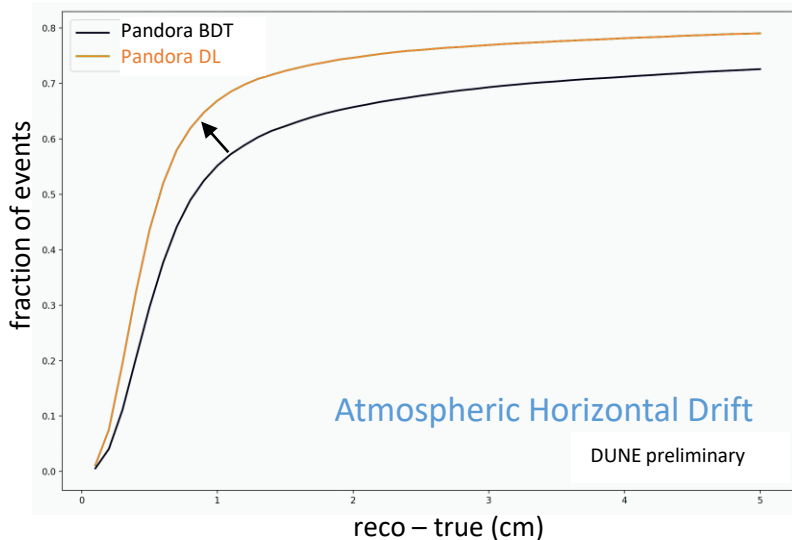


Network infers hit distances and resultant heat map isolates candidate vertex



Vertex reconstruction performance

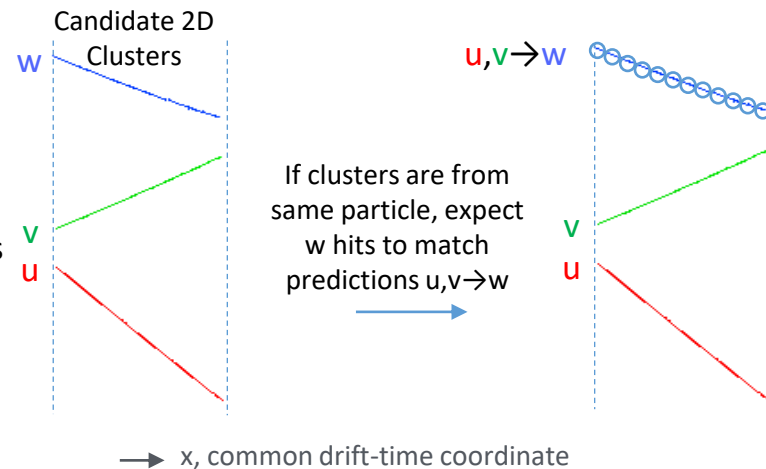
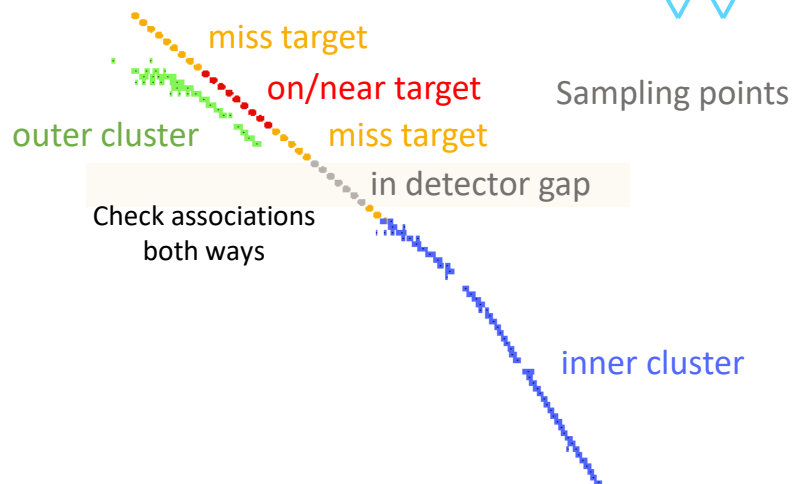
- Network yields performant vertexing in multiple use cases
 - Previous vertexing performed by a BDT
 - Vertical Drift strip pitch larger than Horizontal Drift wire pitch



Pattern recognition and matching

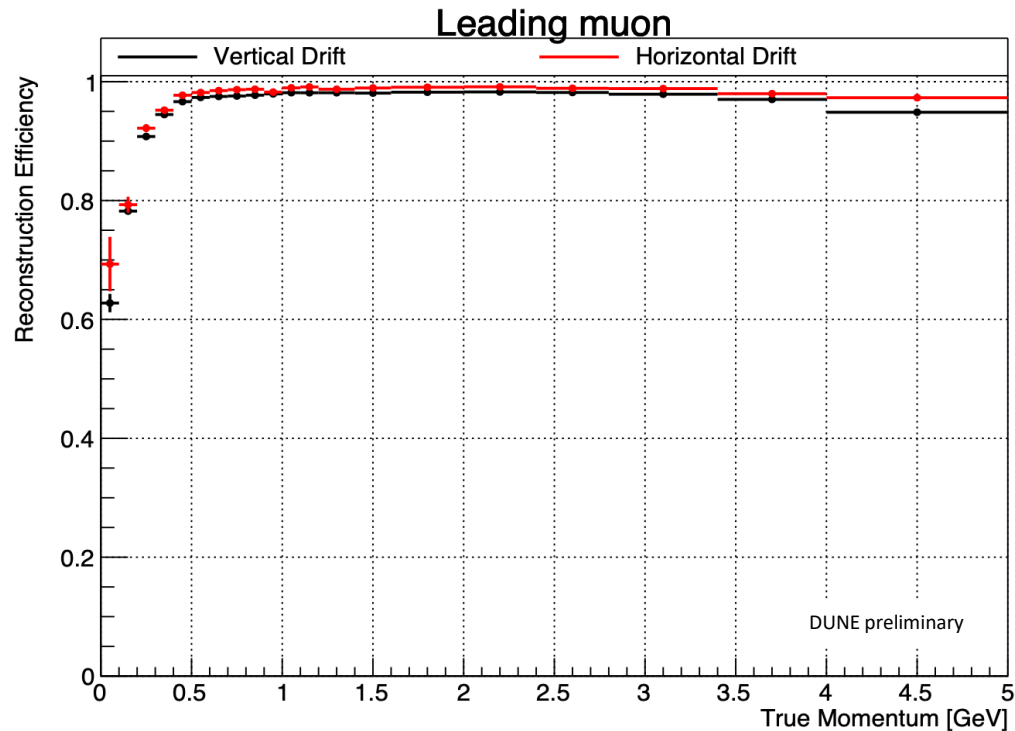
- Produce 2D clusters in small, focused steps
 - Try to maintain purity
 - Try to increase completeness
 - Refine with focused merging and splitting algorithms

