Vertex-finding in a DUNE far-detector using Pandora deep learning

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DEEP UNDERGROUND NEUTRINO EXPERIMENT

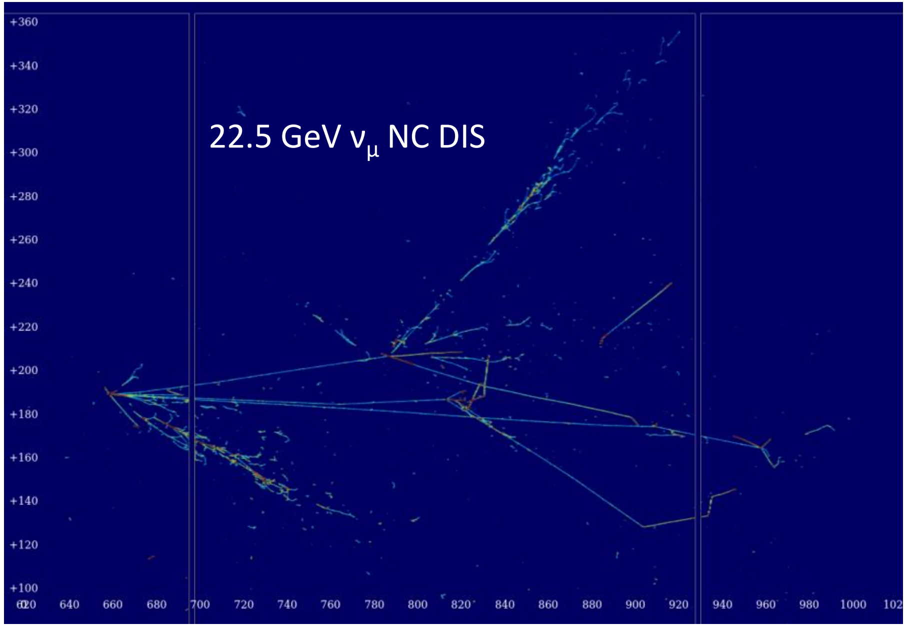
WARWICK

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

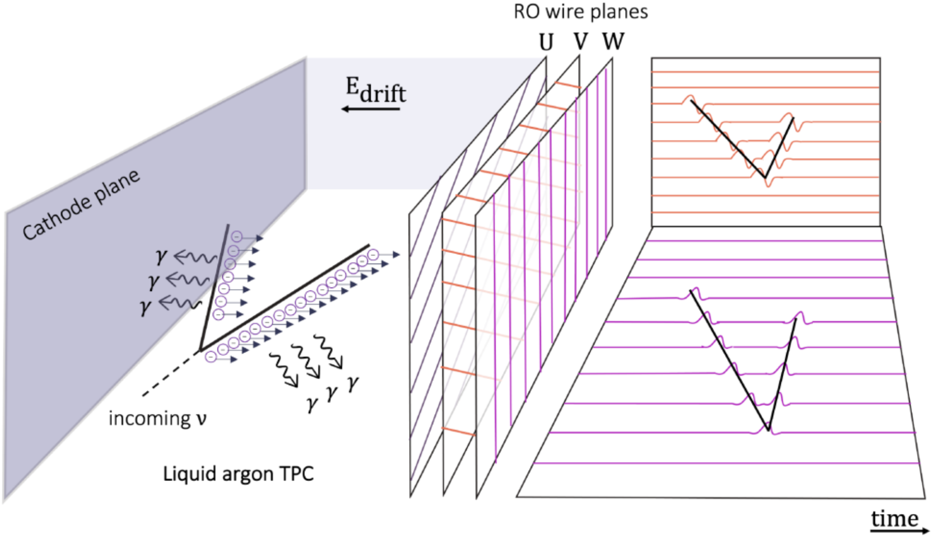


DUNE physics

- 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

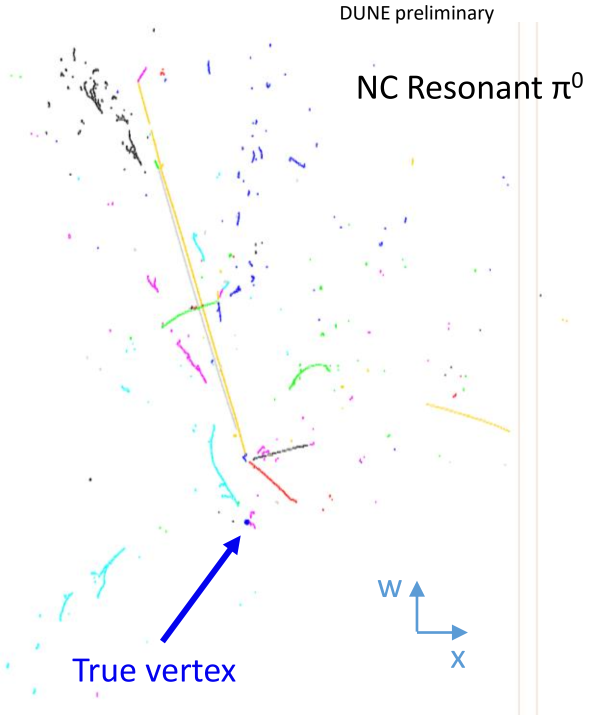
- Fully active interaction medium
- Charged particles ionize argon atoms to produce drift electrons (and scintillation light) along the particle trajectory
- Electrons drift in the electric field
- Three anode wire planes (horizontal drift variant) record the deposited charge using wires of different 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

