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

François Drielsma[1†], Kazuhiro Terao[1], Laura Dominé[2], Dae Heun Koh[2] on behalf of the DeepLearnPhysics Collaboration

[1]SLAC National Accelerator Laboratory, [2]Stanford Univeristy, [†]drielsma@slac.stanford.edu

U.S. DEPARTMENT OF ENERGY | Office of Science | SLAC NATIONAL ACCELERATOR LABORATORY

1. Introduction

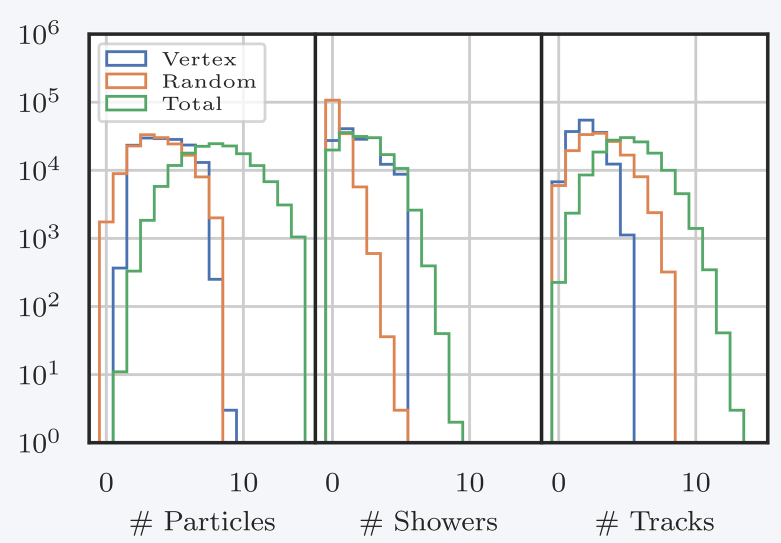
Reconstruction challenges in LArTPC ν experiments:

- High resolution images → huge phase space
- Background-rich environement (SBN program)
- Massive $\mathcal{O}(10)$ tons volume (DUNE-FD)
- Interaction pileups (DUNE-ND)

Simulation of particle interactions in liquid argon:

- 768^3 voxels images ($\sim 12\,\mathrm{m}^3$ of LAr, $3\times3\times3\mathrm{mm}^3$ voxels)
- One `particle bomb' per image (tracks + showers from common vertex)
- Cosmic muons + random showers overlayed

Open dataset: *PILArNet*, arXiv:2006.01993



2. Semantic Segmentation and Point Proposal

***Sparse-UResNet+PPN*, PRD.102.012005, arXiv:2006.14745**

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)

Srategy: **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 overlaps
- Delta/LE confusion due to mislabelling

Point Proposal Network (PPN)

Goal: locate **interesting points**

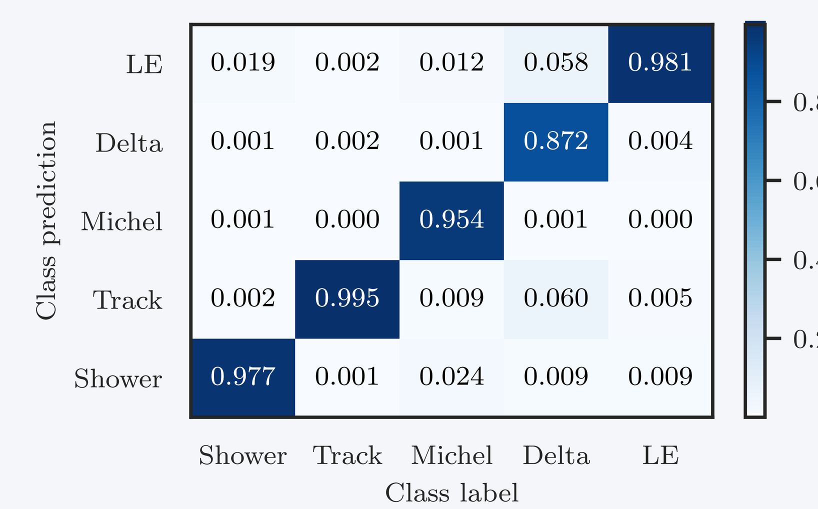
- Identify start/end points of tracks, start points of showers, Michel and delta rays
- Reconstruct exact point locations

