

Machine Learning in Pandora

Andy Chappell

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The Second Wire-Cell Reconstruction Summit

The Warwick University logo, featuring a stylized white mountain peak above the word "WARWICK" in a blue, sans-serif font.

WARWICK

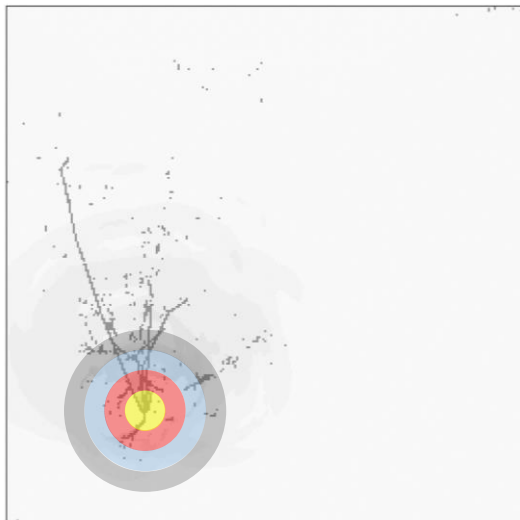
ML in Pandora – Present and future

- Libtorch interface added to Pandora in October 2020
 - Allows us to run deep networks as a standard part of our algorithm chain
 - Libtorch v1.4.0 – fairly limited network architecture support - no sparse networks
- First fully integrated network, running in LArSoft July 2022
 - U-ResNet for vertex finding in DUNE Horizontal Drift far detector in Long Baseline workflow
 - Since demonstrated in various workflows and detector configurations at DUNE and MicroBooNE
 - Same architecture being re-used for signal/background separation in supernova neutrino samples at DUNE and neutrino/cosmic separation at MicroBooNE
 - Extending concept to secondary vertex finding
- LArSoft now supports Libtorch v2+
 - Provides support for GNNs and Transformers
- Expanding ML use in Pandora (all work in progress)
 - Identifying reconstruction errors (Transformer encoder)
 - Re-clustering (GNN)
 - Vertex refinement (GNN)
 - ...

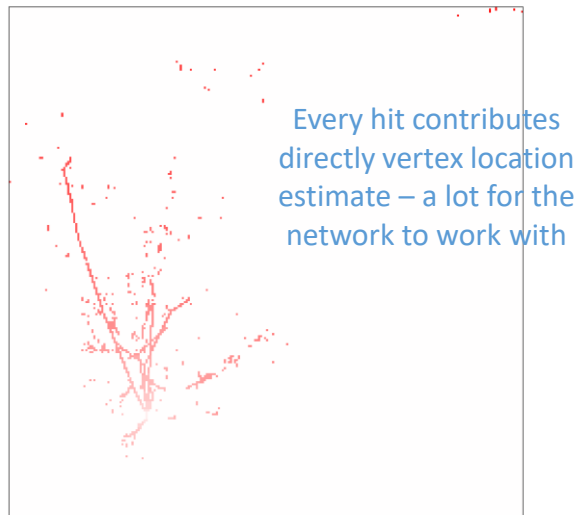
Vertex finding

The concept

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



Network trained to learn those distances from input images

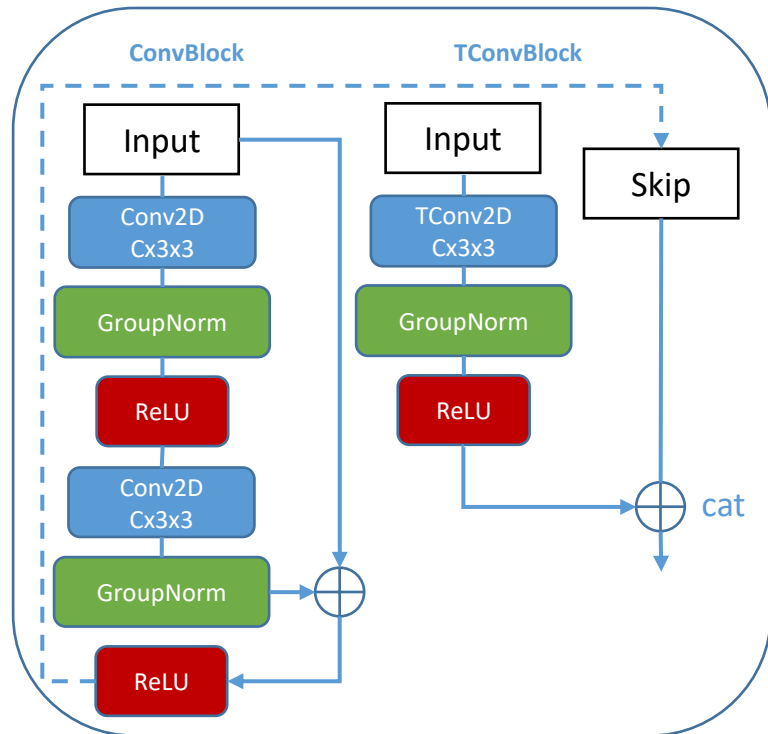
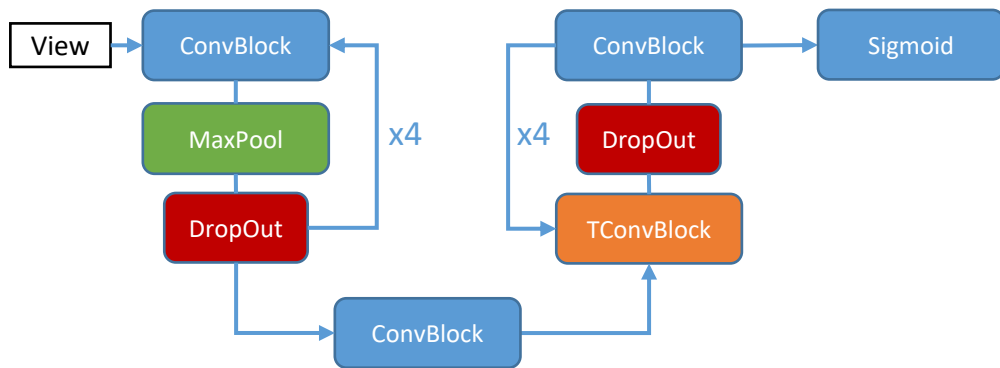


