Graph neural network for 3D node classification in scintillator-based neutrino detectors

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Introduction

- Finely-segmented plastic scintillators aim to resolve and reliably identify short particle tracks complex interactions.
- The detector response to a charged particle is read out into three orthogonal 2D projections.
- Different types of hits are rebuilt when reconstructing the 3D event, introducing non-physical entities that can hinder the reconstruction process.
- An approach of utilizing deep learning is proposed to perform the classification of 3D hits to provide clean tracks for event reconstruction.

Case Study

The **Super Fine-Grained Detector (SuperFGD)**.

- Will be used to upgrade the near detector of the T2K experiment.
- 2 million plastic scintillator cubes, each 1×1×1 cm^3 in size.
- Provides three orthogonal 2D projections of each event.

The light yield measurements in the three 2D views are matched together to form 3D objects, referred to as *voxels*.

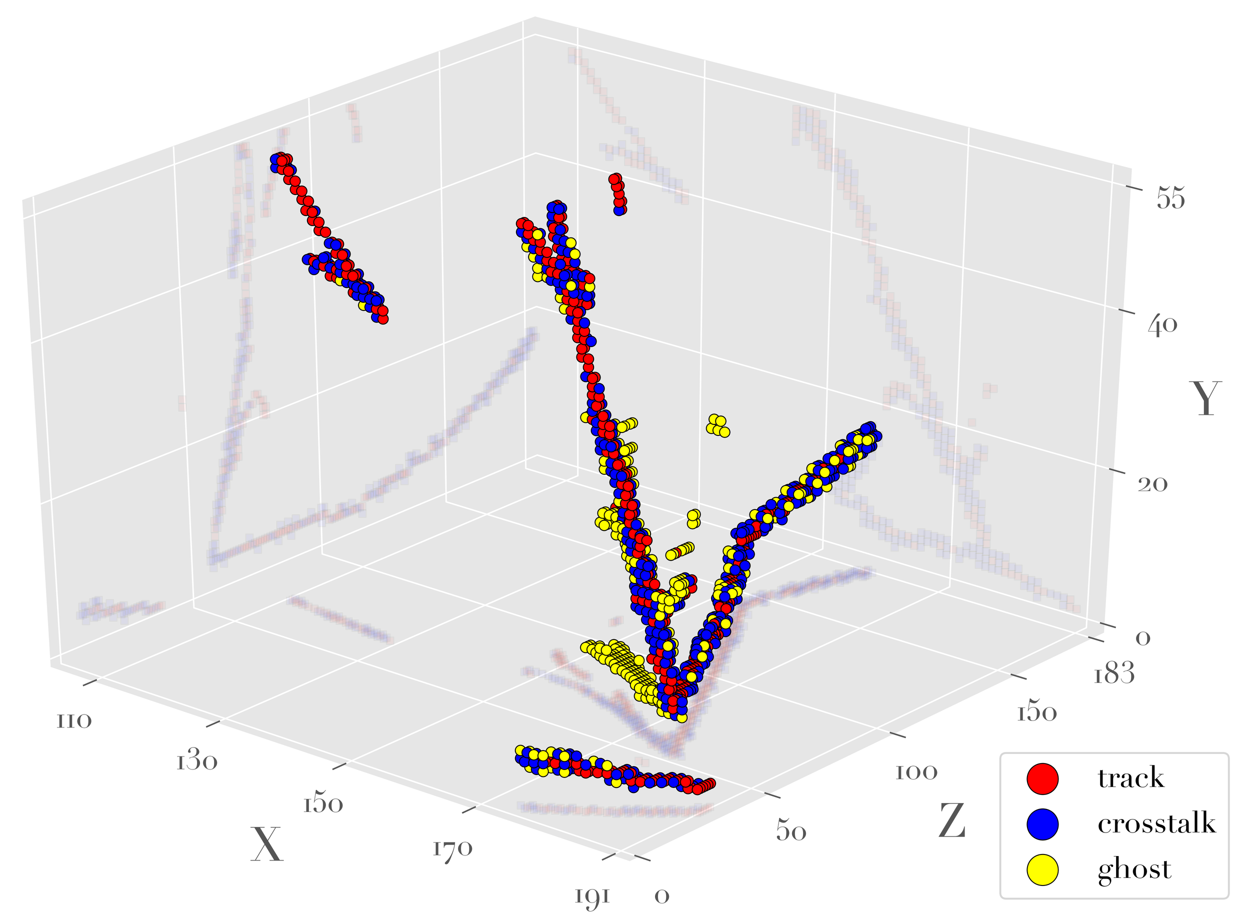
Training details

- Two datasets were generated to train the network: GENIE and P-Bomb.
- The network was trained for 50 epochs using Python 3.6.9 and PyTorch 1.3.0 on an NVIDIA RTX 2080 Ti GPU.
- Adam is used as the optimizer, with a mini-batch size of 32, and an initial learning rate of 0.001 (divided by 10 when the error plateaus).
- The model has a total of 105,347 parameters.

Problem description

To accurately reconstruct neutrino interactions, it is crucial to be able to classify each voxel as one of the three types:

1. **Track**, a real energy deposit from a charged particle.
2. **Crosstalk**, a real energy deposit from light-leakage between neighboring cubes.
3. **Ghost**, fake signals coming from the ambiguity when matching the three 2D views into 3D.



Approach

A graph neural network (GNN) inspired by the GraphSAGE* algorithm is used to classify individual voxels[1] in SuperFGD events.