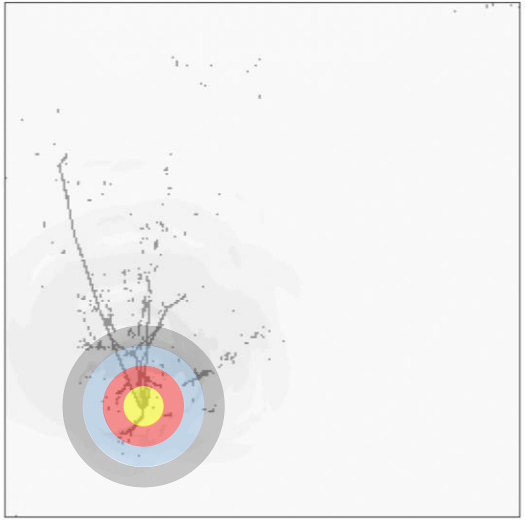
- Why is it important?
  - Vertex acts as anchor for clustering decisions
  - Determining particle flow depends on starting in the right place
- Why is it hard?
  - No a priori precision knowledge of the interaction location
  - 3D interaction projected onto 2D outputs produces overlapping particle trajectories
  - 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 AIDAinnova)
    DUNE isotropic atmospheric samples
    MicroBooNE (cosmic background)
    Low energy supernova neutrinos at DUNE
    Upcoming test-beam interactions at ProtoDUNE

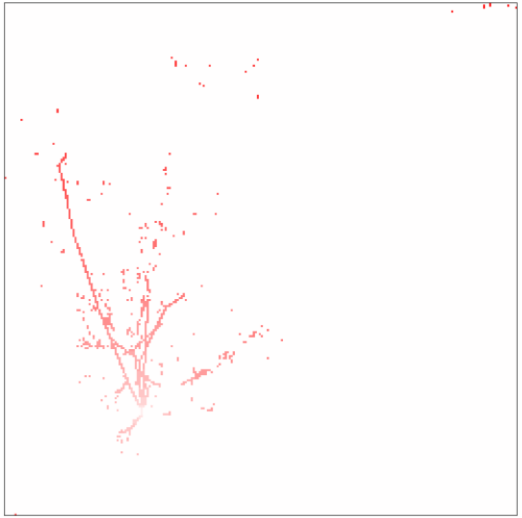


The concept

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



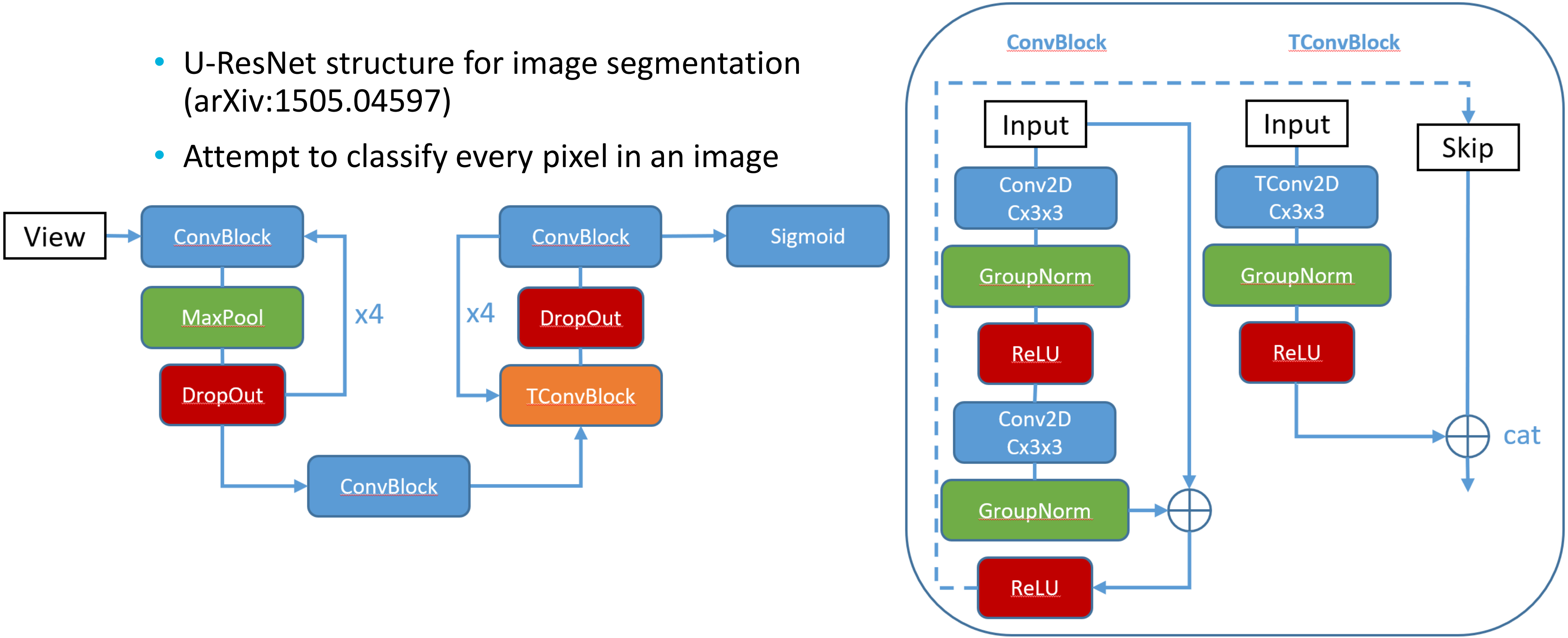
Network trained to learn those distances from input images