Network infers hit distances and resultant heat map isolates candidate vertex

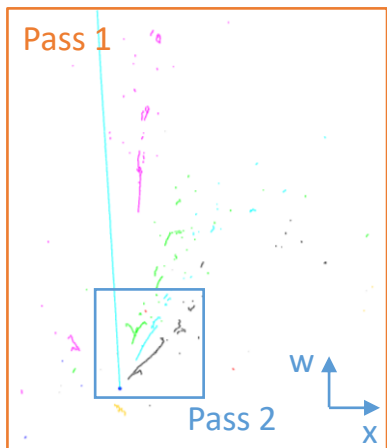


Network architecture

- [U-ResNet structure](#) for image segmentation
- Attempt to classify every pixel in an image



Two pass approach

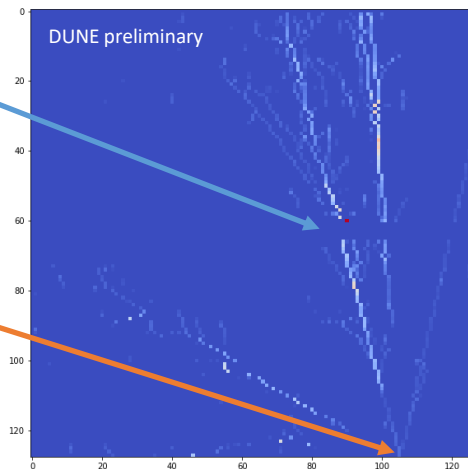


- DUNE events can span a large physical region (many metres)
- 256x256 pixel pass 1 input to maintain computational tractability
- Pixels have low spatial resolution relative to DUNE's ~ 0.5 cm wire pitch
- Solution: Low resolution first pass, zoom in on ROI for second pass