- Match triplets using common x-coordinate overlap
 - Use detector geometry to predict each view using other two views
 - Check predictions against observed hits
 - Construct 3D particles from consistent inter-plane matches



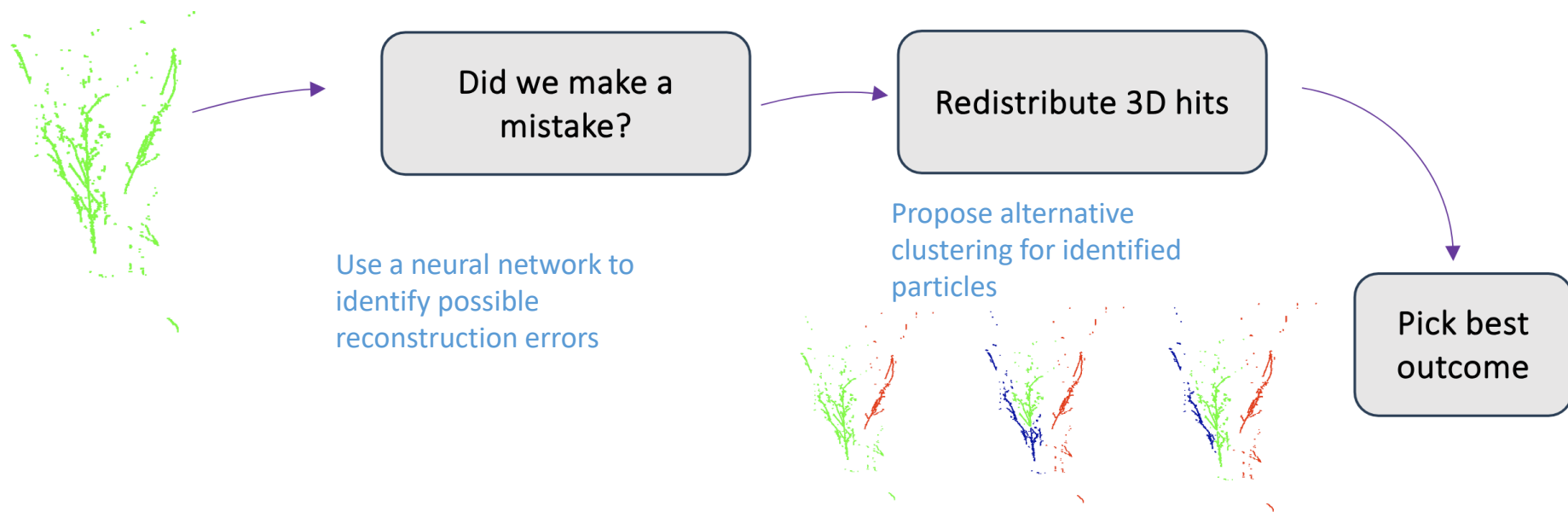
Reconstruction performance

- Reconstruction efficiency for leading muon comparable for DUNE Vertical and Horizontal Drift Far Detector designs
- Accelerator sample
- High and largely flat efficiency above ~ 0.5 GeV



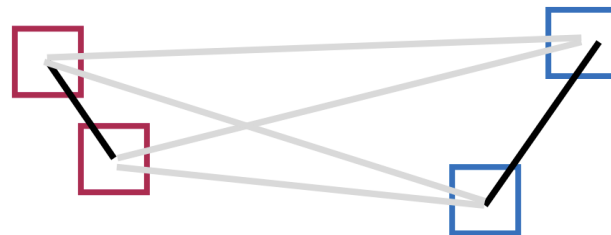
Fixing reconstruction mistakes

- Ideally, reconstruction algorithms build particles correctly from the outset
- In practice, mistakes are made
 - Overlapping shower topologies from, e.g. π^0 decay, can be merged
 - Accept this will happen, identify and fix

