Neutrino interaction vertex-finding in a DUNE far-detector using Pandora deep learning

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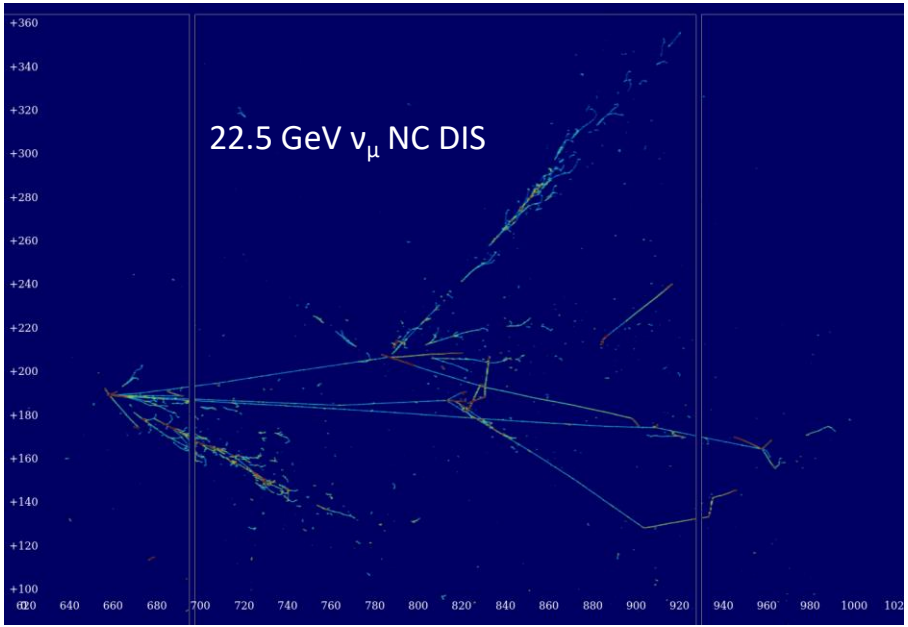
DEEP UNDERGROUND NEUTRINO EXPERIMENT

Pandora

WARWICK

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

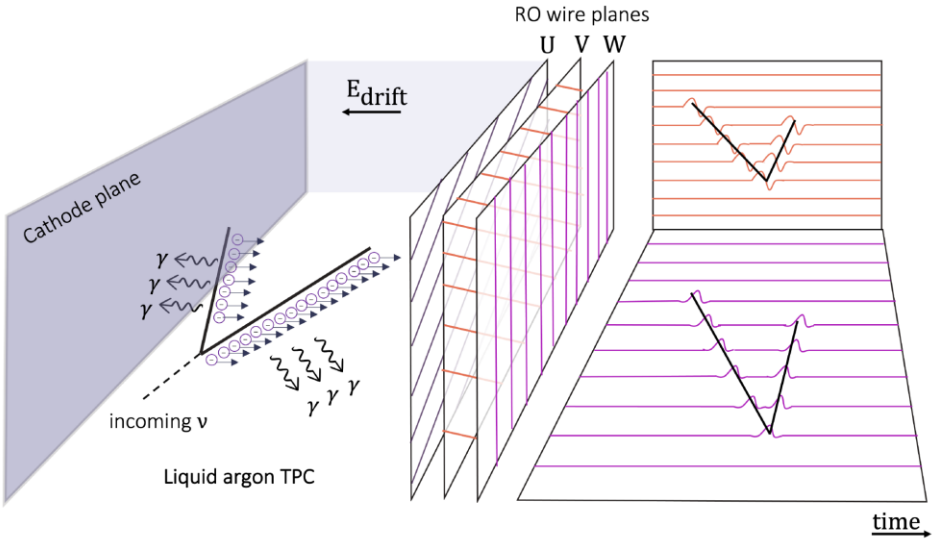


DUNE Physics

- Precision measurements of neutrino mixing parameters and the CP phase
- Measurement of the neutrino mass ordering
- Atmospheric neutrinos
- Exploration of the ν_τ sector
- Sensitive to low energy neutrinos
  - Supernova and solar neutrinos
- Low background
  - Sensitivity to BSM physics
- Achieving this broad program requires effective exploitation of our imaging detectors…

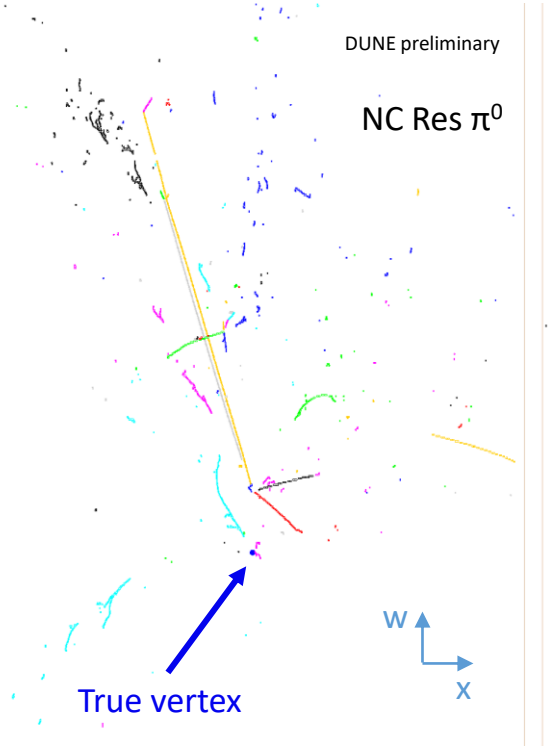
LArTPC operation

- 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 wire planes (horizontal drift variant) record the deposited charge using wires of different orientations
- Result is three different 2D projections of the charged particles in the interaction
- Need to correlate those images to extract distinct 3D particle trajectories and the hierarchical flow relating them



