Machine Learning Reconstruction for DUNE's Near Detector Prototype:

Handling Multi-Detector Input to Identify 3D Particle Signatures

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on behalf of the DUNE Collaboration
IAIFI Postdoc Fellow
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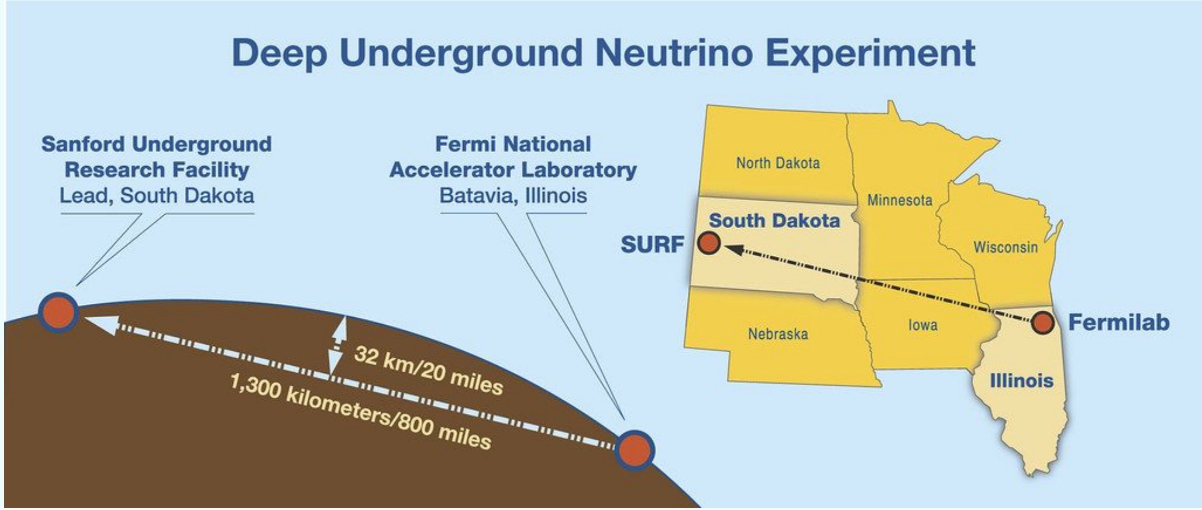
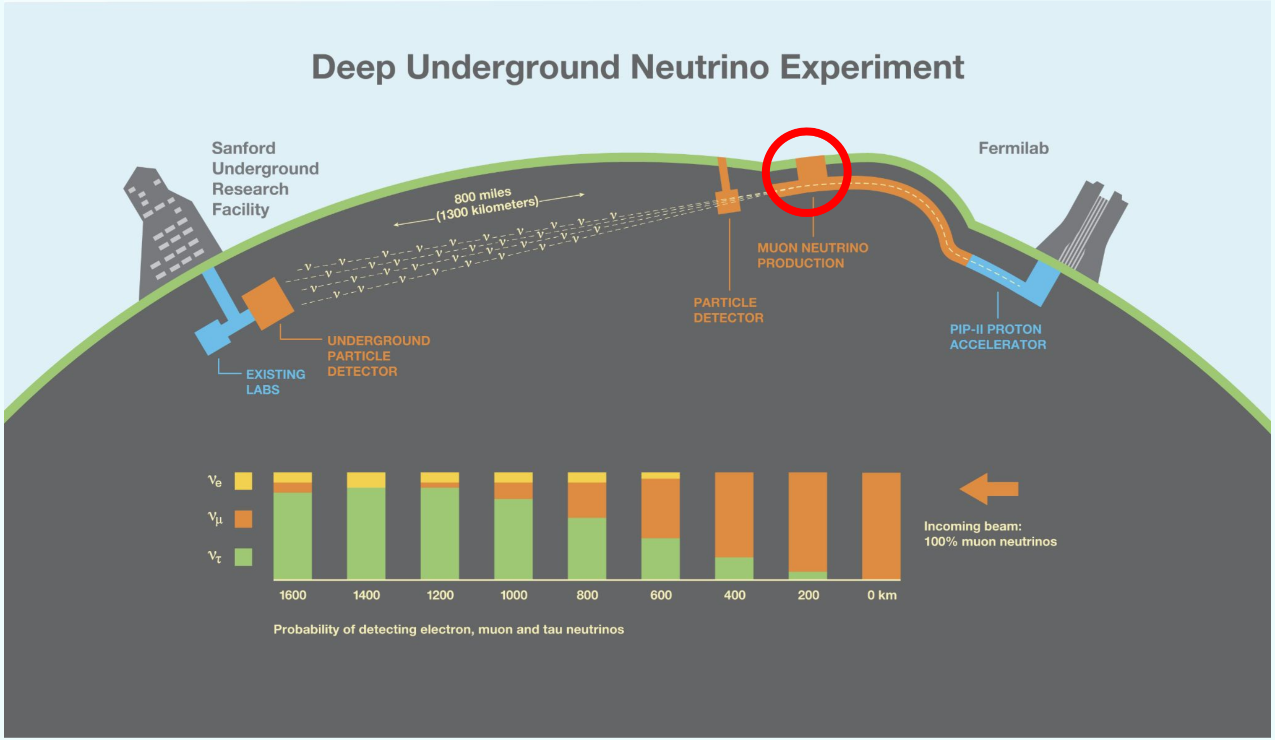
DUNE: Deep Underground Neutrino Experiment

- Answer fundamental questions: ν CP violation and mass ordering
- Perform precision measurements ν oscillation parameters: $\Delta m^2_{32}, \theta_{23}, \theta_{13}$
- Search for potential Beyond Standard Model ν behaviors
- Explore supernova and solar ν



DUNE: Frontier Measurements of Neutrino Physics



- PIP-II upgrade will lead to world's most intense neutrino beam

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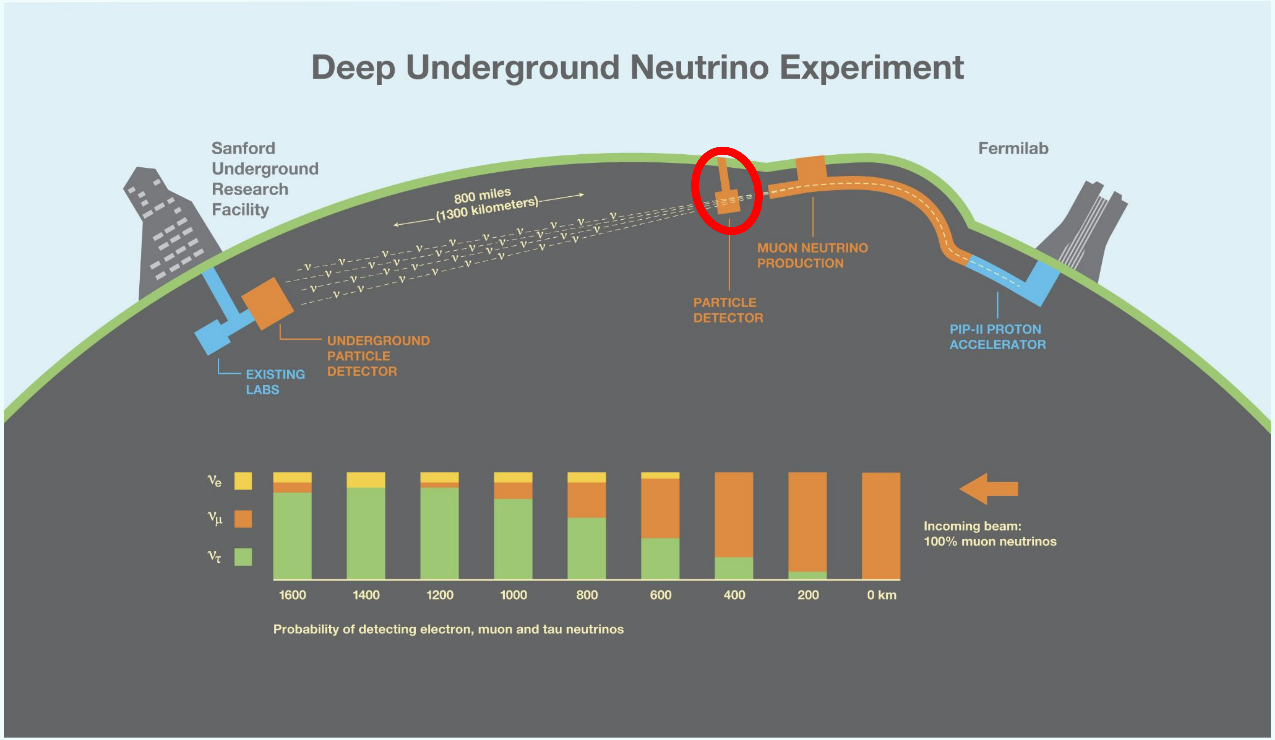

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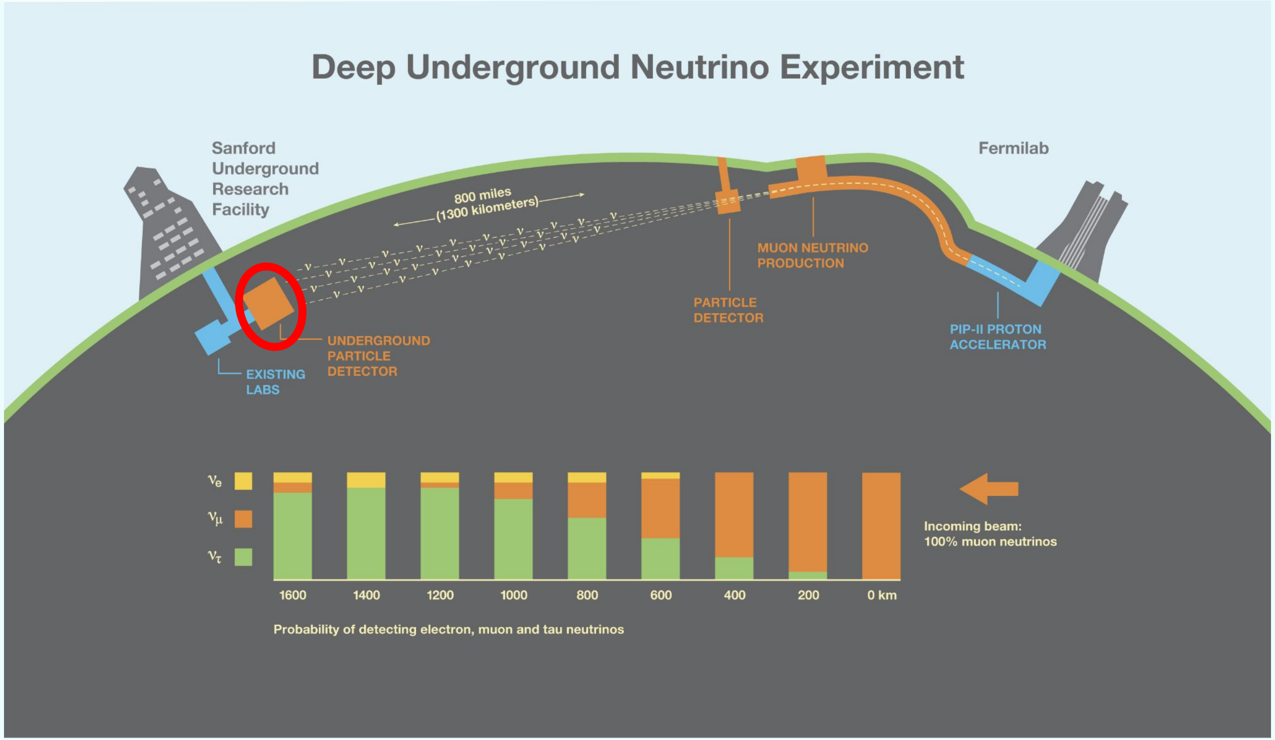


- PIP-II upgrade will lead to world's most intense neutrino beam
- Near detectors at Fermilab (Illinois, USA)
- Far detector at Sanford Underground Research Facility (South Dakota, USA)

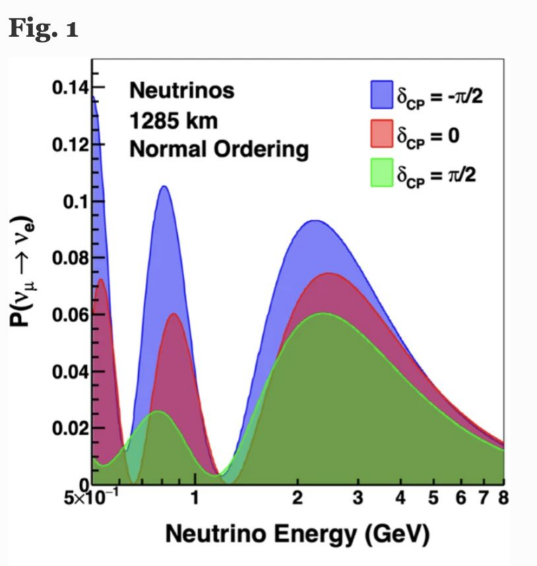
Finding Neutrino Oscillation

$$P_{\alpha\to\beta}(L) \propto \sin^2\left(1.27\,\frac{\Delta m_{ij}^2 L}{E}\right)$$

ν_e

ν_μ

ν_τ



Plot Cedit: Abi, B., Acciarri, R., Acero, M.A. *et al. Eur. Phys. J. C* 80, 978 (2020). https://doi.org/10.1140/epjc/s10052-020-08456-z

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$\boldsymbol{\nu}_e$

$\boldsymbol{\nu}_\mu$

$\boldsymbol{\nu}_\tau$

➢ Flavor (α, β)

$\boldsymbol{\nu}_\mu$ μ

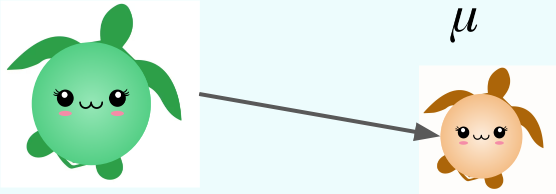
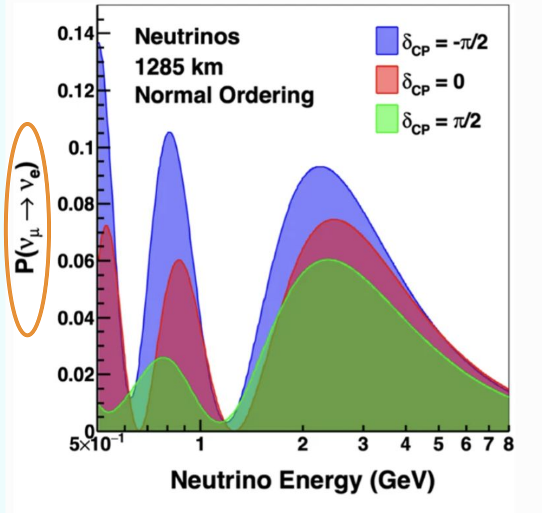


Fig. 1



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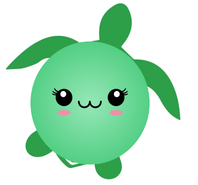
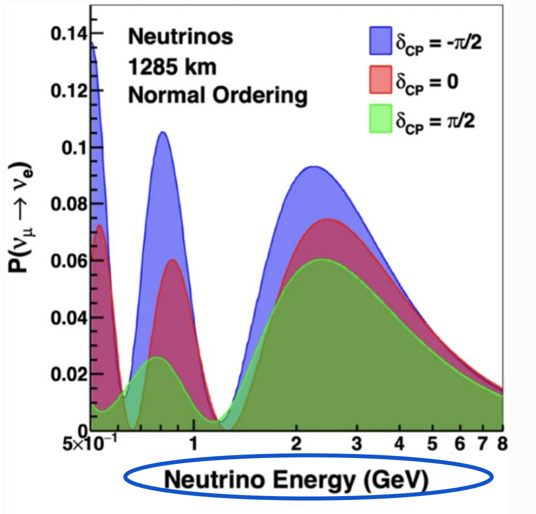


ν_τ

- Flavor (α, β)
- Energy (E)

Fig. 1



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Finding Neutrino Oscillation

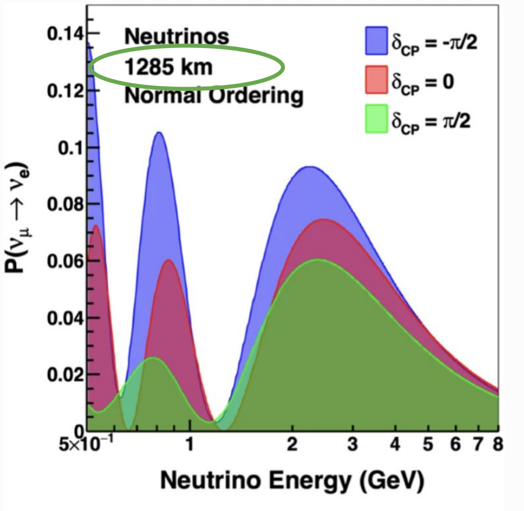
ν_e ν_μ ν_τ

$$P_{\alpha\to\beta}(L) \propto \sin^2\left(1.27\,\frac{\Delta m_{ij}^2 L}{E}\right)$$

- ➢ Flavor (α, β)
- ➢ Energy (E)
- ➢ Distance travelled (L)

  → Known, distance beam has travelled

Fig. 1



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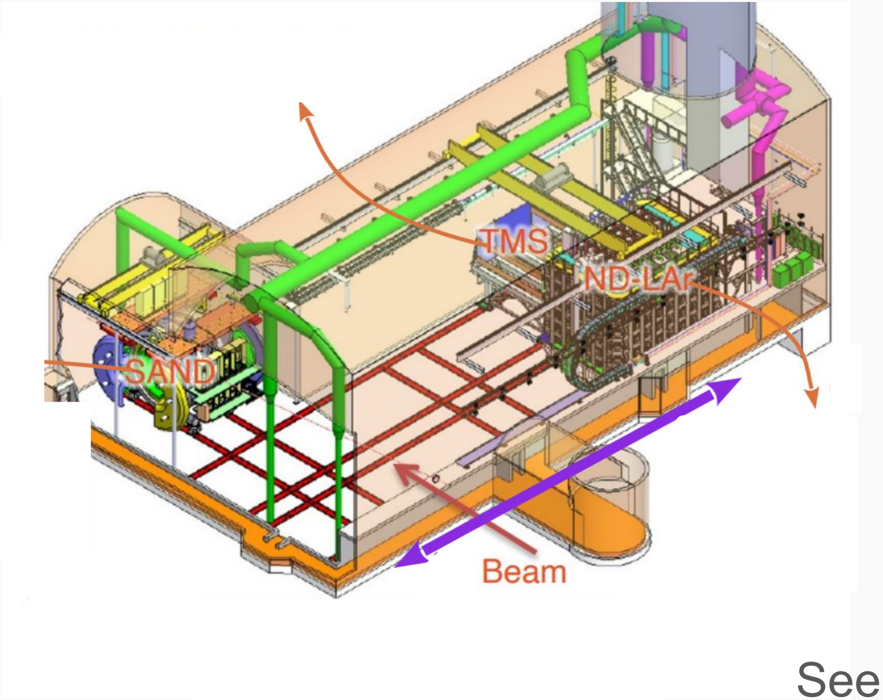
Near Detector (ND) Liquid Argon (LAr)



Important to constrain ν
- Cross section
- Flux
- Detector systematics

with ND that has same target (LAr) as Far detector

See Sindhu's talk tomorrow (9/19) at 4:35pm
https://indico.fnal.gov/event/63406/contributions/297832/

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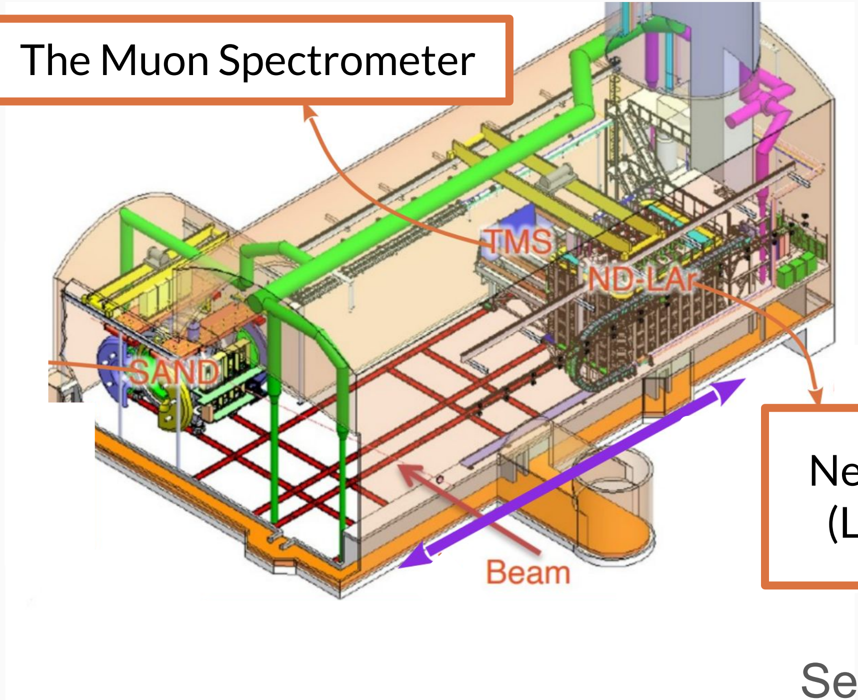

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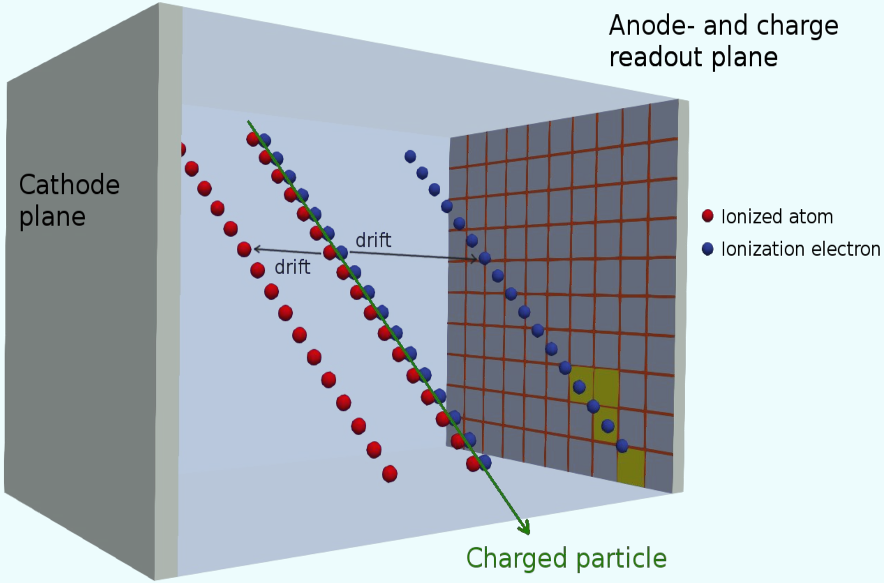
Liquid Argon (LAr) Time Projection Chamber (TPC)



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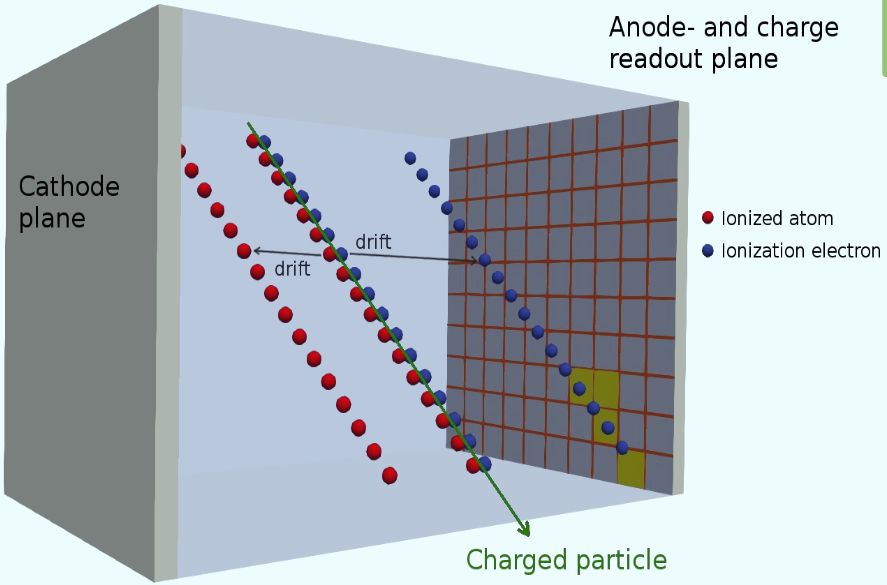
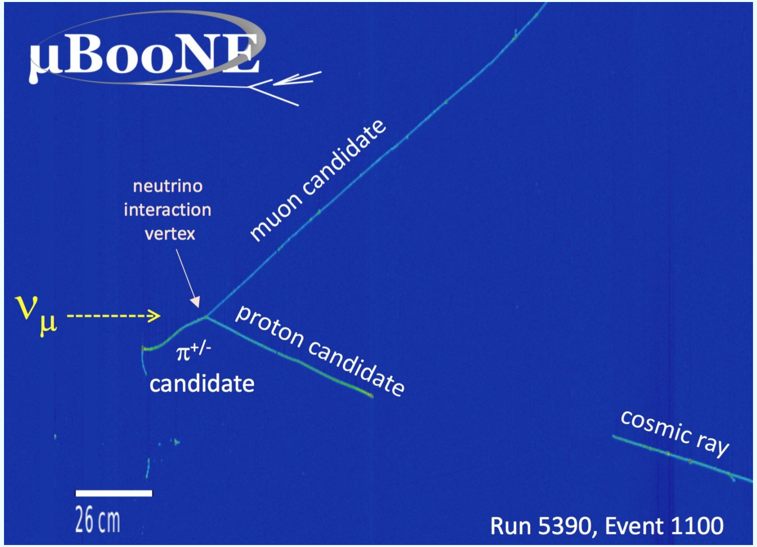
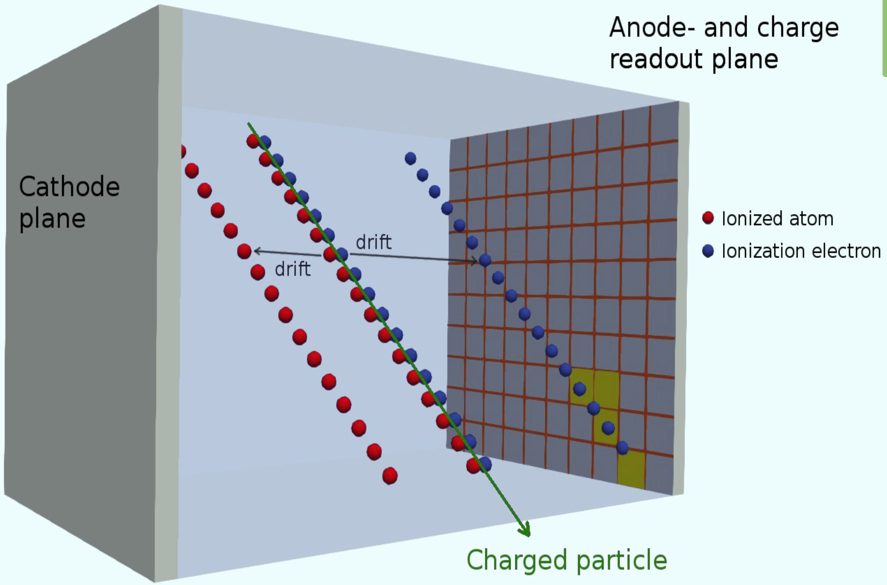


Far Detectors are 4x17-kton wire plane LAr TPC

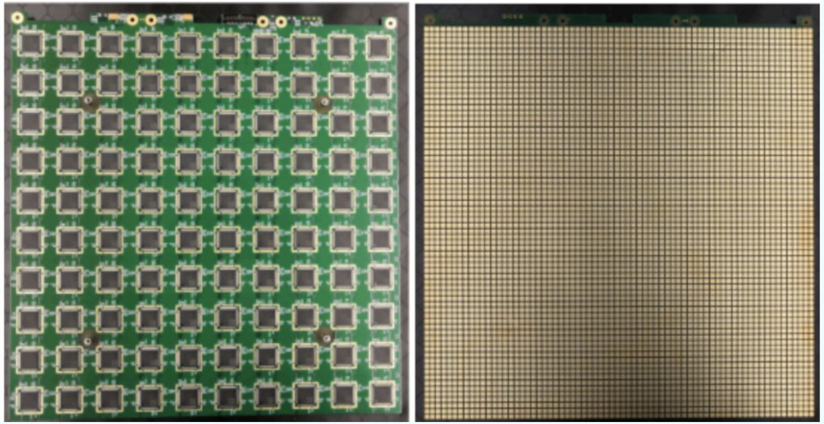


Color = charge deposition

The Near Detector LAr TPC (ND-LAr)



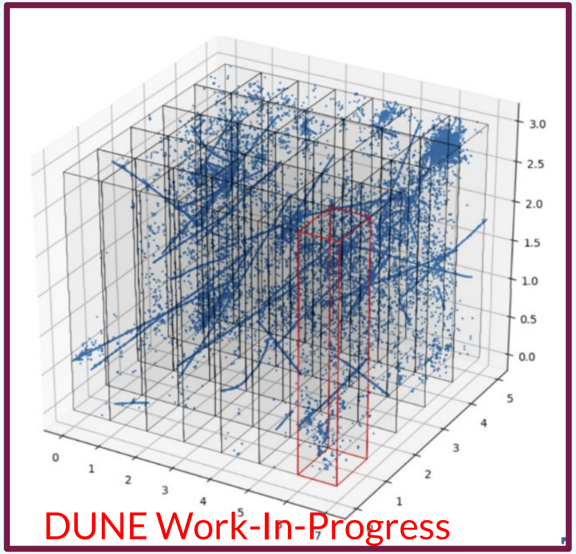
But ND-LAr uses a 2D **pixel plane** readout instead of wires → get a native 3D image!