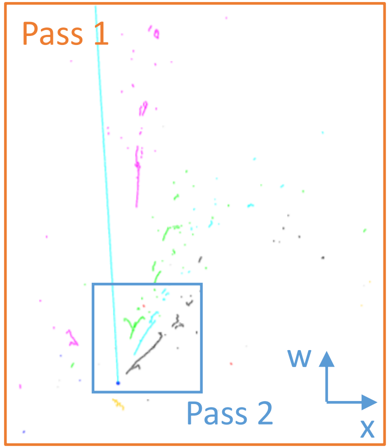
Network infers hit distances and resultant heat map isolates candidate vertex

Network architecture

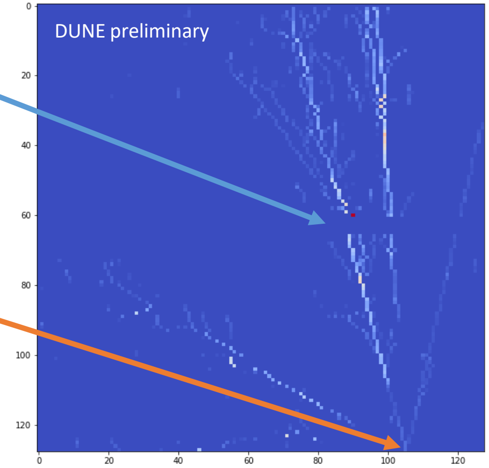
- U-ResNet structure for image segmentation (arXiv:1505.04597)
- Attempt to classify every pixel in an image



Two pass approach



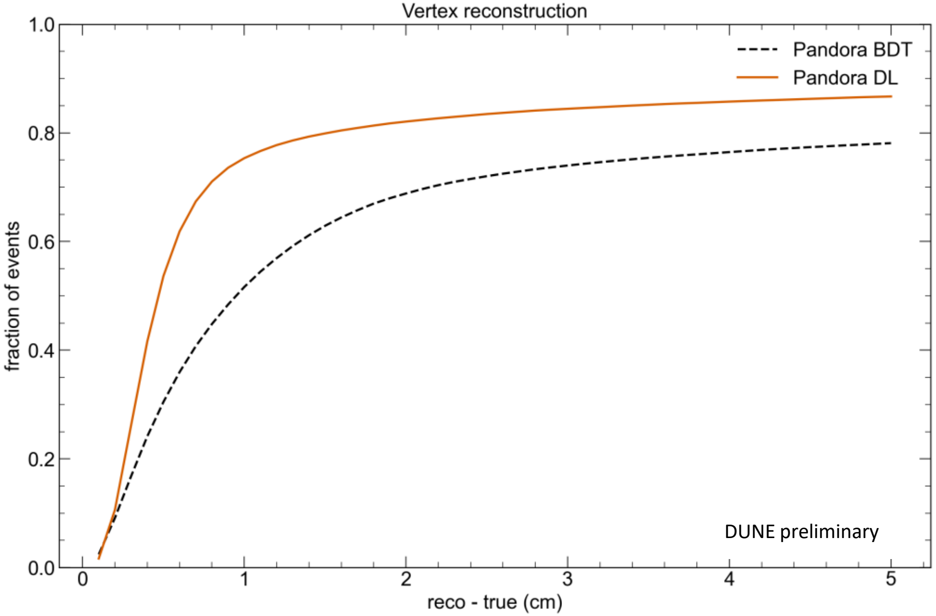
- DUNE events can span a large physical region (many metres)
- 256x256 pixel pass 1 input to maintain computational tractability (including CPU inference)
- Pixels have low spatial resolution relative to DUNE's ~0.5 cm wire pitch
- Solution: Low resolution first pass, zoom in on RoI for second pass