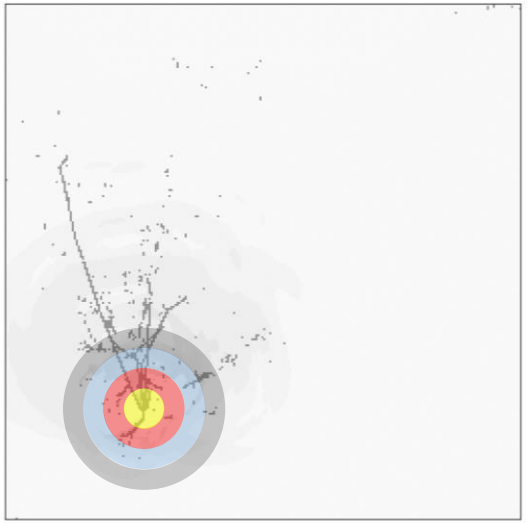
Finding the interaction vertex

- 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?
  - Not a collider experiment, we don't have a priori precision knowledge of the interaction location
  - Highly variable topologies
  - 3D interaction projected onto 2D outputs produces overlapping particle trajectories
  - Not always obvious, even by eye

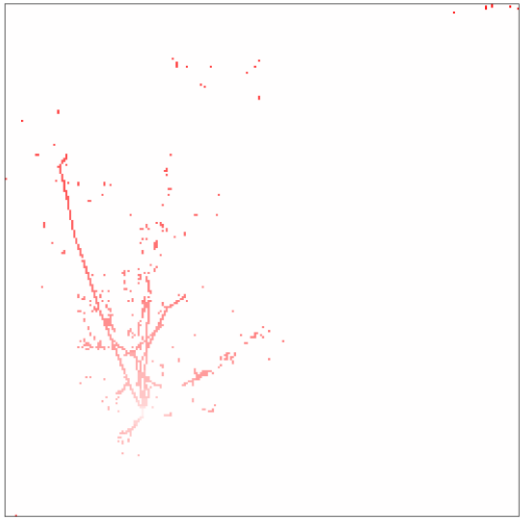


The Concept

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



Network trained to learn those distances from input images

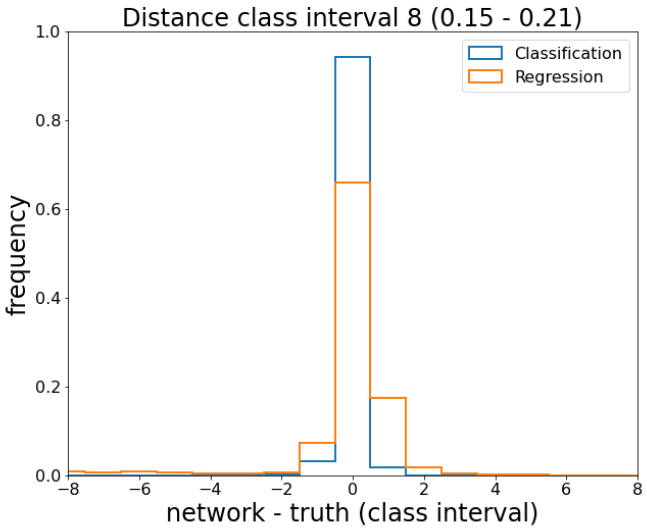


Network infers hit distances and resultant heat map isolates candidate vertex

Classification versus regression

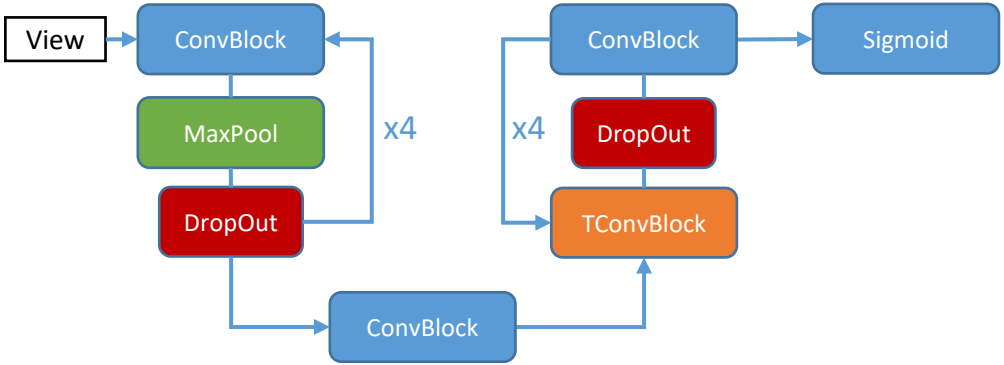
- Why distance classes instead of per-pixel regression?
  - Distance is an inherently continuous variable, but also one that proved challenging to learn
  - Distribution of network estimates with respect to true distance often biased and with broad, asymmetric errors
  - Binning the ranges of distances and treating as classes proved accurate and sufficiently precise

