

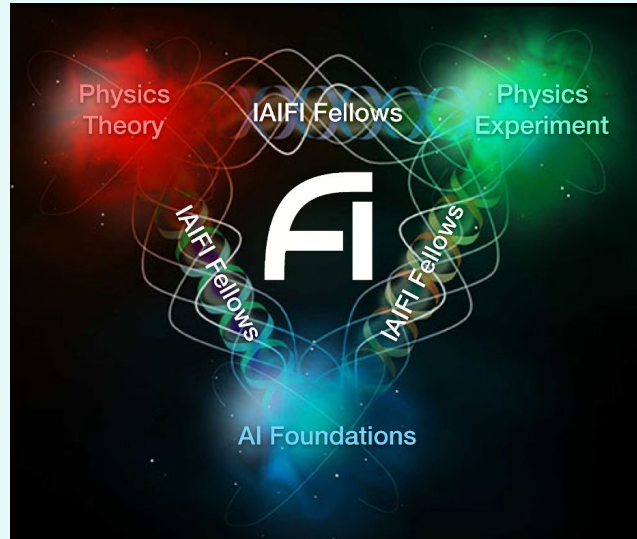
Intense Neutrino Reco: MLReco3D for DUNE's Near Detector

Jessie Micallef
on behalf of the DUNE Collaboration

[IAIFI](#) Postdoc Fellow
jessiem@mit.edu

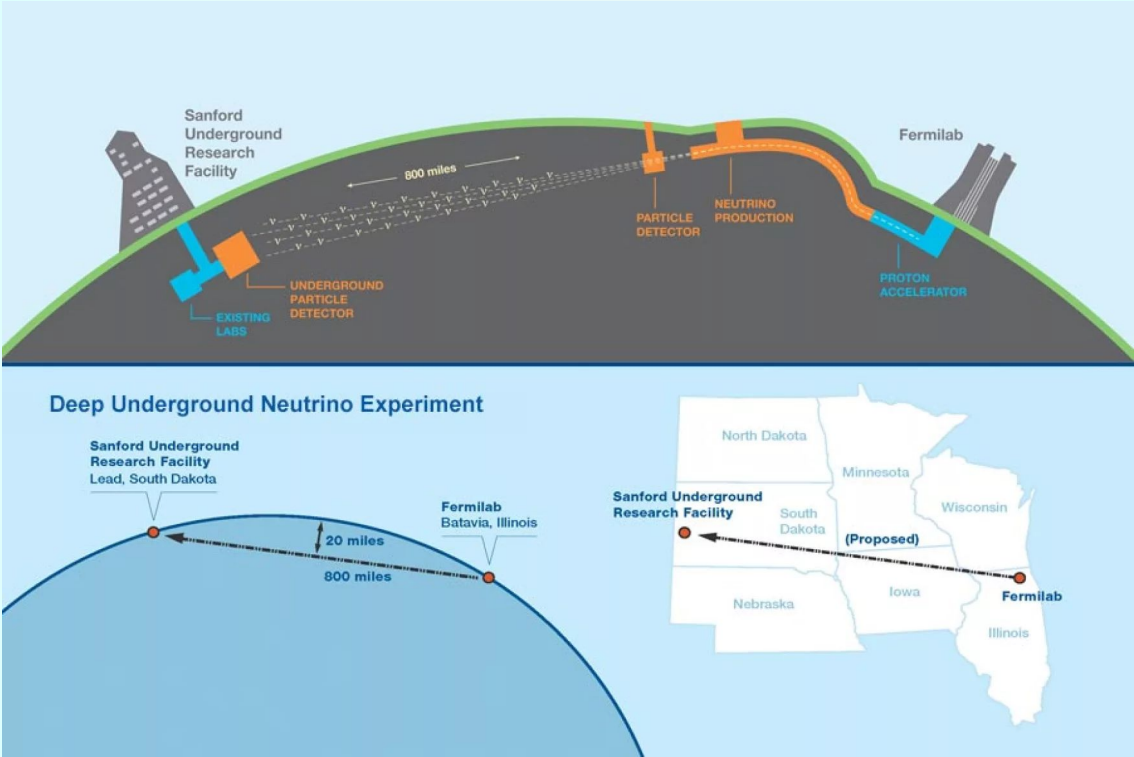
Neutrinos & Machine Learning

Institute for Artificial Intelligence and Fundamental Interactions

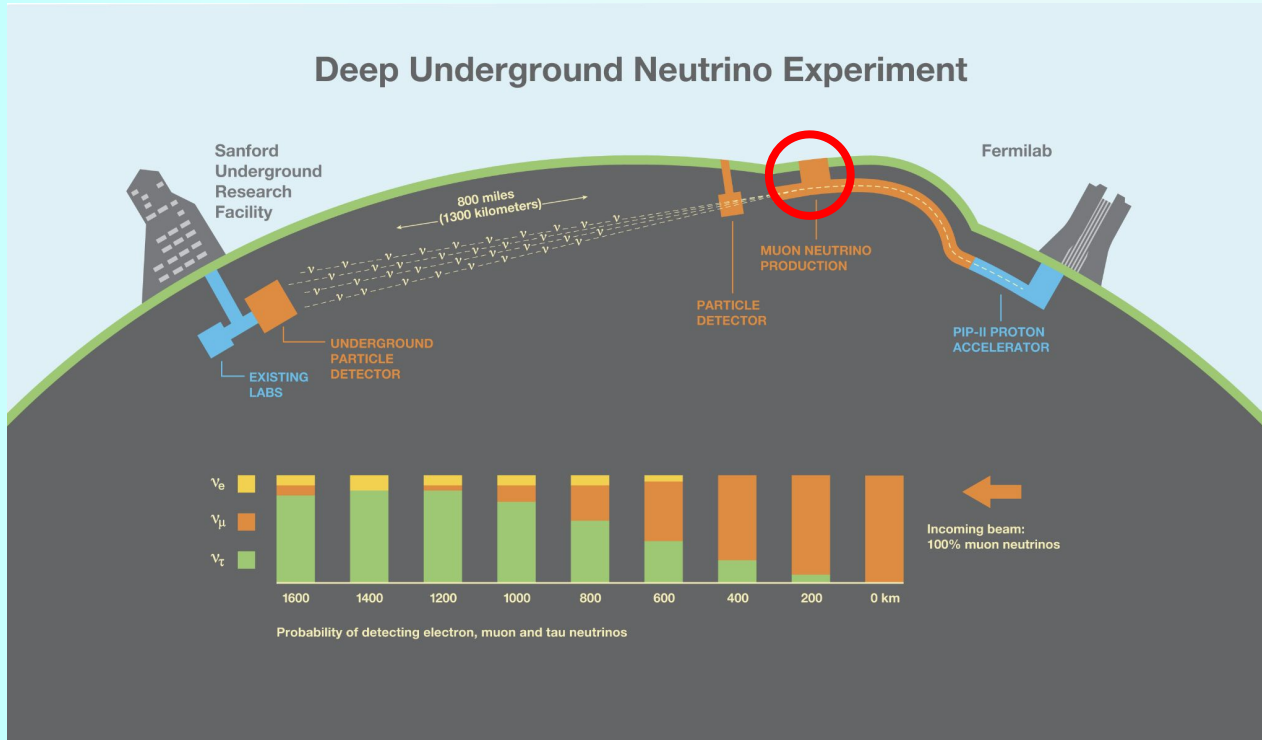


<https://jessimic.github.io/tech-portfolio/>

DUNE: Deep Underground Neutrino Experiment

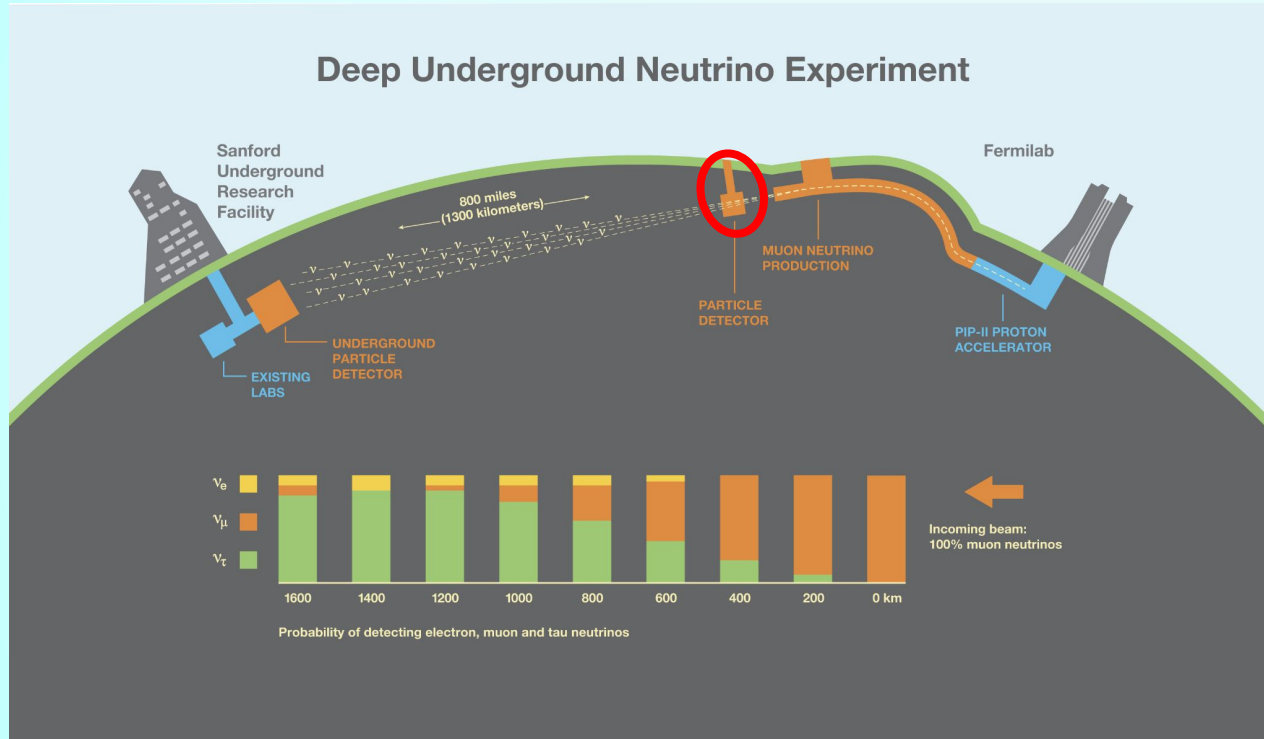


DUNE: Frontier Measurements of Neutrino Physics



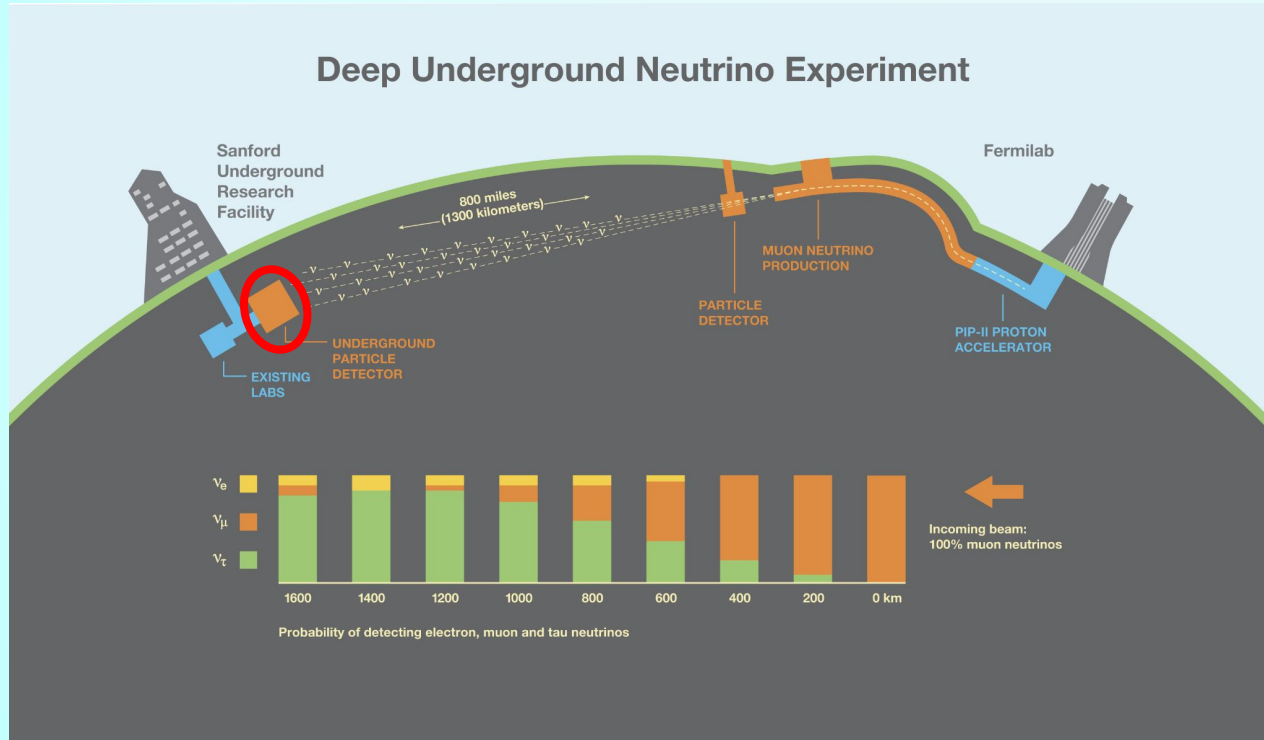