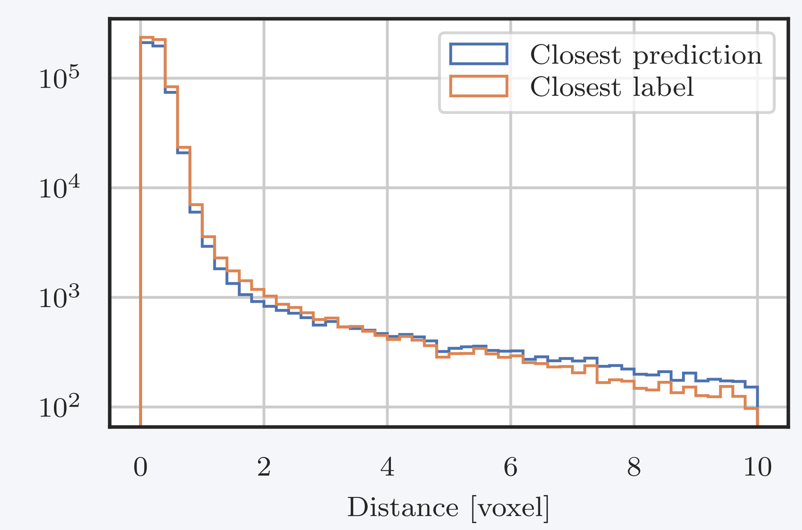
Strategy: share the semantic segmentation Sparse-UResNet for feature extraction

- **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 < 0.35 voxel of proposed points, 95 % < 1.43 voxel
- Traditional methods report 68 % of vertex < 0.73 cm, i.e. 2.43 voxel here





3. Dense Clustering

***SPICE*, arXiv:2007.03083**

Input to this reconstruction step:

- Particle energy deposition images
- Semantic segmentation predictions from previous stage

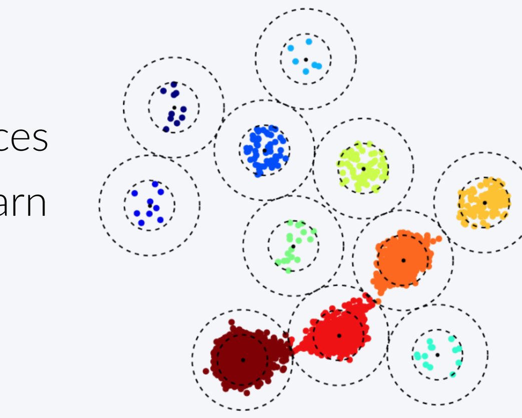
Goal: cluster **densely-connected voxels** into particle instances

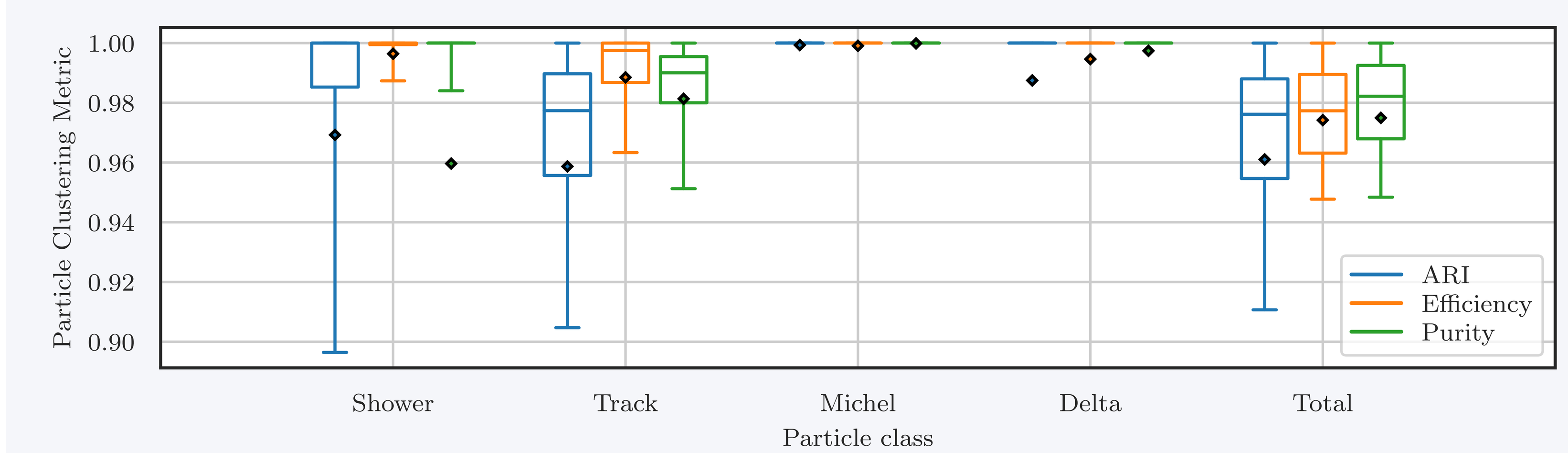
Strategy: use Sparse-UResNet as a feature extractor and learn