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

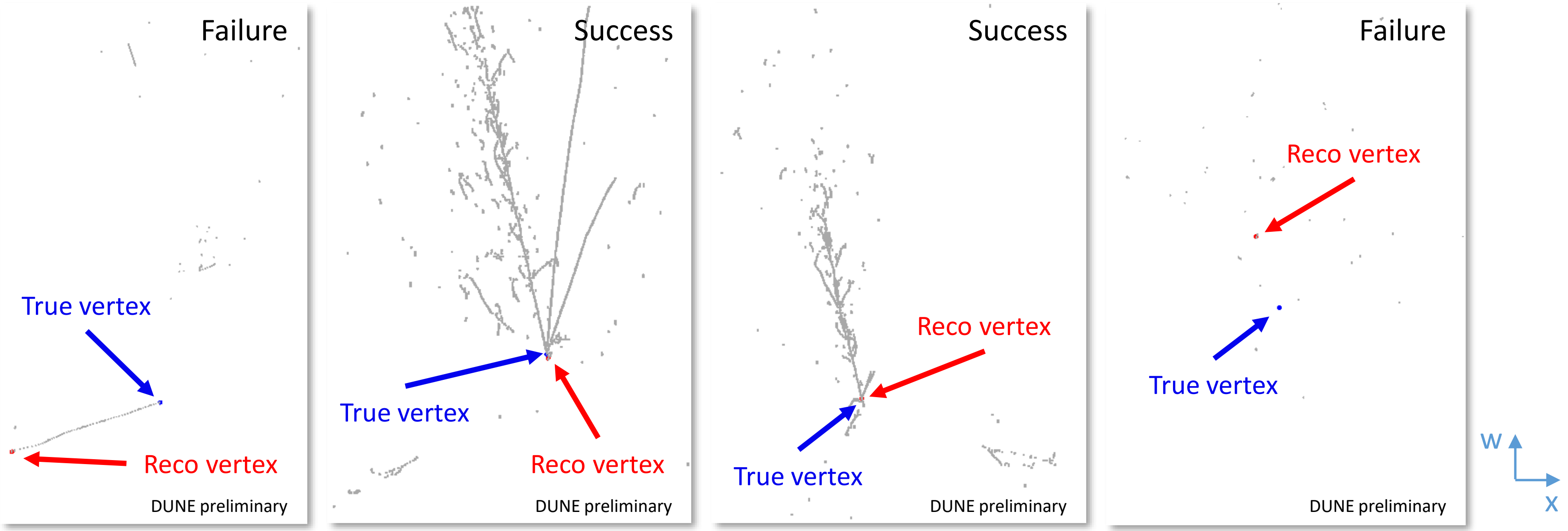
Vertex reconstruction performance

- Network yields performant vertexing
  - Previous vertexing performed by a BDT
  - Notable improvement over previous
  - Remaining efficiency losses outlined in next slide



Vertex reconstruction performance

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



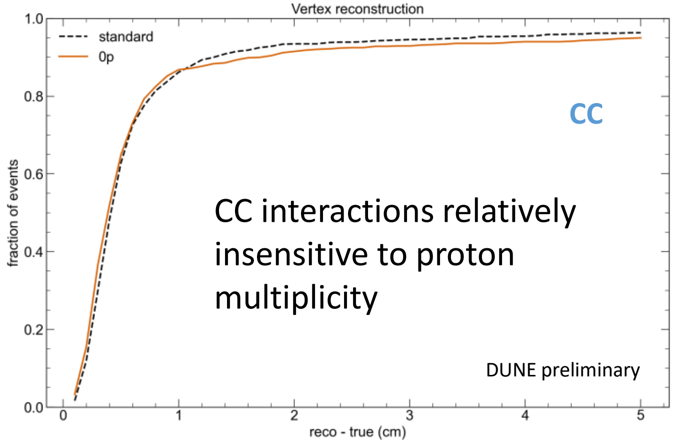
"Model dependence"

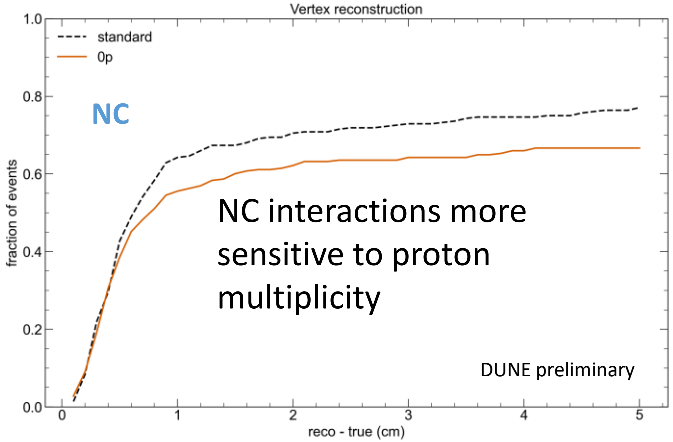
- We expect vertex efficiency/resolution to depend on the number of particles that point back to the true interaction vertex
- Different generators and nuclear models produce different particle multiplicities, particularly for the number of protons with momentum below 0.4 GeV
- Model dependence can lead 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

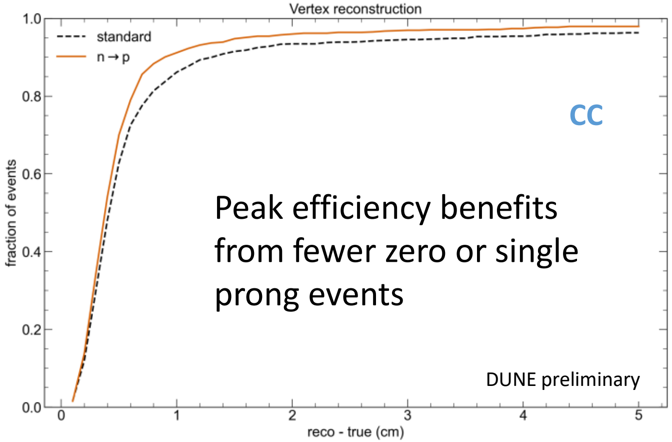
0p	Standard	n → p
Generation as standard p < 0.4 GeV removed	1000 ν_μ, 1000 ν_e Fixed seed for generation Fixed seed for G4 sim	Generation as standard n < 0.4 GeV swapped to p