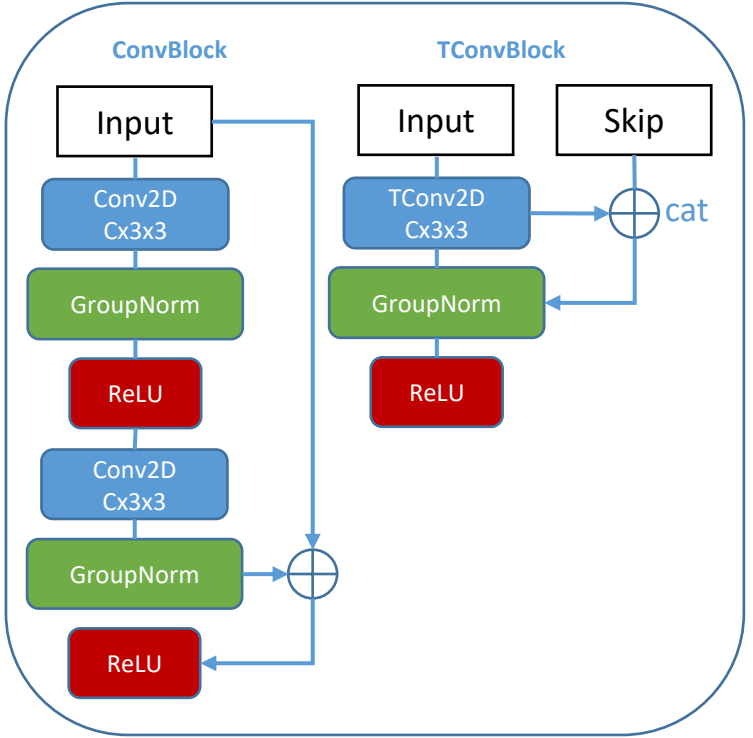
- Plot shows indicative distribution of difference between network inference and truth for a single true distance interval
  - Regression results are mapped onto corresponding classes for comparison



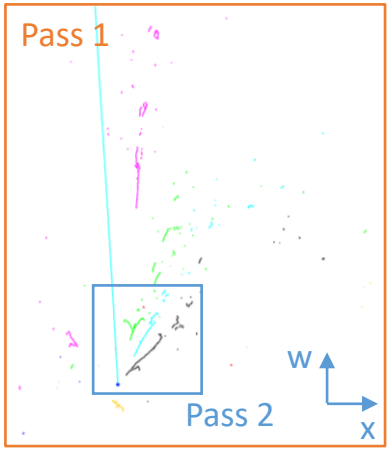
Network architecture

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



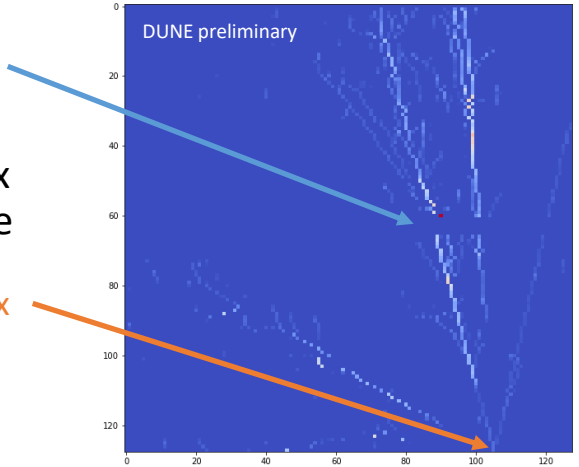


Two pass approach



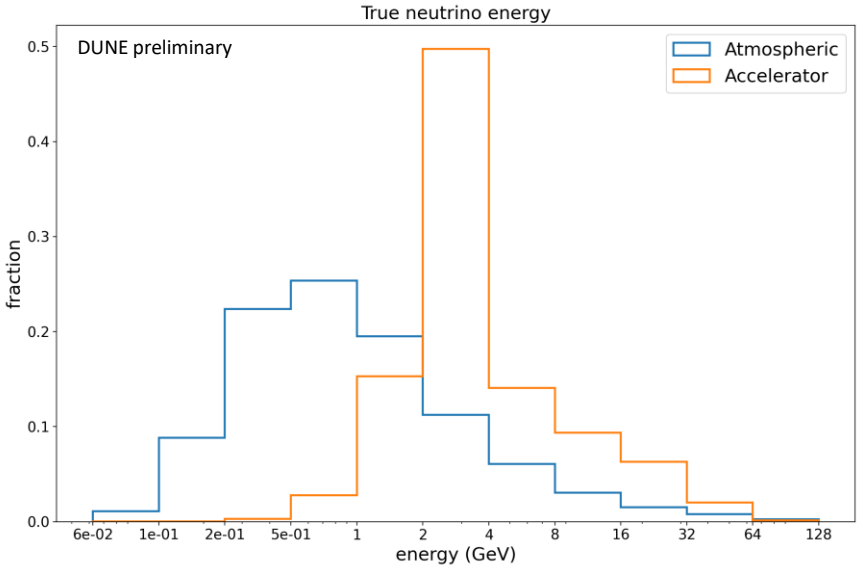
- DUNE events can span a large physical region (many metres)
- 256x256 pixel pass 1 input to maintain computational tractability
- Pixels have low spatial resolution relative to DUNE's ~0.5 cm wire pitch
- Solution: Low resolution first pass, zoom in on RoI for second pass