- PIP-II upgrade will lead to world's most intense neutrino beam

DUNE: Frontier Measurements of Neutrino Physics



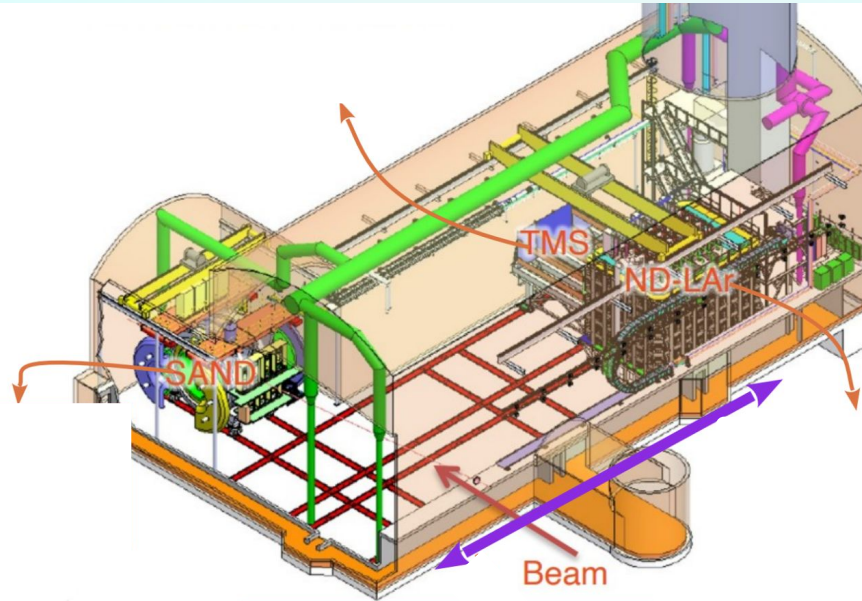
- PIP-II upgrade will lead to world's most intense neutrino beam
- Near detectors at Fermilab

DUNE: Frontier Measurements of Neutrino Physics



- PIP-II upgrade will lead to world's most intense neutrino beam
- Near detectors at Fermilab
- Far detector at SURF

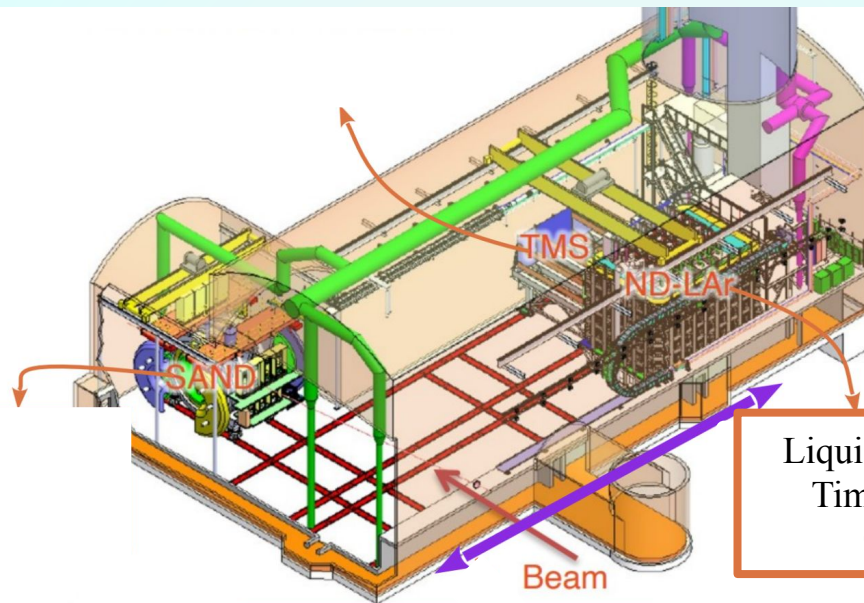
Near Detector Hall



Important to
measure ν ...

- Energy
- Cross section
- Flux

Near Detector Hall

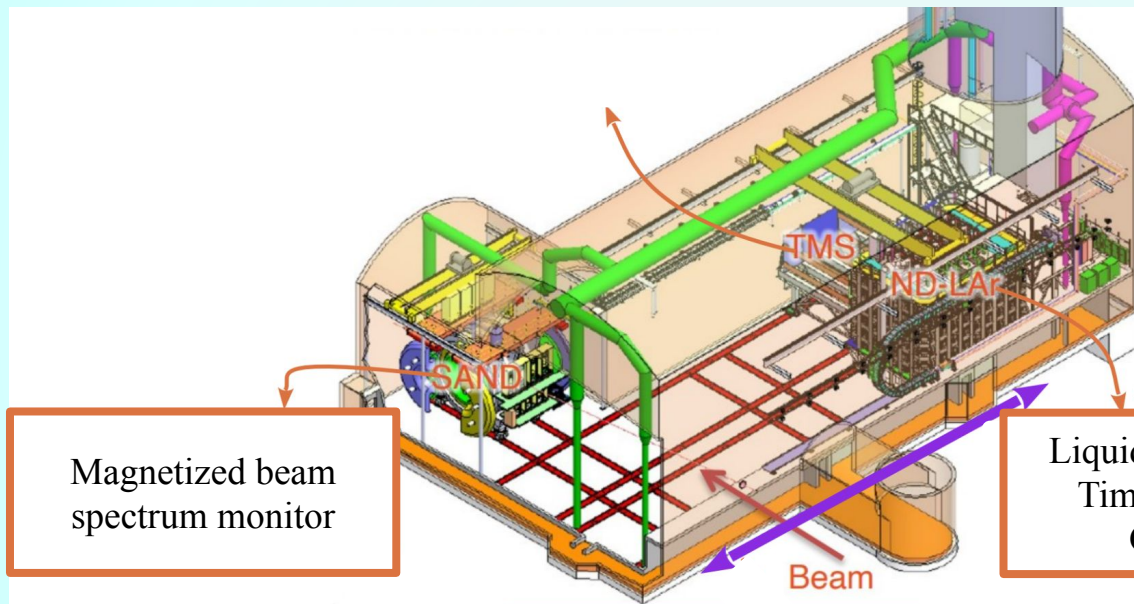


Important to measure ν ...