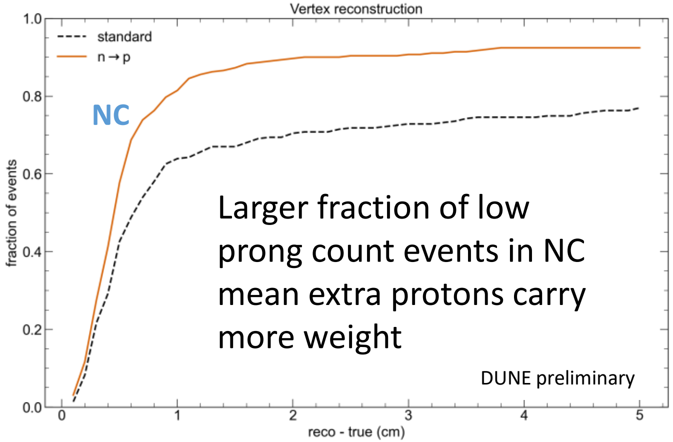
- Provides closest possible equivalence between events to isolate the effect of proton multiplicity as much as possible

"Model dependence"

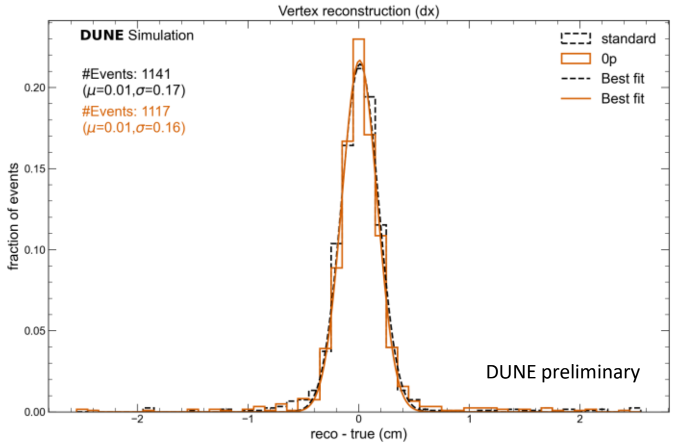


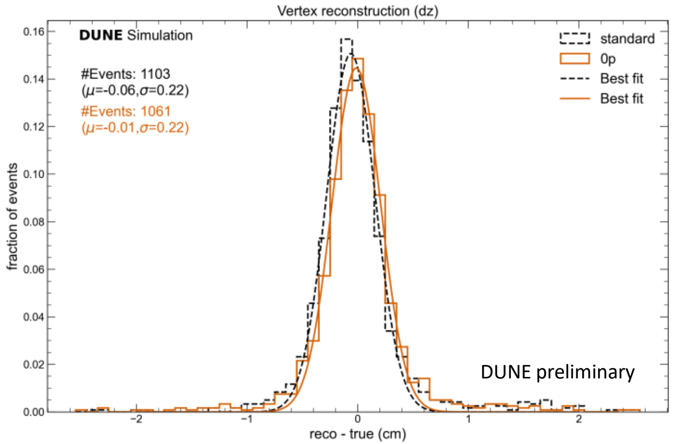




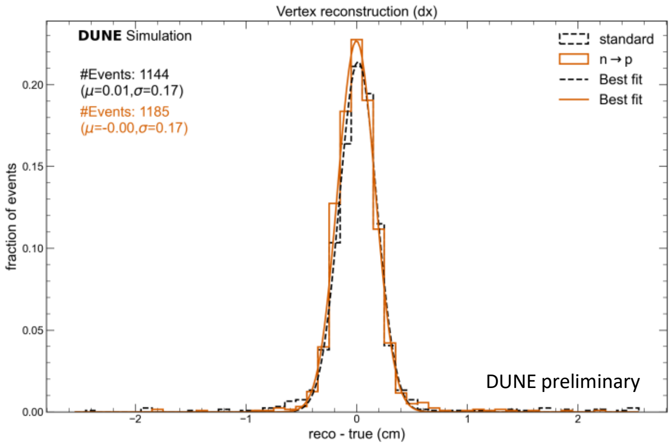


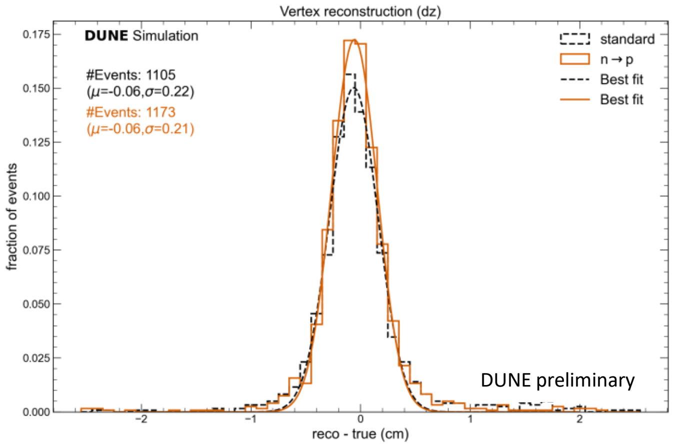
"Model dependence"