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



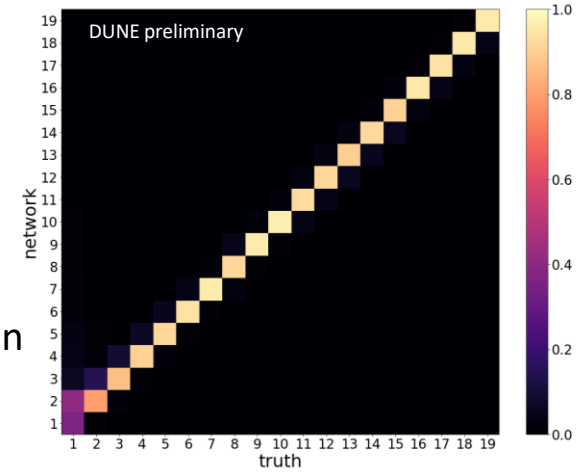
Training samples

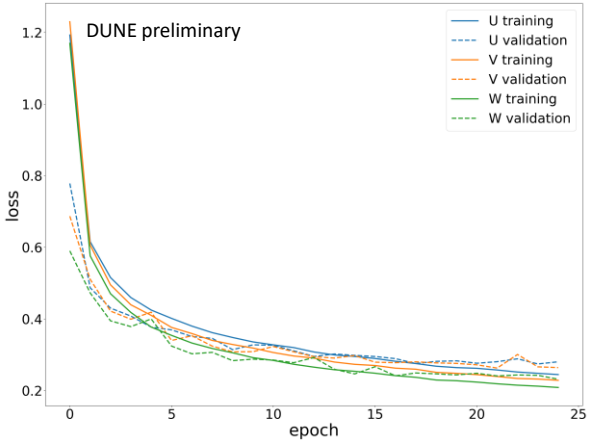
- Accelerator neutrinos
  - Incident direction determined by beam
  - Approx 64,000 training, 22,000 validation and 29,000 testing events
- Atmospheric neutrinos
  - Isotropic
  - Approx 45,000 training, 15,000 validation and 50,000 testing events
- Quite different energy spectra yield different topologies to learn
- Future sample: supernova neutrinos
  - Isotropic direction
  - Very low energy: ~10-40 MeV
  - Considering possibility of mixed training samples to avoid network proliferation

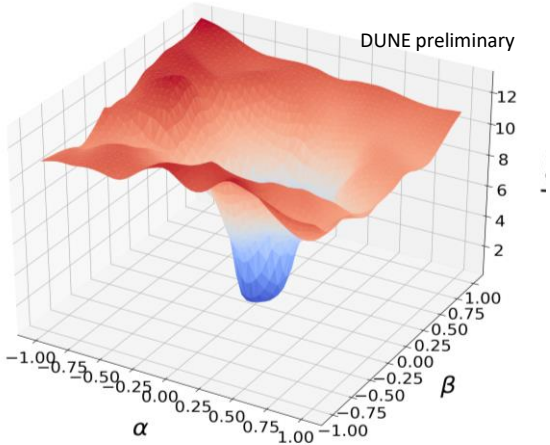


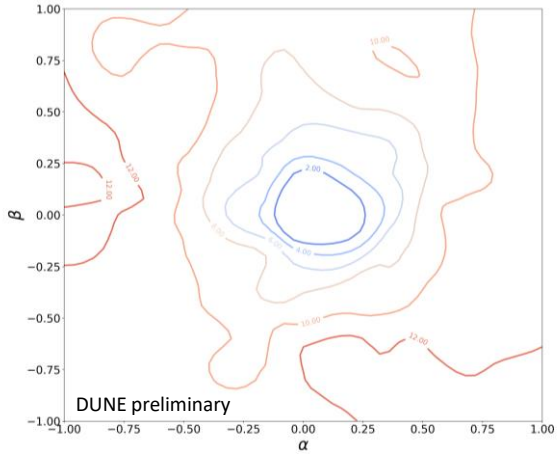
Evaluating training

- Visualize loss landscape as per Li et al (arXiv:1712.09913)
  - Generate random Gaussian direction vectors (N = 2.2M), δ and η
  - Pick α and β on a grid [-1, 1] and step αδ + βη away from training minimum and compute mean loss over 1024 validation set events
- Smooth loss landscape yields smooth loss function evolution
- High classification accuracy across classes