- Energy
- Cross section
- Flux

Liquid Argon (LAr)
Time Projection
Chamber

Near Detector Hall



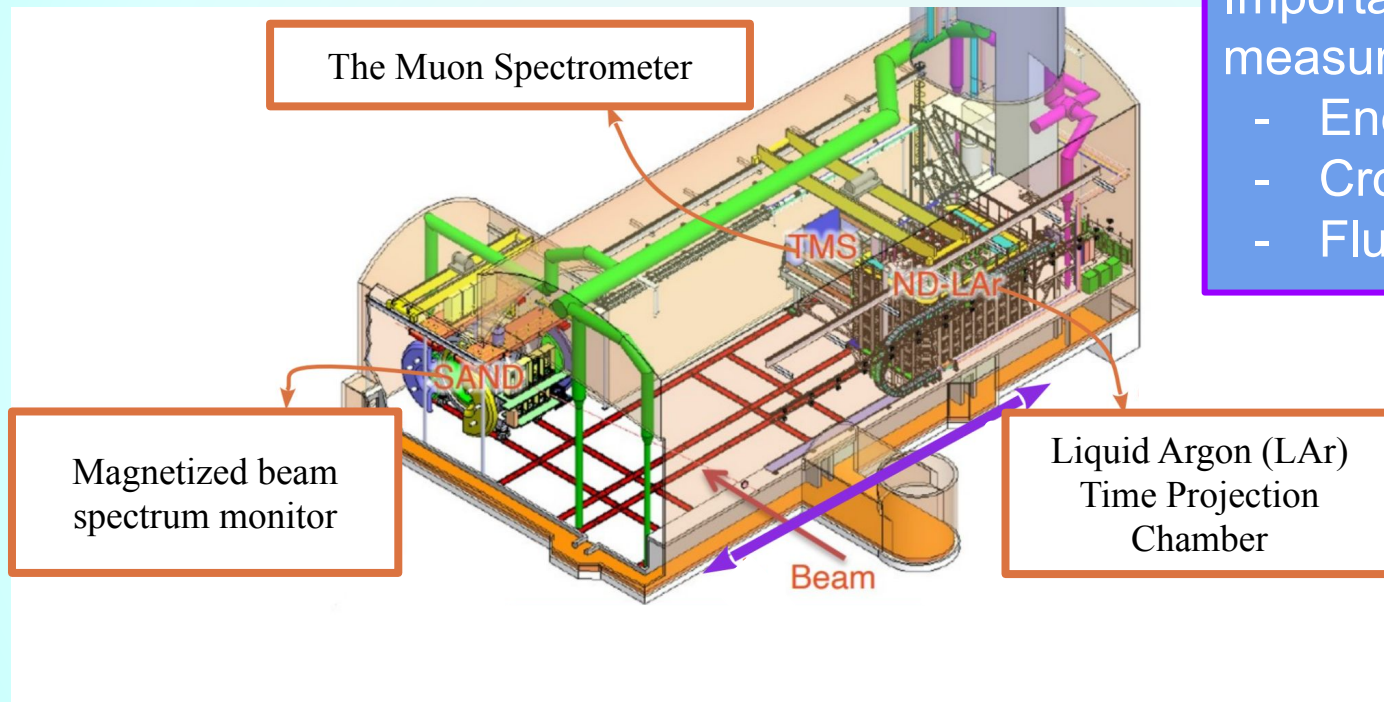
Magnetized beam
spectrum monitor

Liquid Argon (LAr)
Time Projection
Chamber

Important to
measure ν ...

- Energy
- Cross section
- Flux

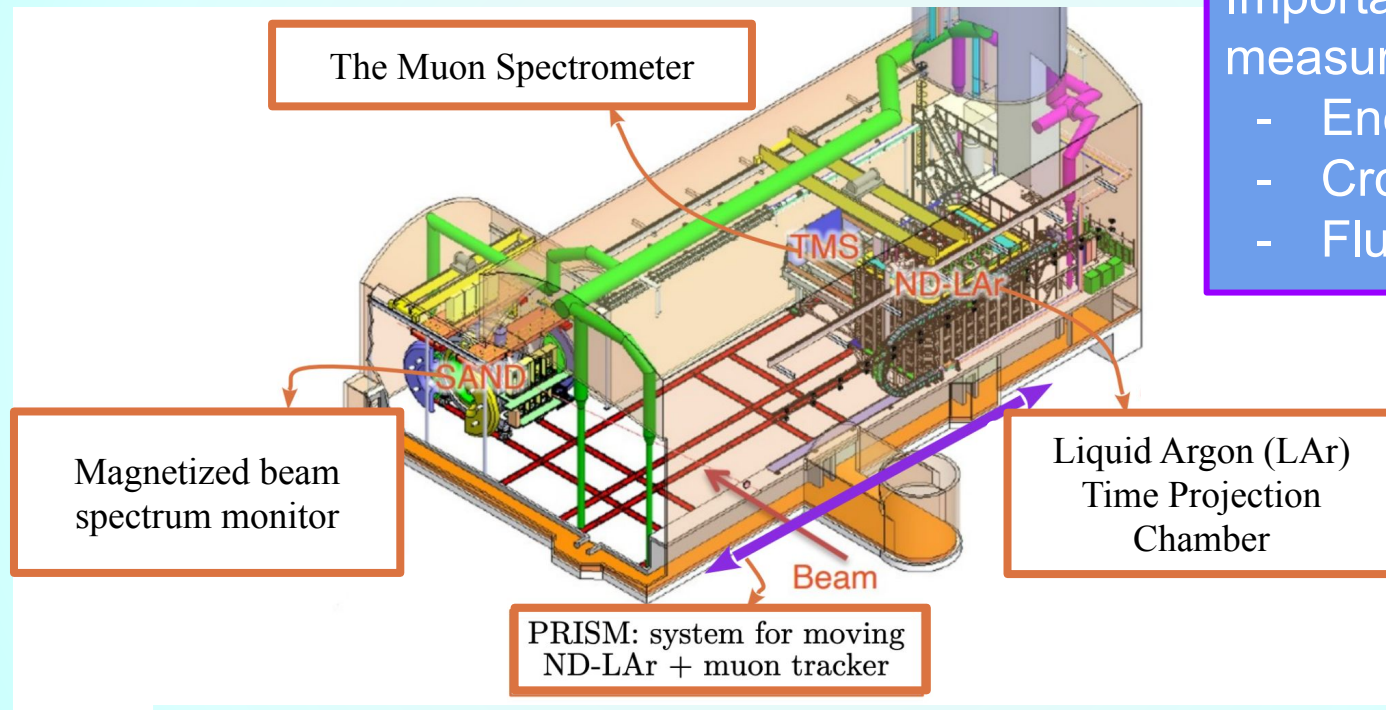
Near Detector Hall



Important to measure ν ...

- Energy
- Cross section
- Flux

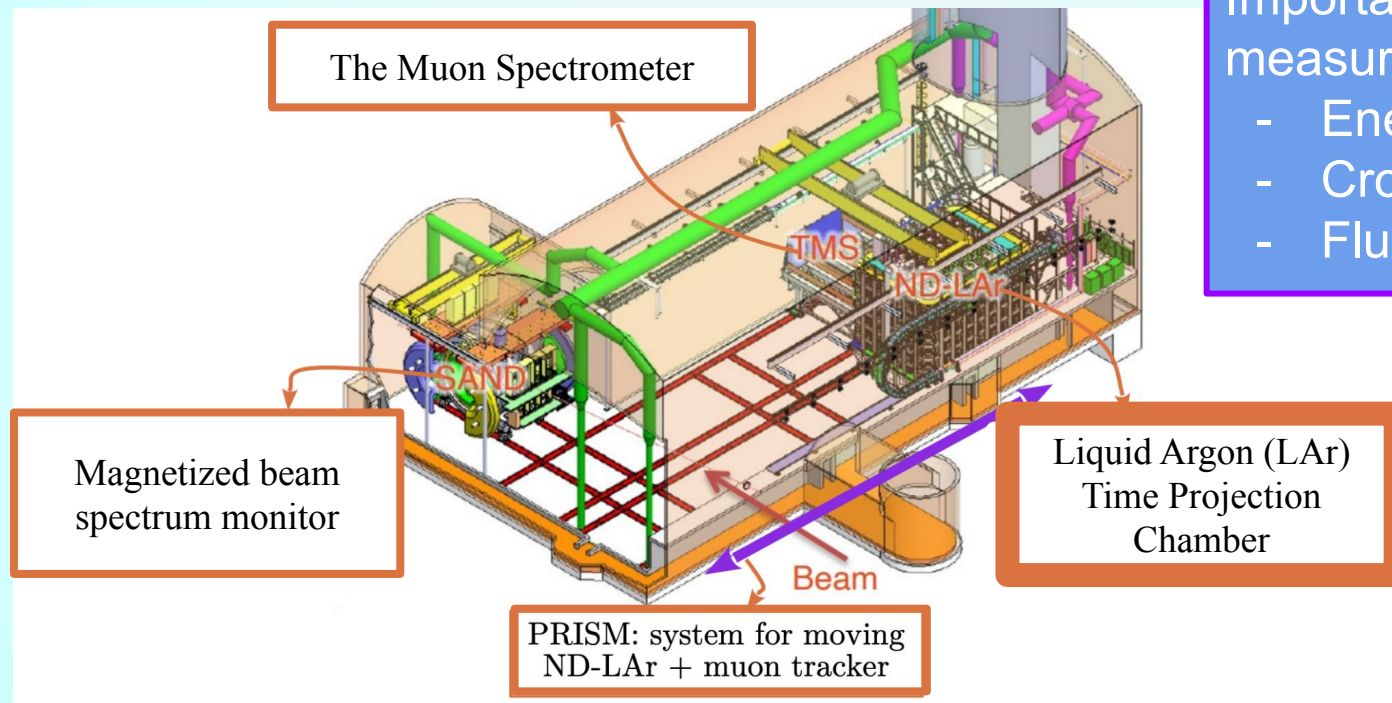
Near Detector Hall



Important to measure ν ...

- Energy
- Cross section
- Flux

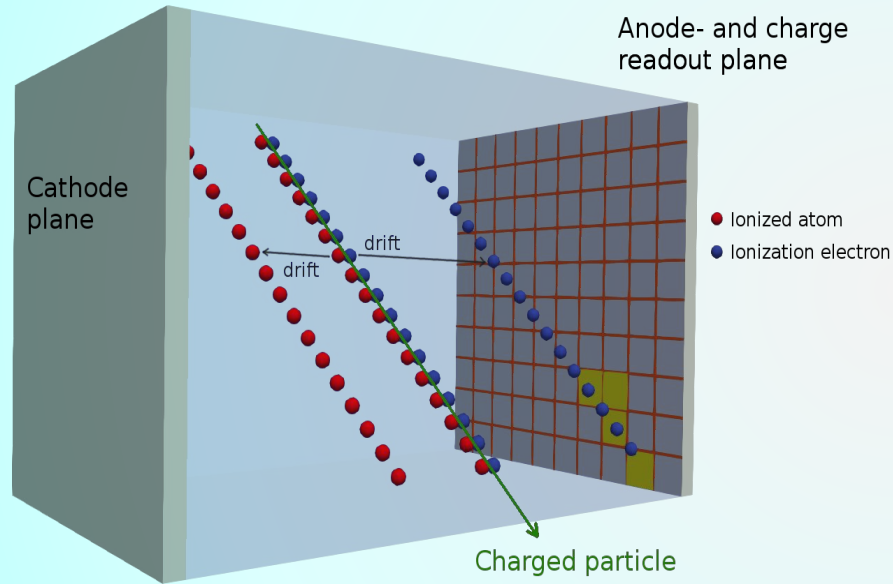
Near Detector Hall



Important to measure ν ...