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

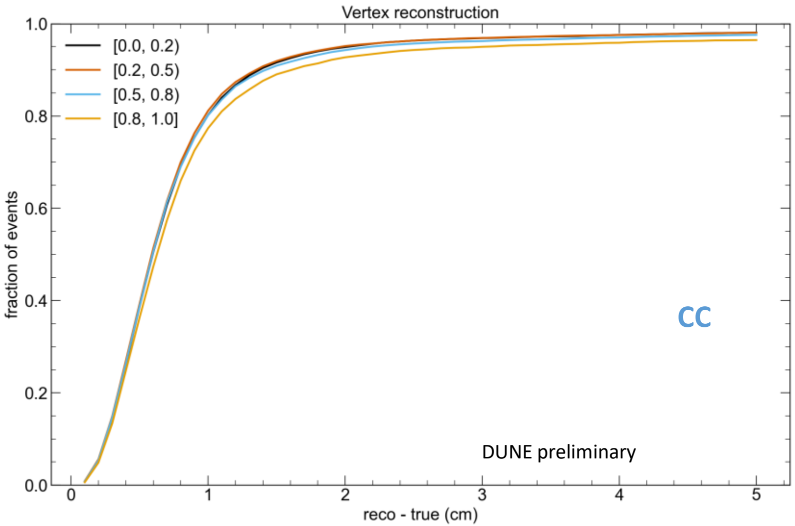


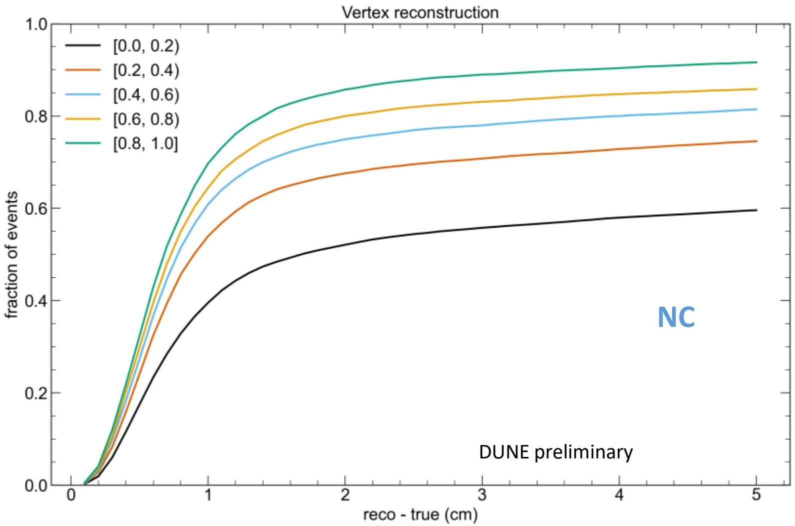


Note: Fiducial volume cuts and event correspondence checks between samples reduce the available sample size

Performance as a function of inelasticity

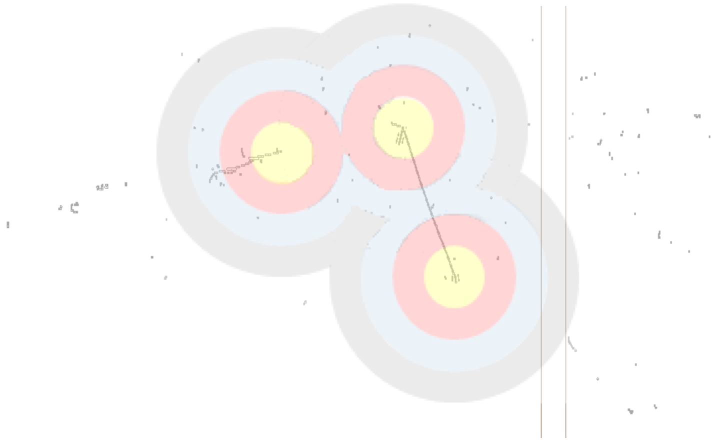
- CC interactions relatively insensitive to inelasticity $(1-\frac{E_{lep}}{E_\nu})$
    - Slight turnover at highest inelasticity – plausible secondary vertices, overlapping trajectories
- NC interactions show strong dependence
    - No leading lepton and lack of hadronic activity yields little pointing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

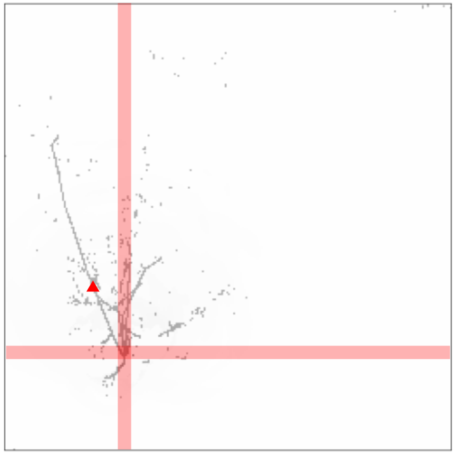




Future work

- Technical changes
  - Sparse convolutions or graph-based methods 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"