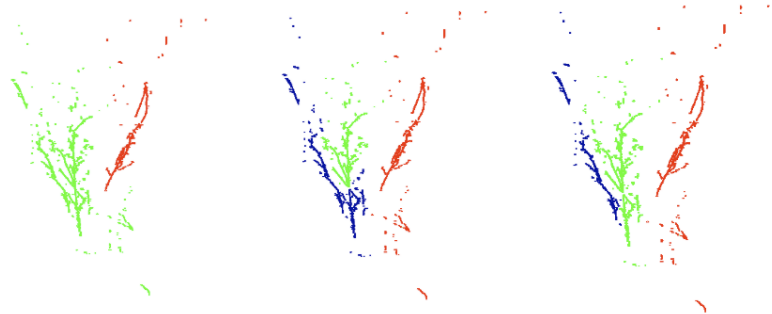


Fixing reconstruction mistakes

- Graph neural networks represent one avenue for redistributing hits from an errant cluster
- Edge classifiers
 - Any given pair of hits connected via an edge
 - True edges connect hits from the same particle
 - False edges connect hits from different particles
 - Need to resolve ambiguities between groups of hits
- Node classifiers
 - Known target number of particles
 - Each node belongs to one such target particle
 - Different GNNs can target different multiplicities
 - Pick the best outcome

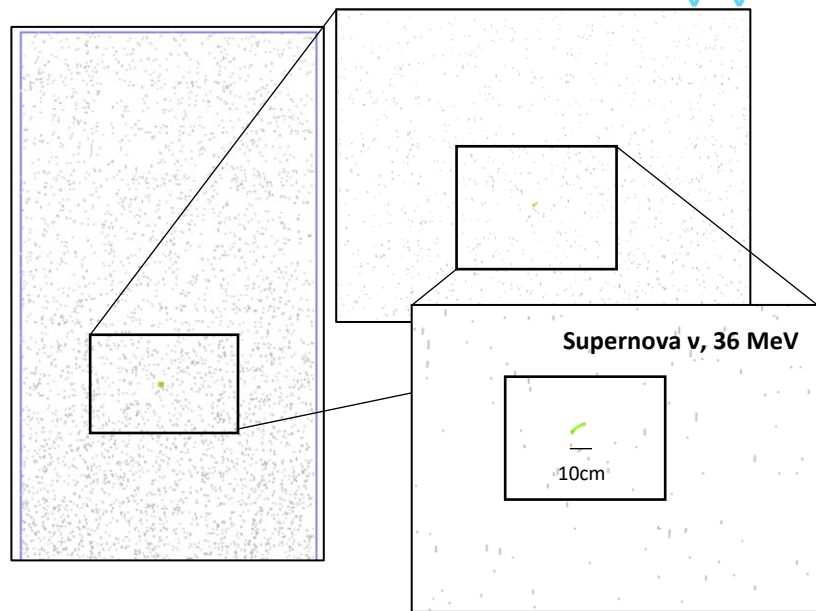


Grey line = false edge
Black line = true edge



Low energy neutrinos

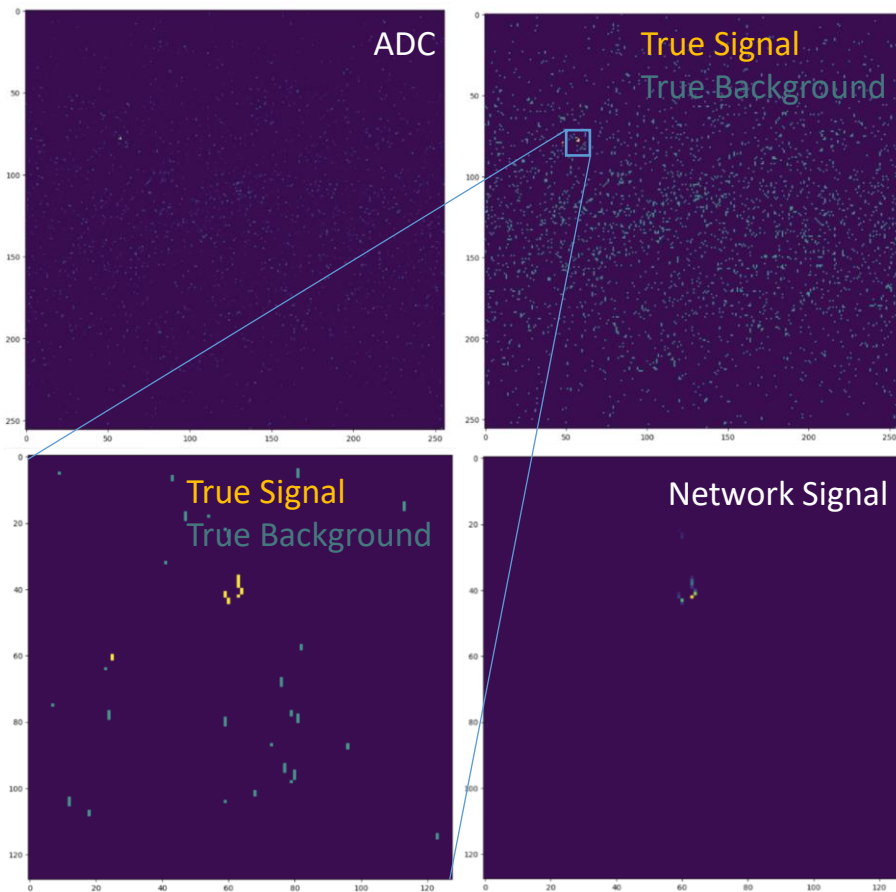
- Supernova neutrinos in presence of radiological background very different proposition to accelerator neutrinos
- Need signal/background separation
- Need to cluster small, fragmented blobs
- Expect to rely more on ML techniques



Beam, 3.8 GeV



Signal/background separation



- U-ResNet for semantic segmentation extracts signal pixels from background
 - Convolutional neural network
 - “U” comes from characteristic shape
 - Down-sampling feature extraction
 - Up-sampling arm to return to full resolution