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

Gap between anode plane assemblies

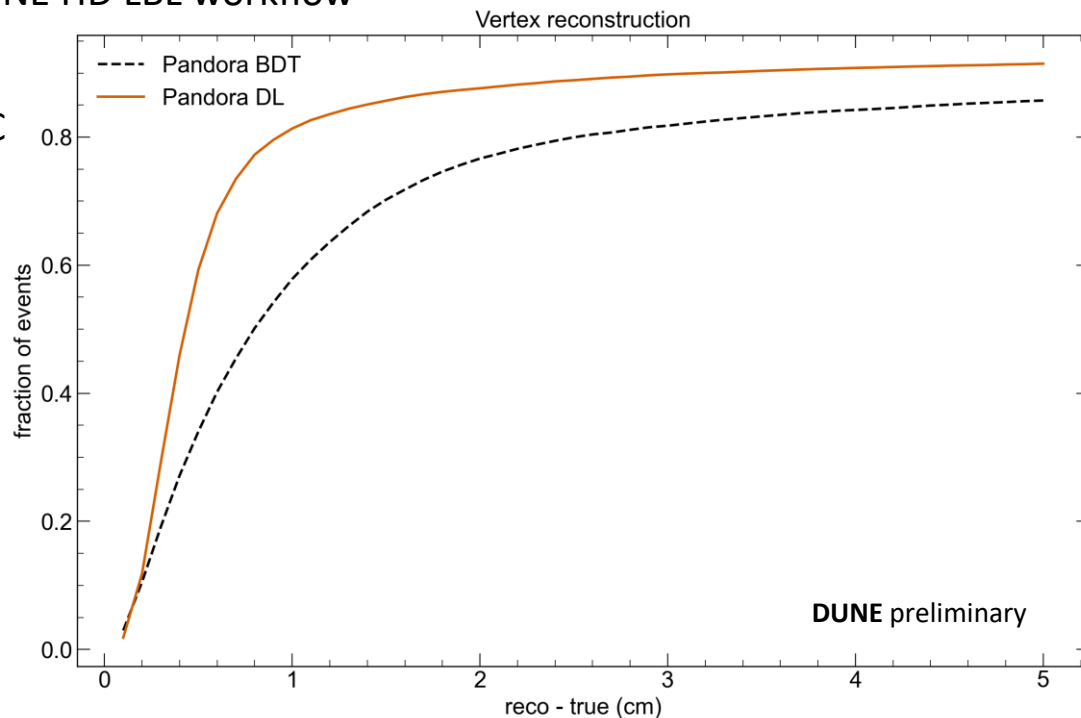
Pass 1 estimated vertex



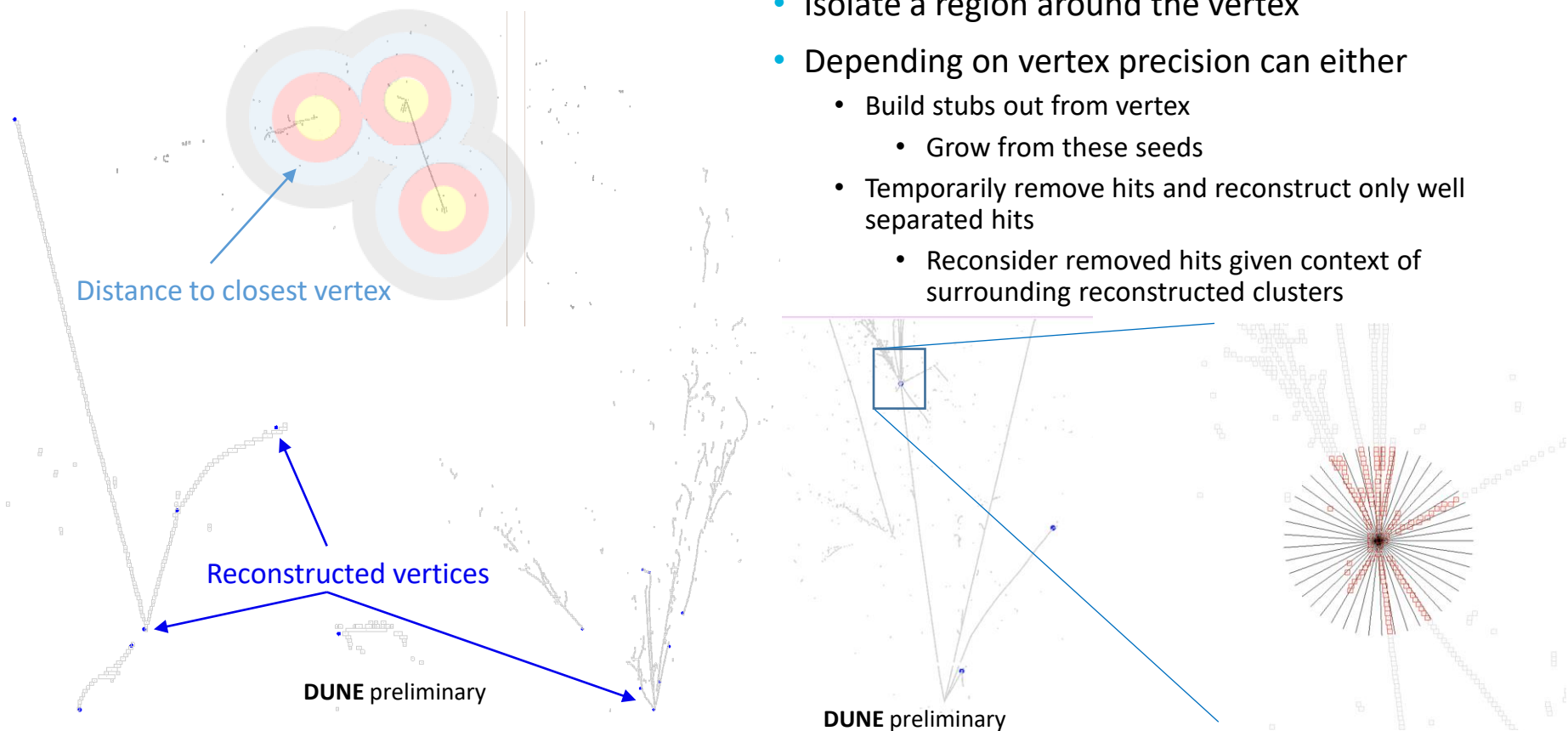
Vertex reconstruction performance

- Substantial improvement over previous BDT based vertex reconstruction
- Example here is from DUNE HD LBL workflow

- About 10% of events (NC dominated) still have “catastrophic failures”
- Some evidence from MicroBooNE that GNNs can reduce such failures
- Potential to replace pass 1 with a GNN