Back of plane with LArPix ASICs (left) & TPC-facing side of pixel plane with pixel pitch ~4mm (right)
LArPix Paper

Handling Beam Intensity in ND-LAr

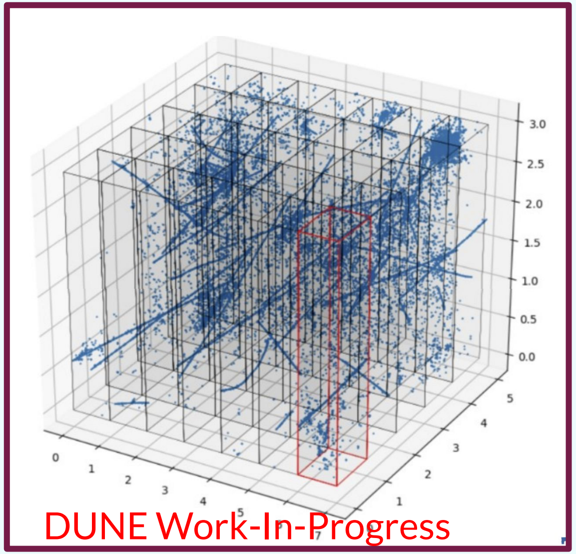
- Expect ~55 ν interactions!
- Need new technology:



Simulation of ND LAr per spill (10μs)

Handling Beam Intensity in ND-LAr

- Expect ~55 ν interactions!
- Need new technology:
  - Time resolution ns scale
  - Optically segmented TPCs for pileup mitigation



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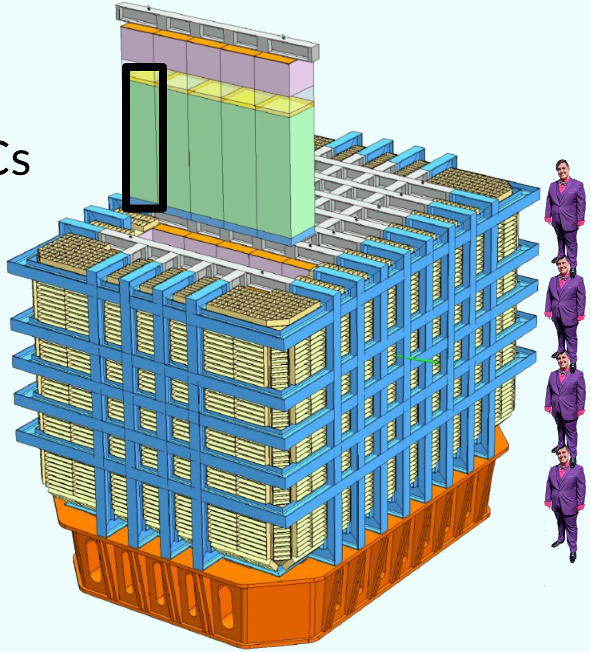
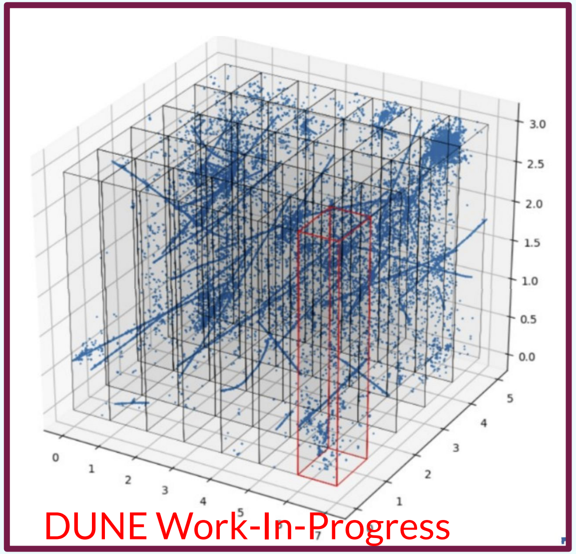


Handling Beam Intensity in ND-LAr

- Expect ~55 ν interactions!
- Need new technology:
  - Time resolution ns scale
  - Optically segmented TPCs for pileup mitigation
  - Native 3D



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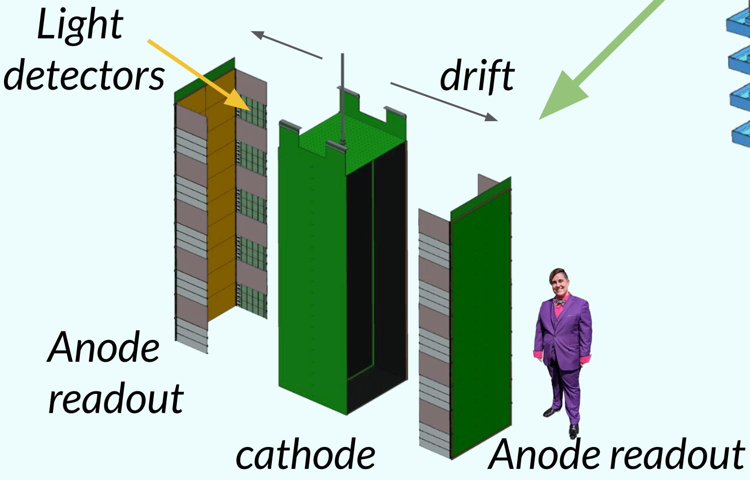
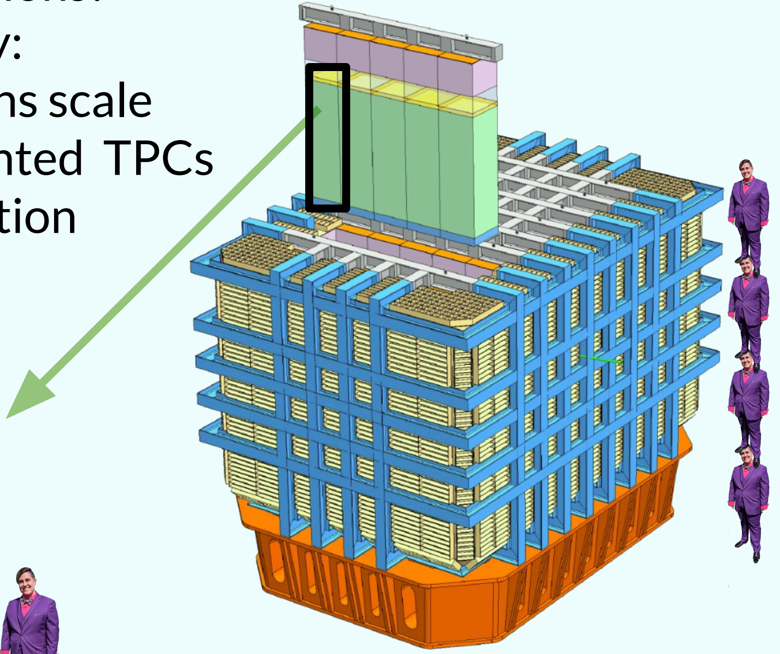
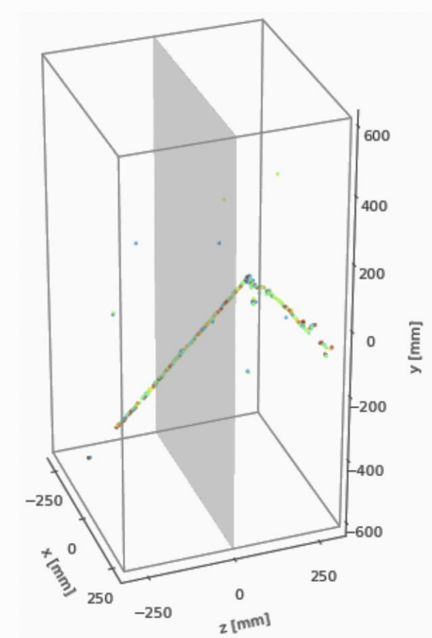




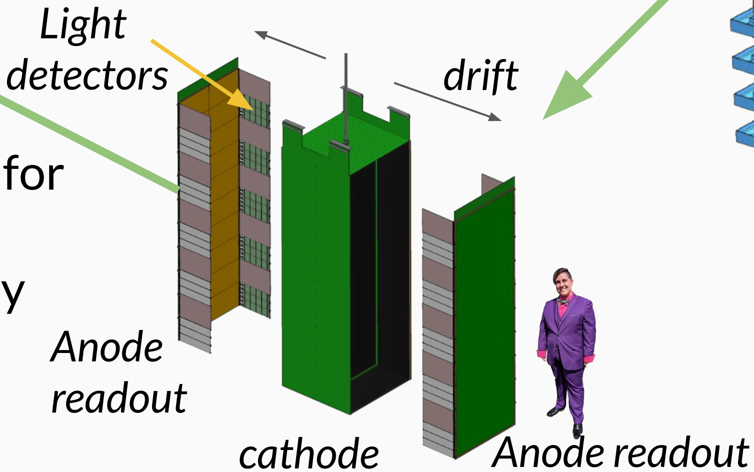
Handling Beam Intensity

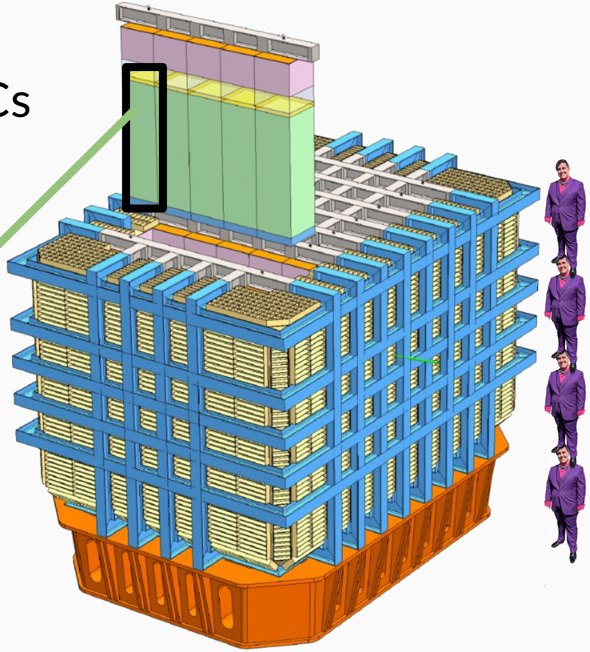
- TPC with center cathode
  - Native 3D
  - Optically segmented TPCs for pileup mitigation



Cosmic data for single LAr TPC [module]

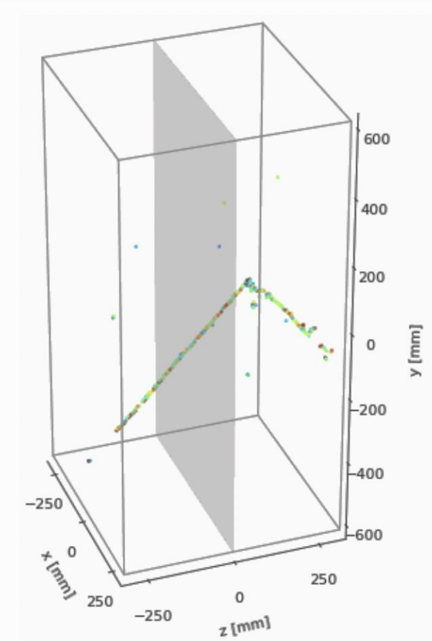
Pixel plane for 3D display





Handling Beam Intensity: 2x2 Prototype

- Novel tech needs to be prototyped!
- 4 smaller modules



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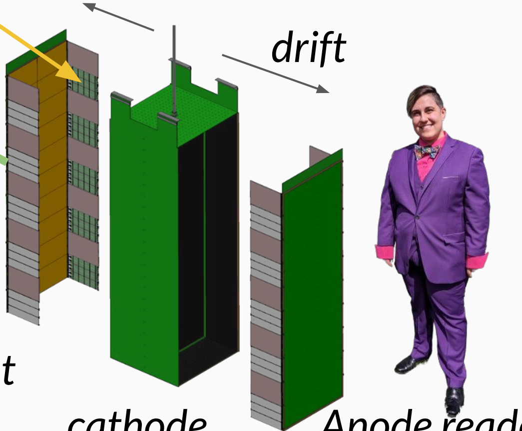
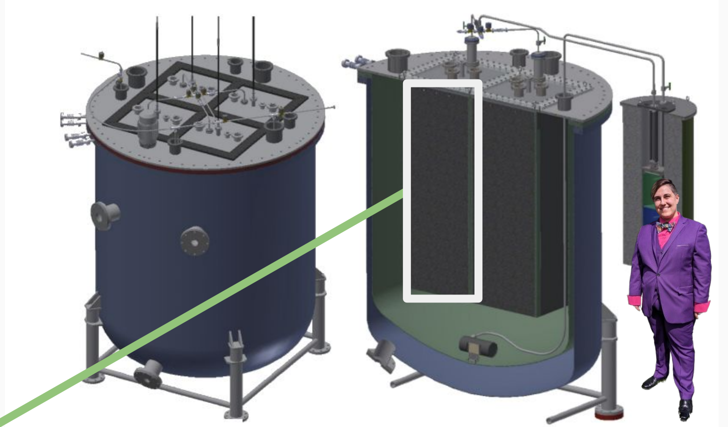
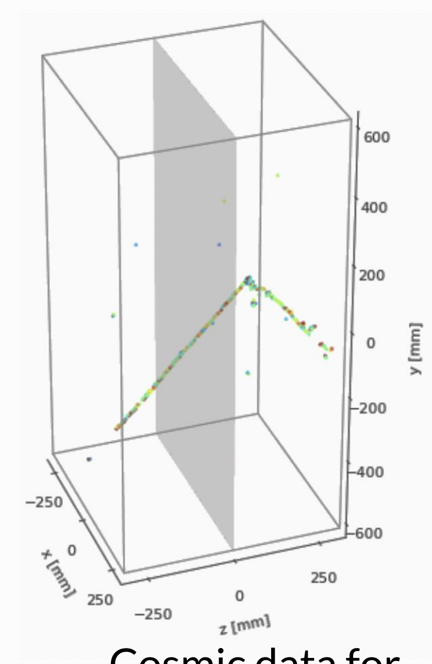


Handling Beam Intensity: 2x2 Prototype

- Novel tech needs to be prototyped!
- 4 smaller modules
- Took ~5 days of data at Fermilab in ν beam





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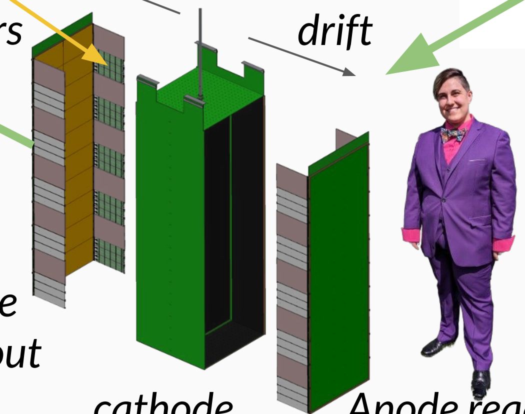
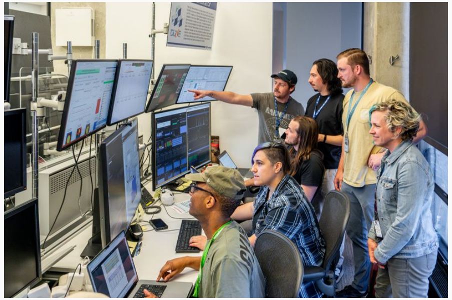
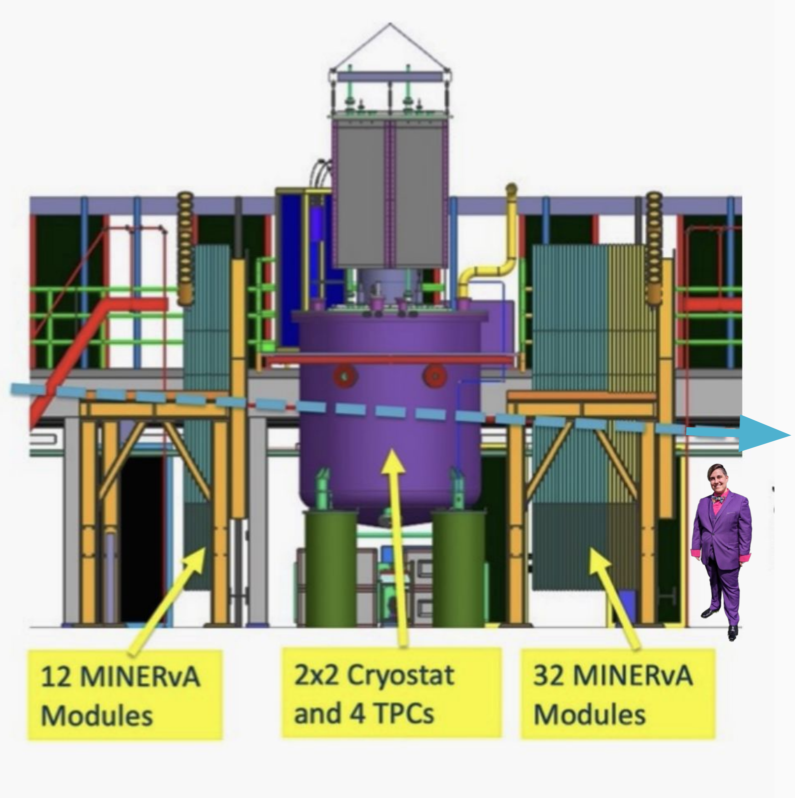