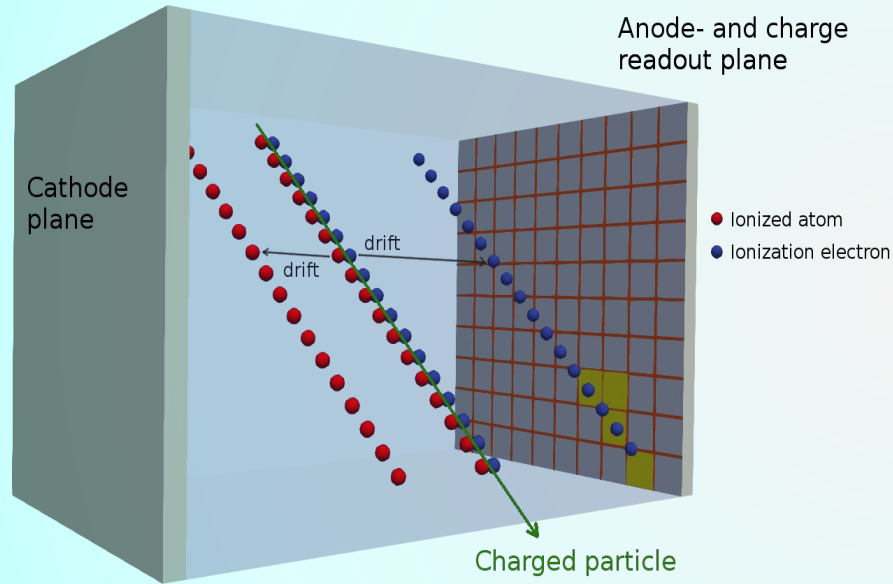
- Energy
- Cross section
- Flux

Liquid Argon (LAr) Time Projection Chamber (TPC)

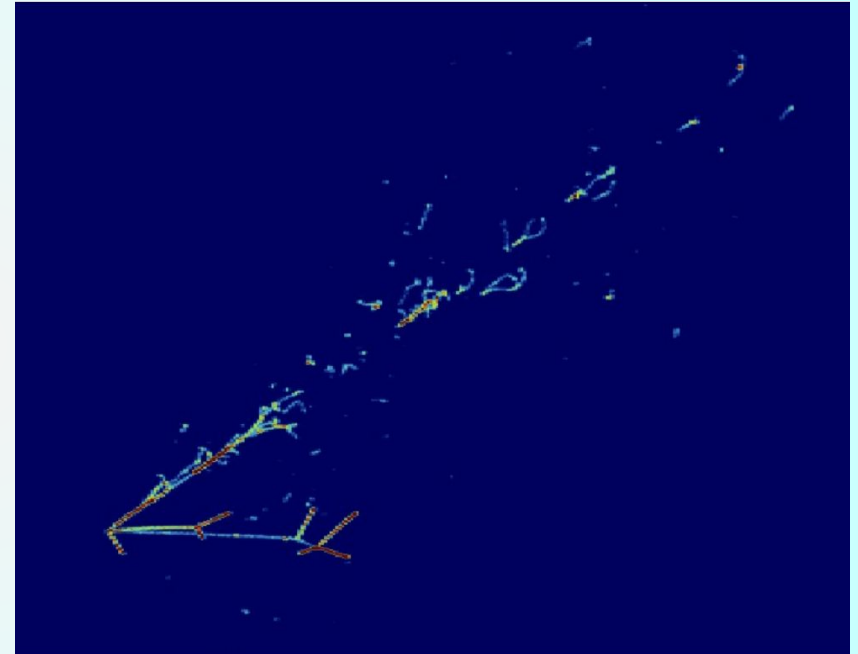


<https://argoncube.org/LArTPCs.html>

Liquid Argon (LAr) Time Projection Chamber (TPC)

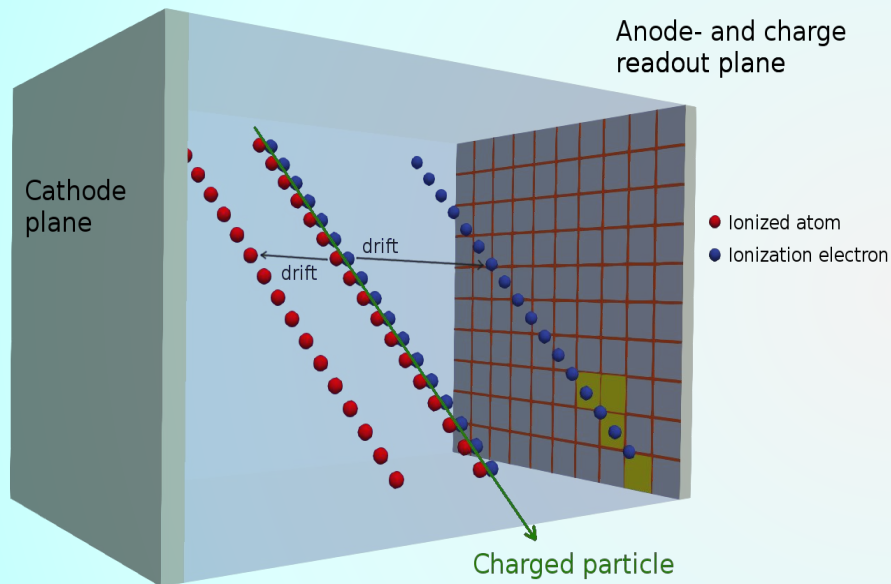


<https://argoncube.org/LArTPCs.html>

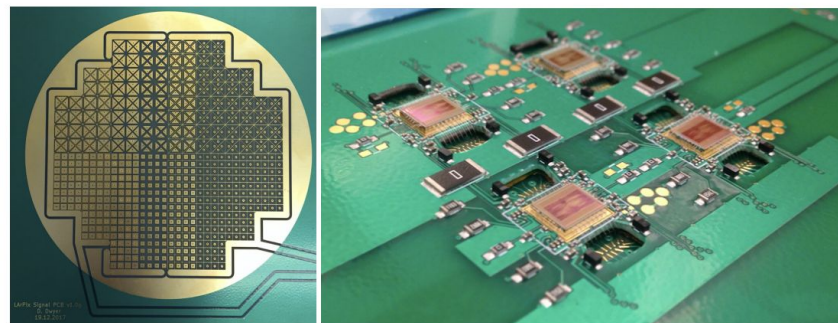


Color = charge deposition
Output: pion and two protons

Liquid Argon (LAr) Time Projection Chamber (TPC)



But we're using a 2D pixel plane readout! So we get a 3D image!



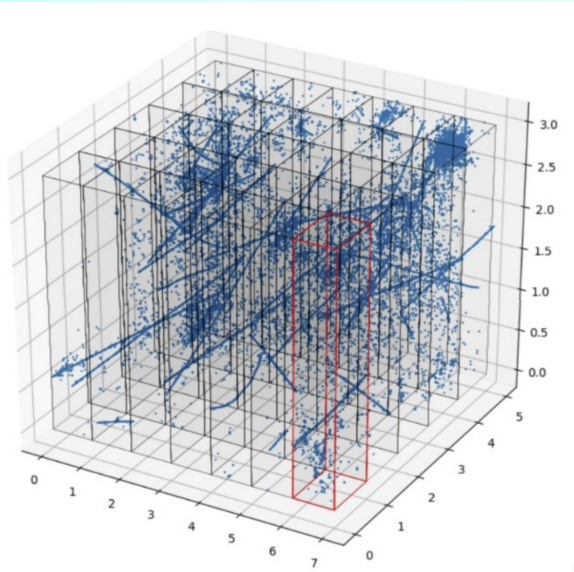
TPC-facing side of pixel plane with 832 pads (left) and back of plane with 4 LArPix ASICs (right).

[LArPix Paper](#)

<https://argoncube.org/LArTPCs.html>

Handling Beam Intensity

- Expect ~ 55 ν interactions!

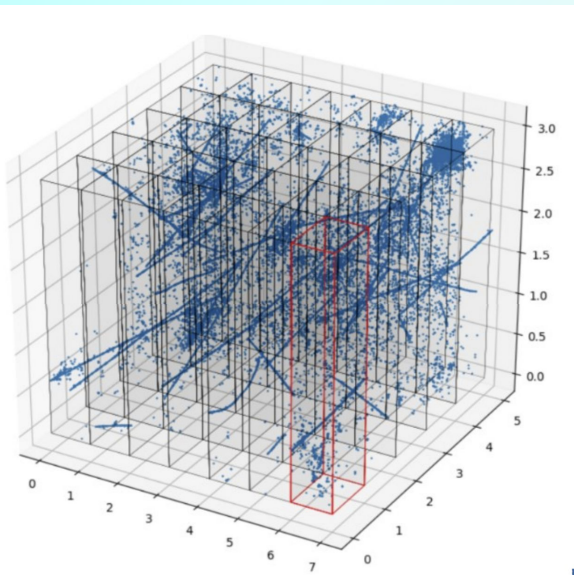


Simulation of ND LAr
beam spill ($10\mu s$)

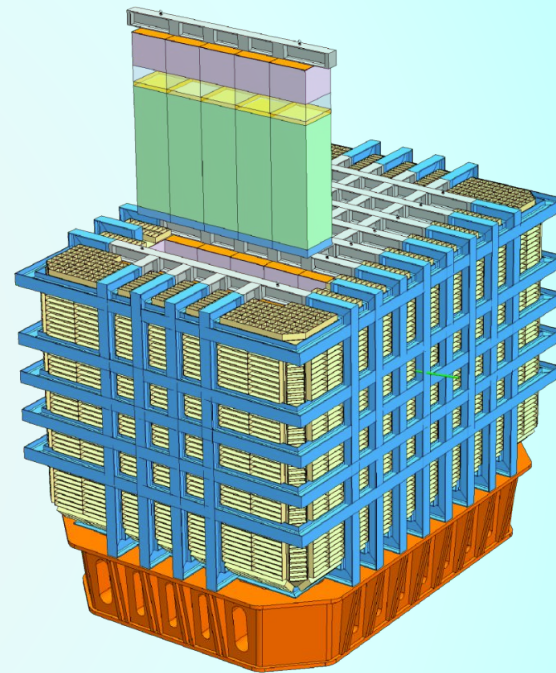
<https://argoncube.org/LArTPCs.html>

Handling Beam Intensity

- Expect ~ 55 ν interactions!
- Need new technology:
 - Modular detector for shorter drift



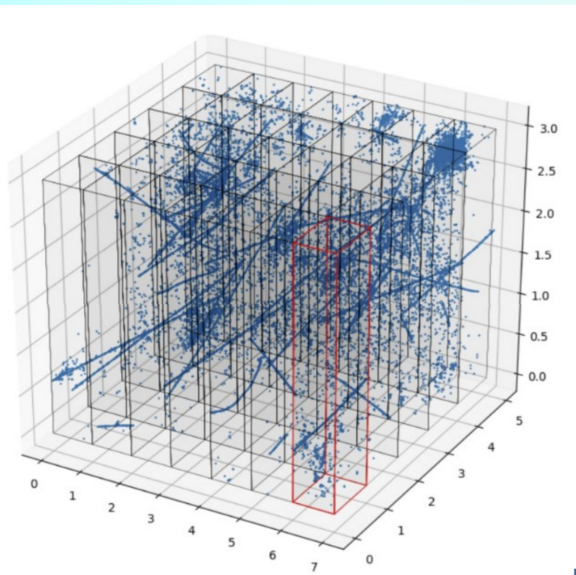
Simulation of ND LAr
beam spill ($10\mu s$)