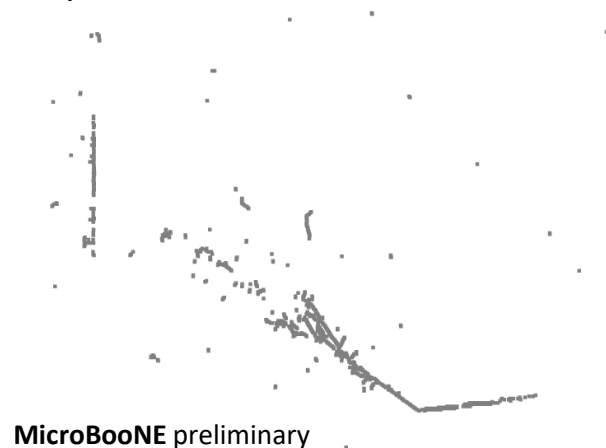
Secondary vertex finding



Vertexing in the presence of cosmics

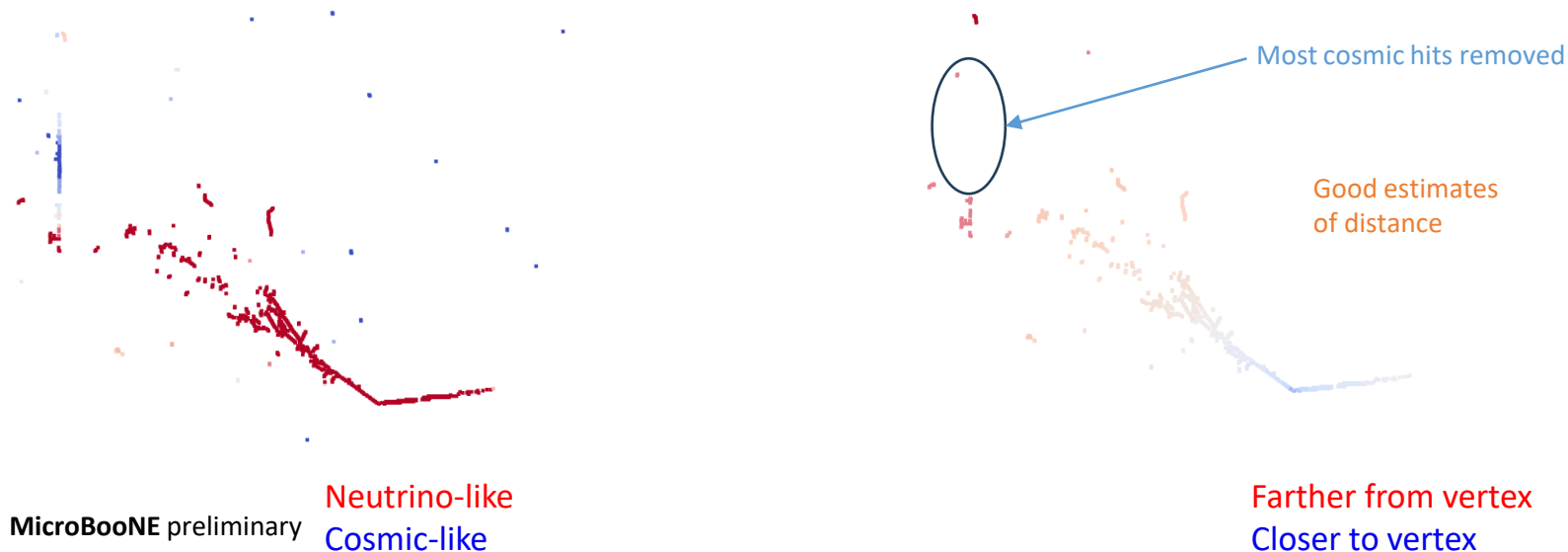
The problem of cosmic remnants

- In experiments like MicroBooNE neutrino interactions are crossed with many cosmics
- Pandora has algorithms to separate cosmics into slices separate from the neutrino, but sometimes contamination can remain
- This is a problem for vertexing because now there are hits with no meaningful relationship to the vertex
- Enough such hits can alter the estimated vertex position



Leveraging the U-ResNet architecture

- A solution to this problem is to use the same U-ResNet architecture to tag cosmic and neutrino hits and remove the cosmics from consideration

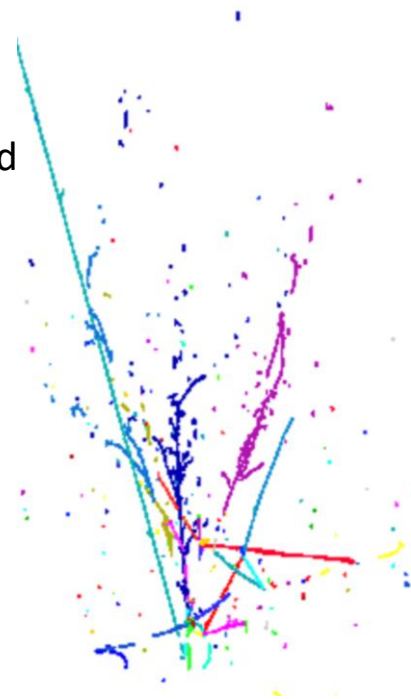


- We are looking at extending this procedure to improve the slicing process itself