		True	
		Bkg	Sig
Network	Bkg	0.93	0.07
	Sig	0.09	0.91

DUNE preliminary

Conclusions

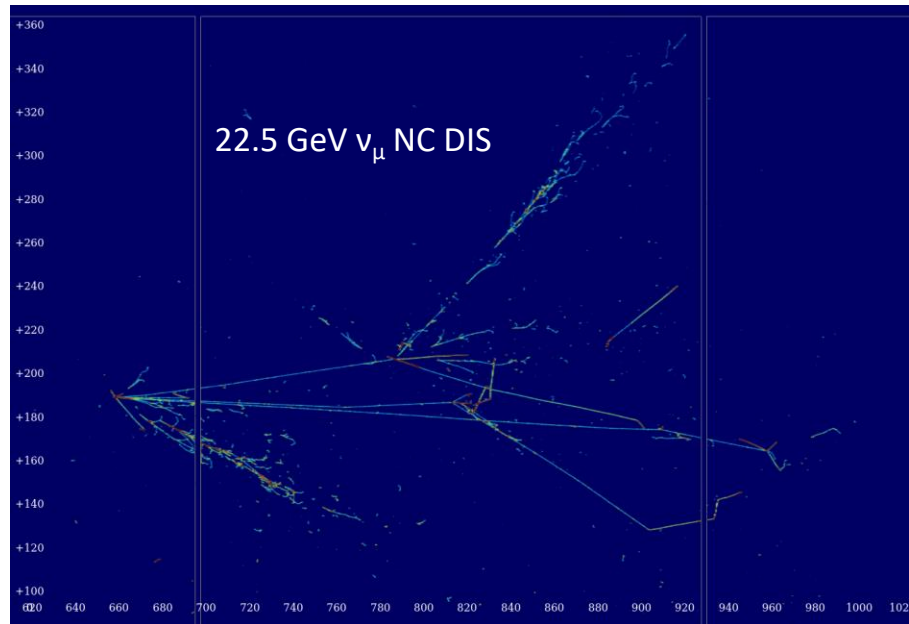
- DUNE's LArTPC detectors provide high spatial and calorimetric resolution
- DUNE's broad physics program yields a range of diverse and complex particle topologies
- This necessitates effective exploitation of our imaging detectors
- Pandora can combine hand engineered algorithms and machine learning techniques to reconstruct interactions for downstream analysis

Backup



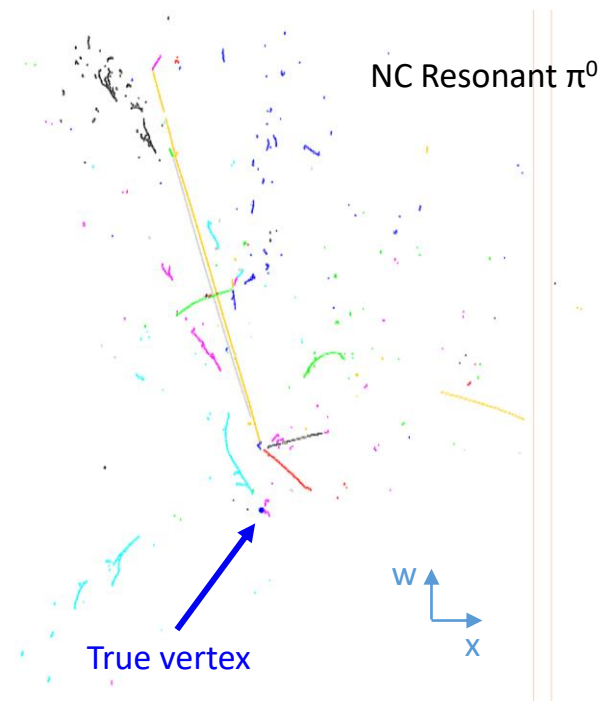
Overview

- Reconstructing neutrino interactions in a liquid-argon imaging detector is a complex task
- A critical component of the pattern recognition procedure is the determination of the initial interaction location
- This talk will present a solution to this vertex finding task that integrates deep learning with an algorithmic pattern recognition chain in the Pandora pattern recognition framework



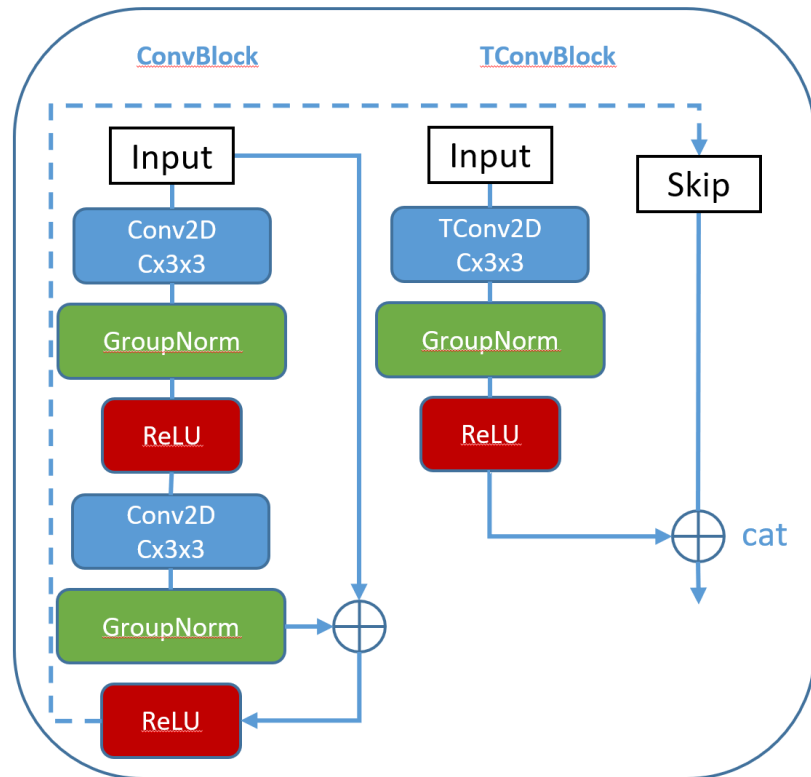
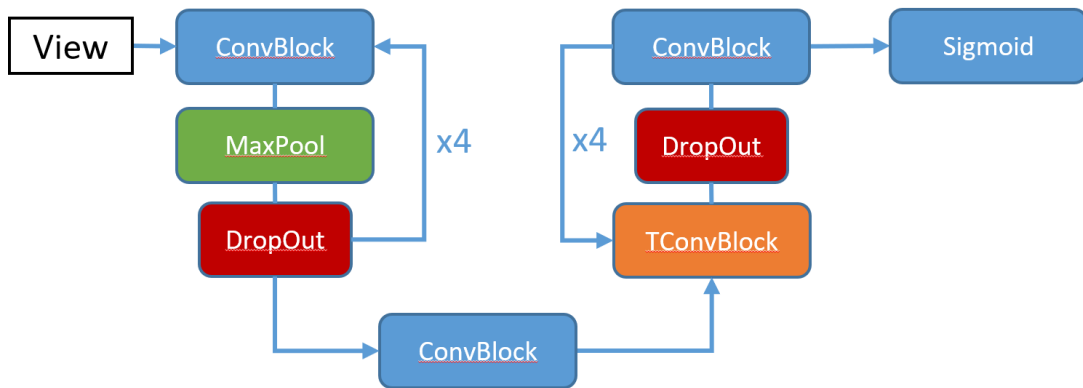
Finding the interaction vertex