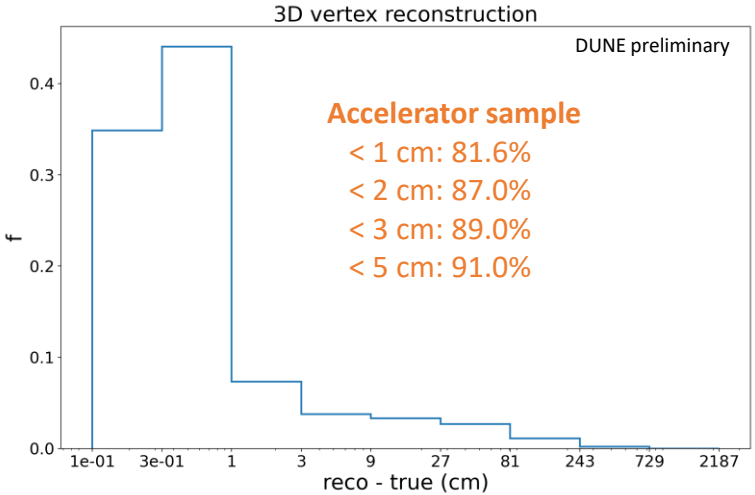


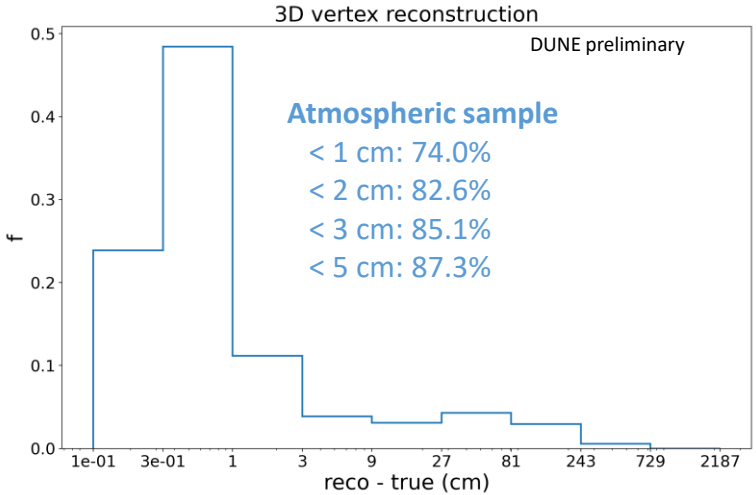




Vertex reconstruction performance

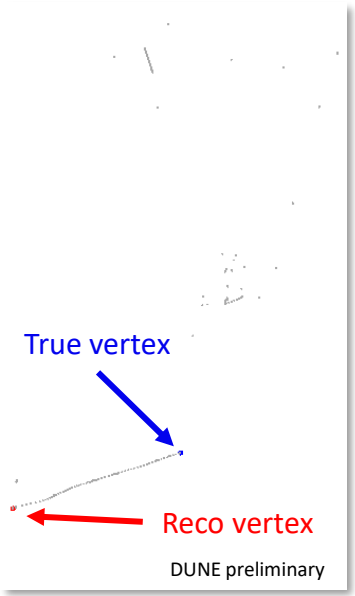
- Both accelerator and atmospheric networks yield performant vertex reconstruction
  - Higher performance of accelerator case plausibly due to consistent incident neutrino direction
  - Notable population in the tails (next slide)
- Pandora approach provides scope to identify and fix failures with downstream algorithms