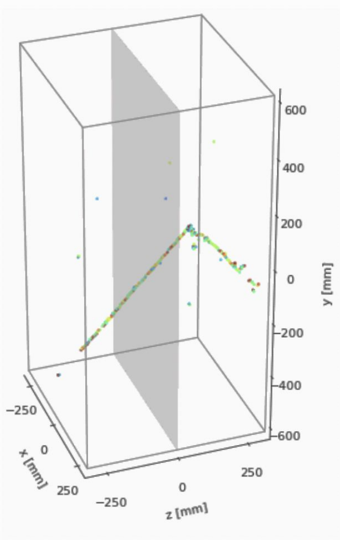


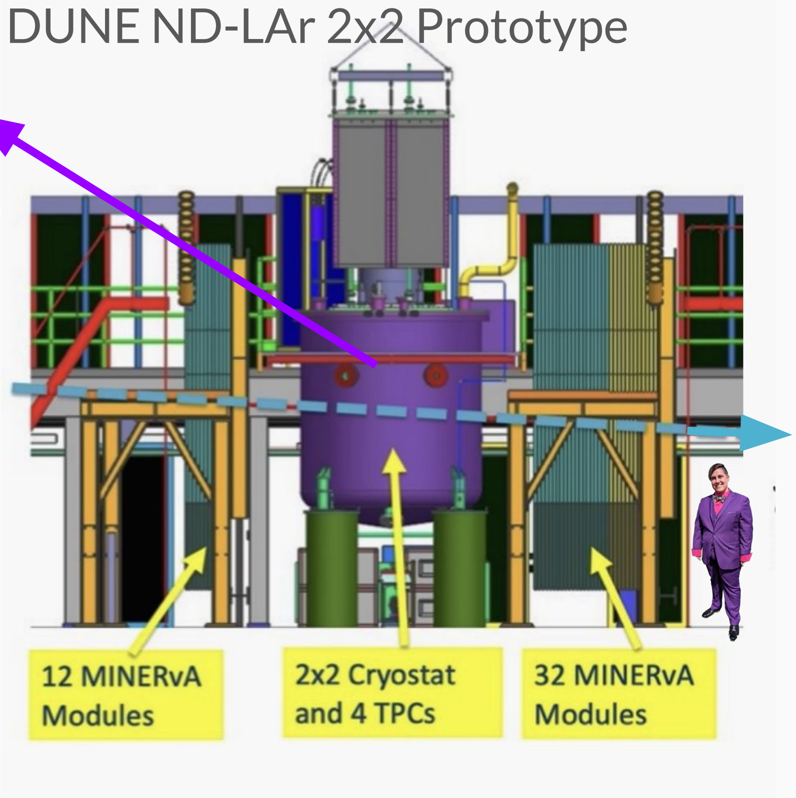
DUNE Near Detector 2x2 Prototype



DUNE 2x2 uses Liquid Argon TPCs

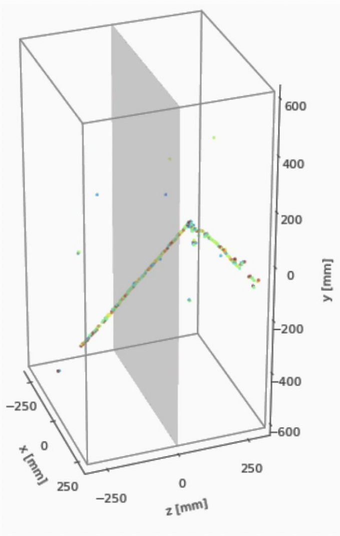
Inherently a 3D pixel readout



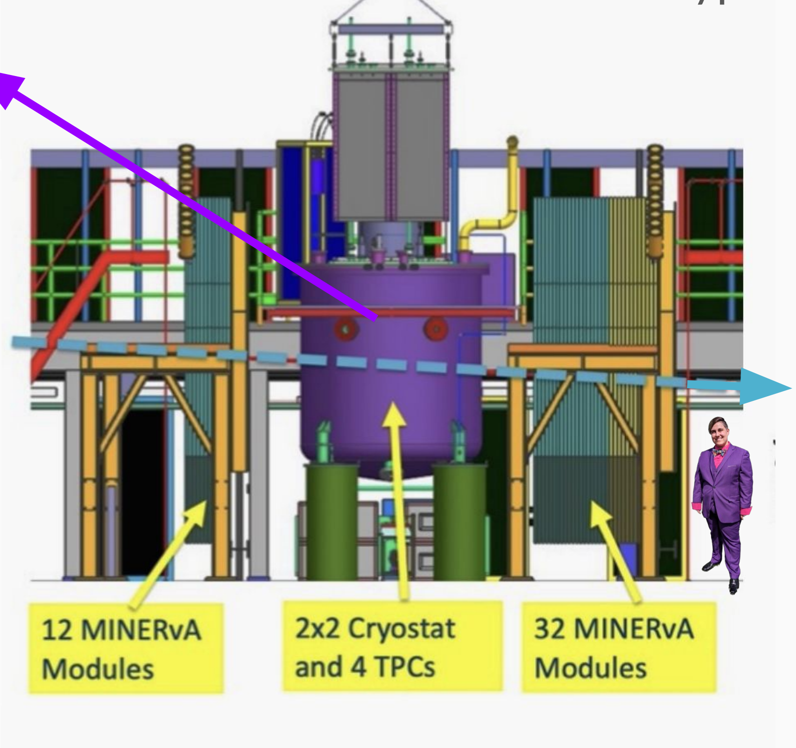


3D Reconstruction

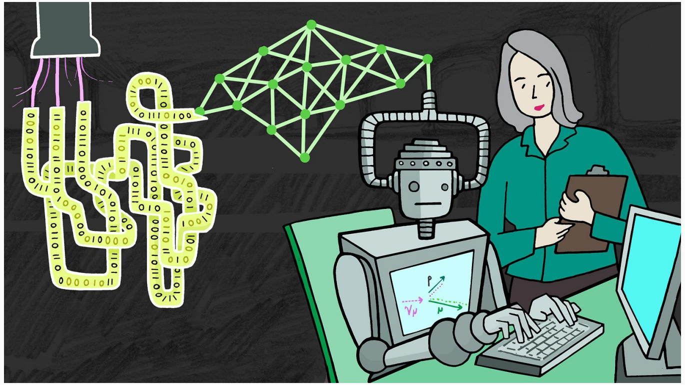
Inherently a 3D pixel readout



DUNE Near Detector 2x2 Prototype

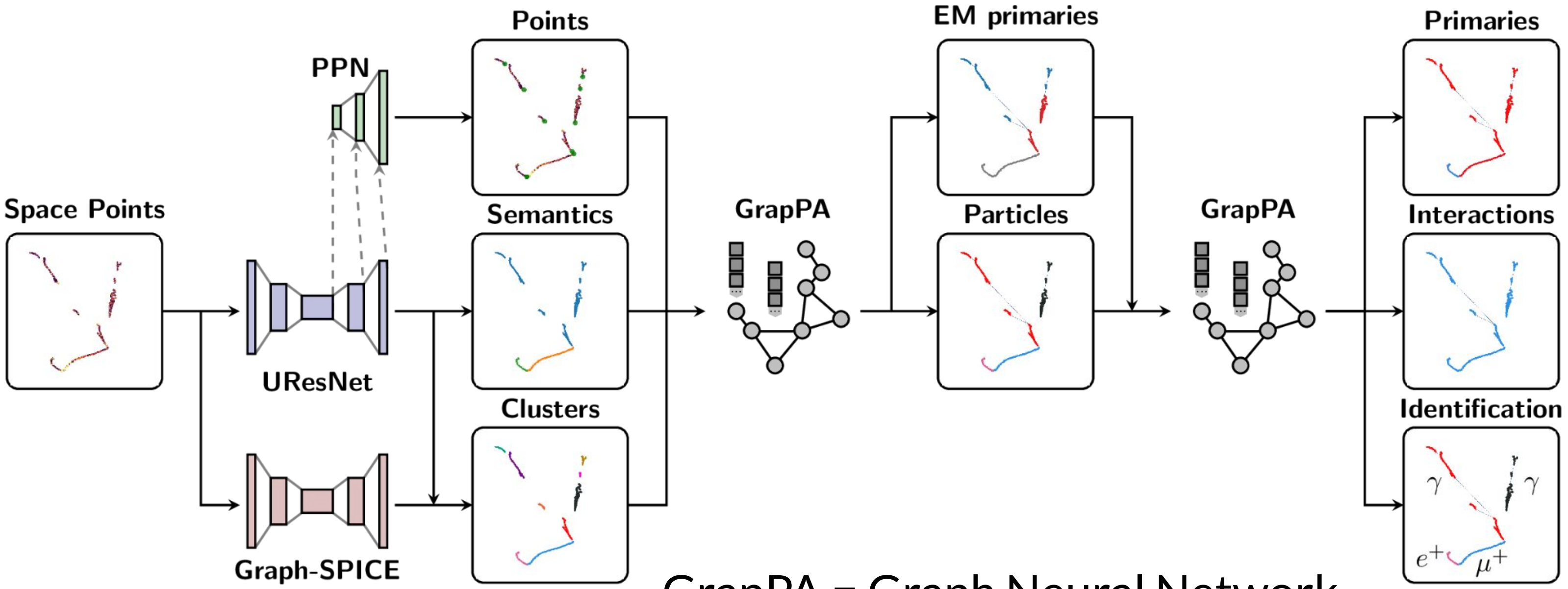


LArTPC 3D reconstructed with machine learning



https://www.symmetrymagazine.org/article/machine-learning-proliferates-in-particle-physics?language_content_entity=und

3D LAr TPC: SPINE Reconstruction



[SPINE Machine Learning Reconstruction 3D]()

GrapPA = Graph Neural Network
UResNet = encoder/decoder, convolutional layers
PPN = Point Proposal Network (convolutional)

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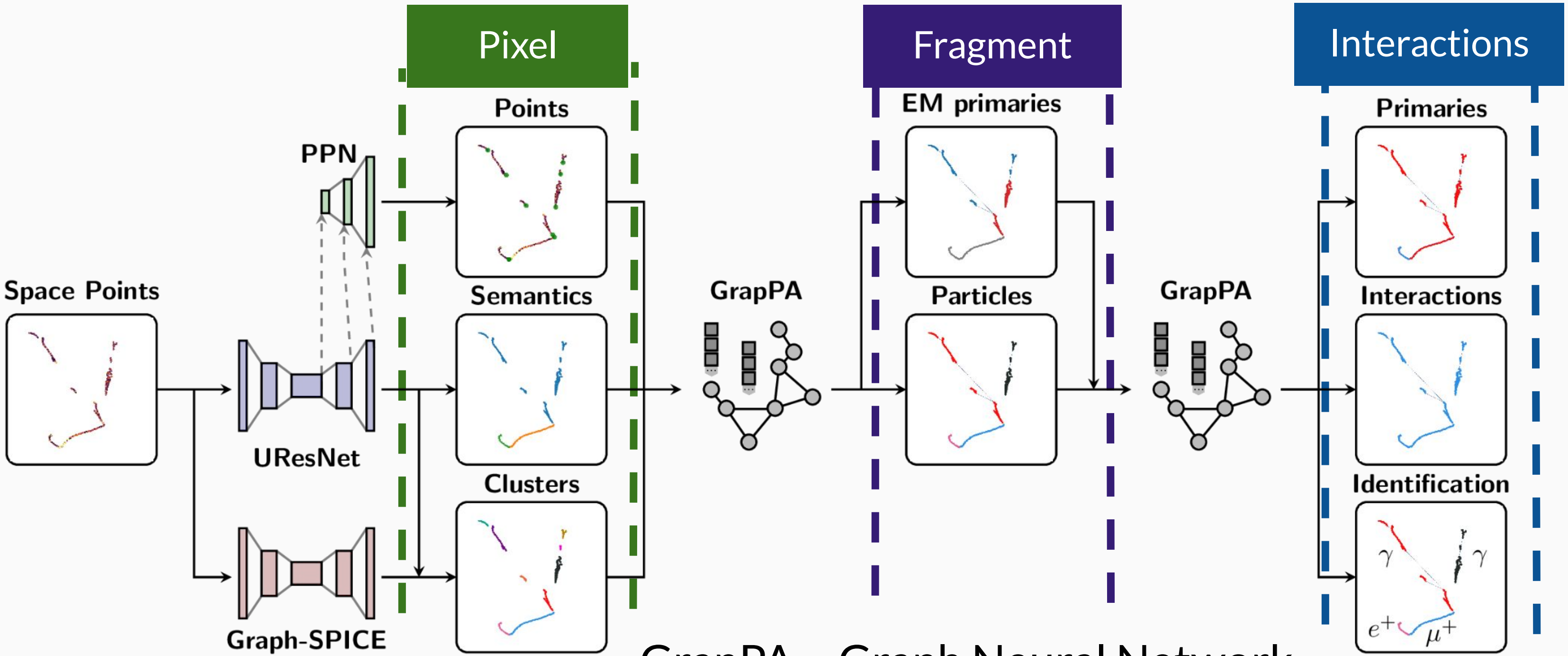

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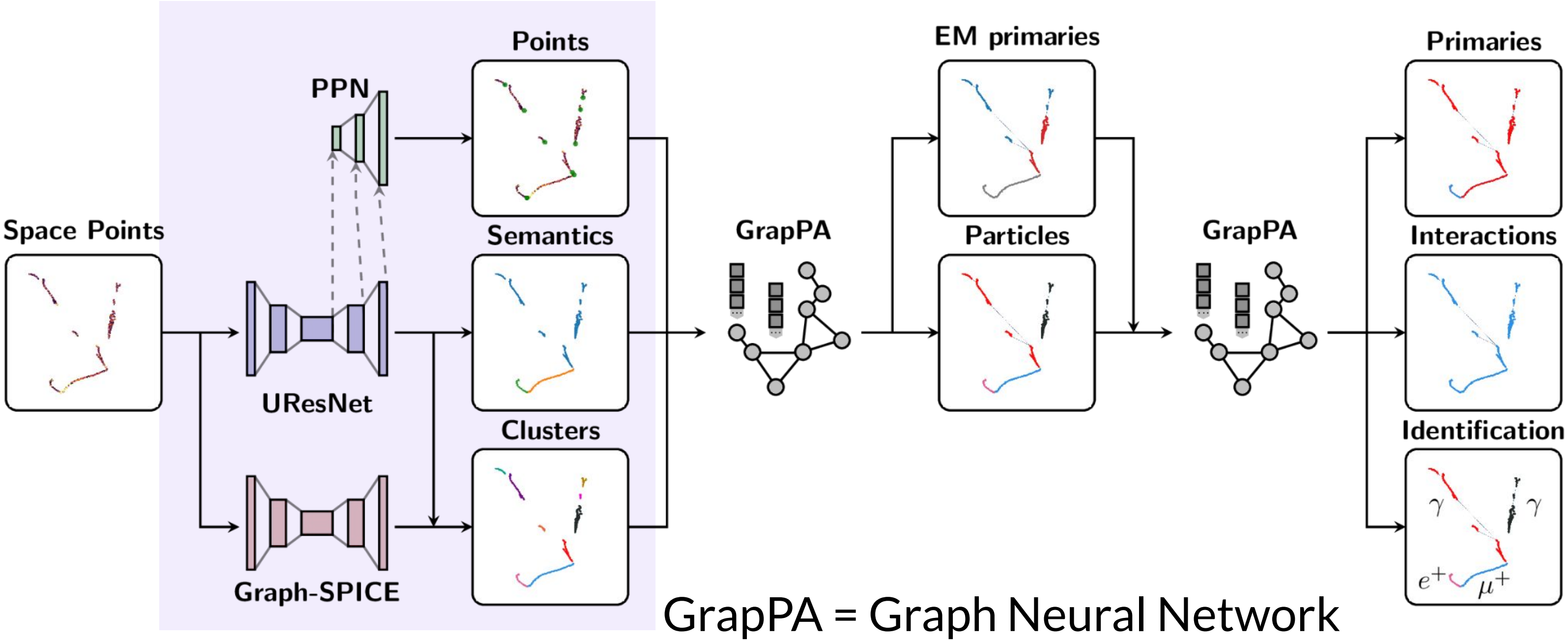

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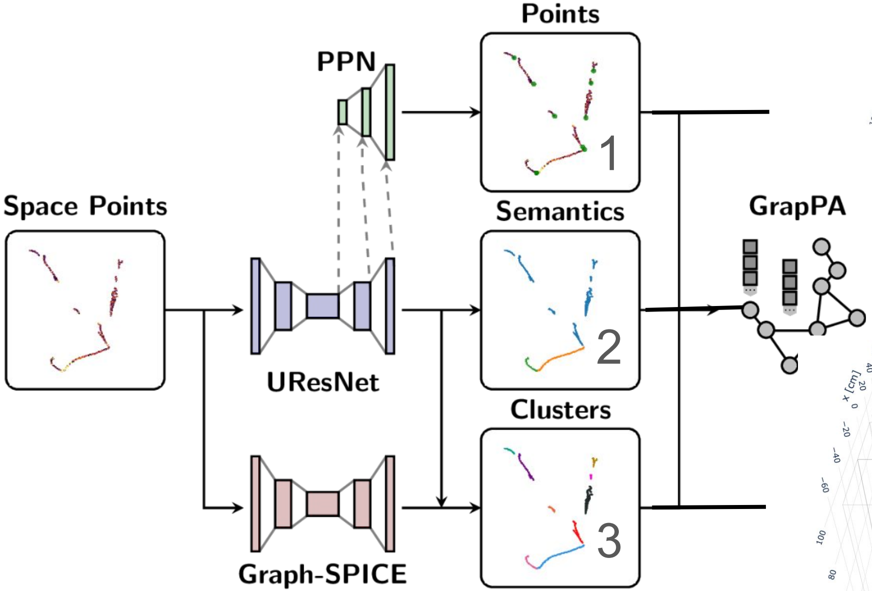
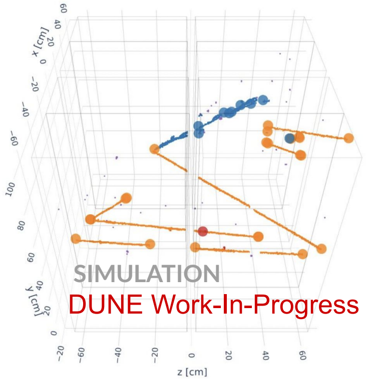
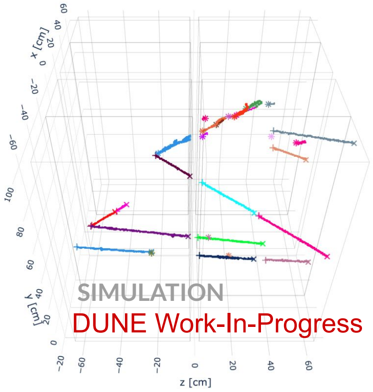
Pixel Features: Output







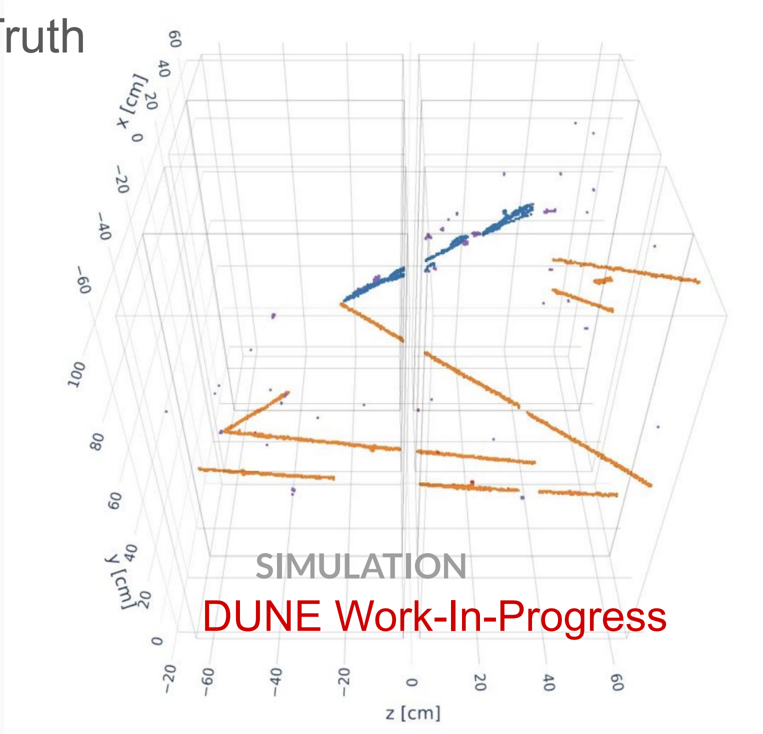
Shower
Track
Michel electron
Delta rays
Low energy scatters

1. Points of interest
   a. Start of tracks & showers
   b. End track
2. Pixel “signature” of particle interaction type
3. Pixel clusters
   a. Including centroids

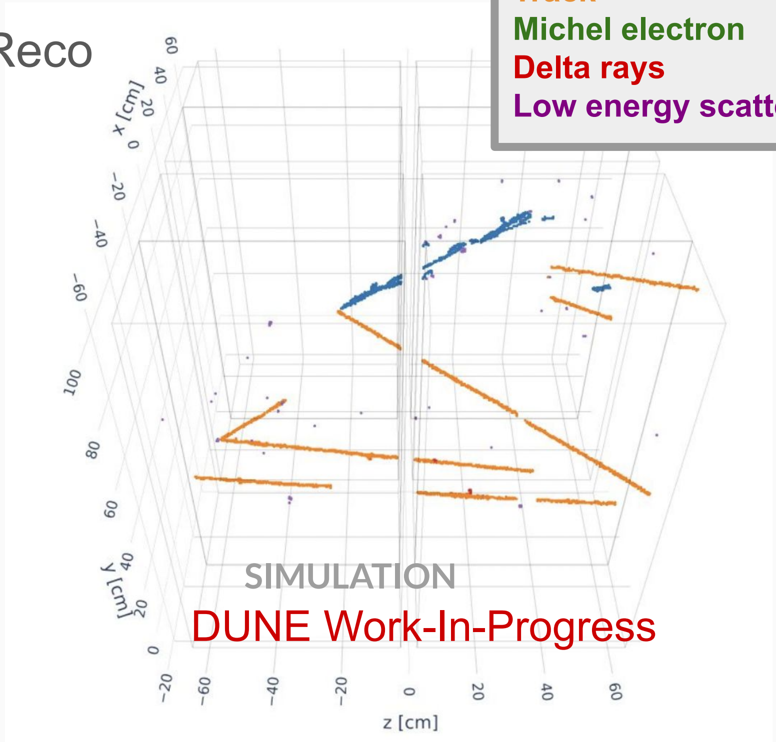
Assign Each Pixel To Label

Shower
Track
Michel electron
Delta rays
Low energy scatters

Truth



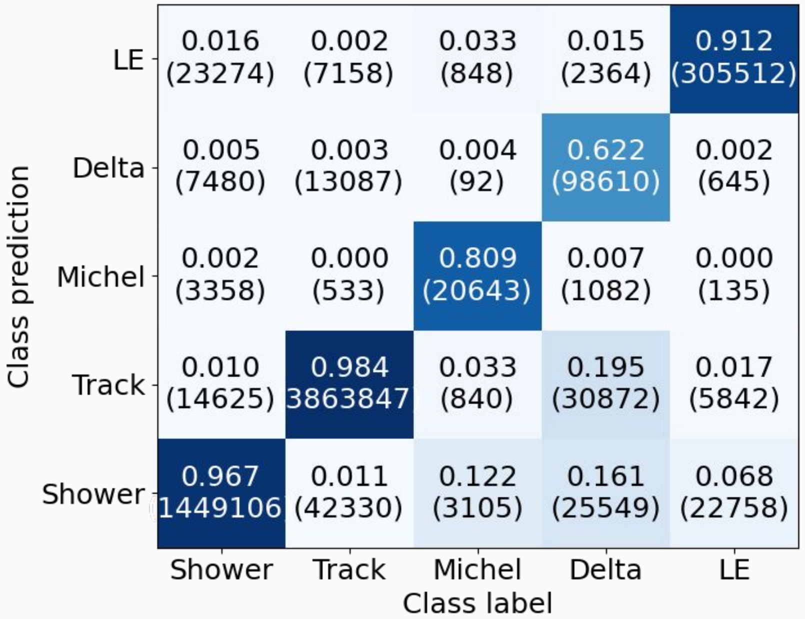
Reco



[PhysRevD (102) 012005](#) & [PhysRevD (104) 032004](#)

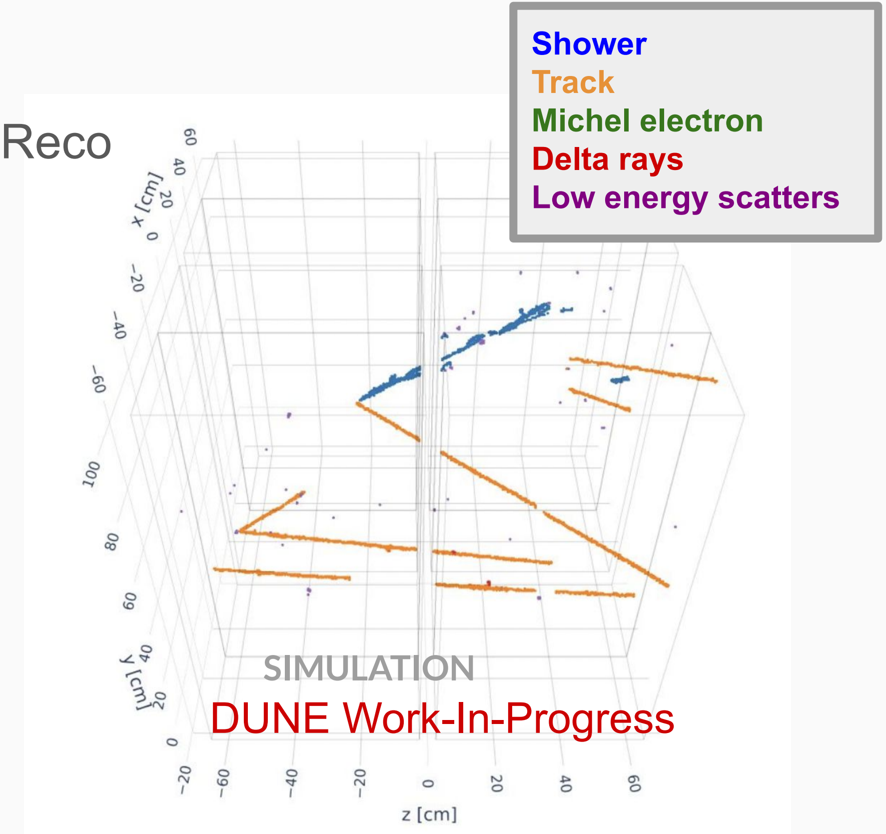
Assign Each Pixel To Label

Performance



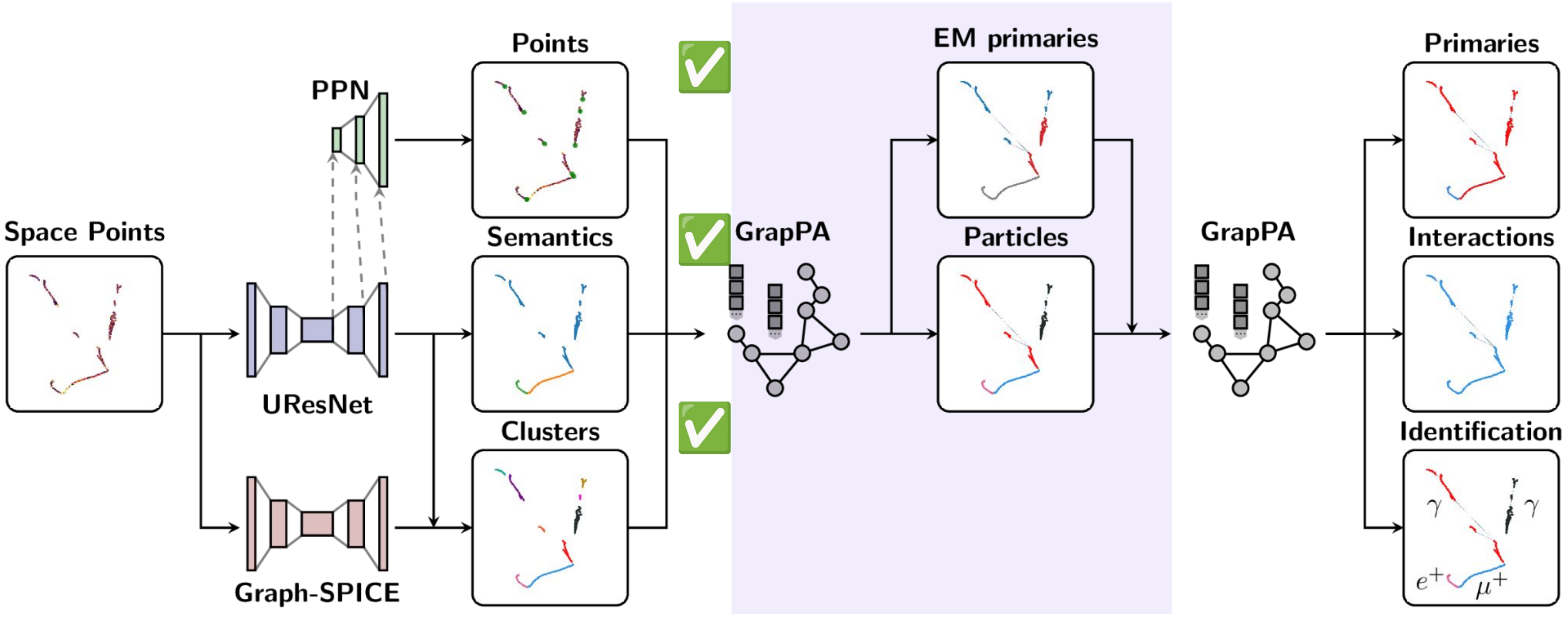
DUNE Work-In-Progress

Reco



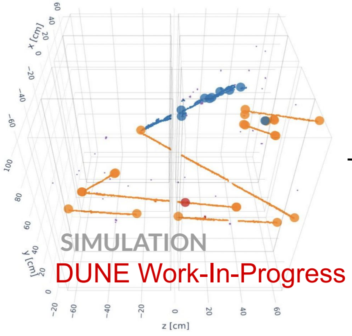
PhysRevD (102) 012005 & PhysRevD (104) 032004