- Why is it important?
 - Vertex acts as anchor for clustering decisions
 - Determining particle flow depends on starting in the right place
- Why is it hard?
 - No a priori precision knowledge of the interaction location
 - 3D interaction projected onto 2D outputs produces overlapping particle trajectories
 - Highly variable topologies, not always obvious, even by eye
- Use cases
 - Unless otherwise stated, all plots focus on accelerator neutrinos in the DUNE horizontal drift (HD) far detector, other use cases include:
 - DUNE vertical drift far detector
 - DUNE Near Detector (under AIDAinova)
 - DUNE isotropic atmospheric samples
 - MicroBooNE (cosmic background)
 - Low energy supernova neutrinos at DUNE
 - Upcoming test-beam interactions at ProtoDUNE

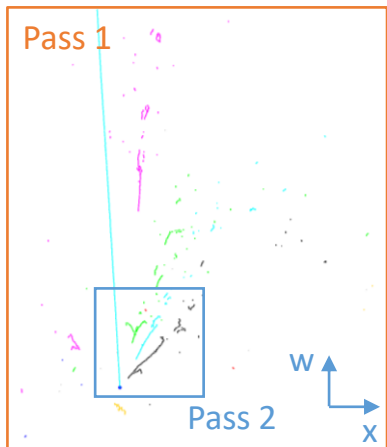


Network architecture

- U-ResNet structure for image segmentation (arXiv:1505.04597)
- Attempt to classify every pixel in an image



Two pass approach

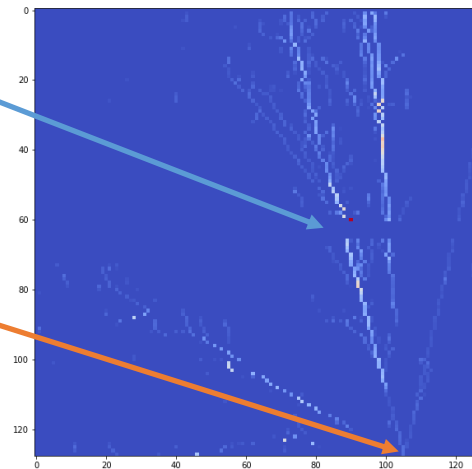


- DUNE events can span a large physical region (many metres)
- 256x256 pixel pass 1 input to maintain computational tractability (including CPU inference)
- Pixels have low spatial resolution relative to DUNE's ~ 0.5 cm wire pitch
- Solution: Low resolution first pass, zoom in on ROI for second pass

- Use hit distribution around pass 1 estimated vertex to frame ROI to include as much context as possible
- 128x128 pixels for pass 2