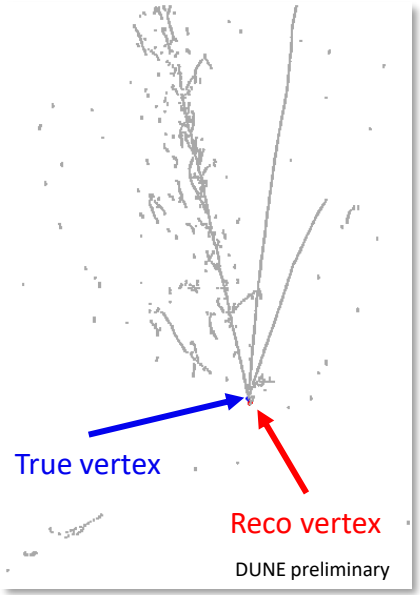


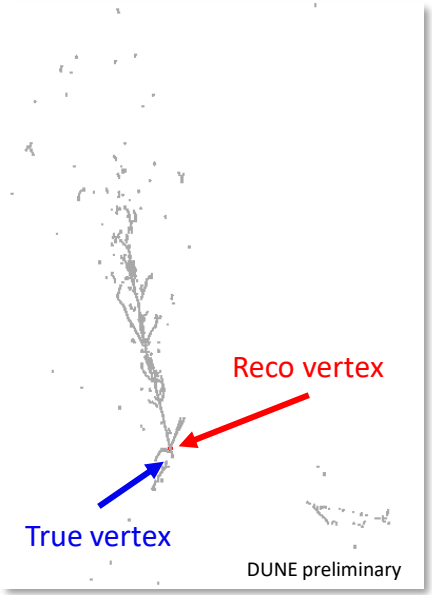


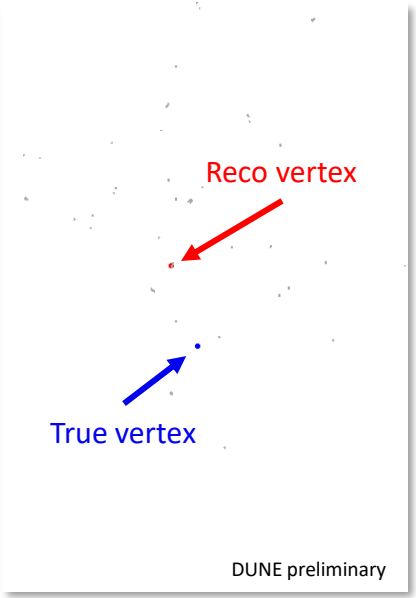
Vertex reconstruction performance

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



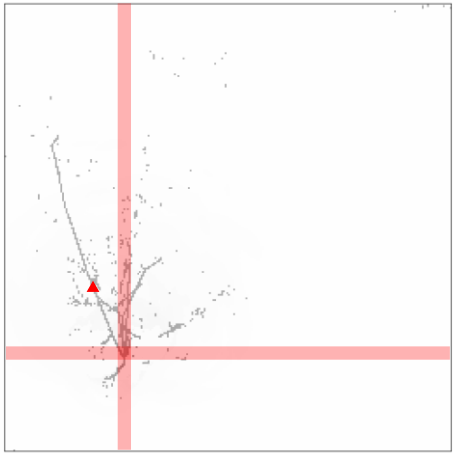


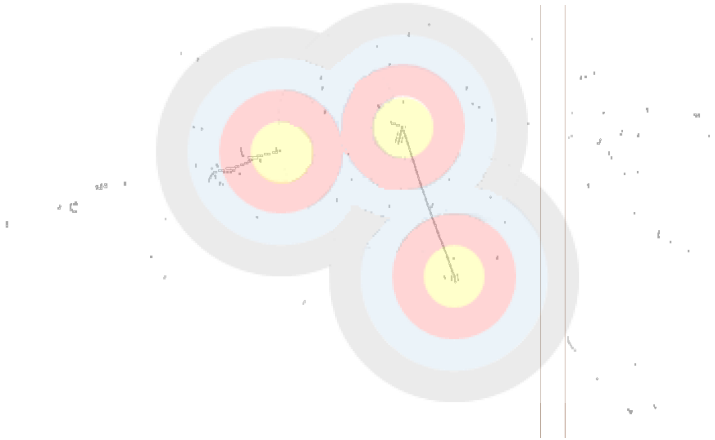




Future work

- Technical changes
  - Sparse convolutions might eliminate need for multiple passes
  - Split distance metric into orthogonal directions to simplify heatmap generation/processing
- Secondary vertices
  - Can extend technique to find secondary vertices
  - Guide reconstruction algorithms to “connect the dots”





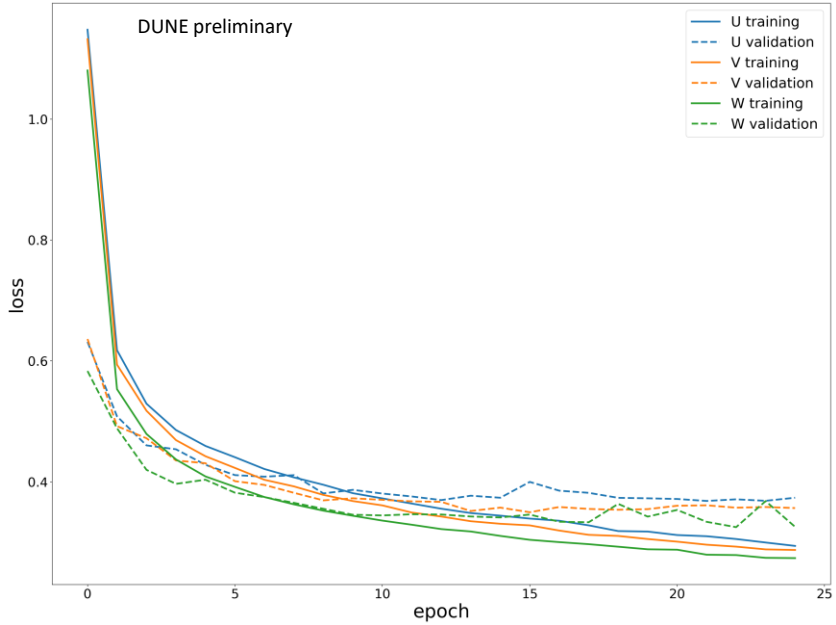
- Robustness tests
  - Is this approach sensitive to the generator/model?