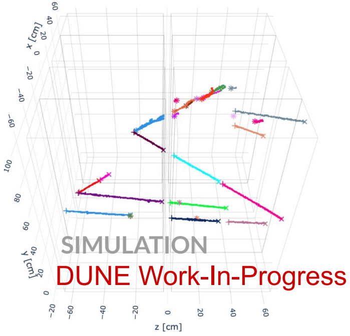
3D LAr TPC: SPINE

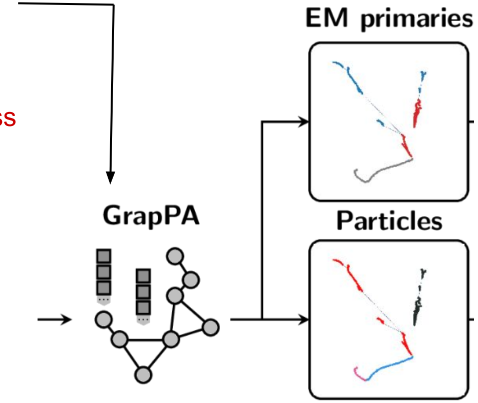


Cluster Clustering

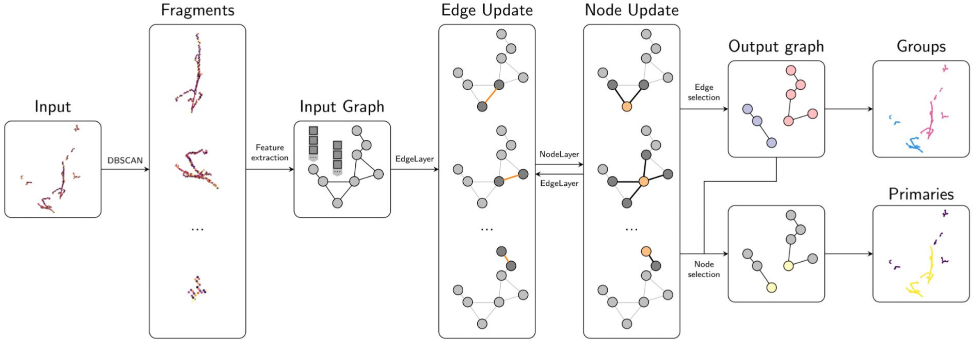
Pixel Features Output







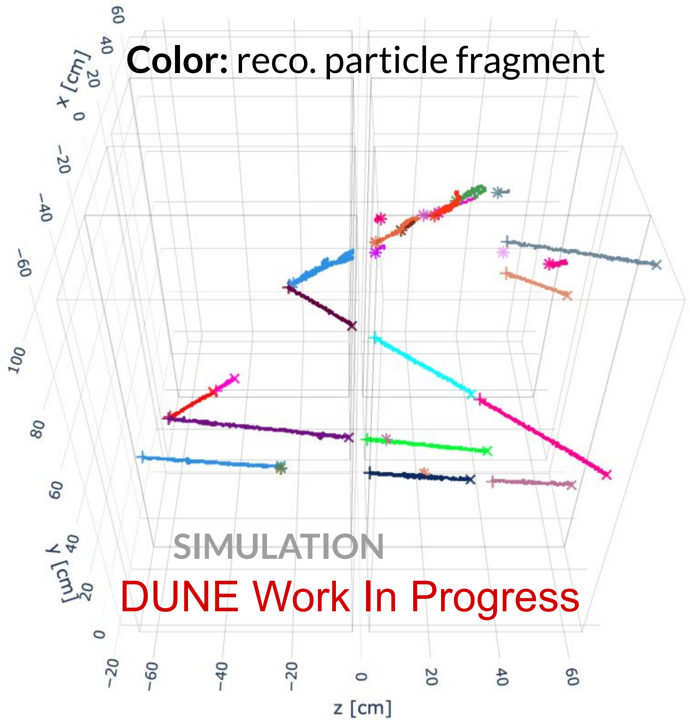
Use Graph Neural Network

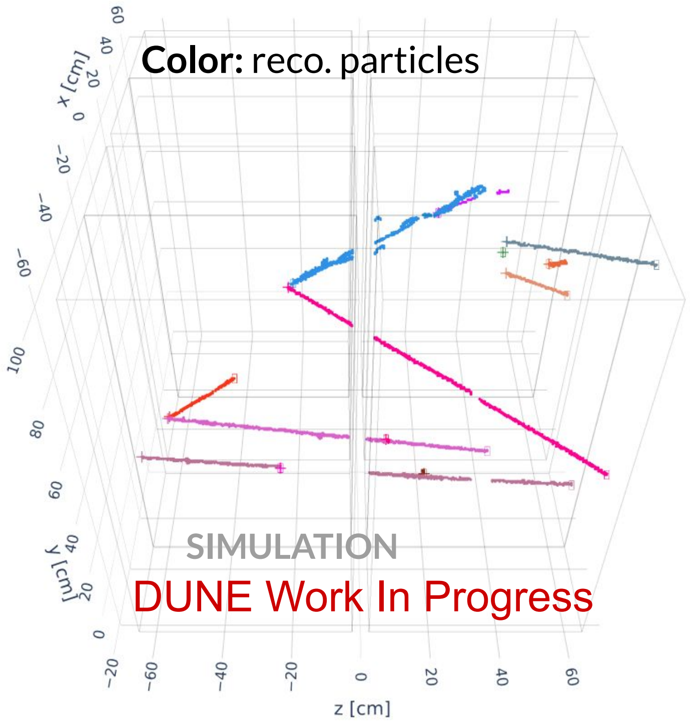


GrapPA: Graph Particle Aggregator

[arxiv 2020]

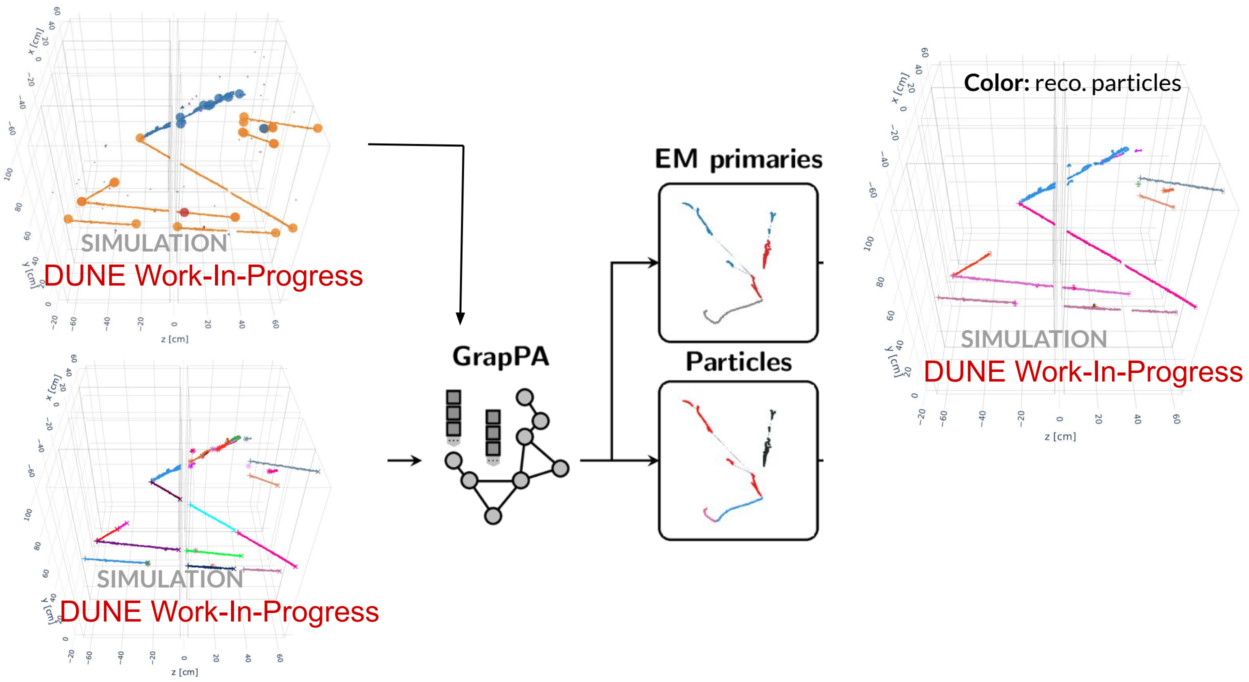
Cluster Clustering: Particle Clustering





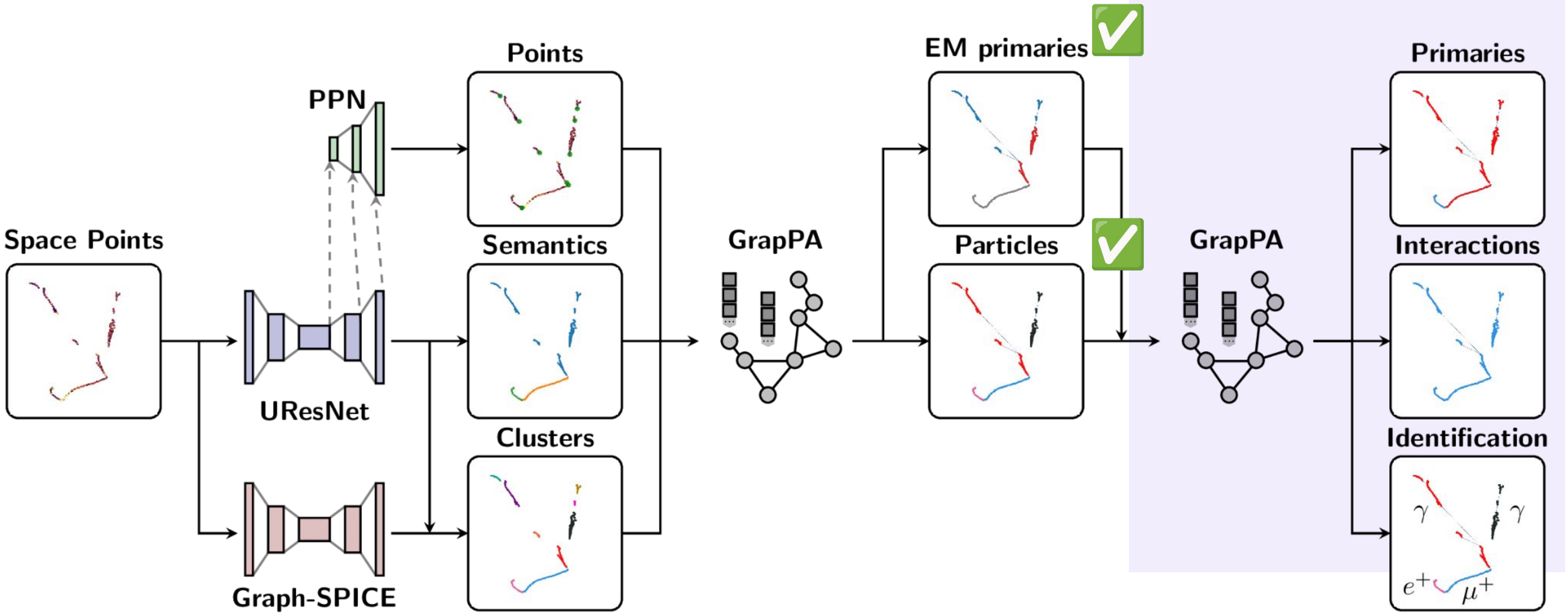
Output: Primaries & Particles

Pixel Features Output



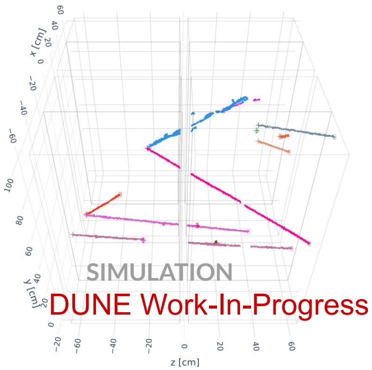
Fragment Features Output

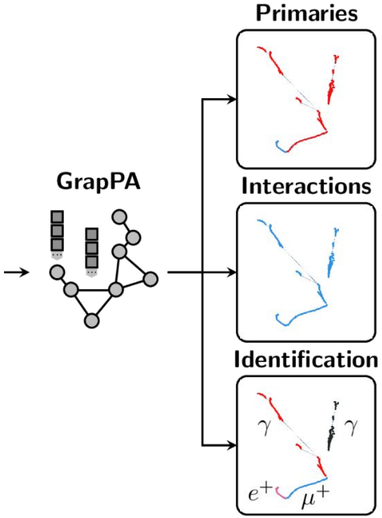
3D LAr TPC: SPINE



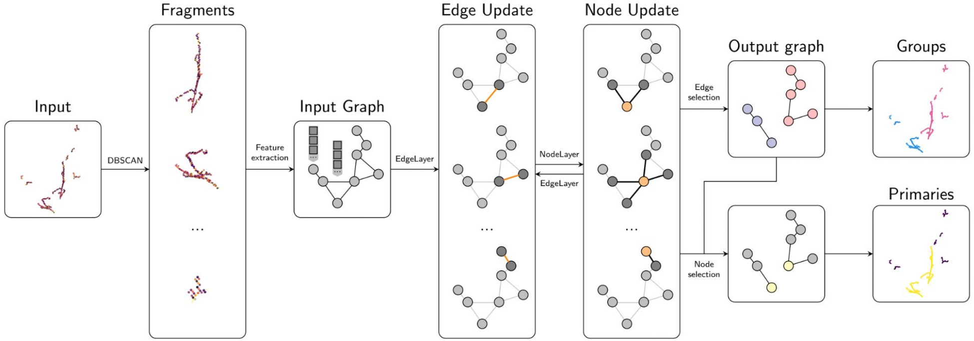
Interactions & Identification

Fragment Features Output





Re-use GrapPA

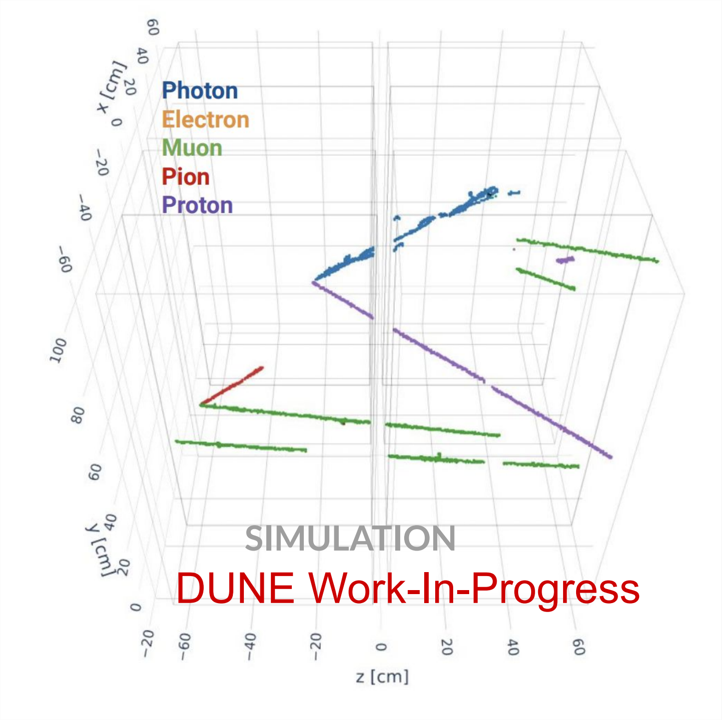


Interactions = find same neutrino source

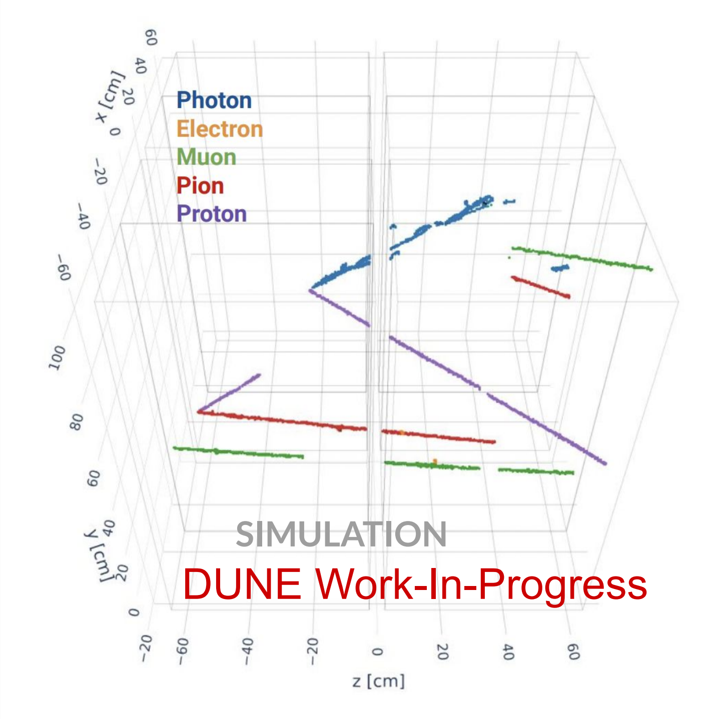
- \+ Edges classification for interactions
- \+ Nodes classification for identification

Performance: Example for 2x2 Prototype

Truth

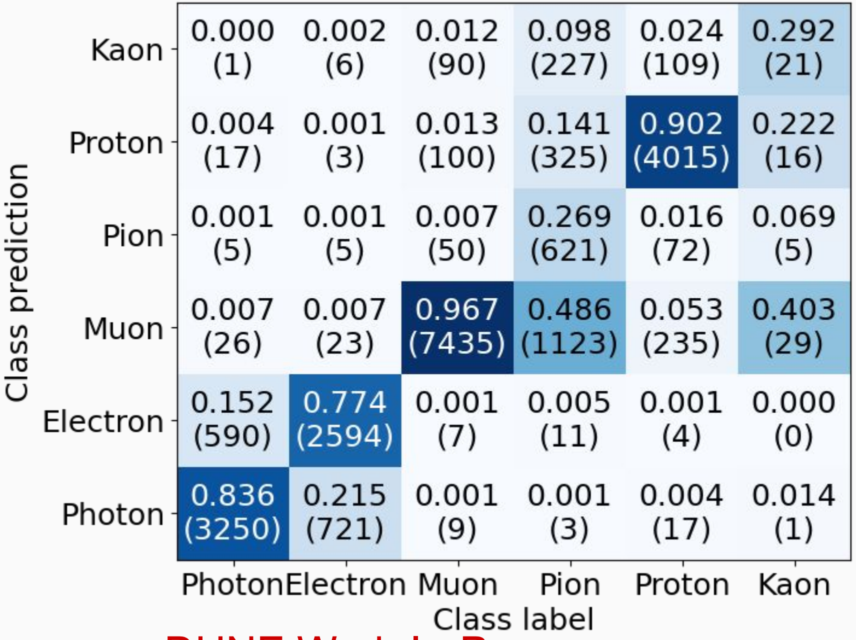


Reco



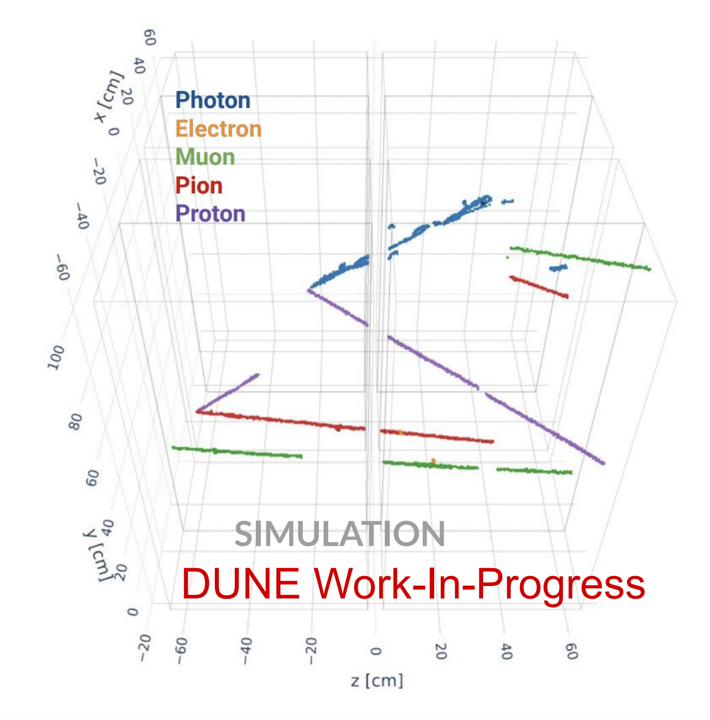
Performance: Metrics

Performance



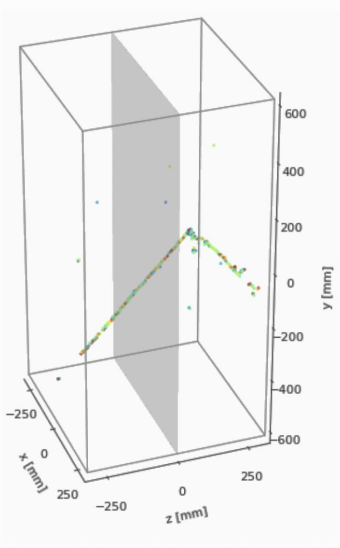
DUNE Work-In-Progress

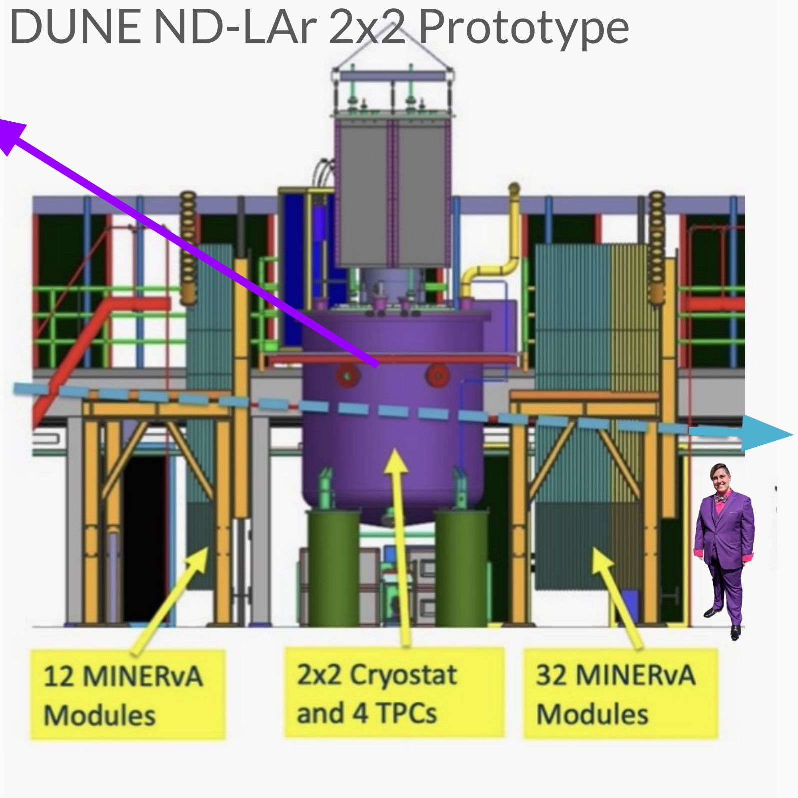
Reco



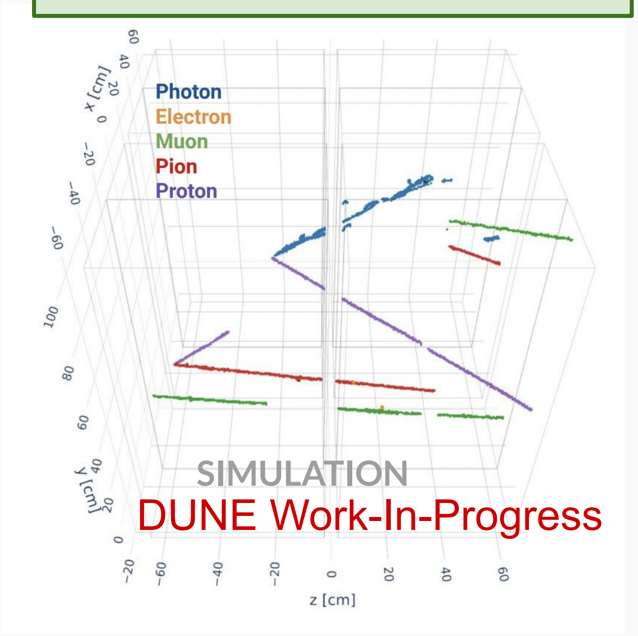
DUNE 2x2 uses Liquid Argon TPCs

Inherently a 3D pixel readout



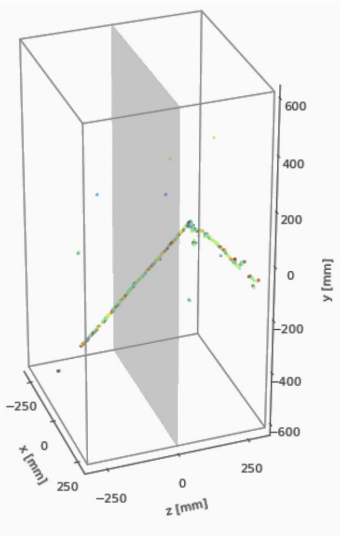


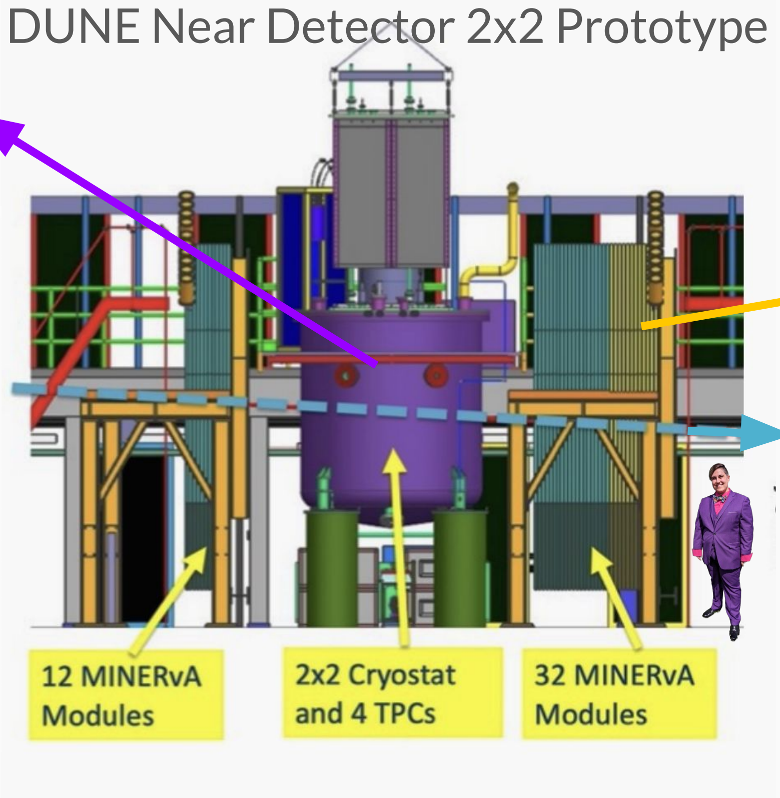
But particles (muons!) leave the 2x2 volume! And we need muon ID for good PID



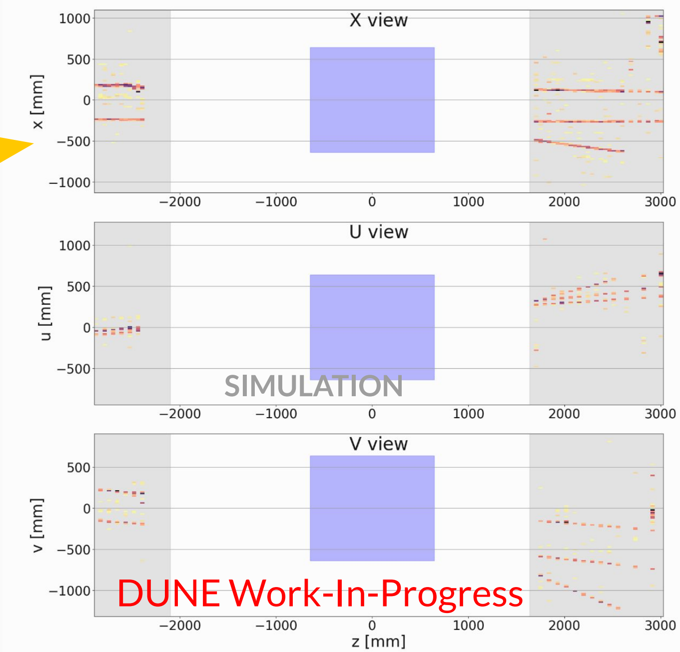
3D vs 2D

Inherently a 3D pixel readout

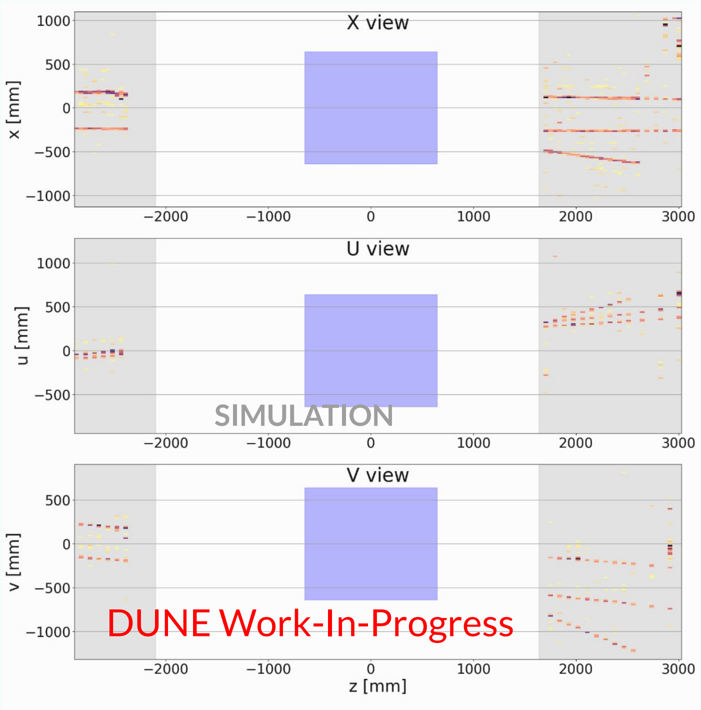




Muon Tagger: Repurpose MINERvA, but inherently a 2D output!