Finding errors and re-clustering

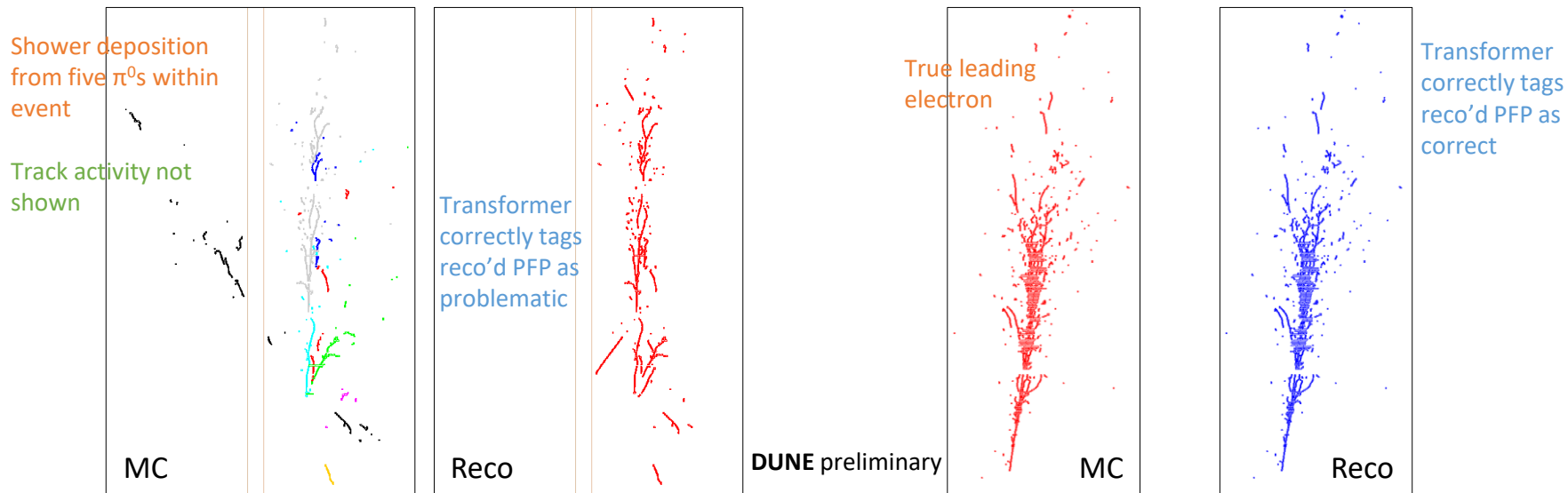
Known problems

- Shower reconstruction is particularly challenging
- Fragmentation of shower clusters makes trade off between purity and completeness challenging
- Overlap, especially with 2D projections, adds to the challenge
- Pandora often over-merges showers as a result
- Two broad approaches
 1. Stop the problem happening in the first place
 2. Spot when the problem has occurred and fix it



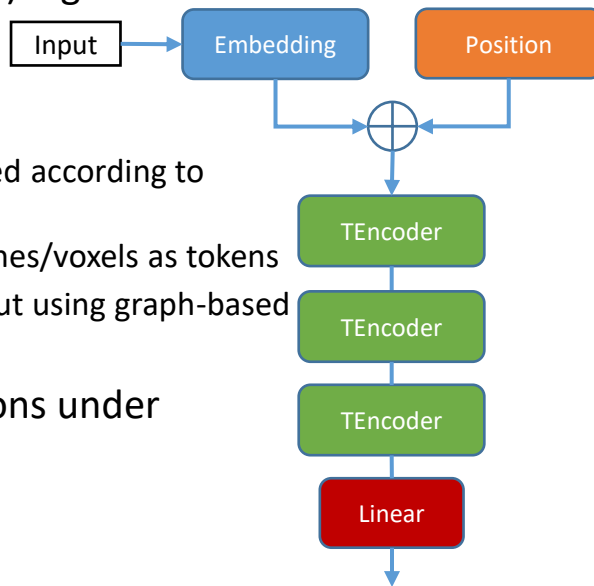
Transformer encoder

- Assess all PFPs reconstructed as shower-like by Pandora
- Train a transformer encoder to identify low purity showers
 - Any shower PFP where the main MC contribution is less than 80% of the total hit contribution
- Poorly reconstructed PFPs can be considered for re-clustering

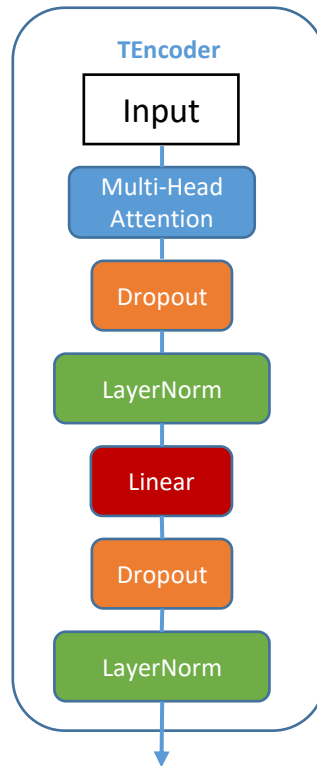


Transformer encoder network architecture

- Similar to encoding half of [Attention is All You Need](#) architecture
- Output is two class (good/bad) logits