Conclusions

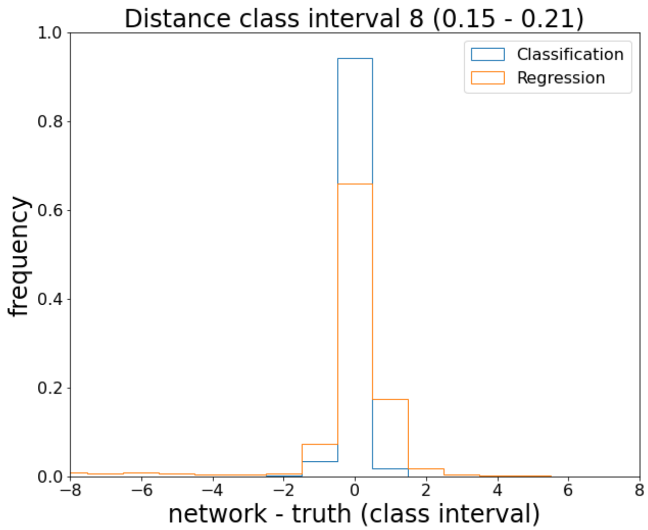
- Combination of deep learning and algorithmic pattern recognition yields performant vertex identification
  - Indirect approach plays to CNN classification strengths
  - Post-processing algorithm picks out the vertex
- Low particle multiplicity can reduce vertex reconstruction efficiency, but does not systematically bias reconstructed vertex position
- A range of potential enhancements and extensions to explore

Backup

Classification versus regression

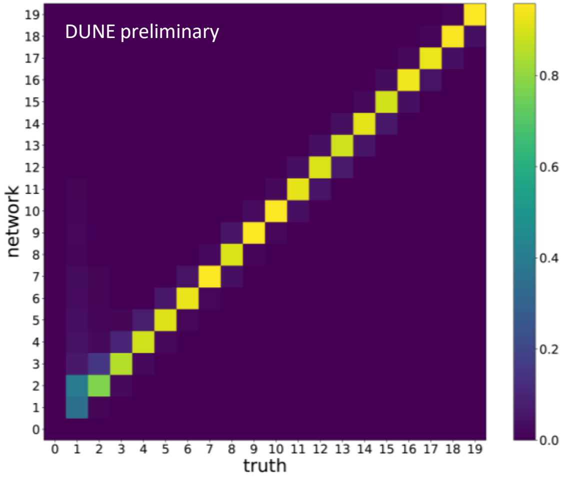
- Why distance classes instead of per-pixel regression?
  - Distance is an inherently continuous variable, but also one that proved challenging to learn
  - Distribution of network estimates with respect to true distance often biased and with broad, asymmetric errors
  - Binning the ranges of distances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

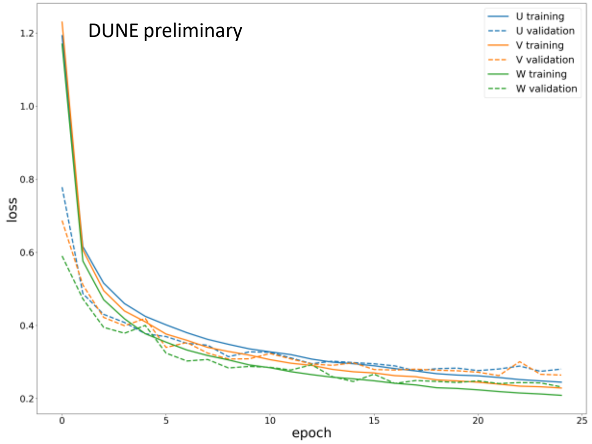
- Plot shows indicative distribution of difference between network inference and truth for a single true distance interval
  - Regression results are mapped onto corresponding classes for comparison