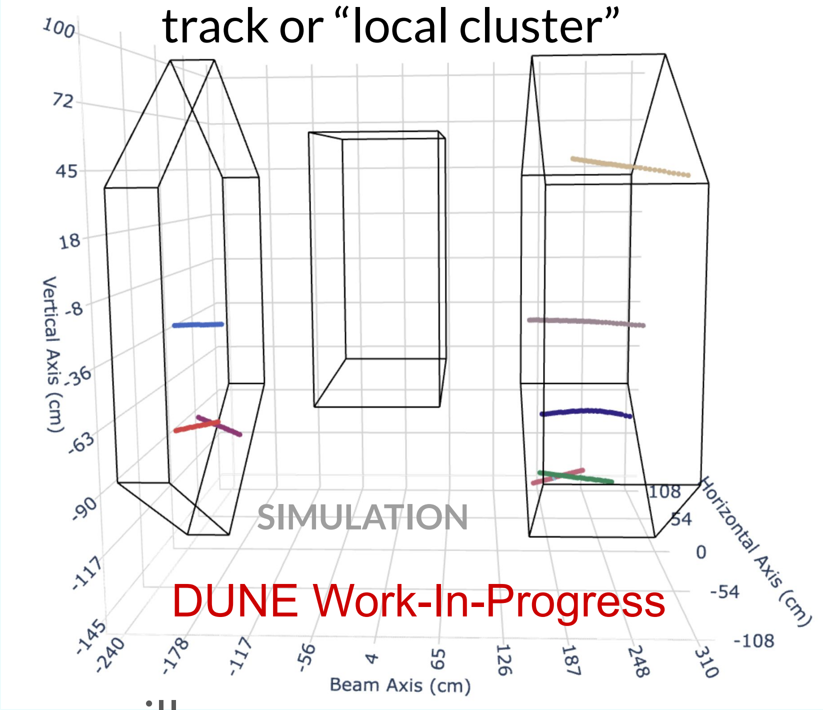


MINERvA "Pixel Clustering"



Traditional Track Reconstruction

Colors indicate reconstructed track or "local cluster"

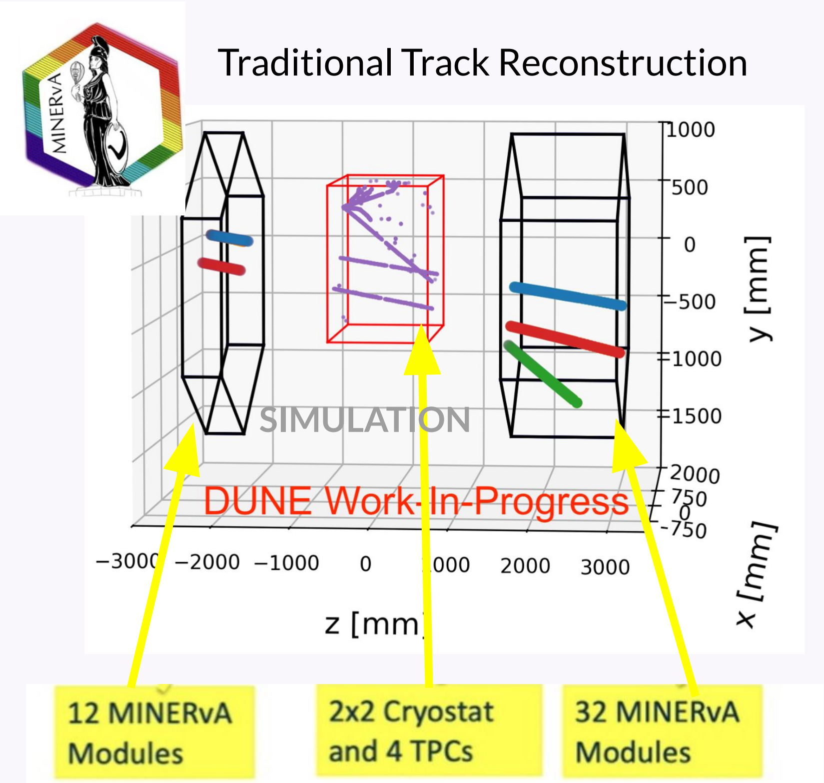


Note: left & right are not the same spill

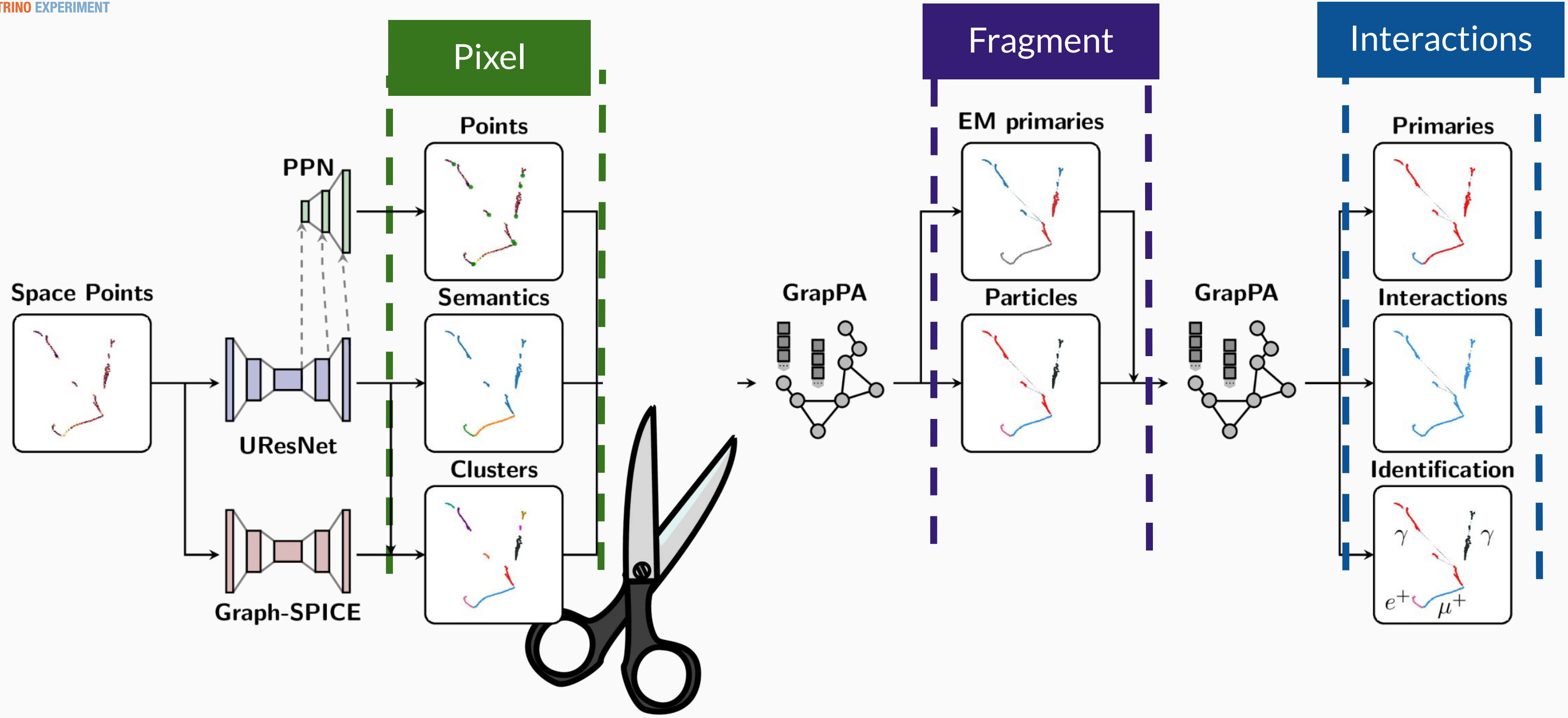
3D Neutrino Detector + 2D Muon Detector

- ✓ SPINE works on 3D LArTPC
- ✓ MINERvA has a 2D → 3D track reconstruction

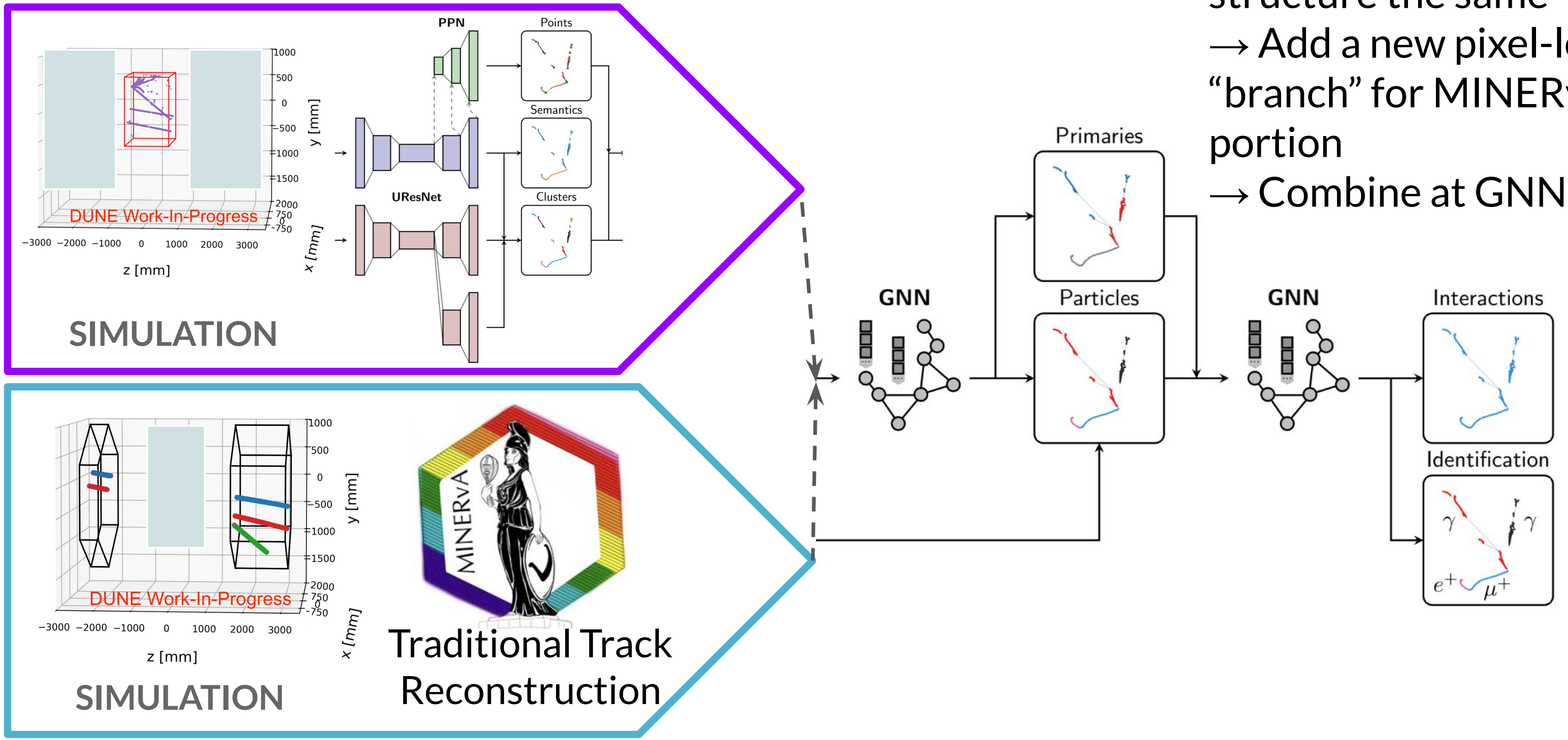
→ Can 3D MINERvA tracks to feed into SPINE?



3D Neutrino Detector + 2D Muon Detector



Inserting Muon Detector



Idea for direction:

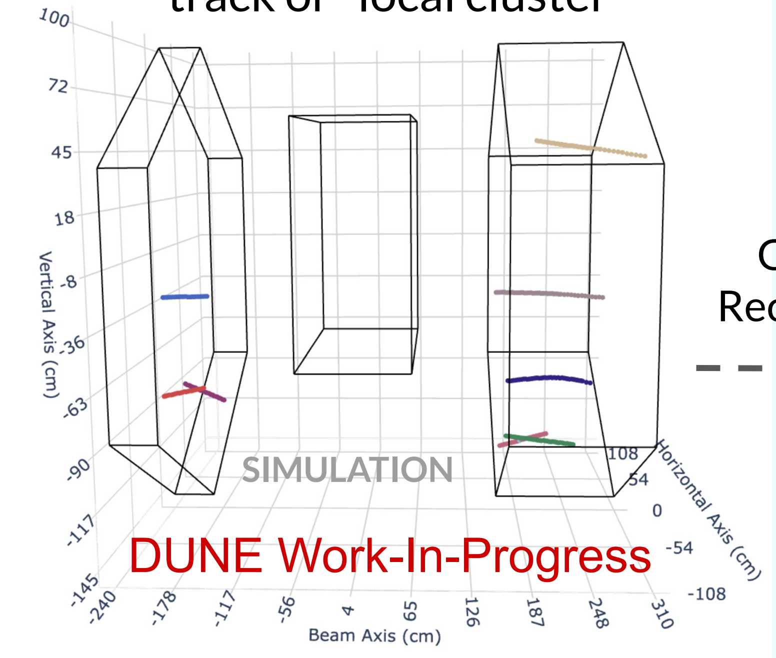
→ Keep SPINE structure the same

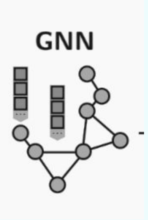
→ Add a new pixel-level "branch" for MINERvA portion

→ Combine at GNN

MINERvA “Clustering”

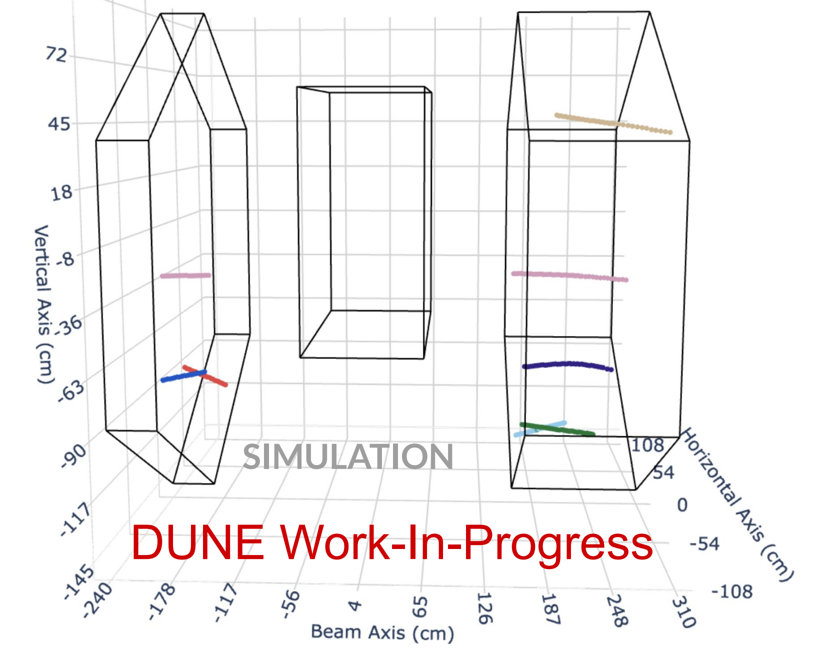
Colors indicate reconstructed track or “local cluster”





GNN Track Reconstruction

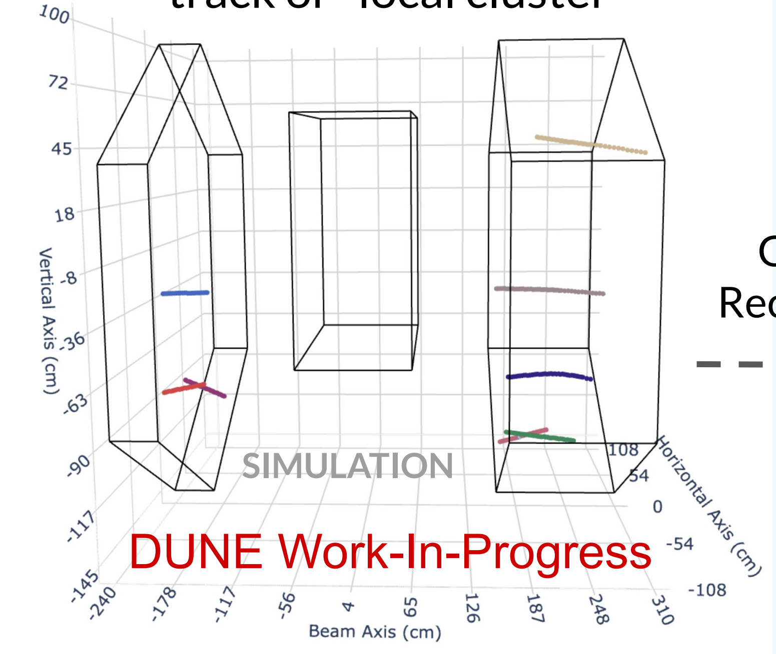
Colors indicate GNN predicted cluster (one connected track)

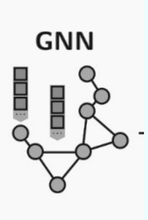


Left & right ARE the same spill

MINERvA “Clustering”

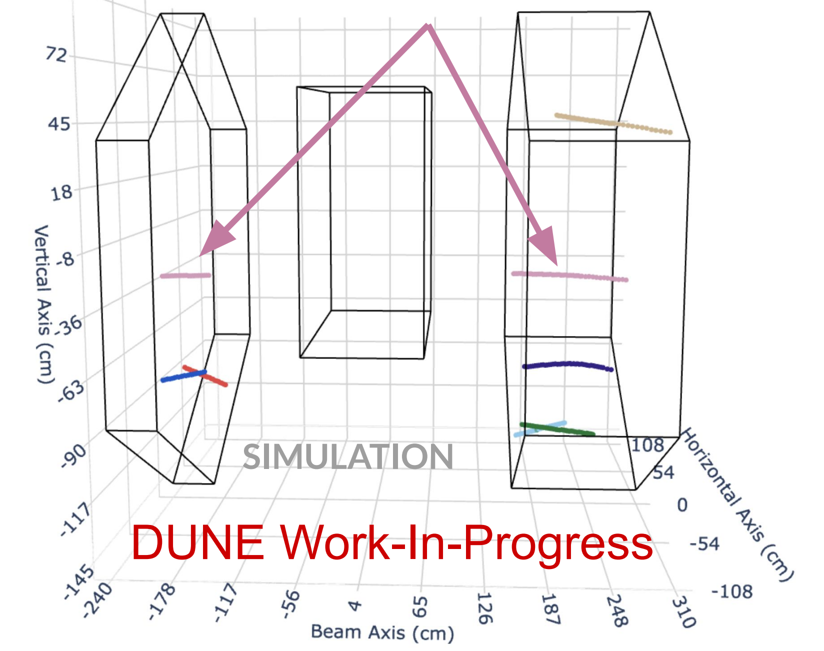
Colors indicate reconstructed track or “local cluster”





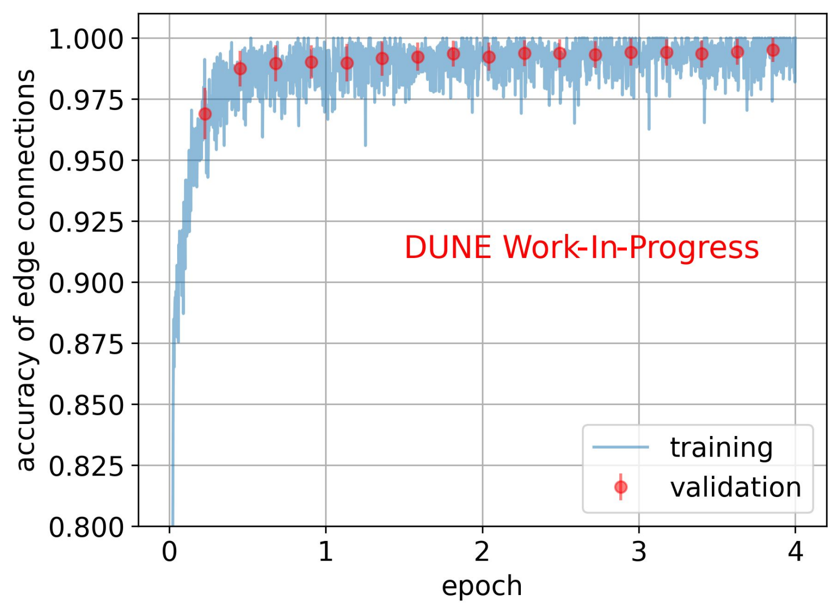
GNN Track Reconstruction

Colors indicate GNN predicted cluster (one connected track)



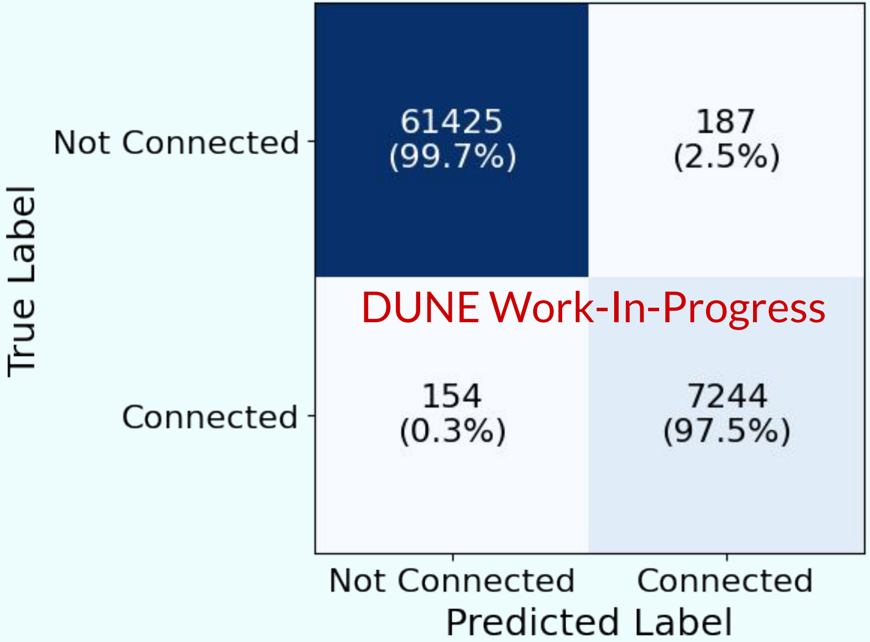
Left & right ARE the same spill

MINERvA "Clustering" Metrics



Accuracy average of 99.5% at 4 epochs with only 14k training events!

