Scalable, End-to-End, Deep-Learning-Based Data Reconstruction Chain for Particle Imaging Detectors

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1. Introduction

Reconstruction challenges in LATPC ν experiments:
- High resolution images → huge phase space
- Background-rich environment (SiPM program)
- Massive O(10^9) tons volume (DUNE-FD)
- Interaction pilesup (DUNE-ND)

Simulation of particle interactions in liquid argon:
- 10^6 voxels images (~ 12 m^3 of LAr; 3 x 3 x 3 mm^3 voxels)
- One “particle bomb” per image (tracks + showers from common vertex)
- Cosmic muons + random showers overlaid

Open dataset: PILArNet, arXiv:2006.01993

2. Semantic Segmentation and Point Proposal

Semantic segmentation
Input: particle energy deposition images
Goal: voxel-wise particle type classification
- Shower-like, track-like, Michel electron, delta ray or low energy (LE)
Strategy: Sparse-UResNet autoencoder
Based on the U-Net architecture (features at different scales and skip connections)
- Convolutions done using ResNet blocks
- Sparse convolutions (SCN package)
- Learn five scores per pixel (one per class)
Sparse convolutions makes this technique scalable to large volumes: computation time grows as the number of active voxels
Inference: argmax on pixel scores
- Top right plot: confusion matrix
- Michel/track or delta/track confusion due to systematic overlap
- Delta/LE confusion due to mislabelling

Point Proposal Network (PPN)
Goal: locate interesting points
- Identify start/end points of tracks, start points of showers, Michel and delta rays
- Reconstruct exact point locations
Strategy: the semantic segmentation
Sparse-UResNet for feature extraction
- Three voxel proposal layers at three scales
- Voxel mask propagated from lowest to highest resolution layer
- 3x3 convolution at last layer to identify offset and class of masked voxels
Inference: use pooling to select points
- Bottom right plot: distance from label point to closest proposed point and vice versa (excludes delta ray points)
- 68% of label points < 0.61 voxel of proposed points, 95% < 1.4 voxel of proposed points
- Traditional methods report 68% of vertex < 0.71 cm, i.e. 2.43 voxel here

3. Dense Clustering

Input to this reconstruction step:
- Particle energy deposition images
- Semantic segmentation predictions from previous stage
Goal: cluster densely-connected voxels into particle instances
Strategy: use Sparse-UResNet as a feature extractor and learn
- Embedding: map points belonging to same instance
- Seedness: give points close to centroid a high score
- Margin: give larger embedded instances larger margins
Inference: iterative Gaussian kernel clustering
- Use highest seedness voxel as centroid
- Cluster points within some distance normalized by margin, repeat

4. Particle Aggregation

Input: image segmented into dense particle instances
Goal: aggregate particles into superstructures
- Shower fragments into shower instances (+ identify primary)
- Particle instances into interactions (+ identify species)
Strategy: use a Graph Neural Network
- Connect particles with every other particle (complete graph)
- Provide node and edges with summary statistic features
- Use message passing to extract useful node and edge features
Inference: features are reduced to scores
- Node scores used to identify primary (99.5%) or species
- Edge scores used to constrain adjacency matrix (clustering)