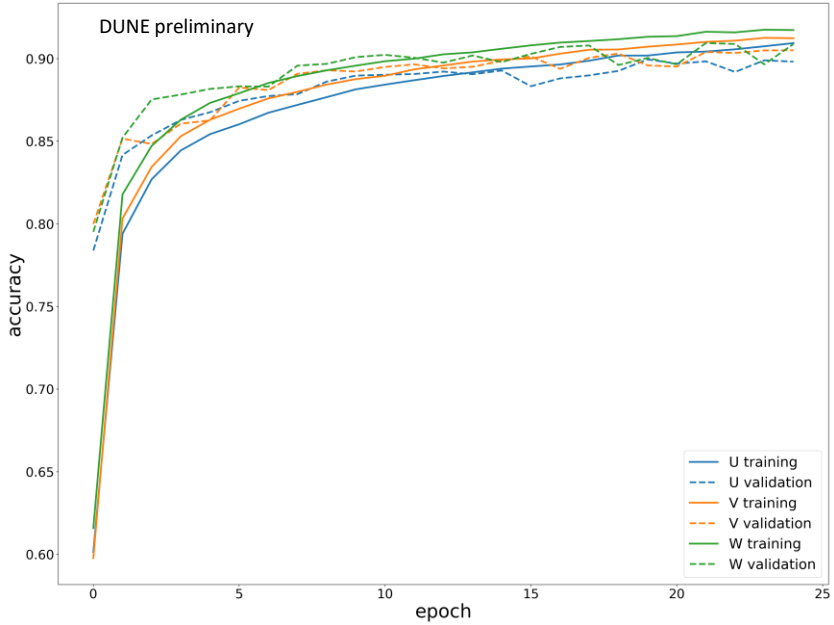
Conclusions

- Combination of deep learning and algorithmic pattern recognition yields performant vertex identification
  - Indirect approach plays to CNN classification strengths
  - Post-processing algorithm picks out the vertex
- A range of potential enhancements and extensions to explore
- Work remains to verify robustness of the technique