Connections vs. Not, No Evident Bias

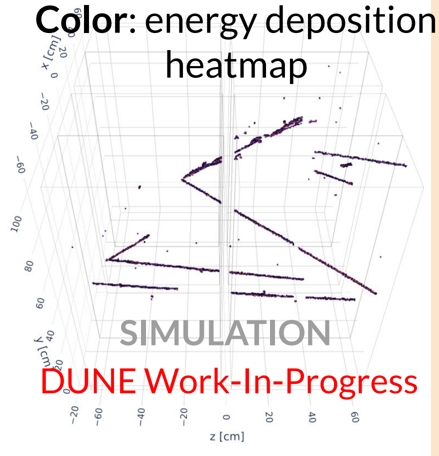


Even with imbalanced training sample, network isn't over-predicting "not connected"

3D LArTPC: SPINE

Input: Charge deposition

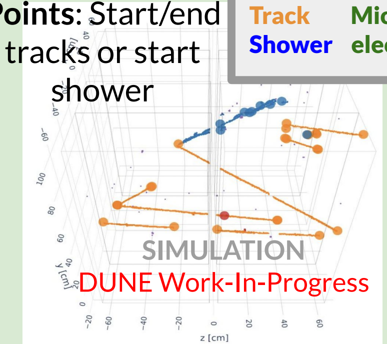
Color: energy deposition heatmap



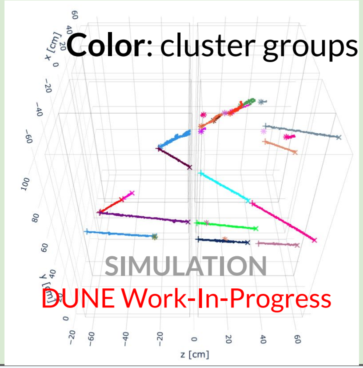
Pixel Features

Points: Start/end tracks or start shower

Track Shower
Michel electron
Delta rays
Low energy scatters

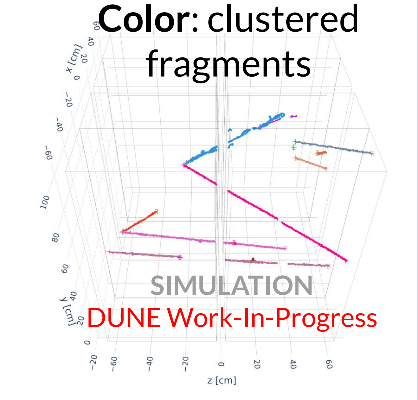


Color: cluster groups



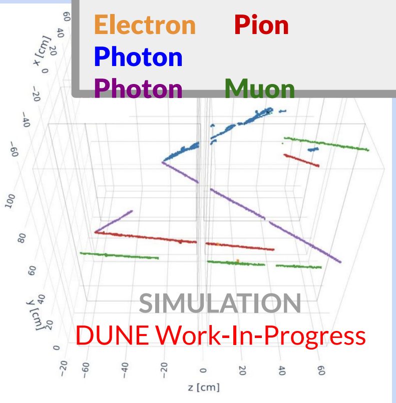
Fragment Features

Color: clustered fragments



Identification & Interactions

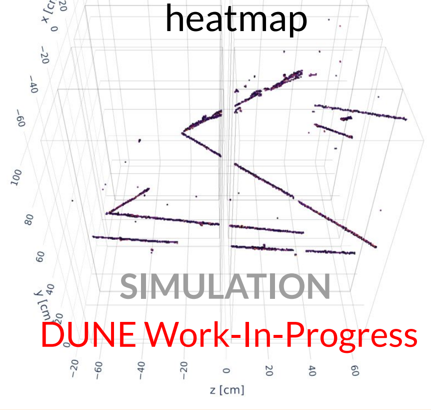
Electron Pion
Photon
Photon Muon



3D LArTPC Plus: SPINE

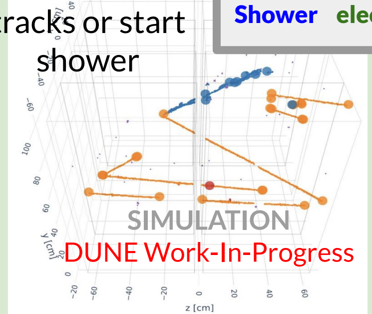
Input: Charge deposition

Color: energy deposition heatmap

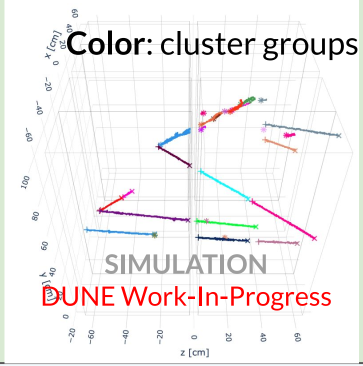


Pixel Features

Points: Start/end tracks or start shower

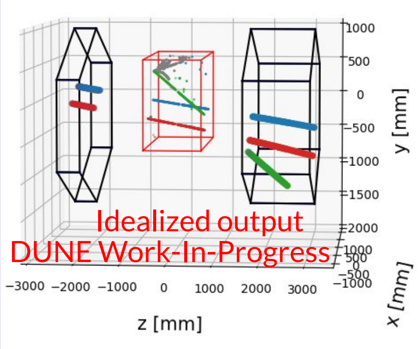


Color: cluster groups

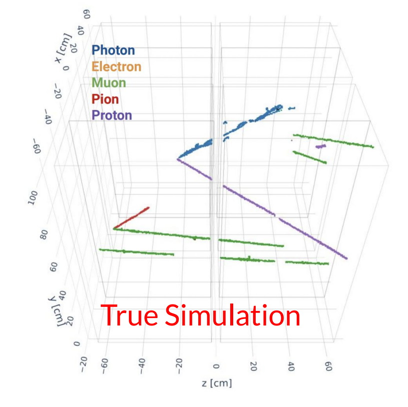


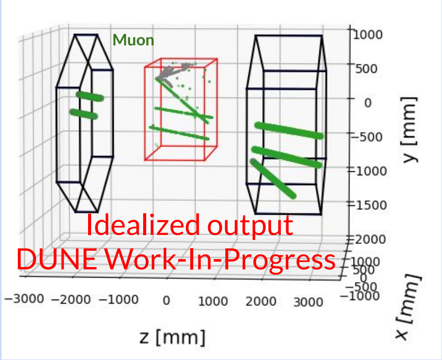
Fragment Features

Color: idealized clustered fragments



Identification & Interactions

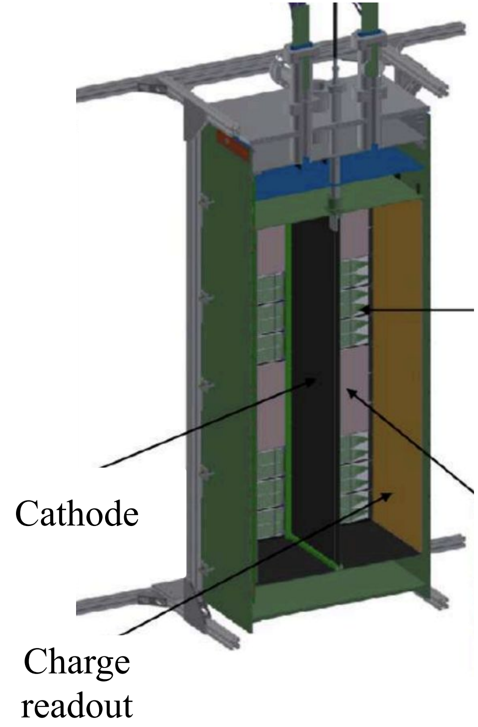


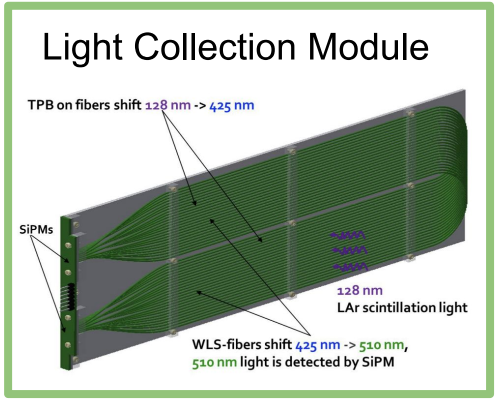


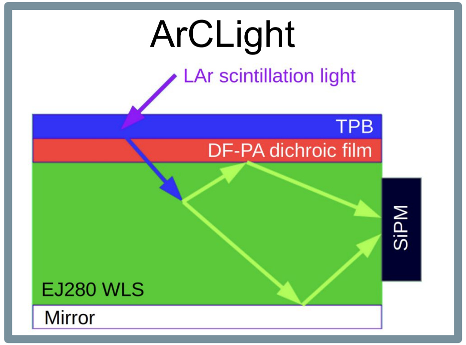
Future Applications

- Integrating detection from multiple detectors into single network
  - Light & Charge

Single ND-LAr Module



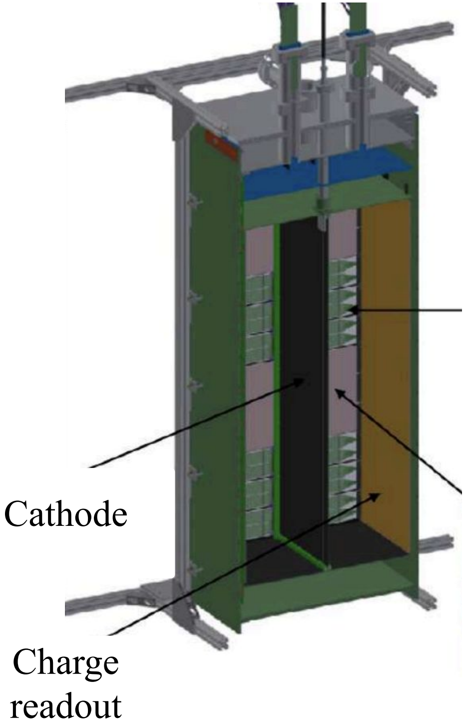


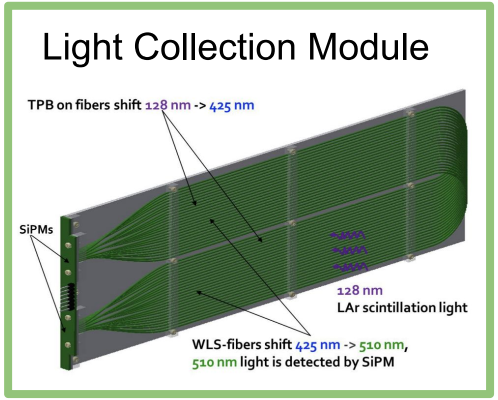


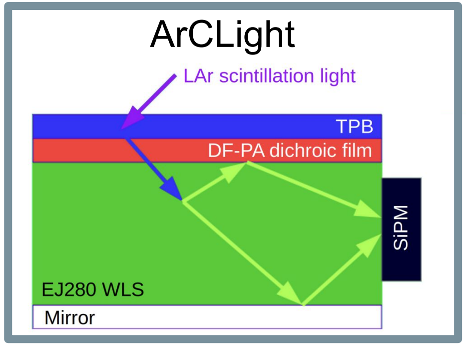
Future Applications

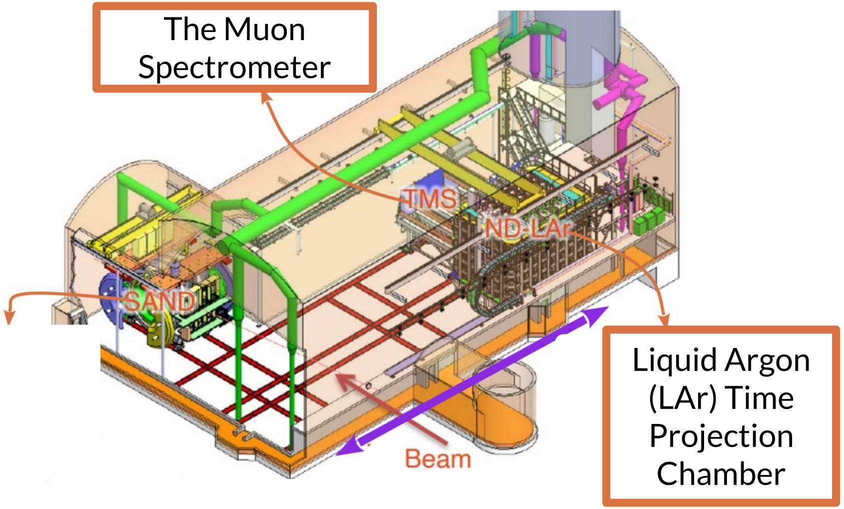
- Integrating detection from multiple detectors into single network
  - Light & Charge
  - ND-LAr & TMS

Single ND-LAr Module





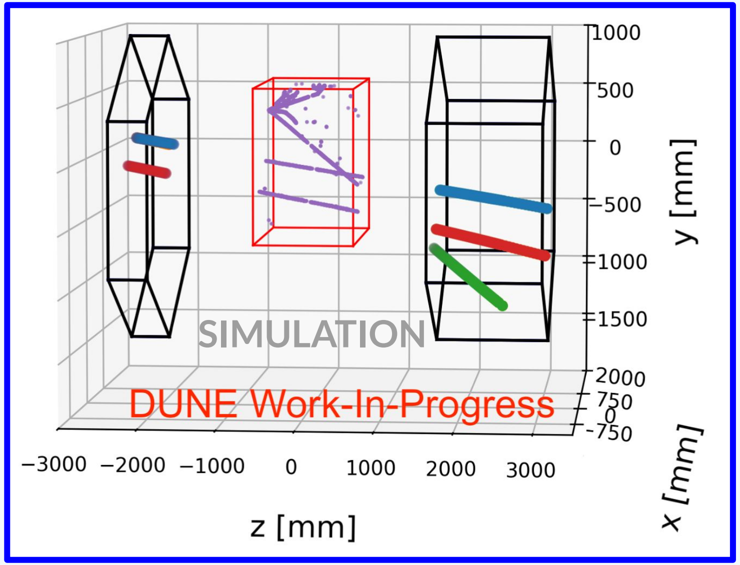


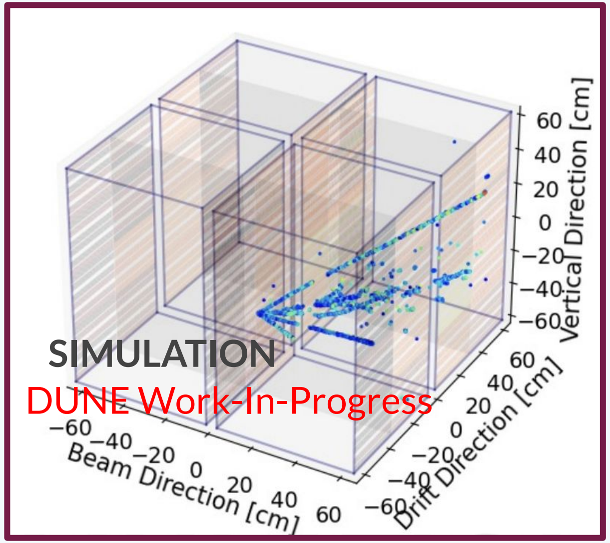


Are there other ways to solve this?

Applying to DUNE Near Detector currently

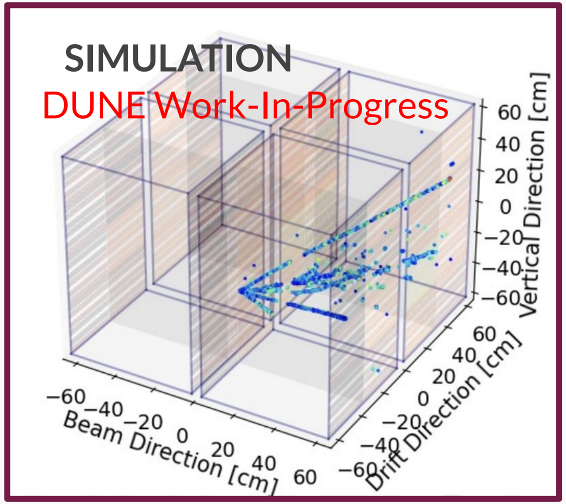
- Gap between MINERvA and 2x2 **O**(m)
- Gap between 2x2 modules **O**(mm)

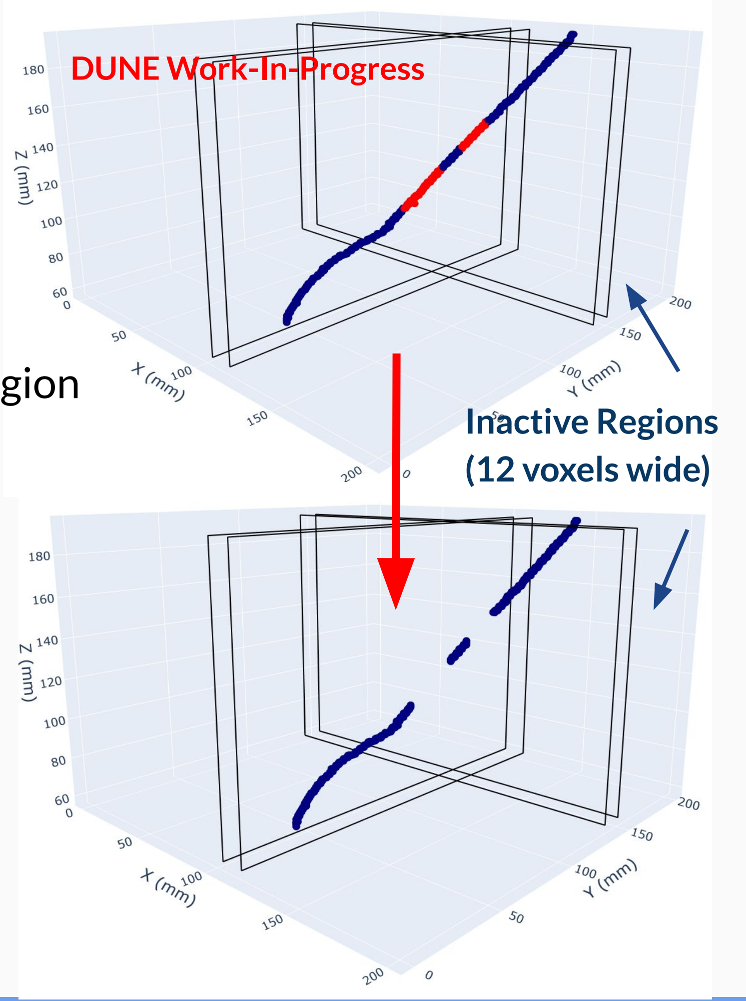




Gap Inference

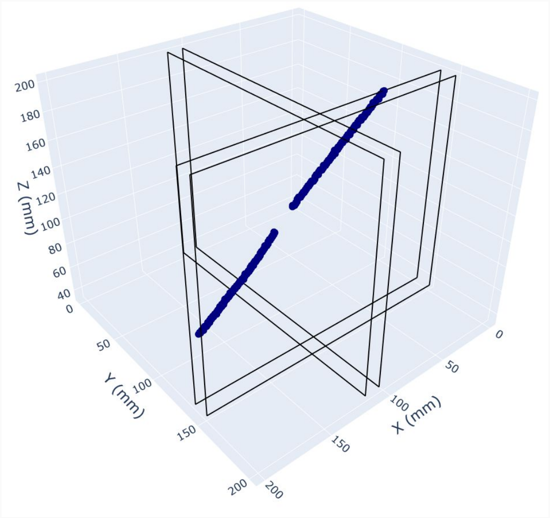
- Focus on missing region with regular grid
- Train network to reassign regular grid energy values, initialized at "null" input (yellow block)
- Should set most voxels to 0, keep others in true track region
- Use similar UResNet Sparse CNN Network



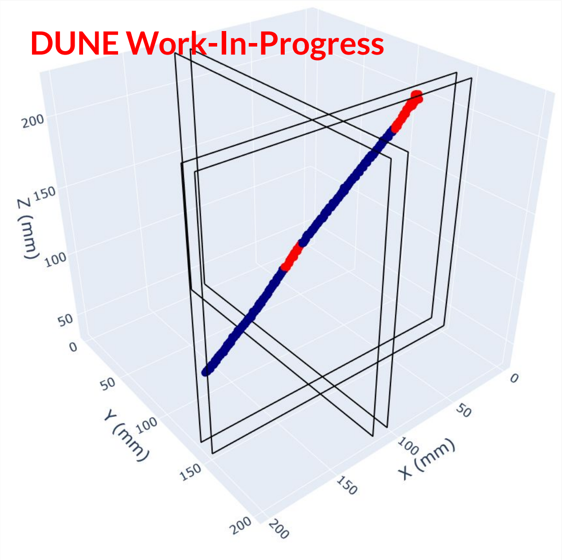


Preliminary Results: Successes

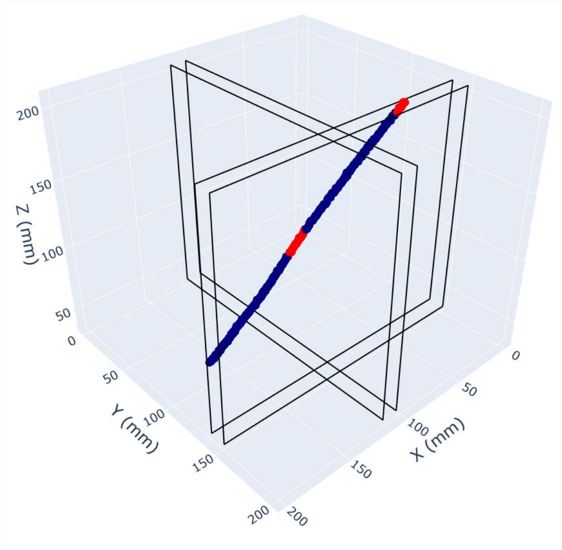
Input



Prediction



Target



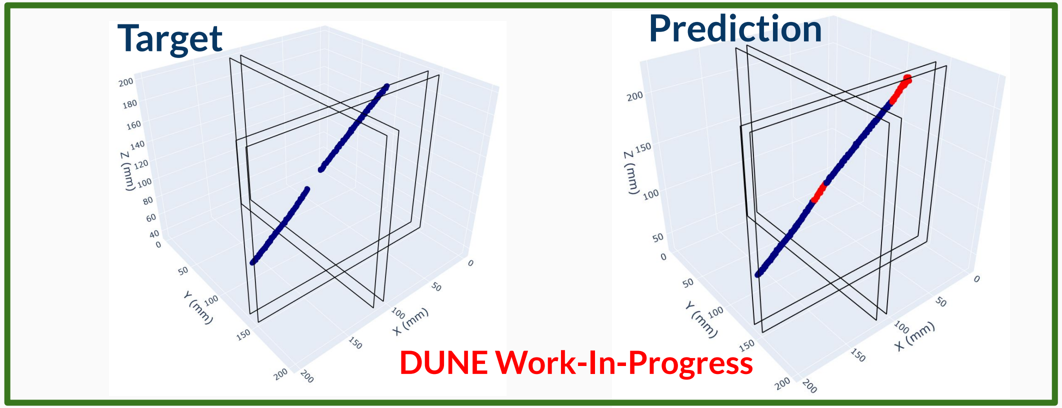
Predicted or Target Region (Inactive)

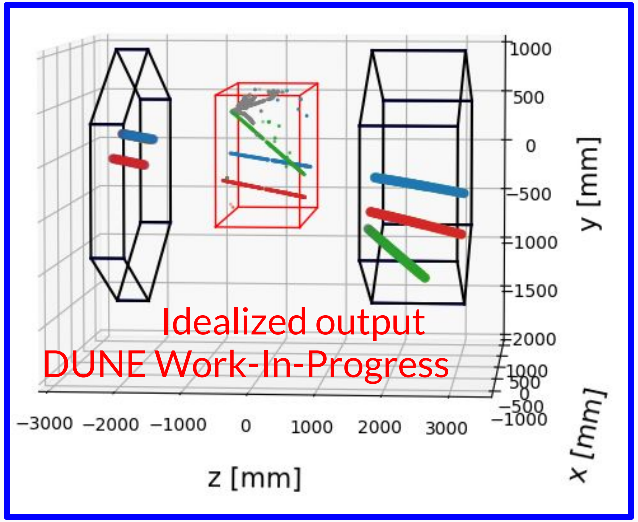
Known Region (Active)

Visually, network prediction does well in red target inference

Summary

- DUNE Near Detector reconstruction challenges:
  - Modularized LArTPC
  - Inform using muon spectrometer?
- Expand SPINE machine learning beyond LArTPC
  - Add multi-detector input
  - Add gap inference
- Interface with existing ML frameworks
  - Integrate & improve existing tools!





Thank you for your attention!