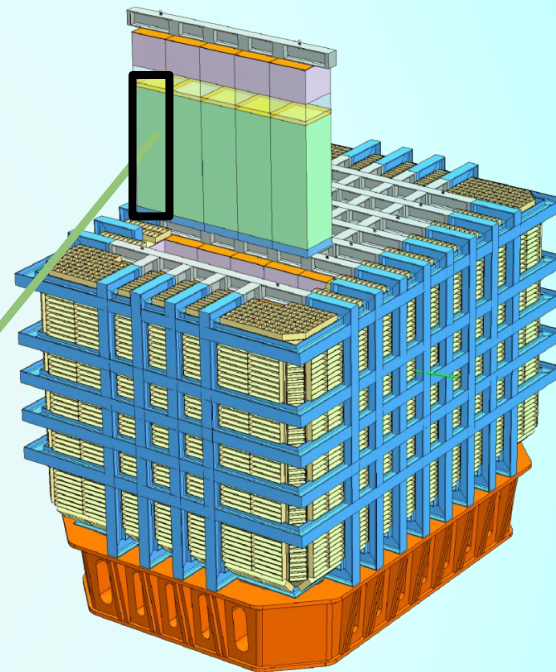
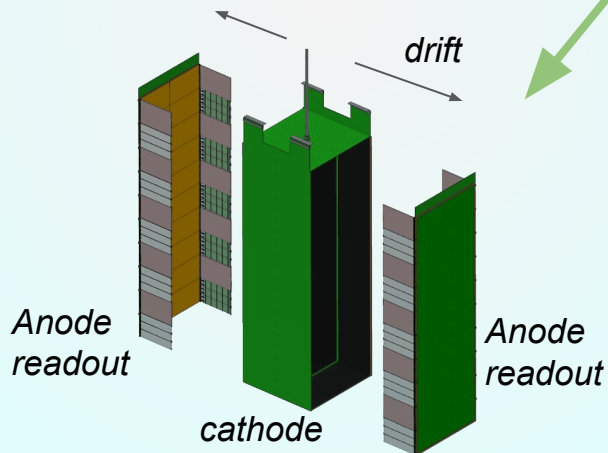
<https://argoncube.org/duneND.html>

Handling Beam Intensity

- Expect $\sim 55 \nu$ interactions!
- Need new technology:
 - Modular detector for shorter drift
- TPC with central cathode

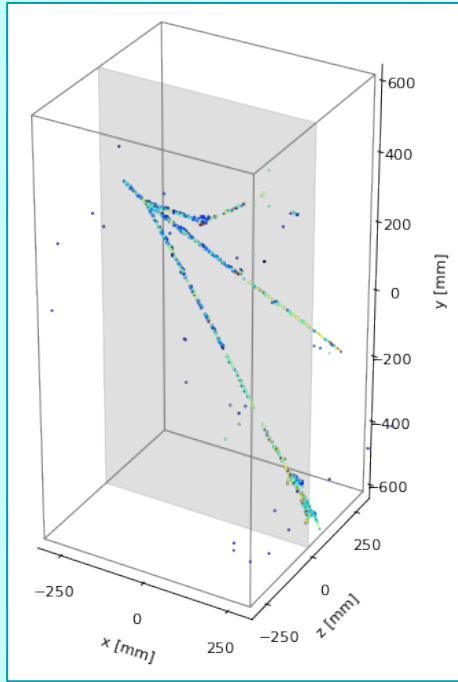


Simulation of ND LAr
beam spill ($10\mu s$)



<https://argoncube.org/duneND.html>

Handling Beam Intensity



Simulation of 1 ND
LAr TPC module

- Expect $\sim 55 \nu$ interactions!
- Need new technology:
 - Modular detector for shorter drift
- TPC with central cathode

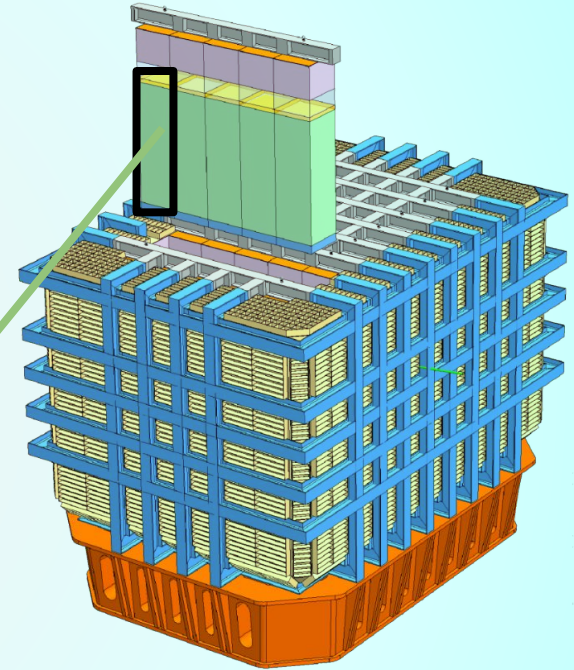
Pixel
plane for
3D
display

Anode
readout

cathode

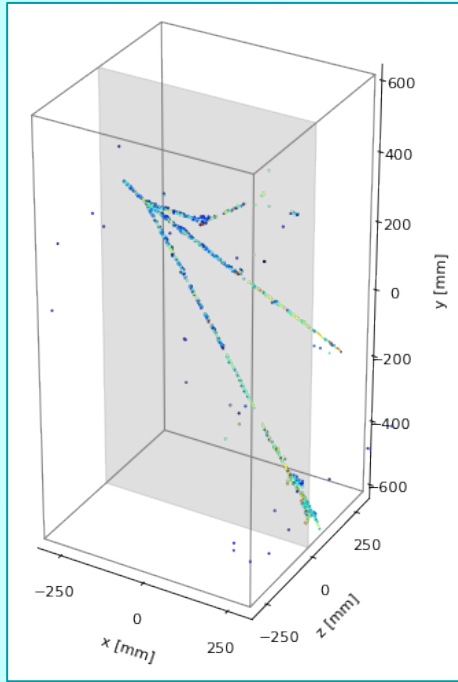
Anode
readout

drift



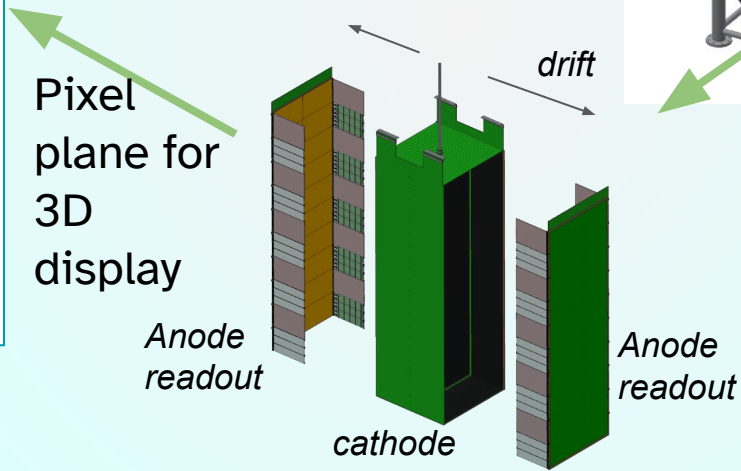
<https://argoncube.org/duneND.html>

Handling Beam Intensity: 2x2 Prototype



Simulation of 1 ND LAr TPC module

- Expect $\sim 55 \nu$ interactions
- Need new technology
 - Modular detector
 - shorter drift
- TPC with central cathode