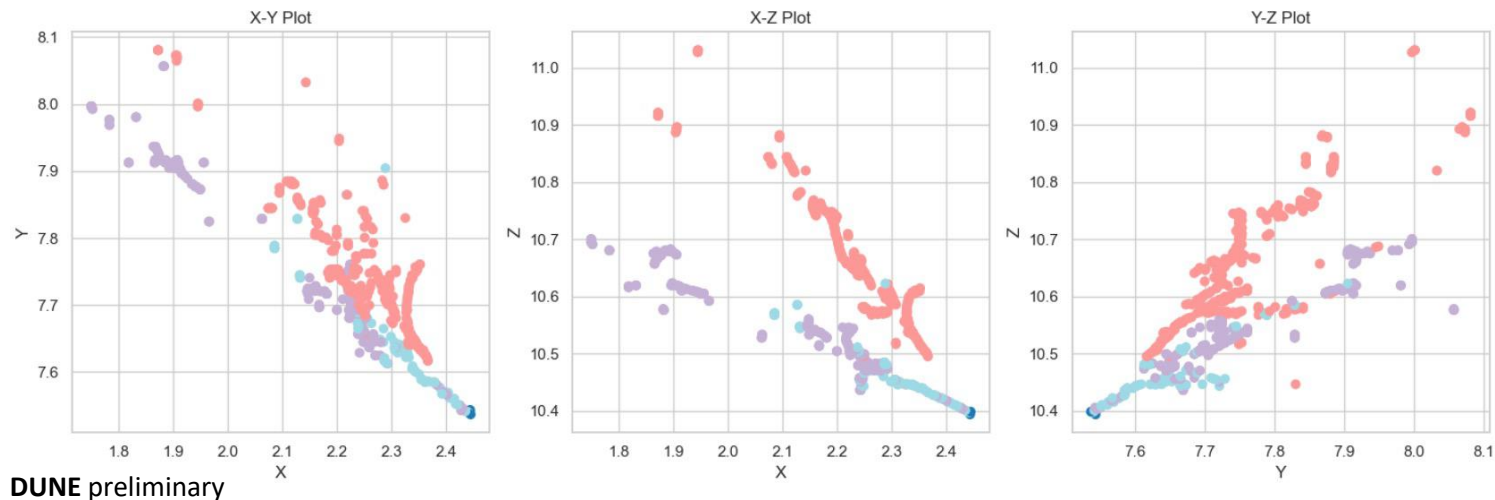


- Nature of input
 - PFP hits act as tokens sequenced according to distance from PFP reco vertex
 - Could consider PFP image patches/voxels as tokens
 - Could consider hits as tokens but using graph-based sequencing (later)
- Various hyperparameter options under consideration
 - Size of embedding
 - Number of encoders
 - Number of attention heads



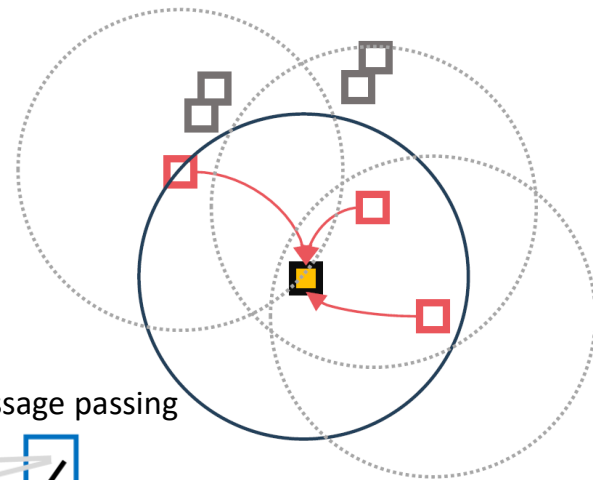
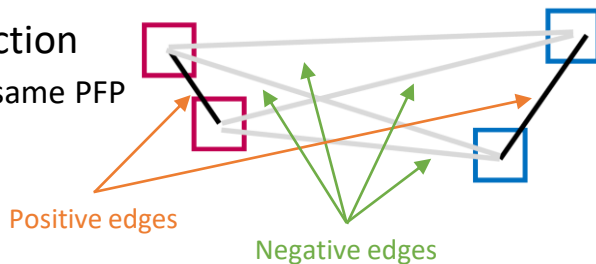
GraphSAGE for re-clustering

- Given a PFP tagged as being impure, consider re-clustering options
 - Intention is to allow support for multiple re-clustering options, but here we'll just look at a GNN
- Example training input where a single shower is actually composed of three separate, partially overlapping showers



GraphSAGE for re-clustering

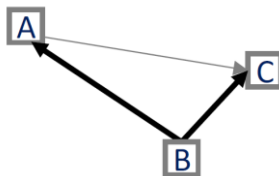
- Interpret 3D hits from PFP as a graph
 - 1 node per hit (Features: x , y , z , ADC)
 - 1 edge per node pair within 10 cm (Features: is from same particle?)
- GraphSAGE aggregates features among nearby nodes
 - Currently mean
 - Further aggregation is possible for indirectly connected nodes via message passing
- Currently performs edge prediction
 - Decide if two hits belong to the same PFP
 - Node prediction also possible



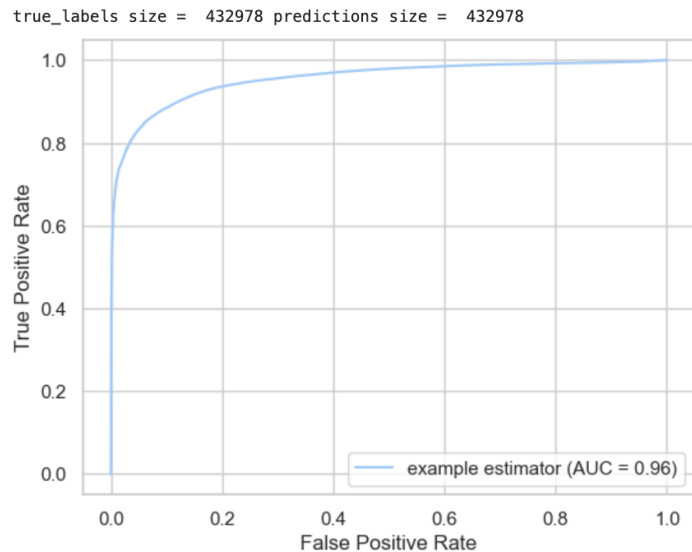
- Concatenate features of positively or negatively connected nodes and pass to fully connected layer to get out a final score

Performance and use

- Provisional, low stats training yields encouraging performance
- How to use it?
- Results can be ambiguous
 - Classify AB, BC connected
 - Classify AC not connected
 - Four choices:

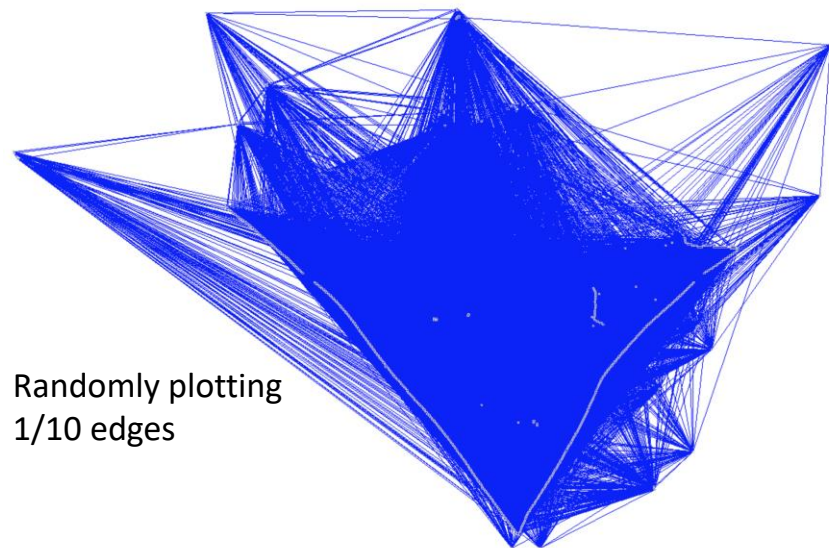


- Need a way to decide what the correct choice should be



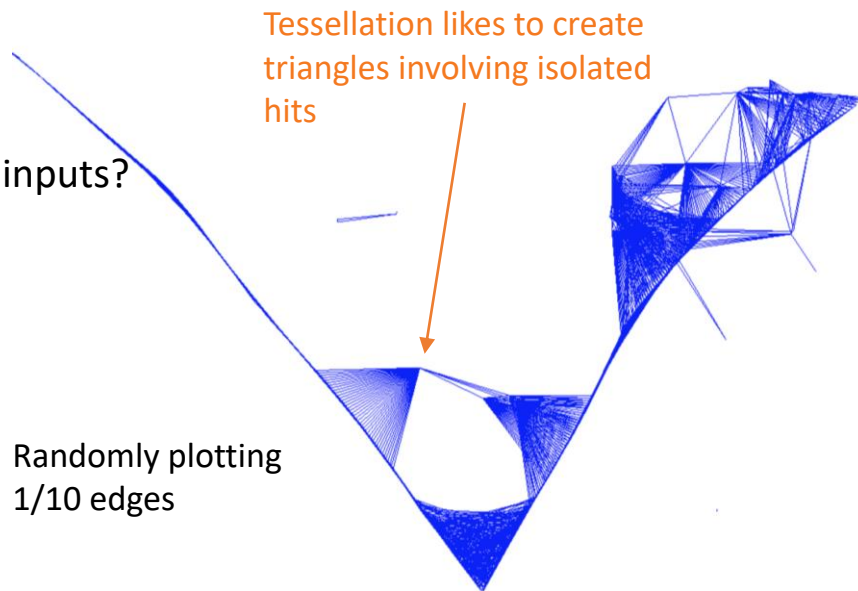
An aside on graph and transformer inputs

- One challenge of GNNs and transformers is the need to figure out input format
- Common approaches to graph inputs include distance-based connections and Delaunay triangulation
- Tessellation produced by Delaunay triangulation works well for nodes drawn from a spatially uniform distribution
- Our events don't look like that
- Hits are typically correlated, yields many often dubious edges
- There are, at least, no disconnected regions



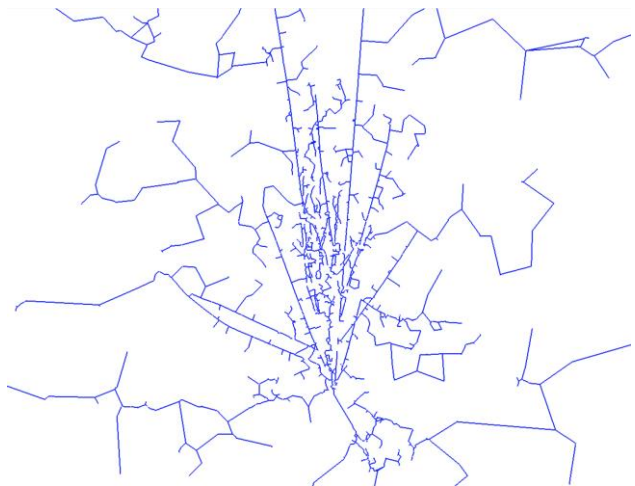
An aside on graph and transformer inputs

- We can prune the graph
- But still many dubious edges
- It's also a lot of wasted computation
- Can we do better and produce more useful inputs?

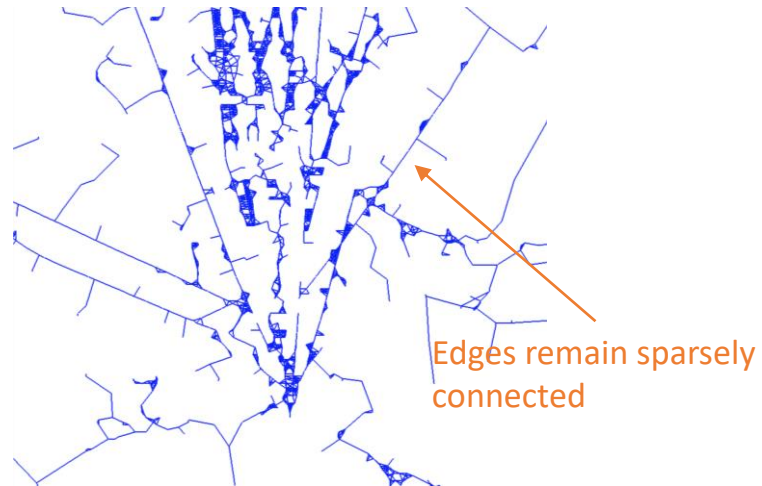


An aside on graph and transformer inputs

- With the help of vectorization we can build limited, locally connected graphs
- Extra step required to connect disconnected sub-graphs
- Edge multiplicity on left is probably too low for GNNs and could negatively impact message passing, but perhaps is useful to make sequencing choices for Transformers
- Allow for high local edge density but veto co-linearity