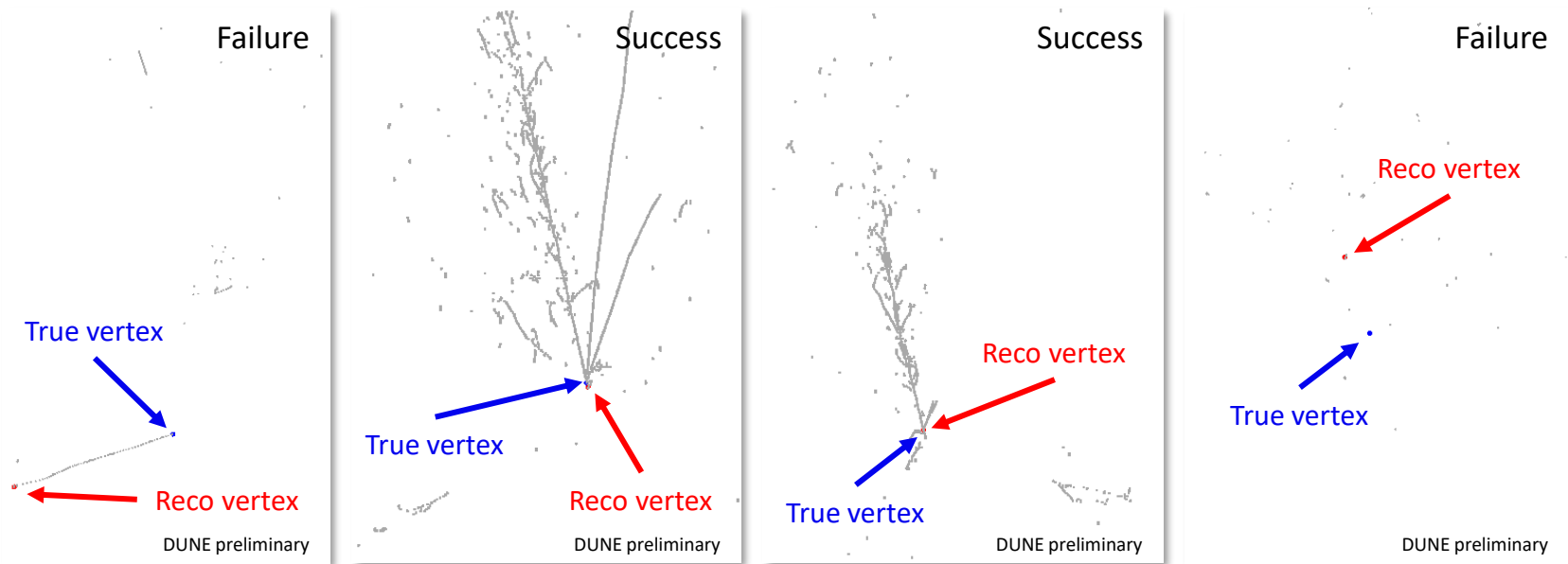
Gap between anode plane assemblies

Pass 1 estimated vertex



Vertex reconstruction performance

- Network performs particularly well when there is clear pointing information
- Failures emerge as pointing information becomes ambiguous or hits very sparse



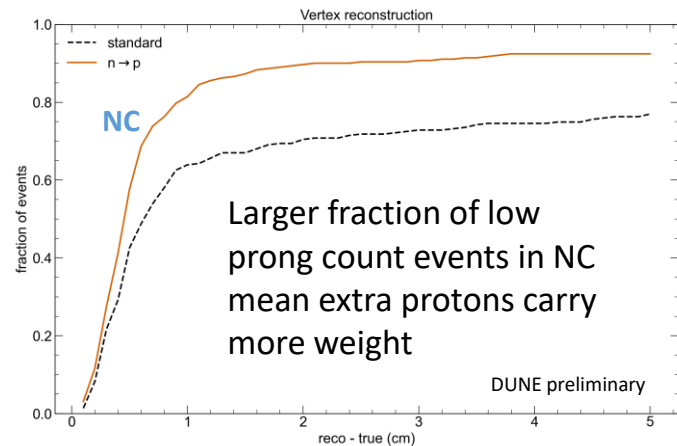
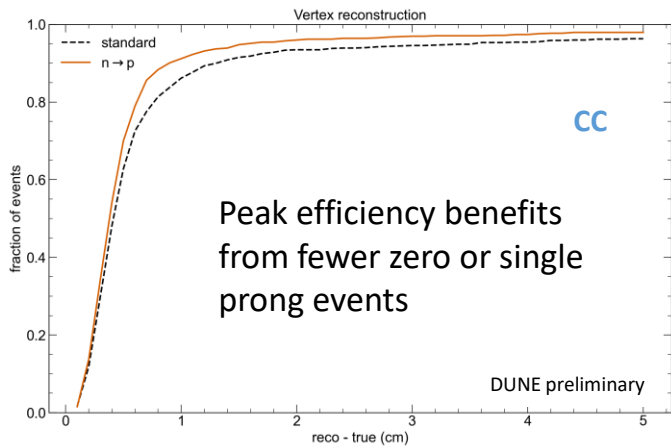
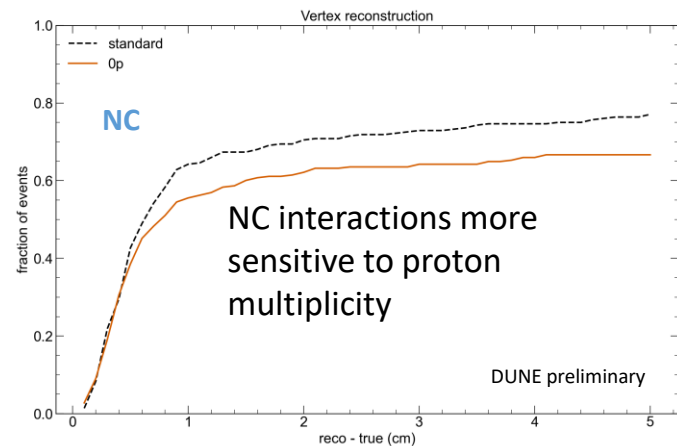
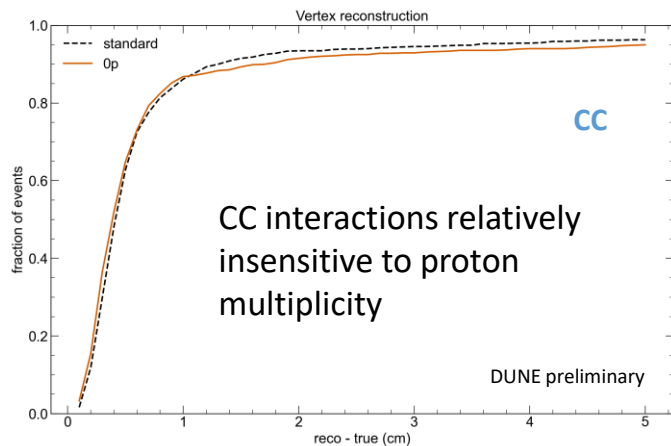
“Model dependence”