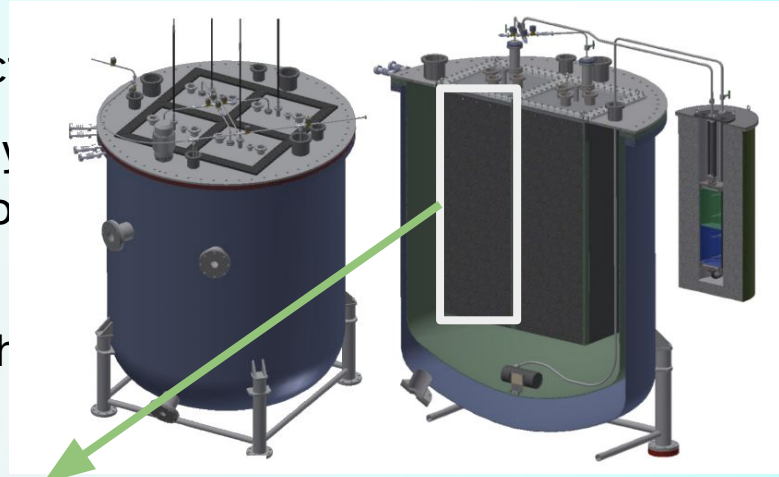


Pixel plane for 3D display

Anode readout

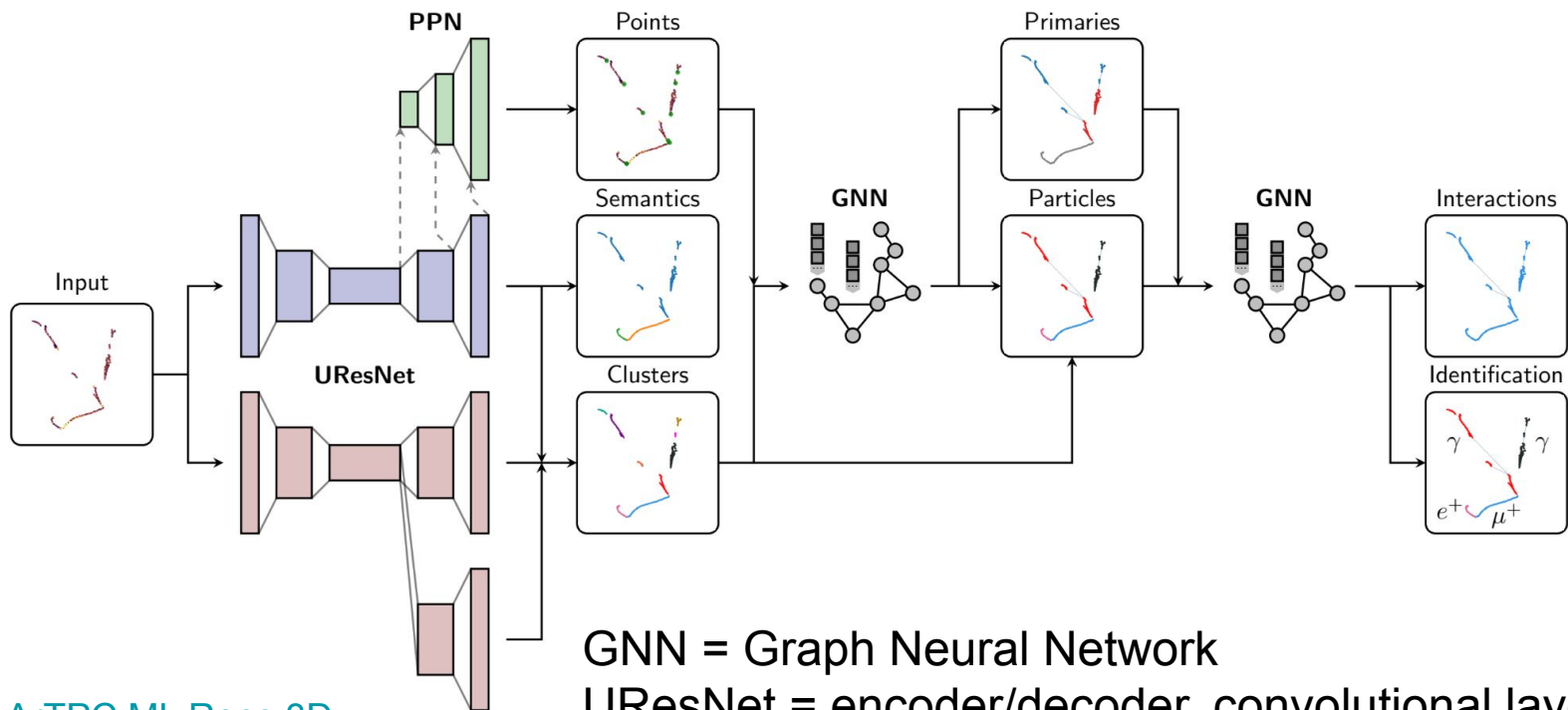
cathode

Anode readout



See Brooke's [ND-LAr Overview](#) and Richie's [2x2 Software](#) talks from Thursday!

3D LAr TPC: ML Reco 3D



GNN = Graph Neural Network

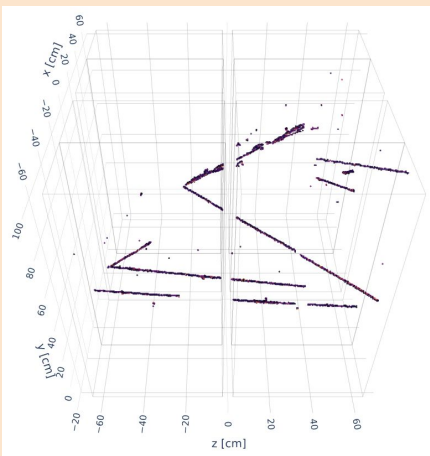
UResNet = encoder/decoder, convolutional layers

PPN = Point Proposal Network (convolutional)

[LArTPC ML Reco 3D](#)

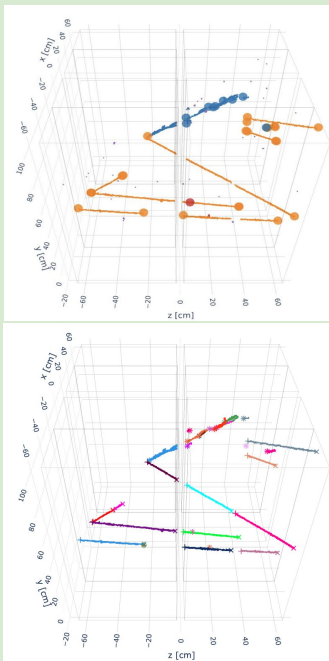
3D LAr TPC: ML Reco 3D

Input: Charge deposition

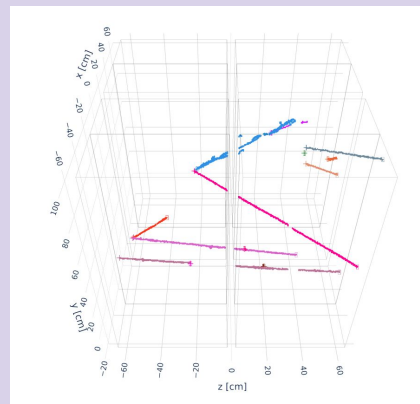


Color: energy deposition heatmap

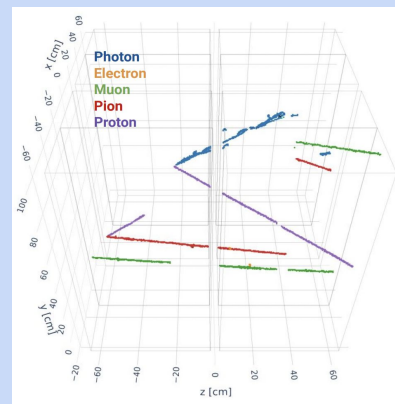
Pixel Features



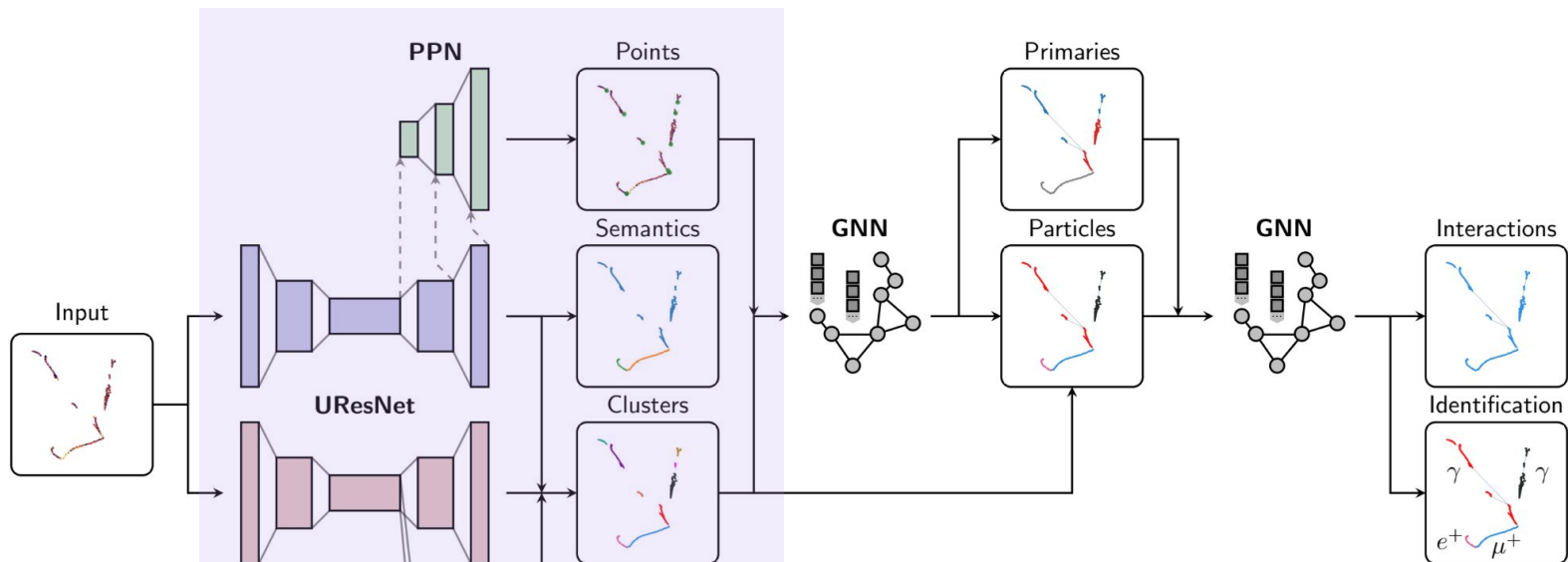
Fragment Clustering



Identification & Interactions



3D LAr TPC: ML Reco 3D

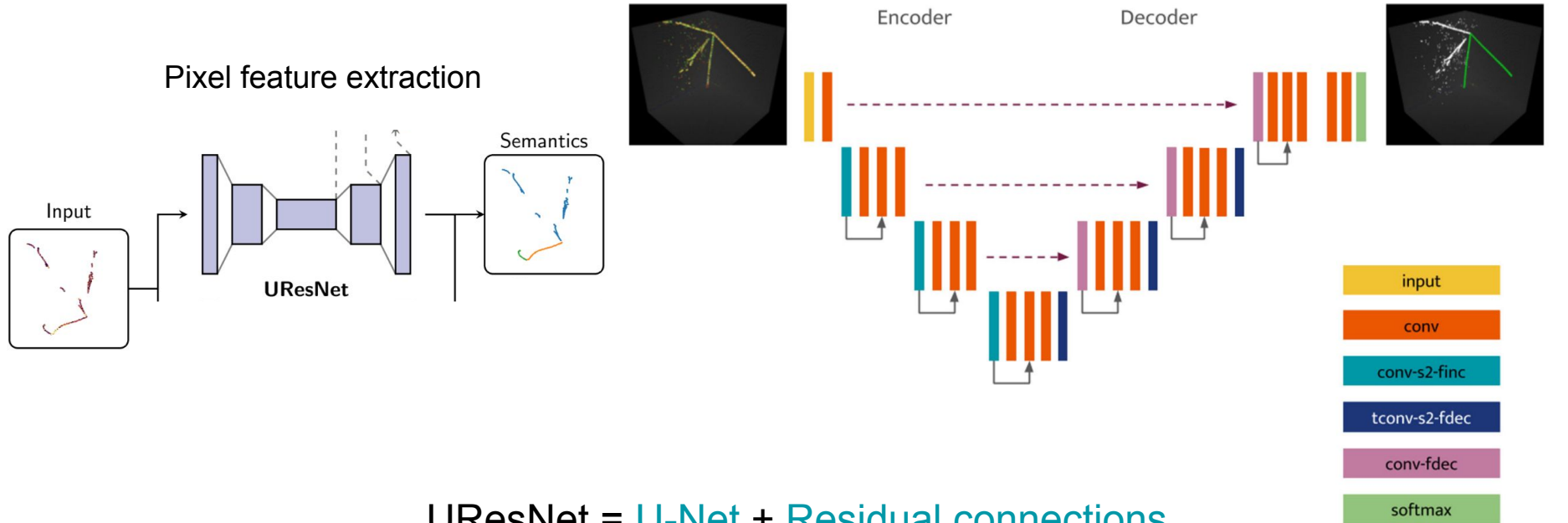


GNN = Graph Neural Network

UResNet = encoder/decoder, convolutional layers

PPN = Point Proposal Network (convolutional)