U.S. DEPARTMENT OF ENERGY | Office of Science

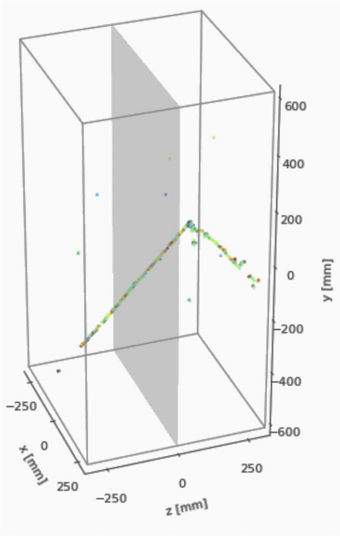
2x2 Analysis Workshop May 2024

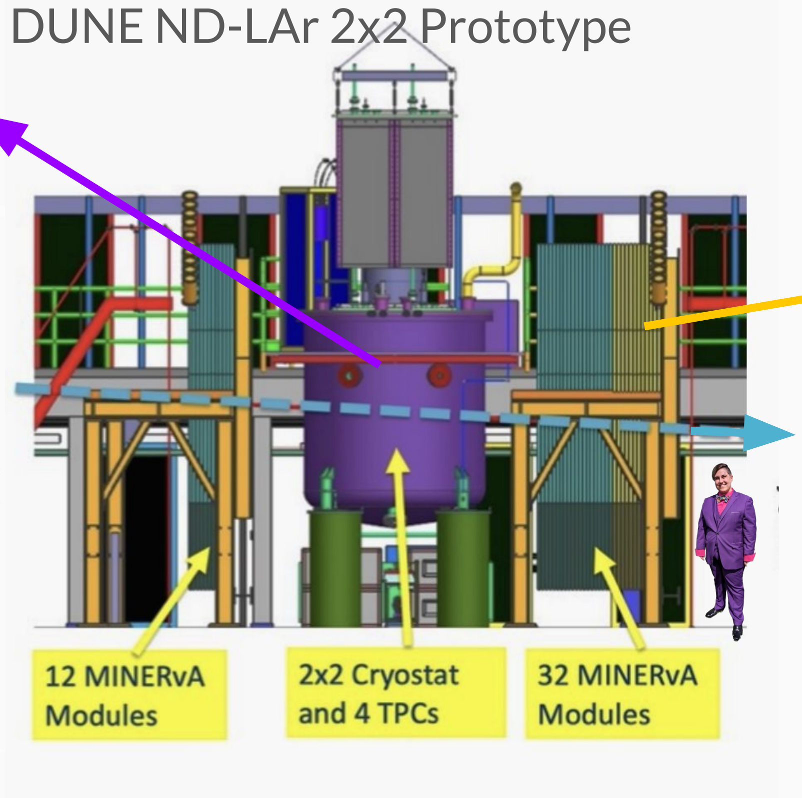
SPINE ML Reco Workshop July 2024

Backup

DUNE 2x2 uses Liquid Argon TPCs

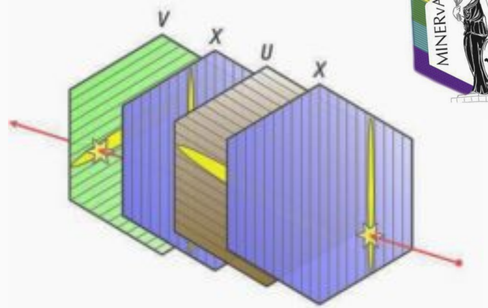
Inherently a 3D pixel readout

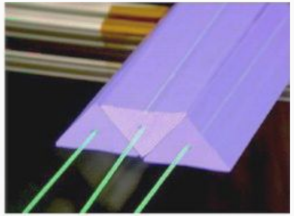




Muon Tracker:

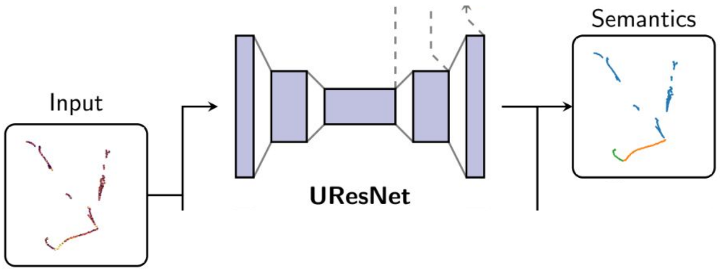
MINERvA: Solid scintillation particle detector with 3 orientations

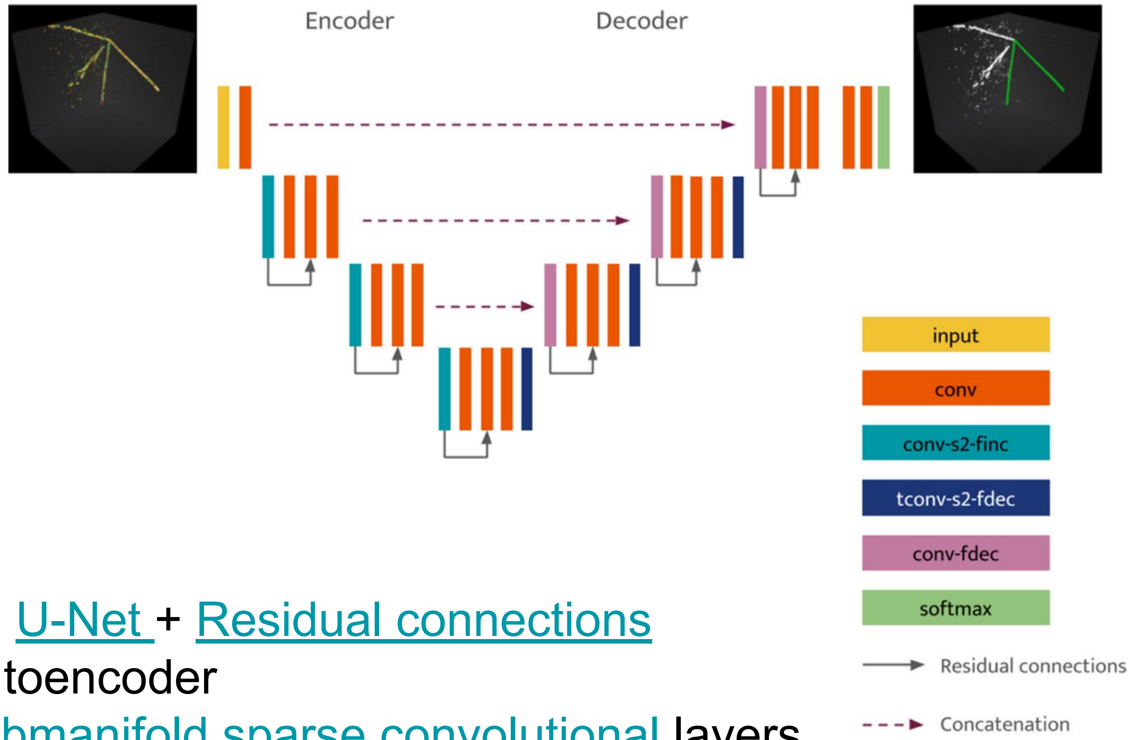




Pixel Features: Semantics

Pixel feature extraction



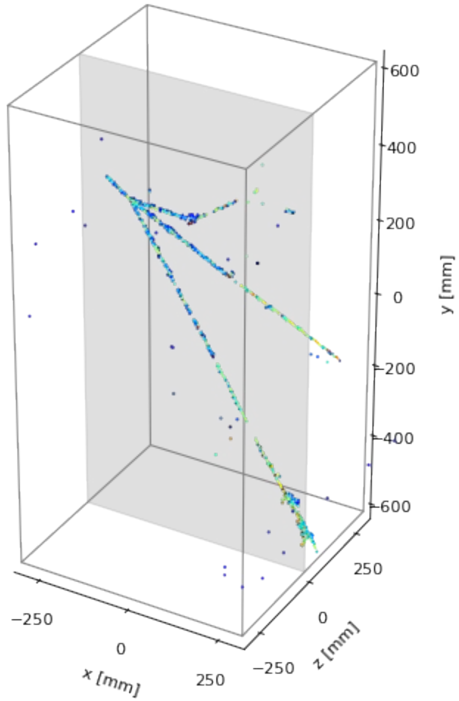


UResNet = U-Net + Residual connections
→ Uses autoencoder
→ Uses submanifold sparse convolutional layers

Phys Rev D (102) 012005

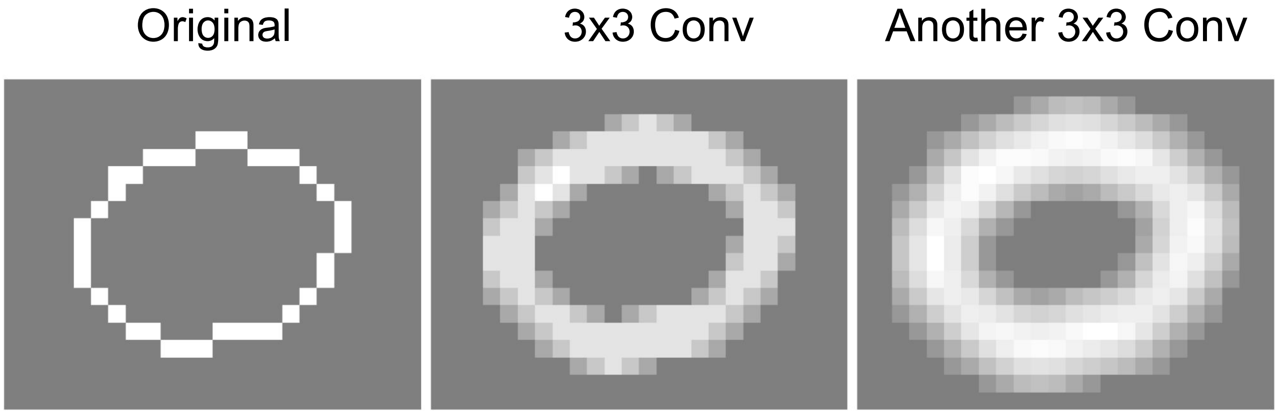
Sparse

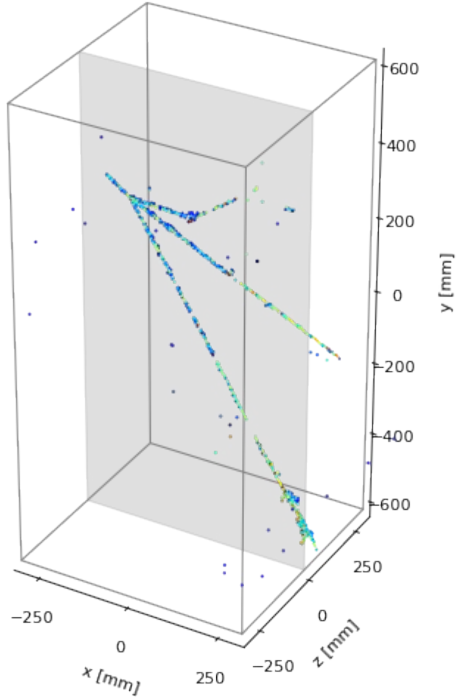
< 0.01 % of the pixels are non-zero!



Submanifold Sparse Convolutions

< 0.01 % of the pixels are non-zero!





❗ Applying regular convolutions reduces sparsity

https://arxiv.org/pdf/1706.01307.pdf

Sparse CNNs on LArTPCs

*Gives capability to train on **entire** LArTPC image, instead of multiple crops!*

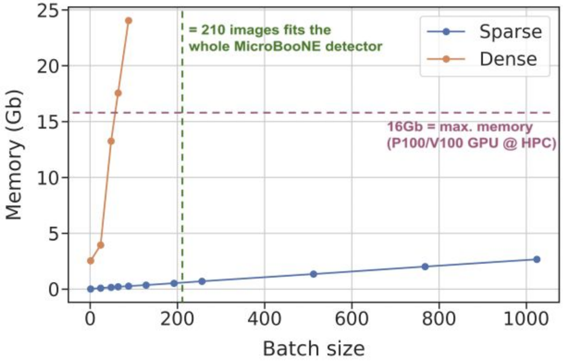


FIG. 3. GPU memory usage as a function of batch size at inference time [2D, 512px, 5-16].

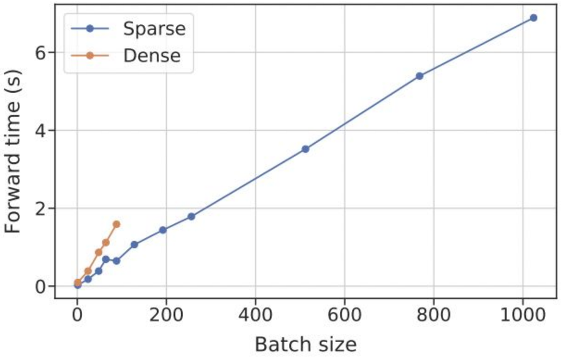


FIG. 4. Computation wall-time as a function of batch size at inference time [2D, 512px, 5-16].

Advantage of sparse conv:

✓ Classification error ~equal

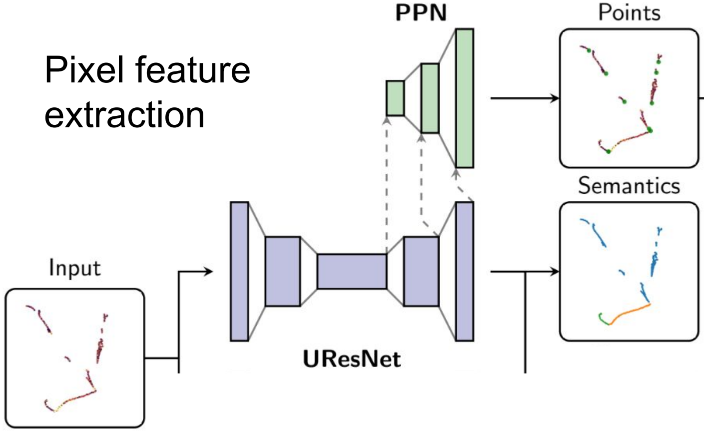
✓ Faster per batch

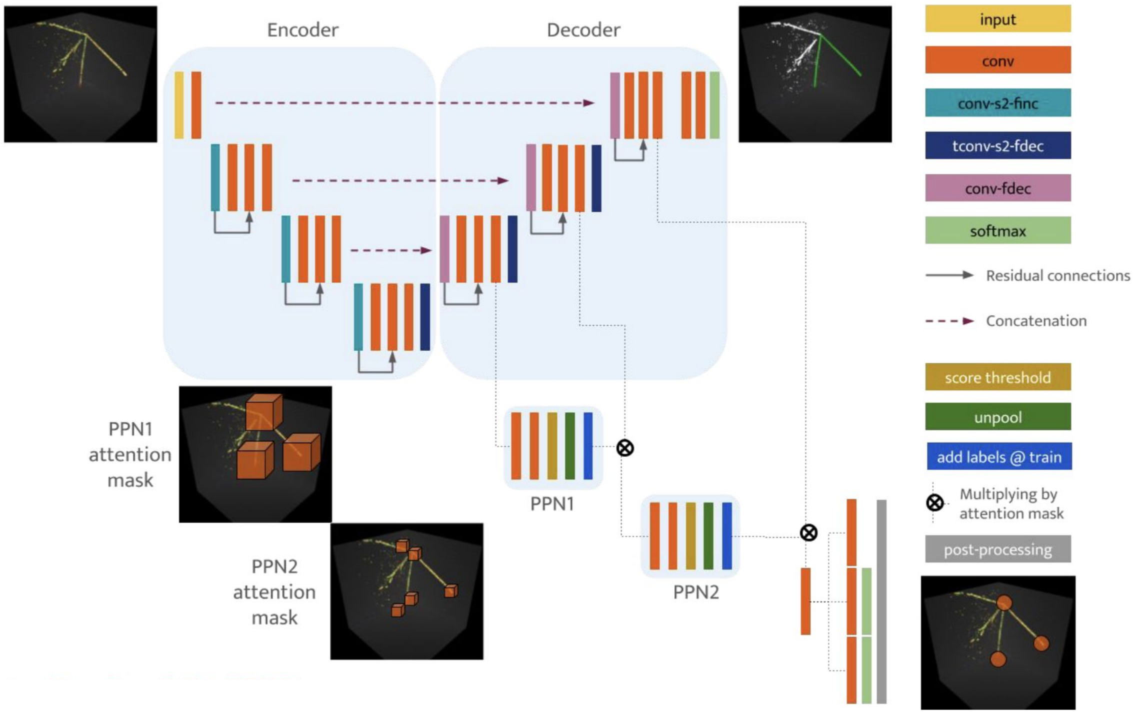
✓ Less memory for even larger batches!

[Scalable CNNs for LArTPCs]

Pixel Features: Points of Interest

Pixel feature extraction

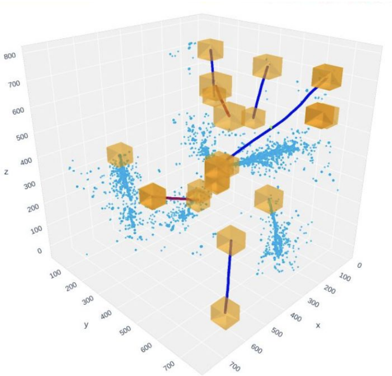


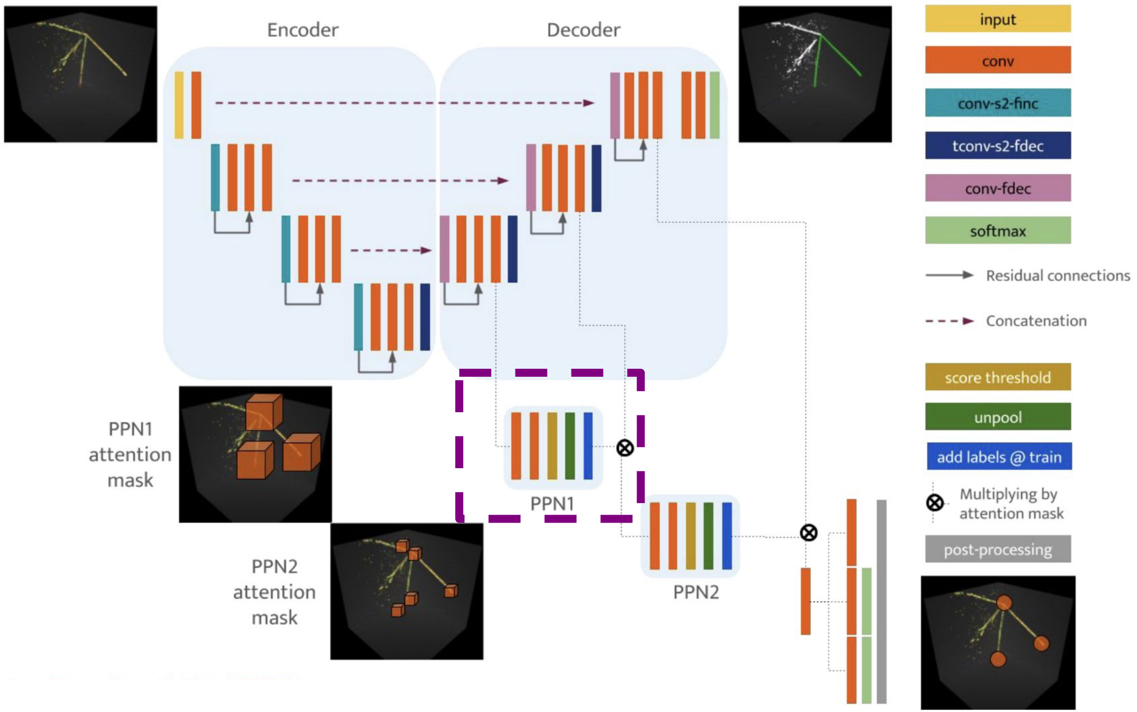


[Phys Rev D (104) 032004]()

Pixel Features: Points of Interest

Pixel feature extraction at low resolution (PPN1)

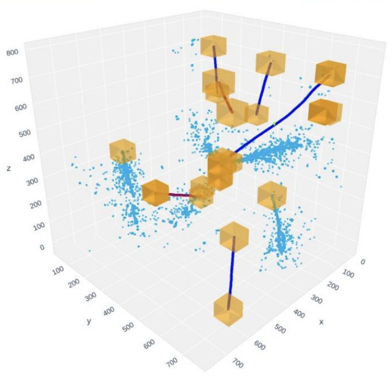




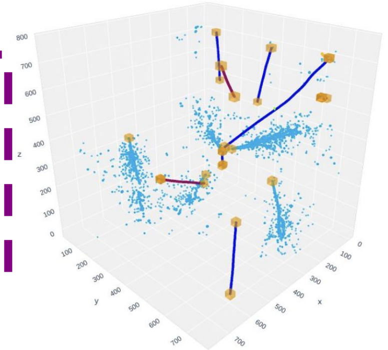
[Phys Rev D (104) 032004](#)

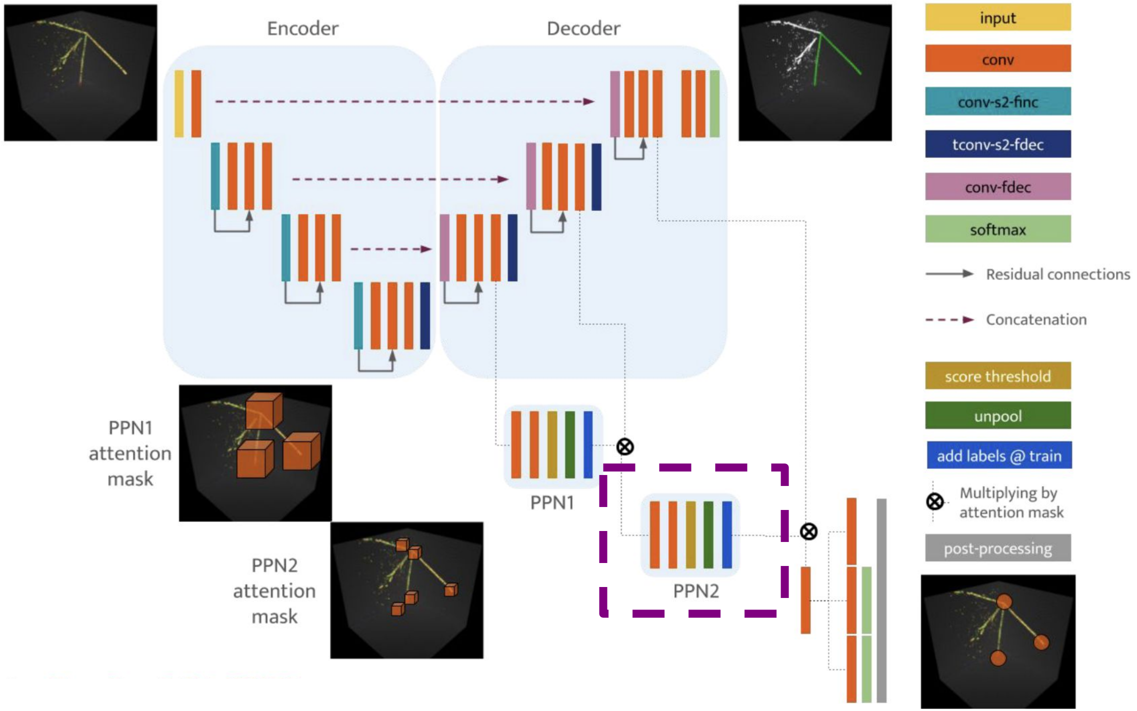
Pixel Features: Points of Interest

Pixel feature extraction at low resolution (PPN1)



Pixel feature extraction at higher resolution (PPN2)





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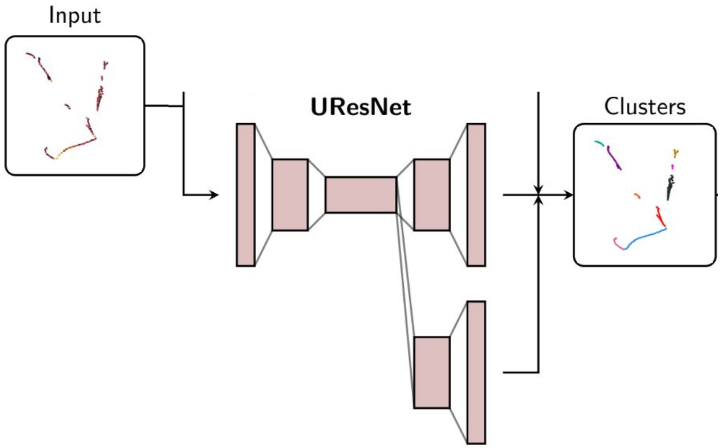
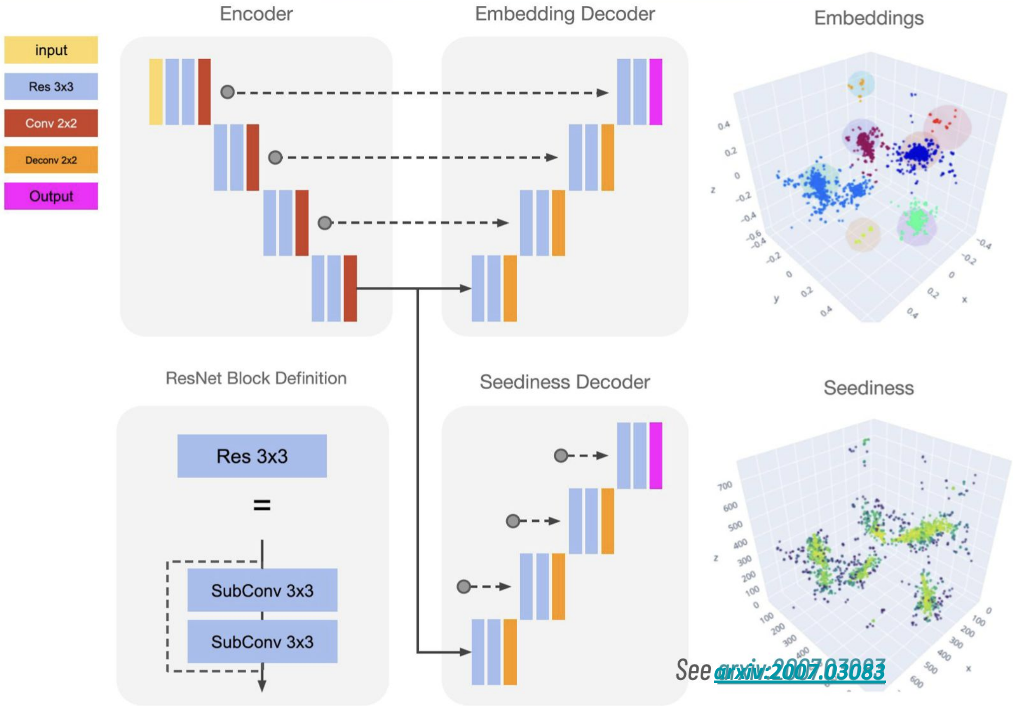
Pixel Features: SPICE Clustering

Scalable Particle Instance Clustering using Embedding
→ Points in cluster flow normal distribution, loss uses this



Embedding decoder	Transformation
Seediness decoder	Centroids



See arxiv:2007.03083

GrapPA

PhysRevD. 104. 072004

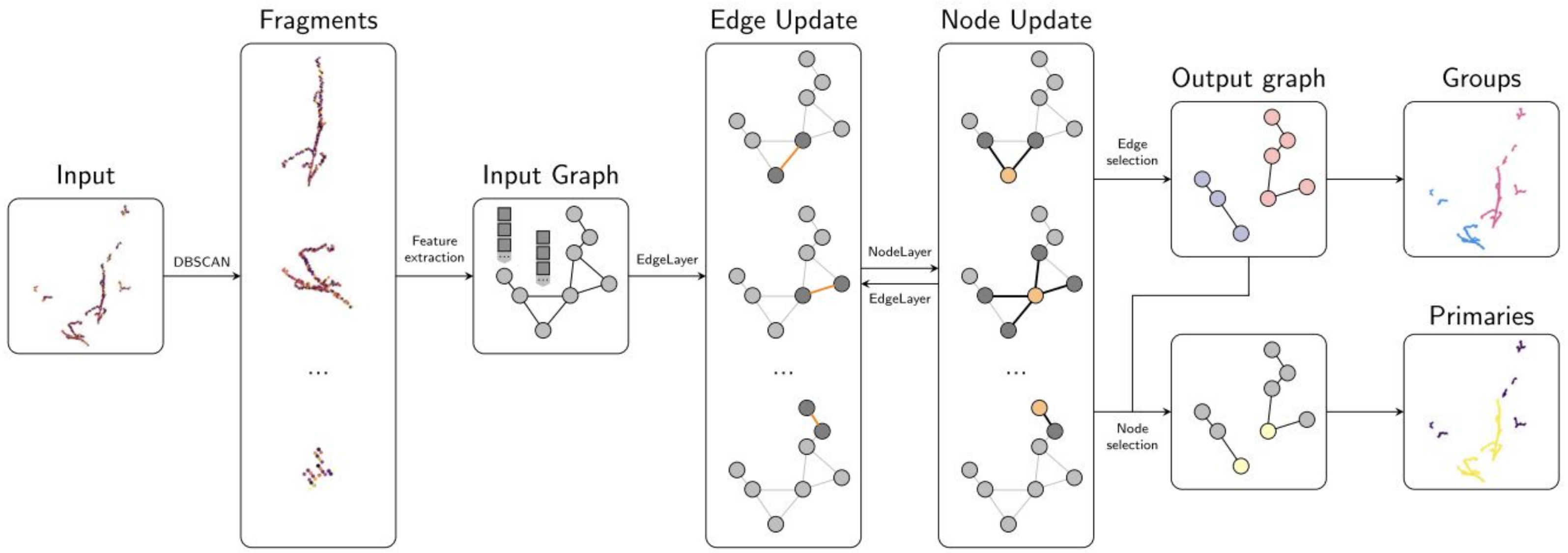


FIG. 1. Architecture of the graph particle aggregator (GrapPA) for shower clustering and primary identification. The input set of voxels associated with electromagnetic showers is passed through a density-based clustering algorithm that forms dense shower fragments. Each fragment is encoded into a set of node features in a graph connected by arbitrary edges carrying edge features. Edge and node features are updated through a series of message passing composed of edge and node updaters. The updated edge features are used to constrain the connectivity graph and the updated node features to identify primaries.