**GraphSAGE (arXiv:1706.02216) is a technique that leverages the features of graph nodes to generate efficient representations on previously unseen samples by learning aggregator functions from training nodes.*

Results (I)

			GENIE Training				P-Bomb Training		
			Track	Crosstalk	Ghost		Track	Crosstalk	Ghost
GENIE Testing	Per Voxel	Efficiency	93%	90%	84%	Efficiency	93%	89%	80%
		Purity	93%	87%	91%	Purity	91%	86%	89%
			Track	Crosstalk	Ghost		Track	Crosstalk	Ghost
	Per Event	Efficiency	94%	94%	88%	Efficiency	94%	93%	88%
		Purity	96%	91%	92%	Purity	95%	91%	91%
			Track	Crosstalk	Ghost		Track	Crosstalk	Ghost
P-Bomb Testing	Per Voxel	Efficiency	94%	93%	87%	Efficiency	95%	93%	88%
		Purity	95%	90%	92%	Purity	95%	91%	92%
			Track	Crosstalk	Ghost		Track	Crosstalk	Ghost
	Per Event	Efficiency	94%	94%	87%	Efficiency	95%	93%	88%
		Purity	96%	90%	92%	Purity	96%	91%	92%

Table: Mean efficiencies and purities of voxel classification, calculated for the whole sample (per voxel) and as a mean of the event-by-event efficiencies and purities (per event).

Results (II)

Comparison of the results of a conventional charge cut with those of the GNN.

GNN		
	Track	Other
Efficiency	94%	96%
Purity	96%	95%
Charge Cut		
	Track	Other
Efficiency	93%	80%
Purity	80%	91%

Table: Mean efficiencies and purities of voxel classification for the GNN and a simple charge cut.

Conclusion

- The neural network was able to identify ambiguities and scintillation light leakage between neighboring active scintillator detector volumes.
- It also recognizes real signatures left by particles with efficiencies and purities in the range of 94-96% per event, with a clear improvement with respect to less sophisticated methods.

Reference

S. Alonso-Monsalve, D. Douqa, C. Jesús-Valls, T. Lux, S. Pina-Otey, F. Sánchez, D. Sgalaberna, and L. H. Whitehead.
Graph neural network for 3D classification of ambiguities and optical crosstalk in scintillator-based neutrino detectors.
arXiv e-prints, September 2020. arXiv:2009.00688.

[1]Each detector voxel is represented as a node in a graph, and each node consists of a list of input variables called features that describe the physical properties of the detected signal.