- We expect vertex efficiency/resolution to depend on the number of particles that point back to the true interaction vertex
- Different generators and nuclear models produce different particle multiplicities, particularly for the number of protons with momentum below 0.4 GeV
- Model dependence can lead to bias that yield incorrect physics conclusions or significant systematics
- To investigate the effect, we generate events which vary only in their sub 0.4 GeV proton multiplicity

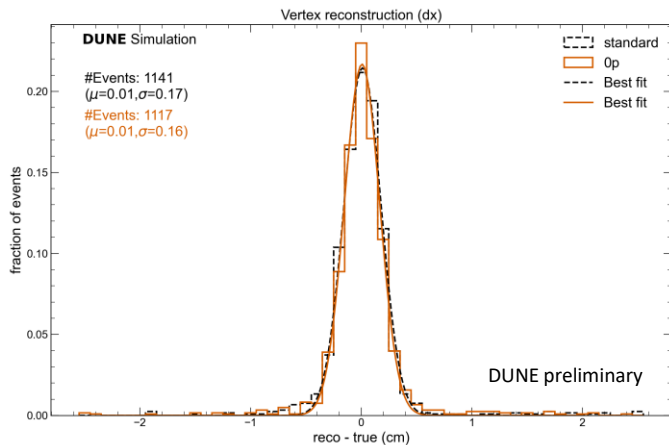
0p	Standard	n → p
Generation as standard p < 0.4 GeV removed	1000 ν_{μ} , 1000 ν_e Fixed seed for generation Fixed seed for G4 sim	Generation as standard n < 0.4 GeV swapped to p

- Provides closest possible equivalence between events to isolate the effect of proton multiplicity as much as possible

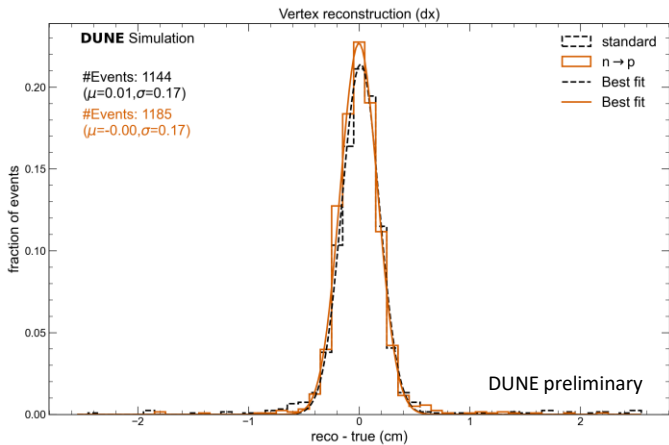
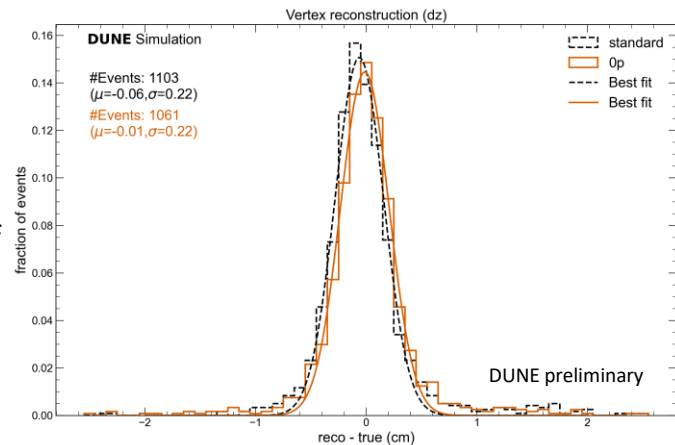
“Model dependence”



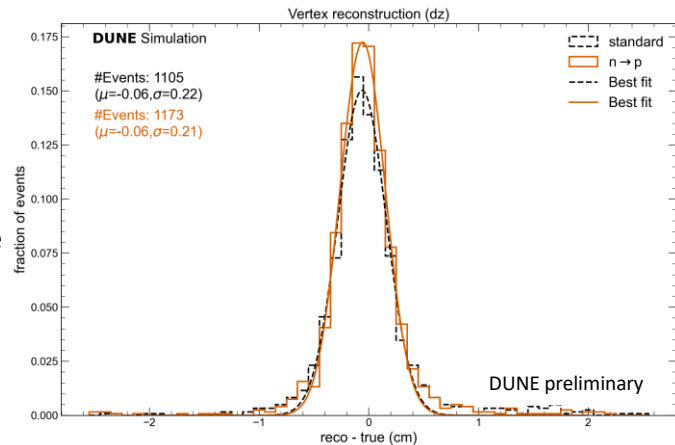
“Model dependence”



While peak efficiency varies, no evidence of bias or reduction in peak resolution