GrapPA: Edge Loss

PhysRevD. 104. 072004

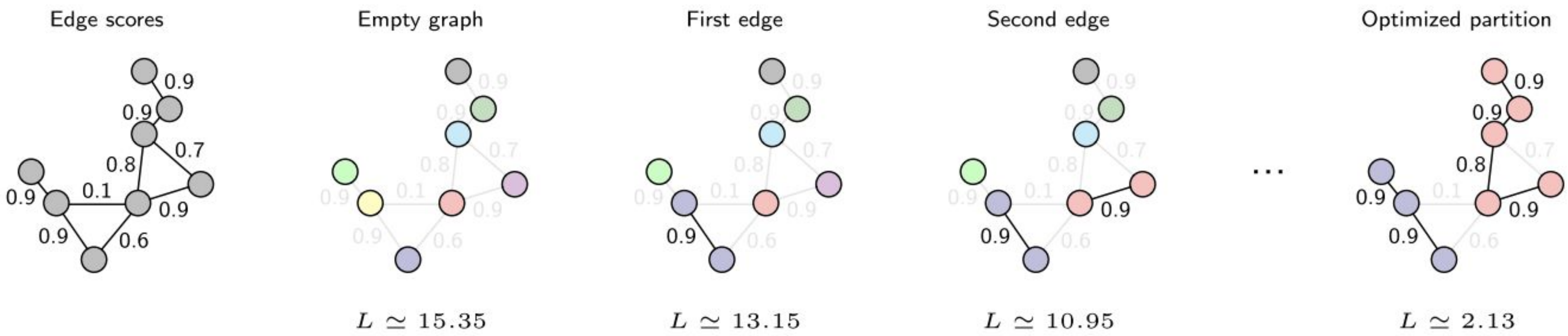
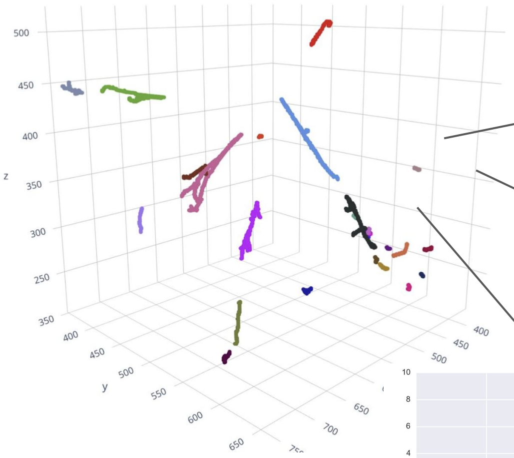
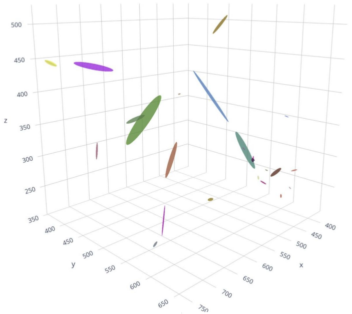


FIG. 7. Schematics of the edge selection mechanism at the inference stage. The partition loss defined in equation (6) is first calculated for an empty graph in which each node forms its own group. Edges are sequentially added in order of decreasing score only if the new partition they form decreases the partition loss. The edge with score 0.6 is not added to the graph because it would put the nodes connected by the edge with score 0.1 in the same group and increase the partition loss.

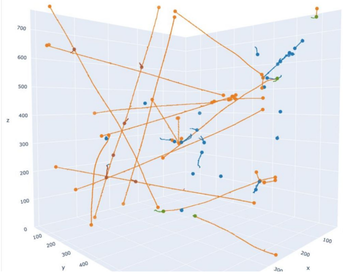
Cluster Clustering: Inputs

Input: Encode Fragments into set of node features





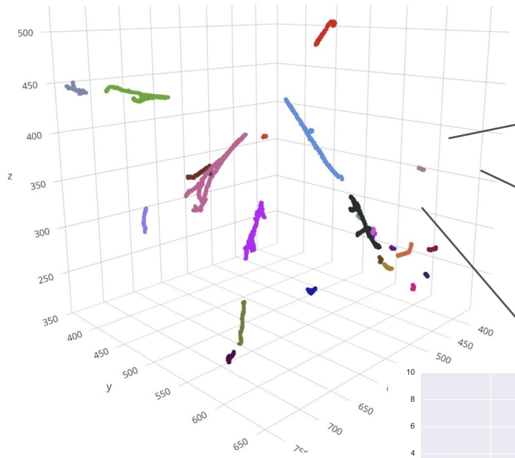
PCA (plot not related to LArTPC data)

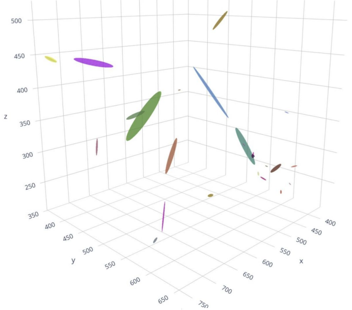


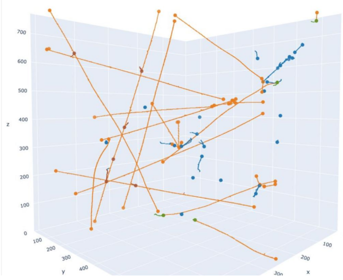
Fragment Summary	# Features
Number of voxels	1
Initial Point	3
Normalized initial direction	3
Normalized covariance matrix	9
Normalized principal axis	3
Centroid	3

Cluster Clustering: Inputs

Input: Encode Fragments into set of node features

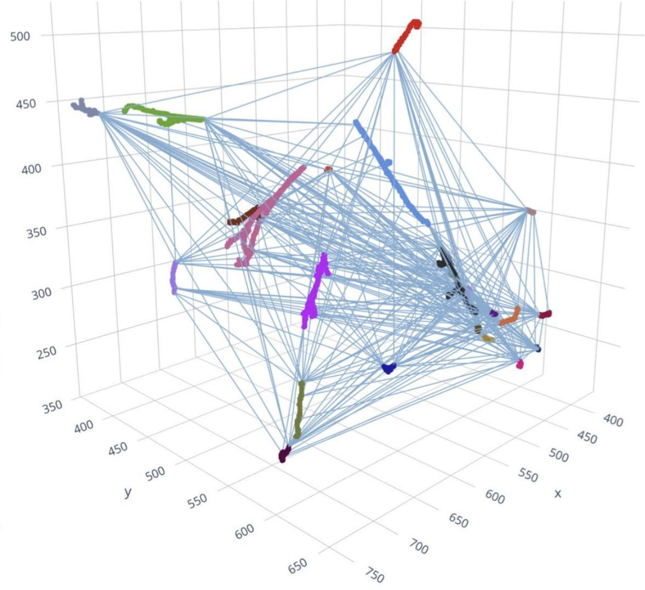




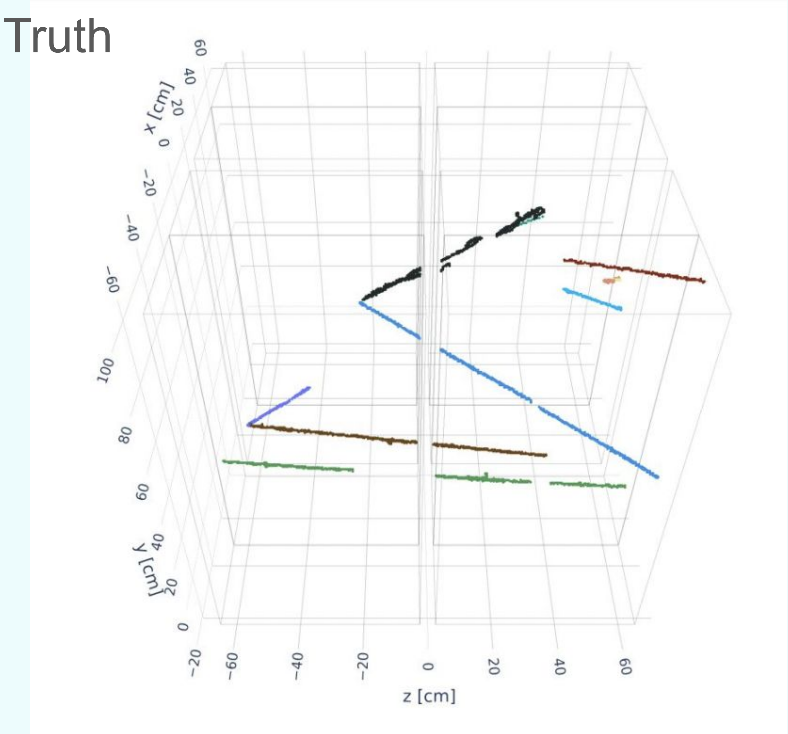


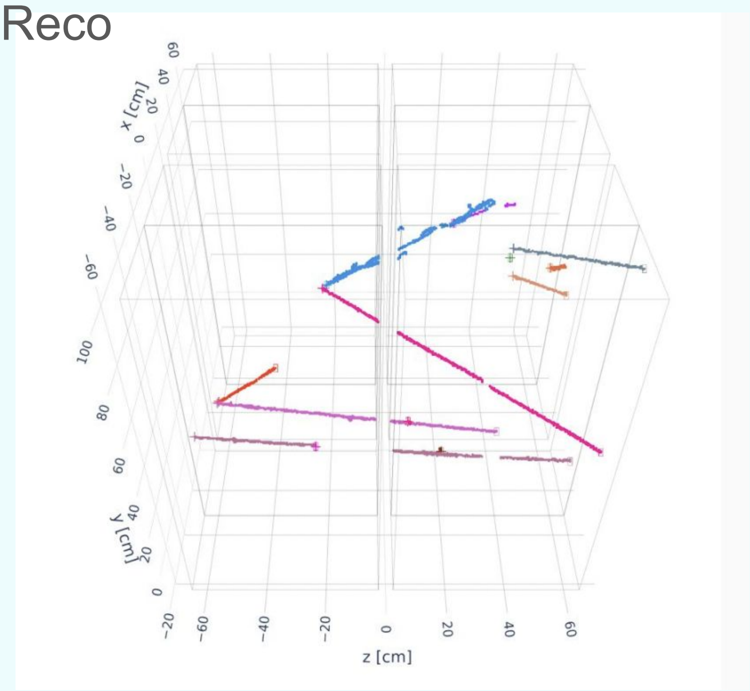
PCA (plot not related to LArTPC data)

Fully connect nodes



Pixel Features: Output

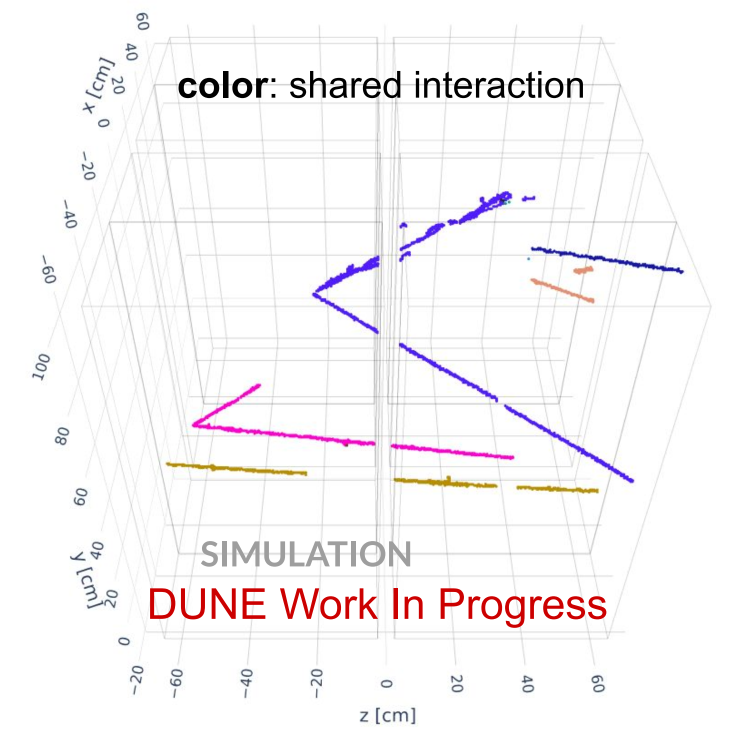




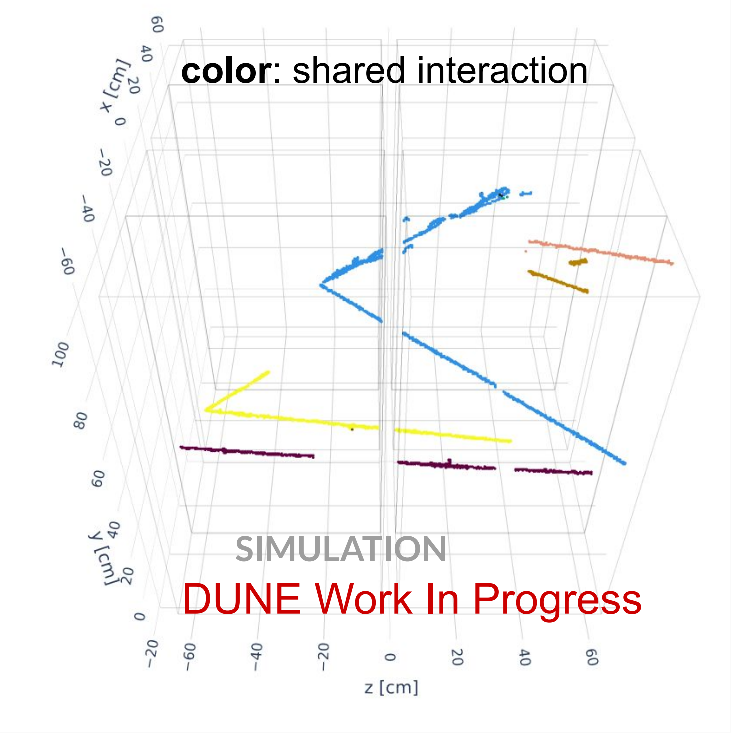
[Phys Rev D (102) 012005]()

Performance Shared Interaction

Truth



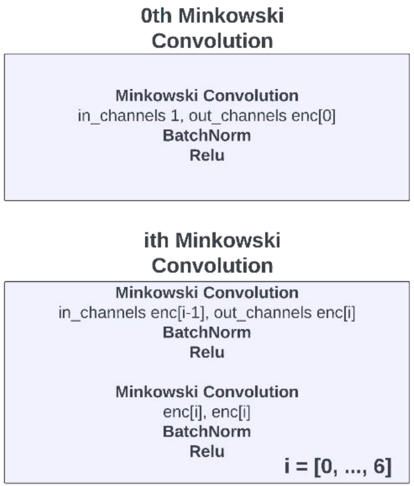
Reco

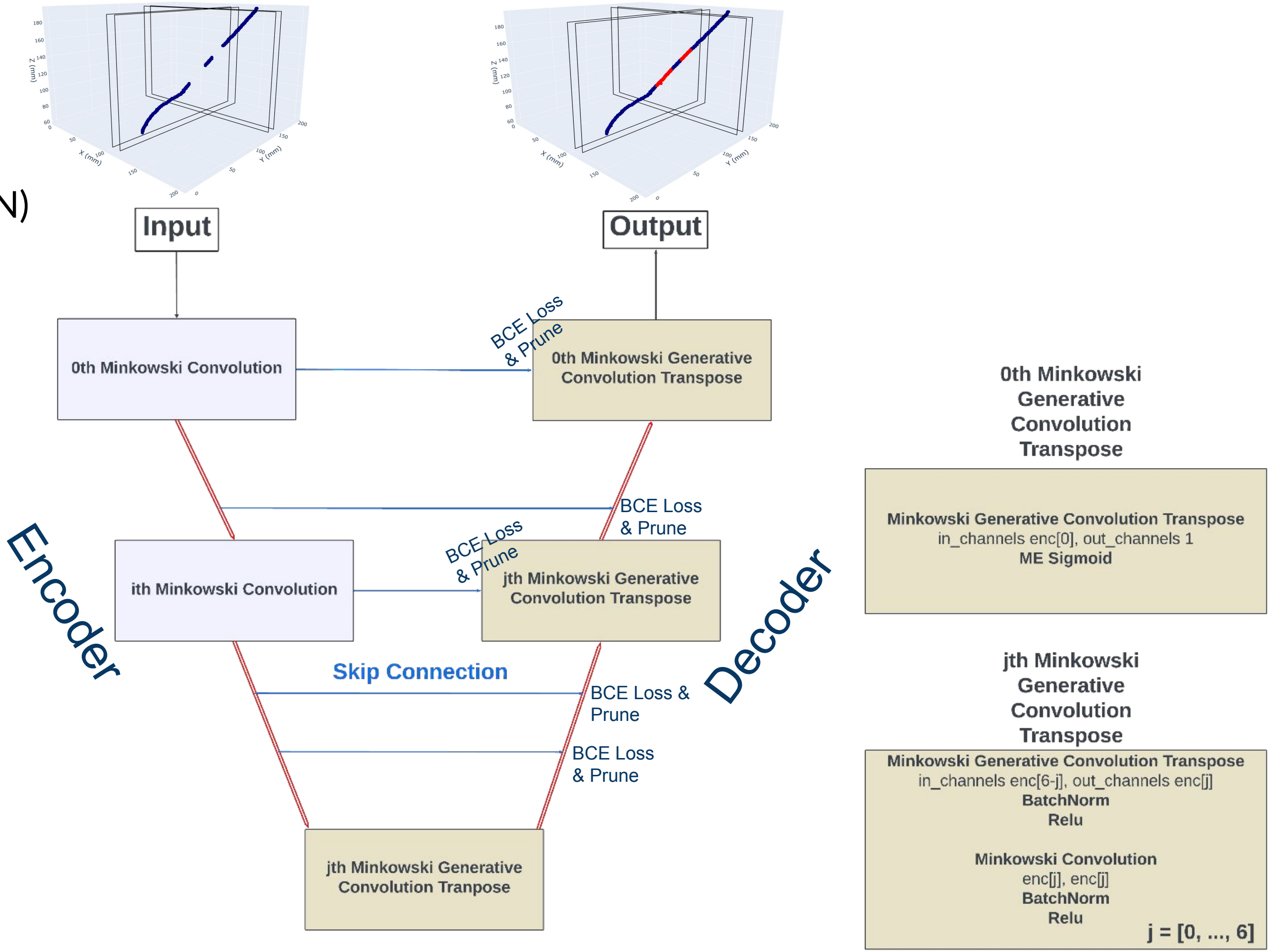


Architecture UNet

- Minkowski Engine (Sparse CNN)
  - Auto-Differential library for Sparse tensors
- BCE loss and prune bad coordinates

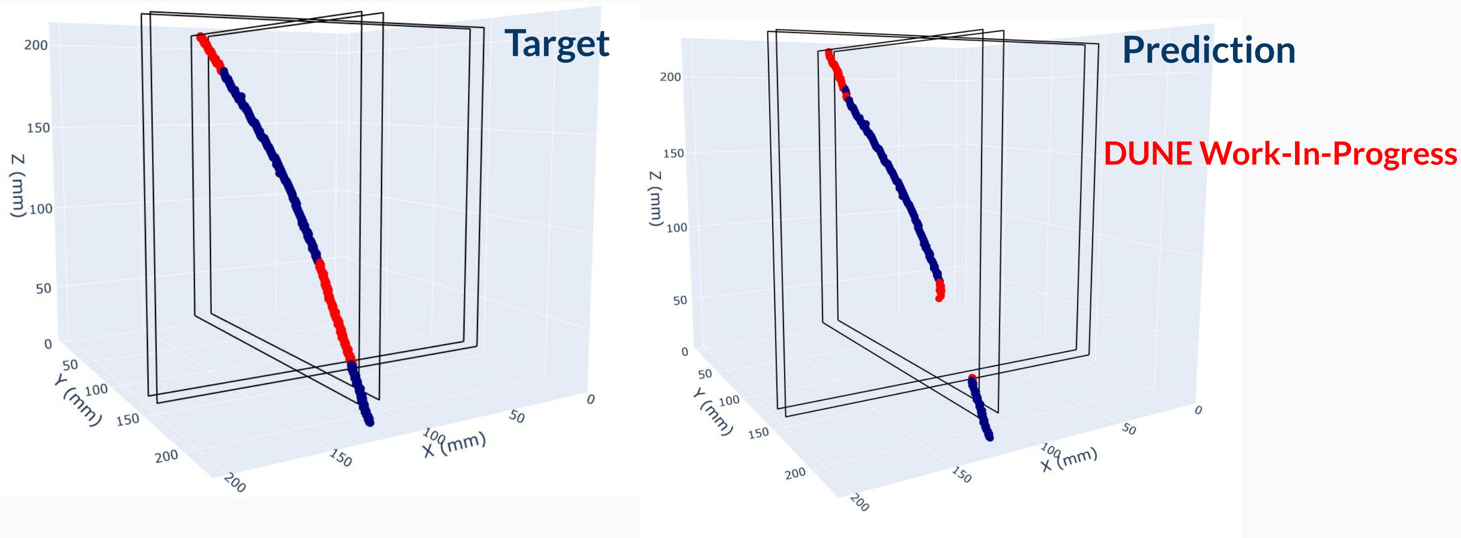
  after each skip connection!





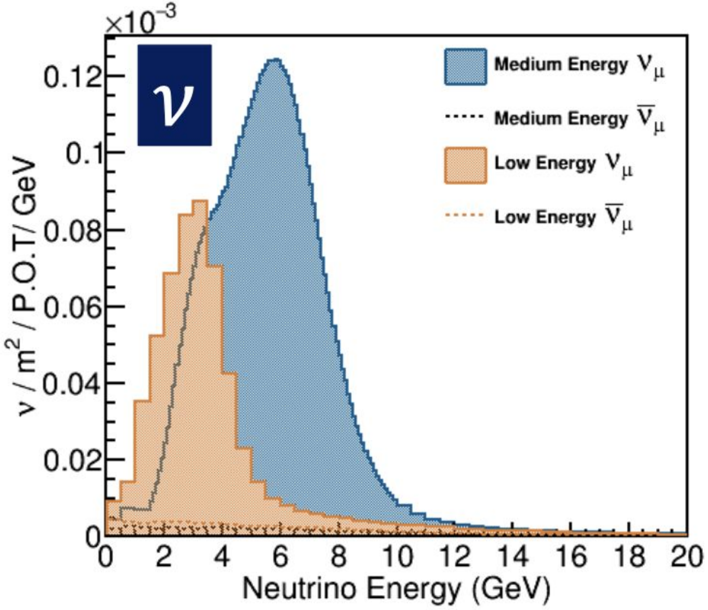
Preliminary Results: Work in Progress

Network doesn’t always fully reconstruct missing region.
→ Exploring adding more input feature information



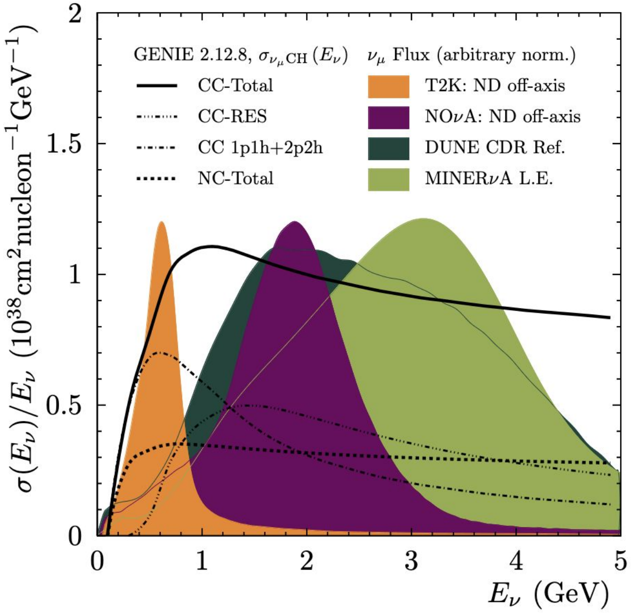
2x2 Prototype Beam vs DUNE Beam

NuMI



https://indico.cern.ch/event/881216/contributions/5048756/attachments/2534229/4361050/Klustova_MINERvAFlux_NuINT22.pdf

DUNE (dark green)



https://arxiv.org/pdf/1803.08848.pdf