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

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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 $\nu_\tau$ 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

- 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 ($N = 2.2M$), $\delta$ and $\eta$
  - Pick $\alpha$ and $\beta$ on a grid $[-1, 1]$ and step $\alpha\delta + \beta\eta$ 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