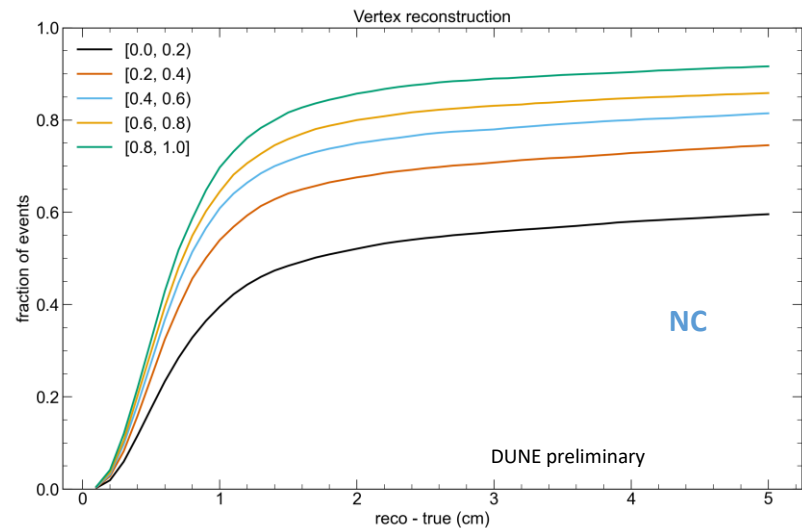
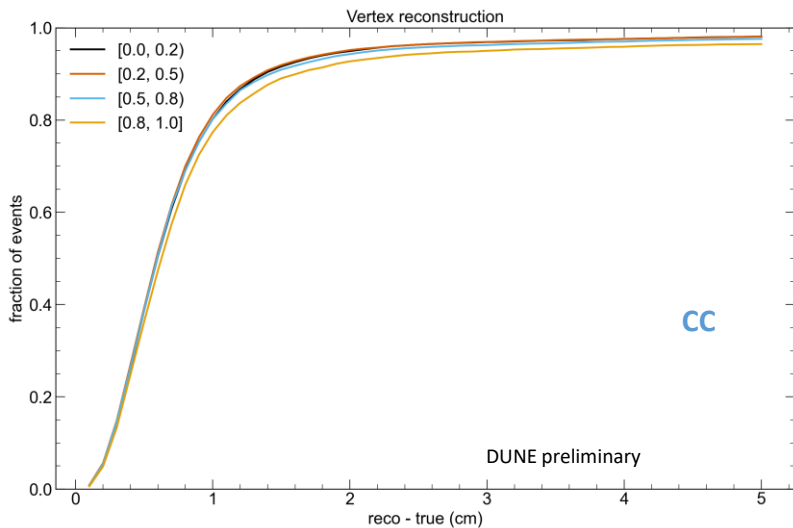


Note: Fiducial volume cuts and event correspondence checks between samples reduce the available sample size



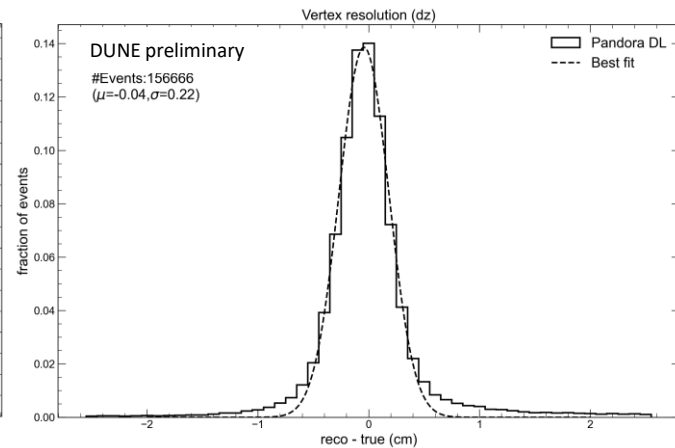
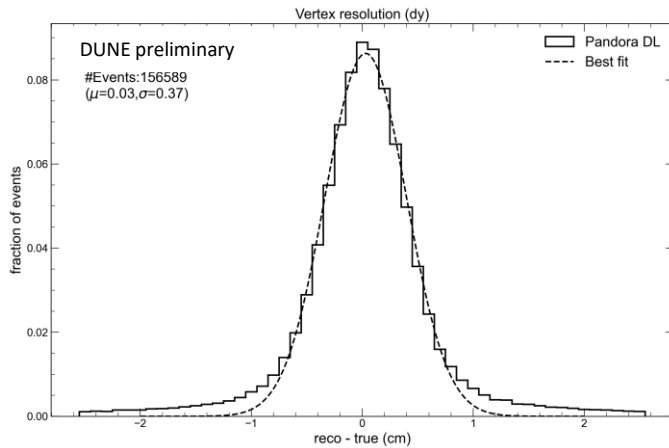
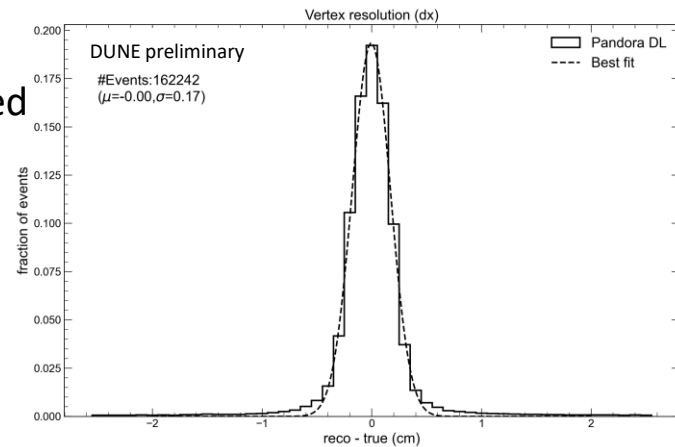
Performance as a function of inelasticity

- CC interactions relatively insensitive to inelasticity ($1 - \frac{E_{lep}}{E_\nu}$)
 - Slight turnover at highest inelasticity – plausible secondary vertices, overlapping trajectories
- NC interactions show strong dependence
 - No leading lepton and lack of hadronic activity yields little pointing information



Vertex reconstruction performance

- Large majority of events have accurately reconstructed interaction vertex
- Precise and unbiased



Performance as a function of multiplicity

- Importance of pointing information evident in performance as a function of particle multiplicity
 - A single additional particle, of any flavour, notably improves performance
 - Ideally you want at least two track-like particles emerging from a common vertex
 - In general, greater multiplicity yields greater performance