Pixel Features: Semantics



UResNet = U-Net + Residual connections

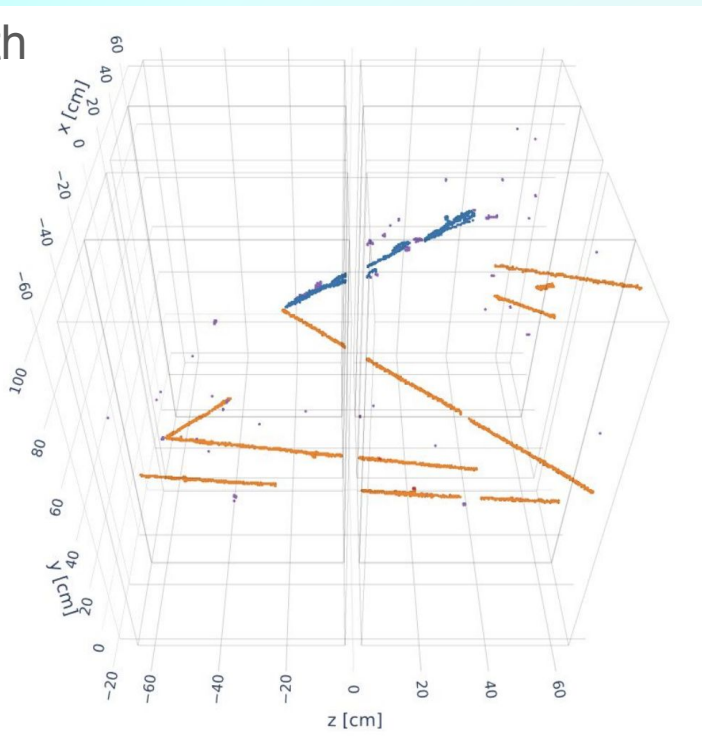
→ Uses autoencoder

→ Uses submanifold sparse convolutional layers

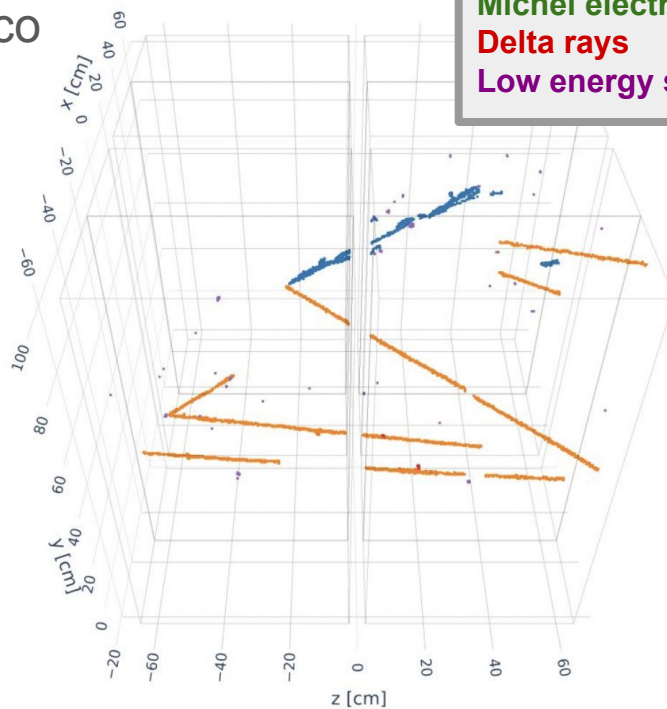
[Phys Rev D \(102\) 012005](#)

Assign Each Pixel To Label

Truth



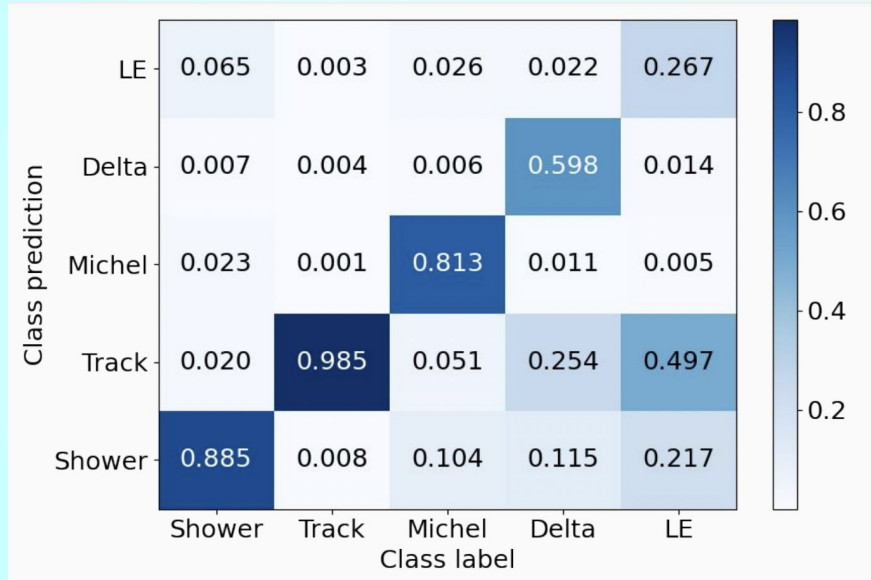
Reco



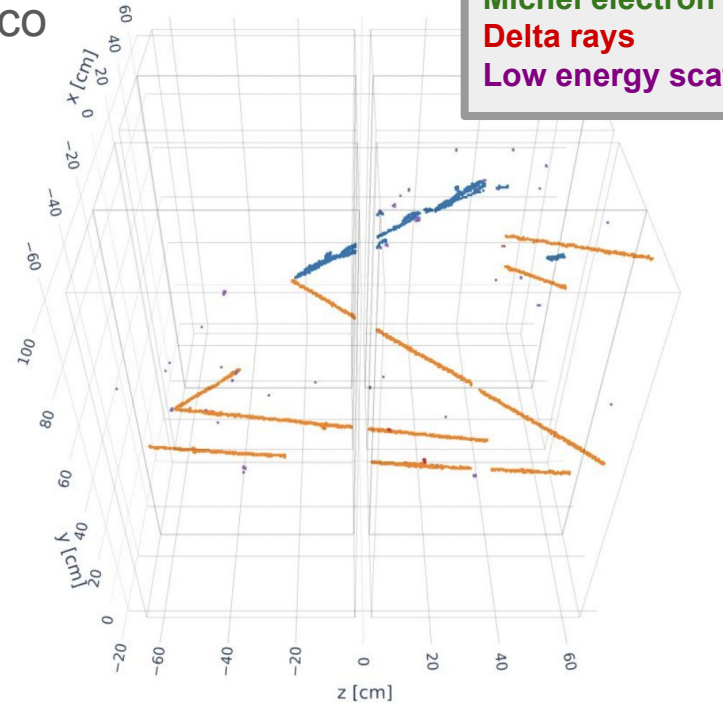
Track
Shower
Michel electron
Delta rays
Low energy scatters

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

Assign Each Pixel To Label

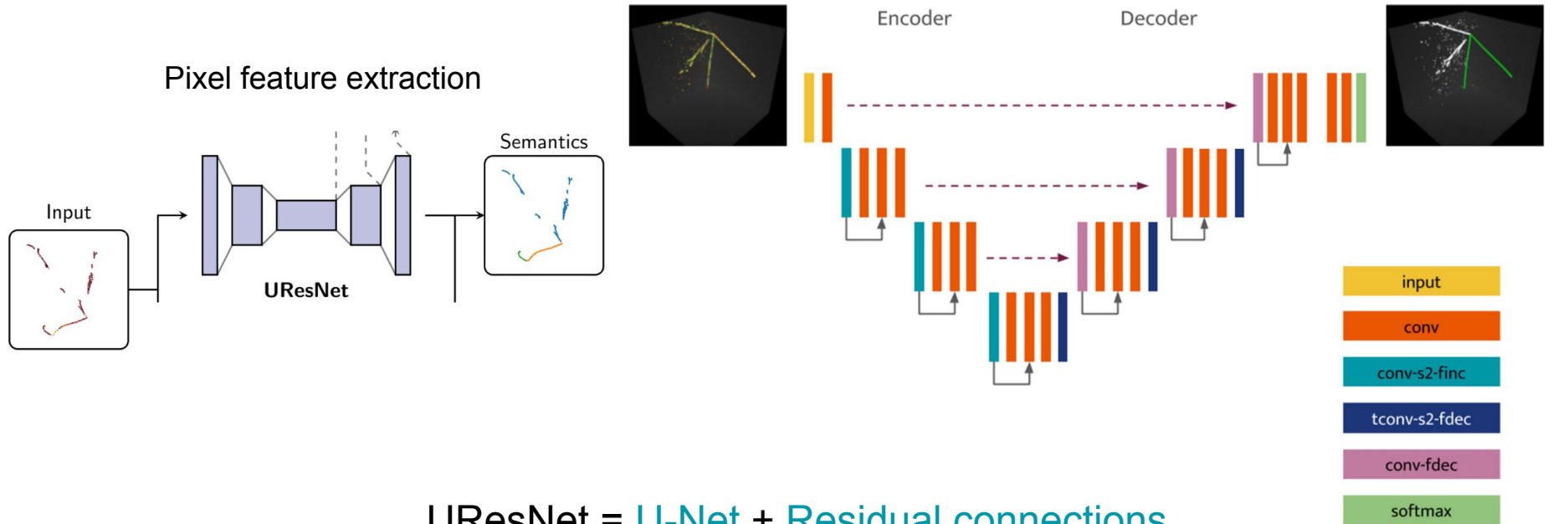


Reco



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

Pixel Features: Semantics



UResNet = U-Net + Residual connections

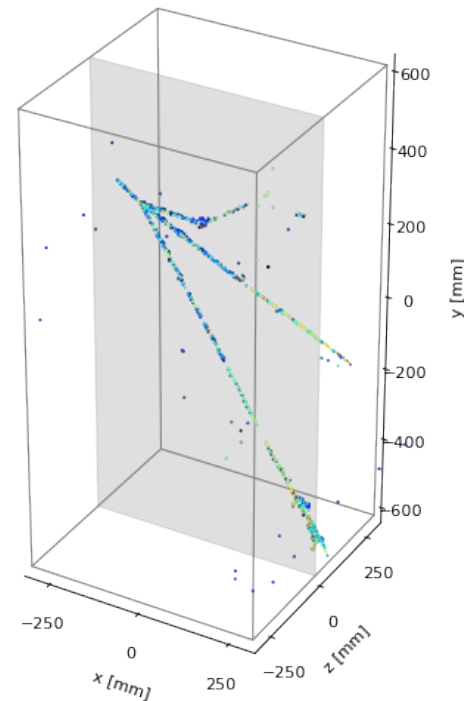
→ Uses autoencoder

→ Uses submanifold sparse convolutional layers

[Phys Rev D \(102\) 012005](#)

Sparse

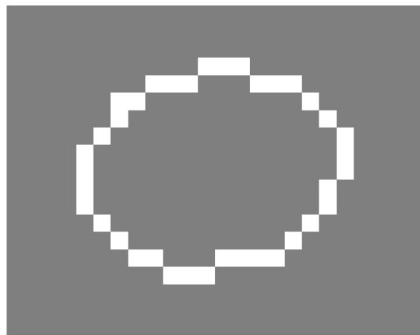
< 0.01 % of the pixels are non-zero!