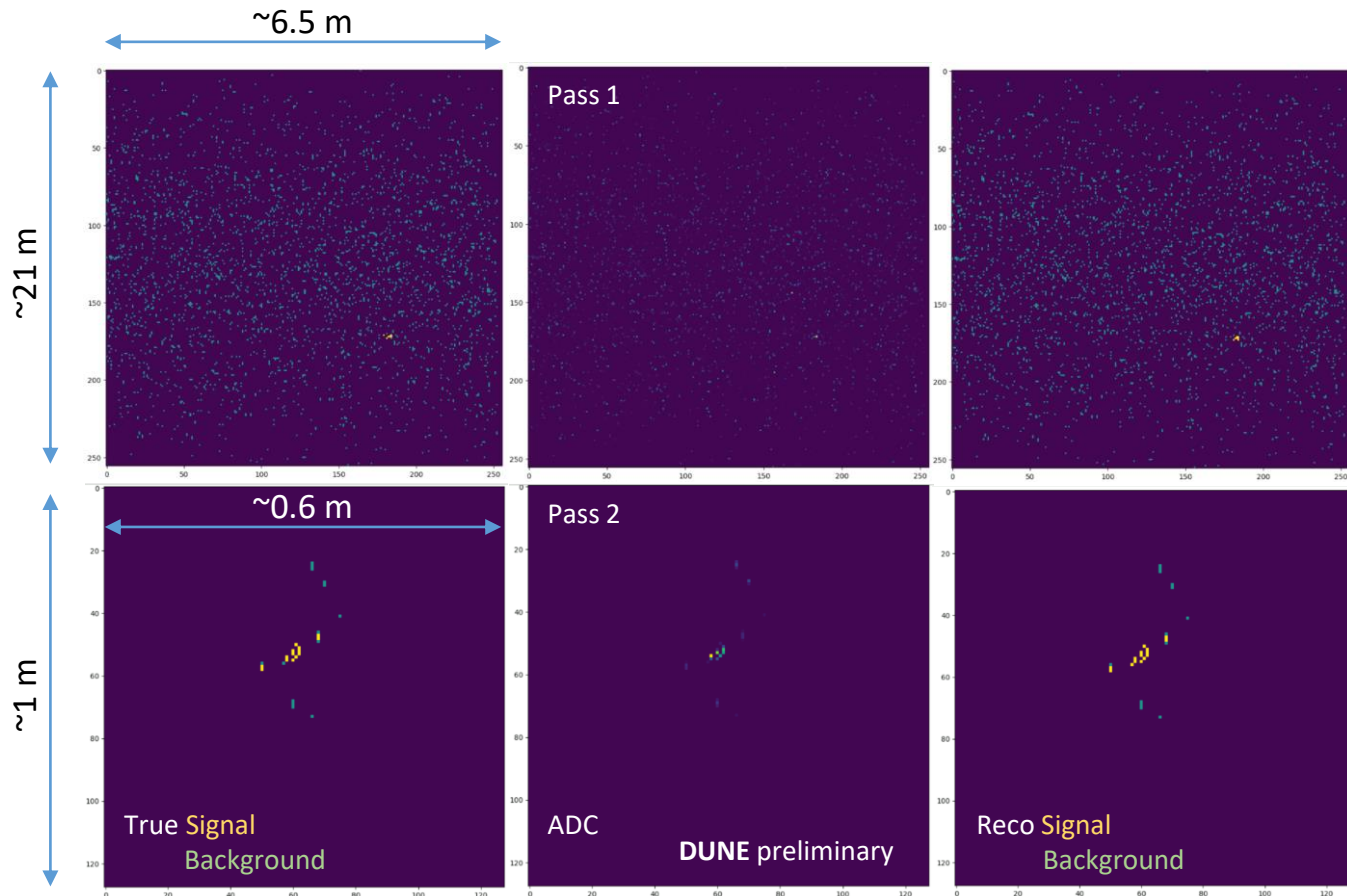
Zooming in on a
dense shower



Supernova neutrino reconstruction

Example signal/background separation

- Need to extract supernova neutrino interaction from radiological background
- Expect U-ResNet to be well suited to this task
- Physical extent of input images very large
 - Need low-res region finding in pass 1
 - High-res classification in pass 2
- A lot of activity in pass 1 images, much less so in pass 2
- Provisional tests look promising



Conclusions

- Pandora has been capable of running neural networks for a few years
- ML-based vertex finding now well established in a number of workflows
 - Ongoing work to further refine performance
- Range of reconstruction tasks for which ML is being investigated now expanding
- ML solutions can fit neatly into Pandora's existing multi-algorithm paradigm