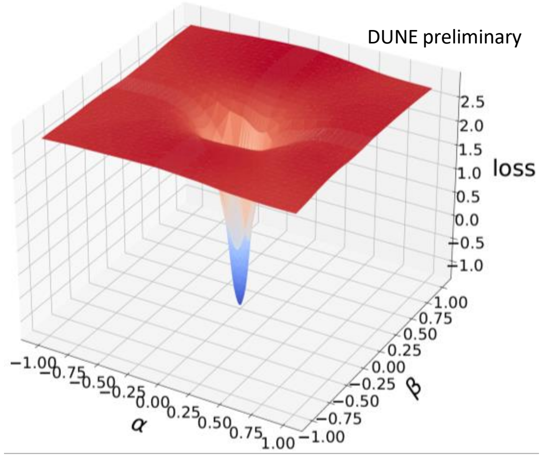


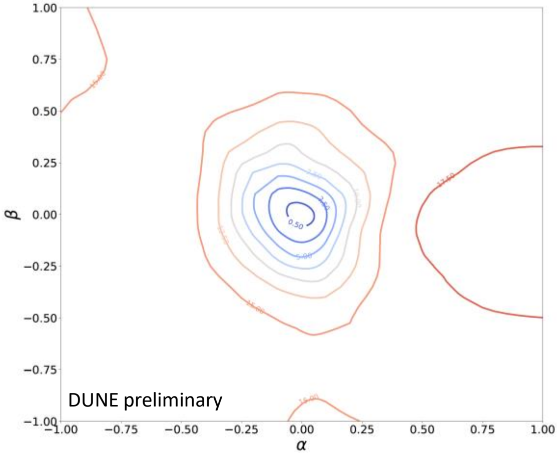
Evaluating training

- 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



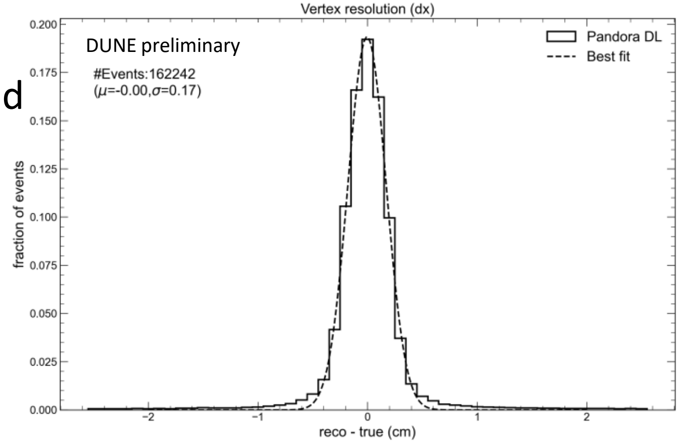


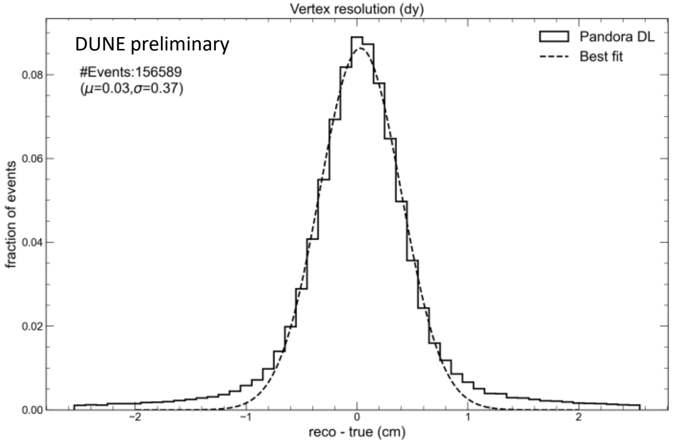


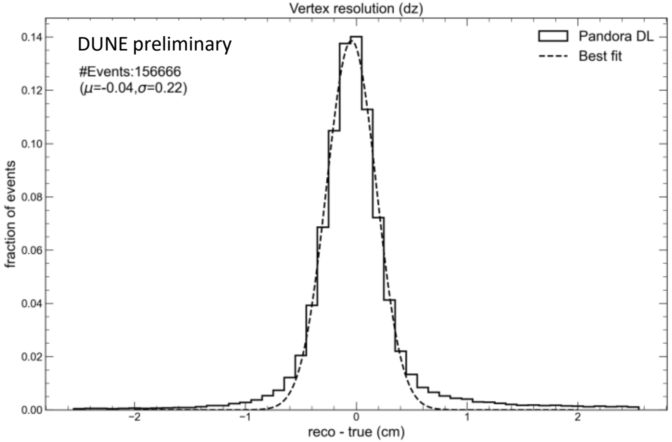


Vertex reconstruction performance

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

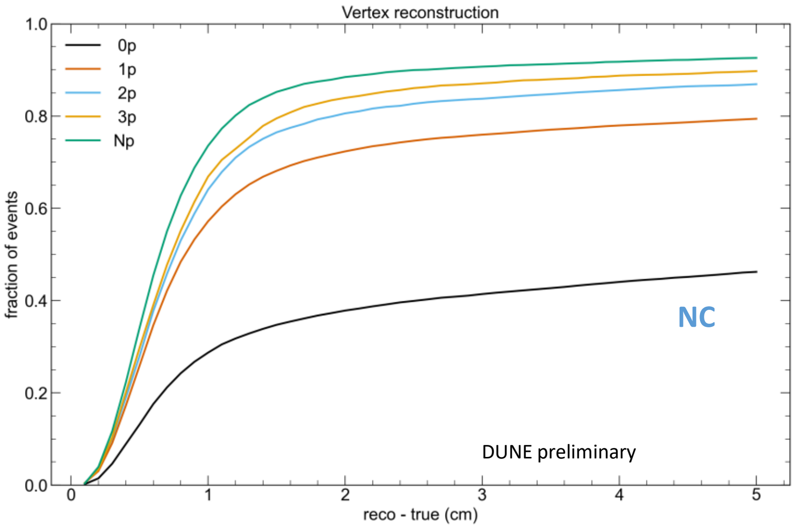


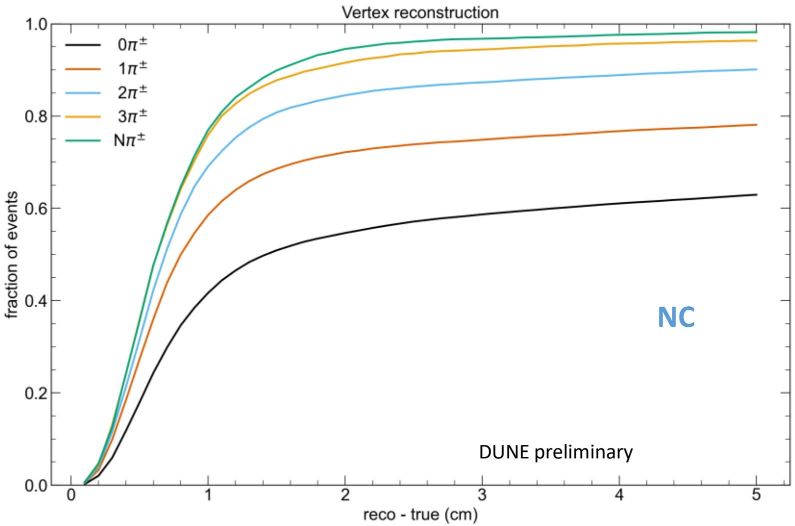




Performance as a function of multiplicity

- 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





Performance in atmospheric neutrino sample

- DUNE HD FD atmospheric neutrino