Backup

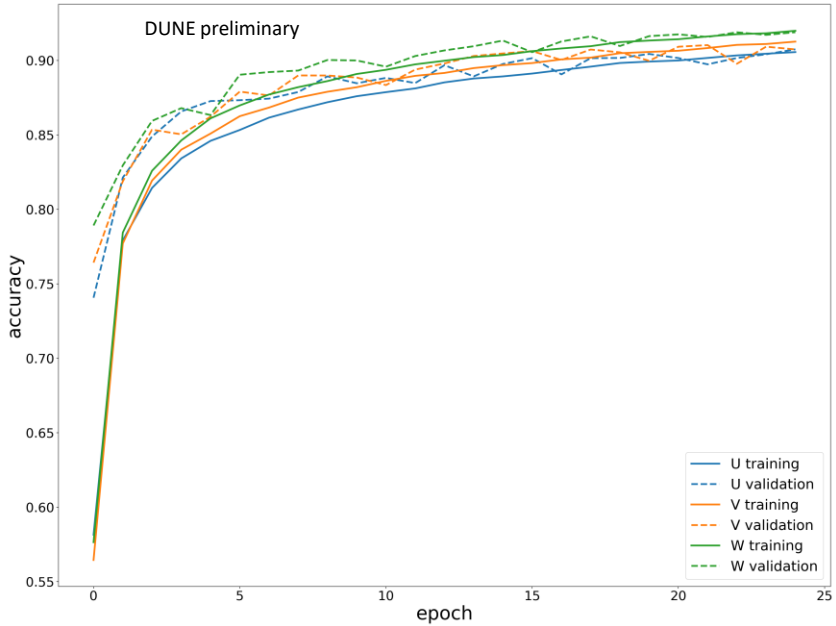
Training metrics





Accelerator Pass 2

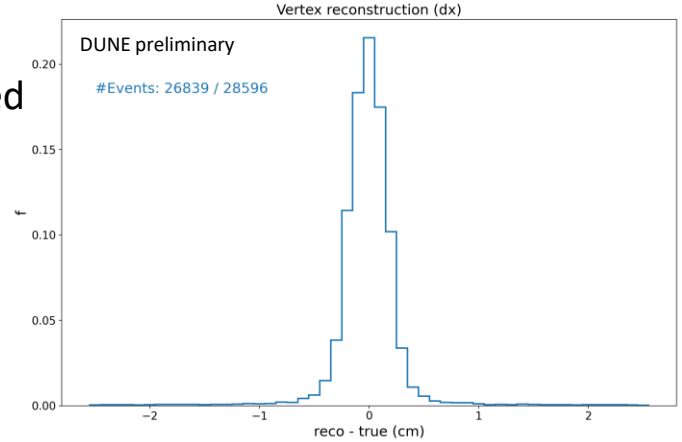
Training metrics

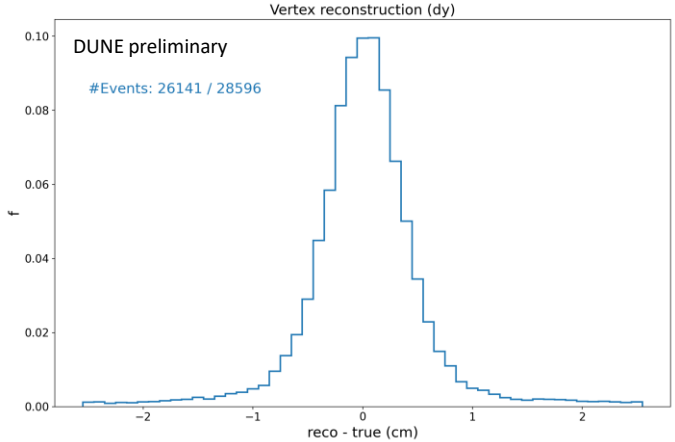


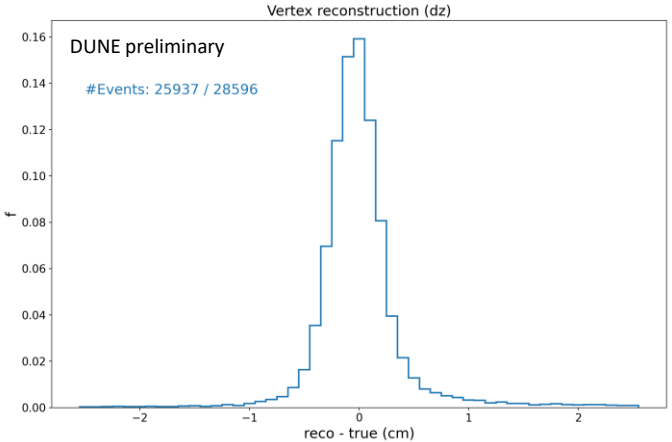
Accelerator Pass 1

Vertex reconstruction performance - accelerator

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

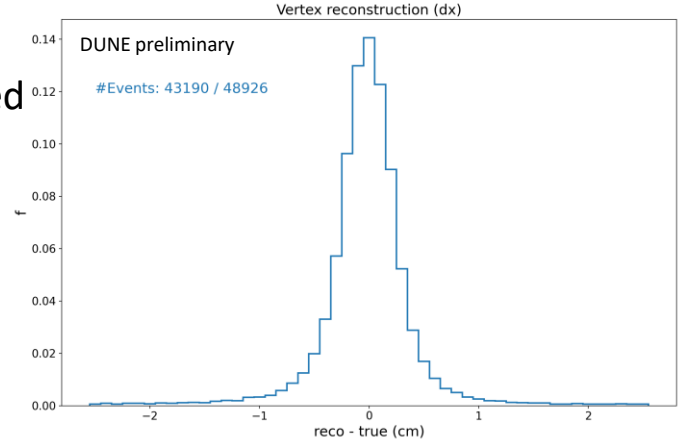


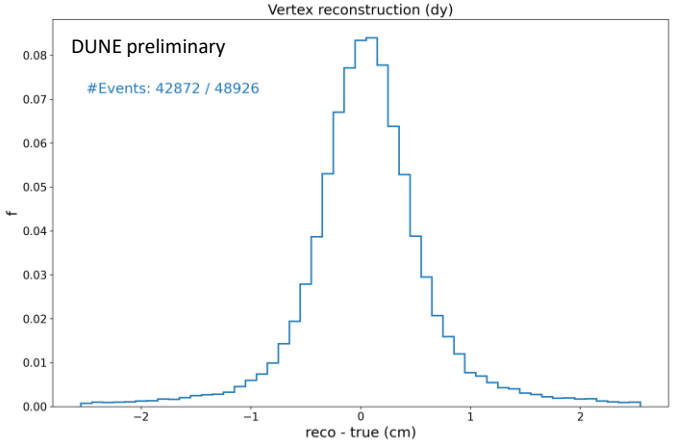


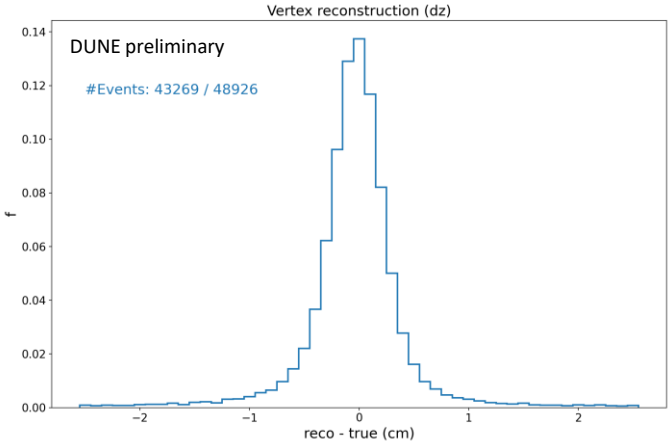


Vertex reconstruction performance - atmospheric

- Large majority of events have accurately reconstructed interaction vertex
  - Larger errors dominated by neutral current interactions with largely diffuse activity
- Precise and unbiased







Comparison to accelerator BDT

- Deep network out-performs the previous BDT vertex selection