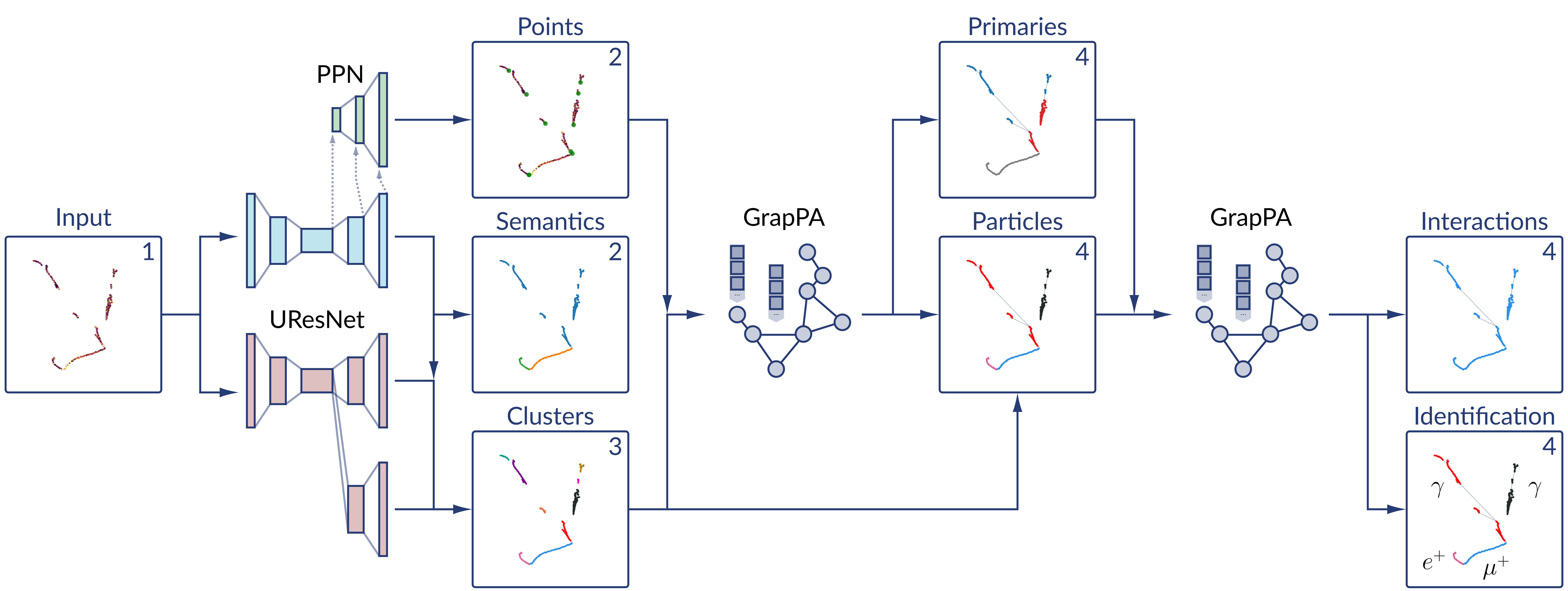
- *Embedding*: map points belonging to same instance close
- *Seediness*: give points close to centroid a high score
- *Margin*: give larger embedded instances larger margins

Inference: iterative Gaussian kernel clustering

- Use highest seediness voxel as centroid
- Cluster points within some distance normalized by margin, repeat







4. Particle Aggregation

***GrapPA*, arXiv:2007.01335**

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)