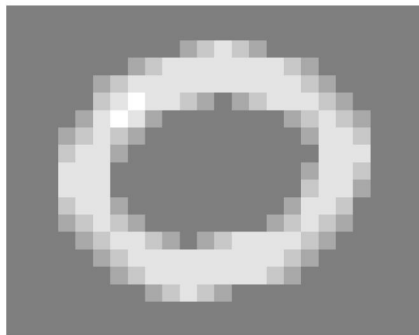
Submanifold Sparse Convolutions

< 0.01 % of the pixels are non-zero!

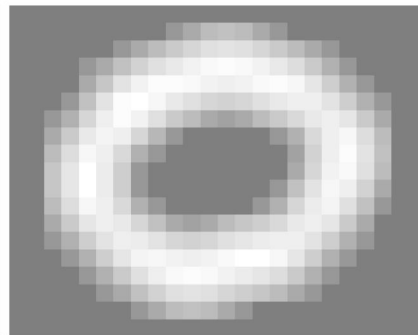
Original



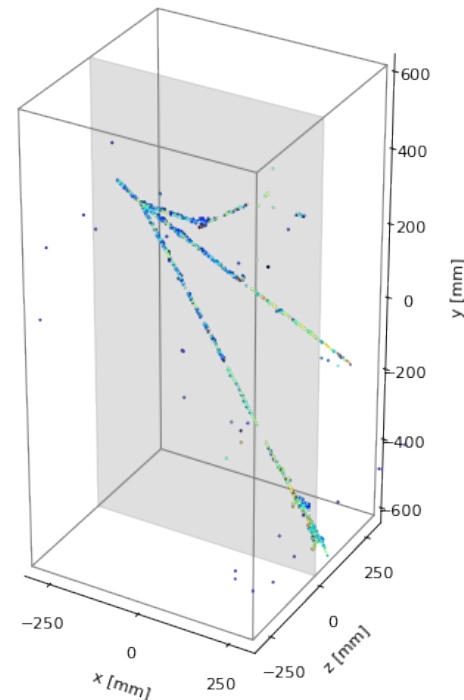
3x3 Conv



Another 3x3 Conv



! 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!*

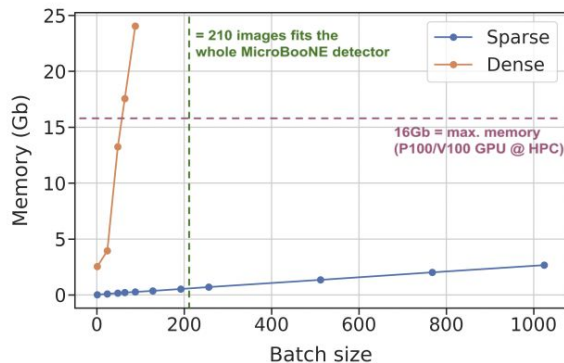


FIG. 3. GPU memory usage as a function of batch size at inference time [2D, 512px, 5-16].

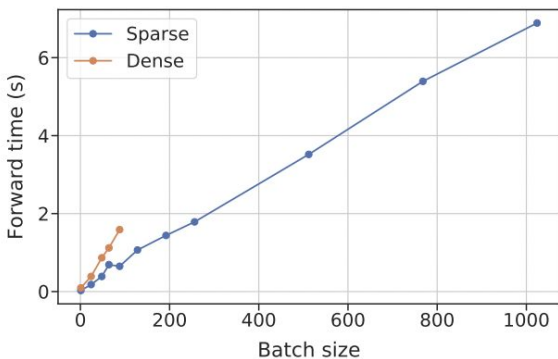


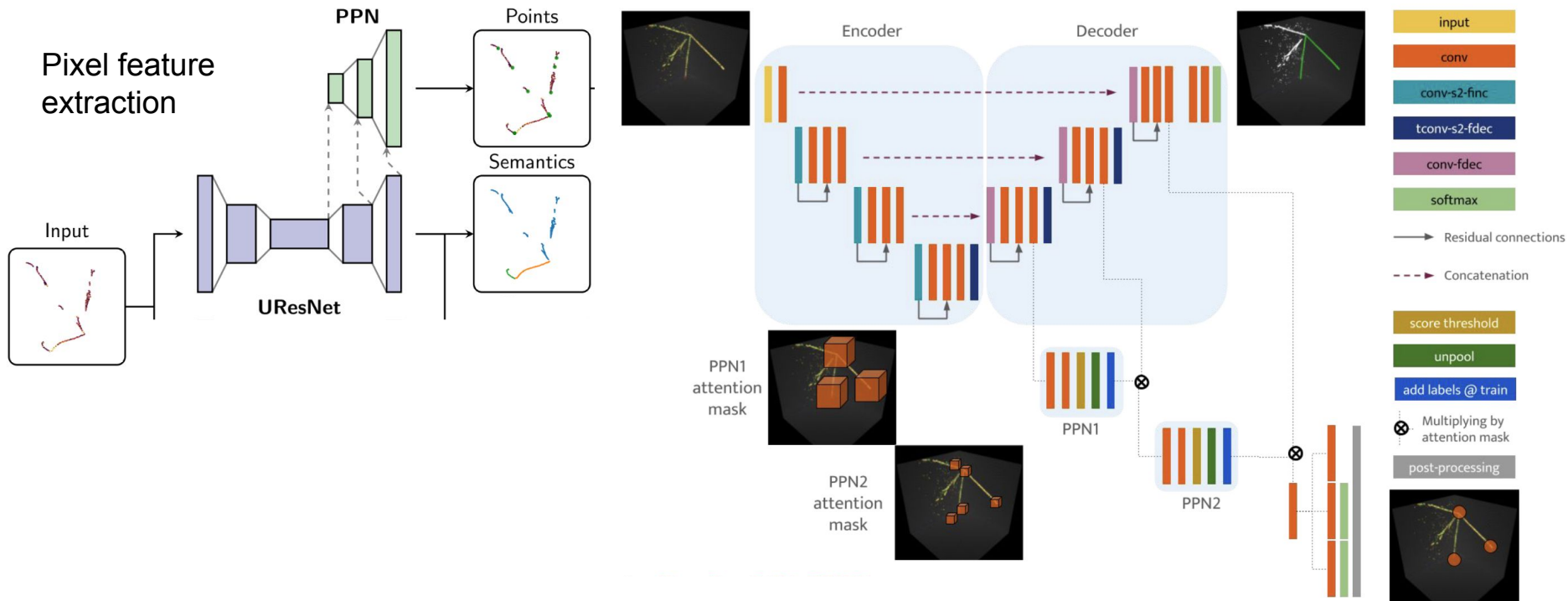
FIG. 4. Computation wall-time as a function of batch size at inference time [2D, 512px, 5-16].

Advantage of sparse conv:

- ✓ Classification error ~equal
- ✓ Faster per batch
- ✓ Less memory for even larger batches!

[Scalable CNNs for LArTPCs](#)

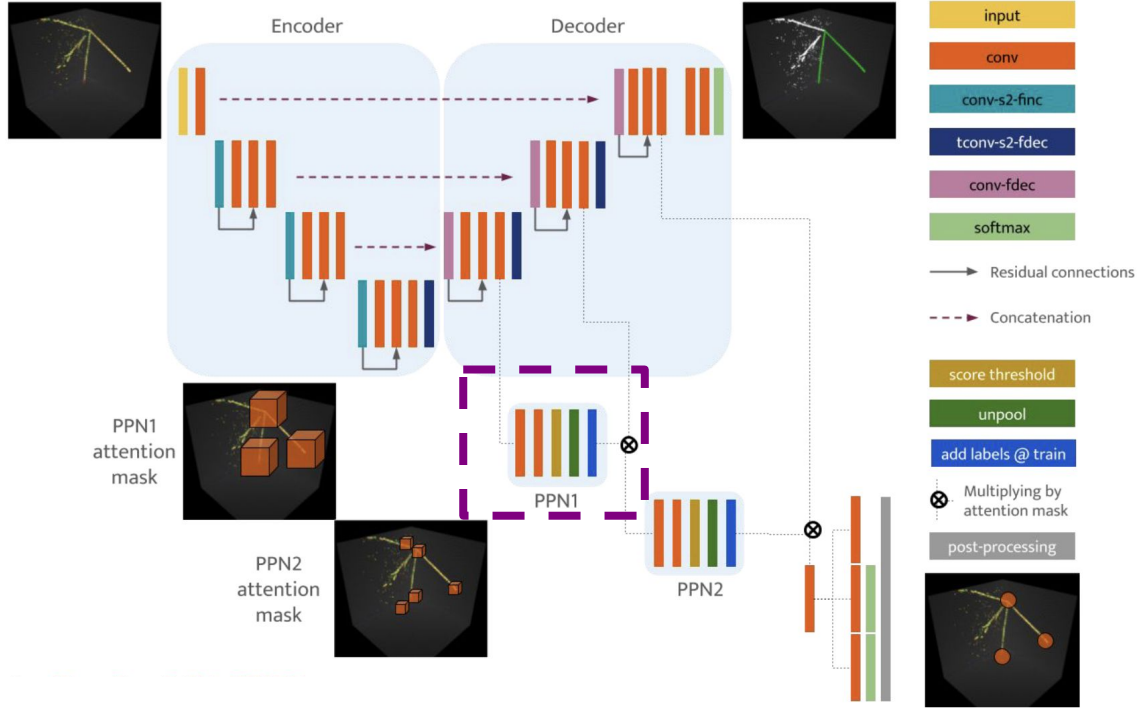
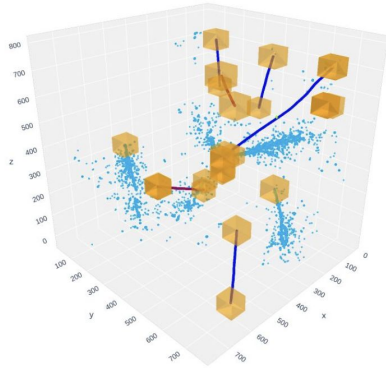
Pixel Features: Points of Interest



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

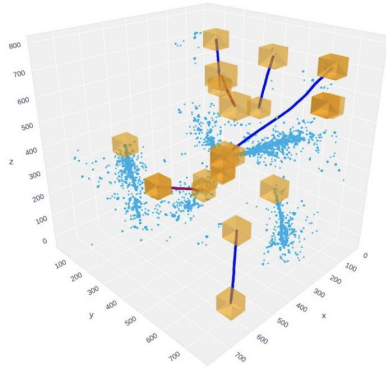
Pixel Features: Points of Interest

Pixel feature extraction at low resolution (PPN1)

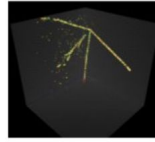
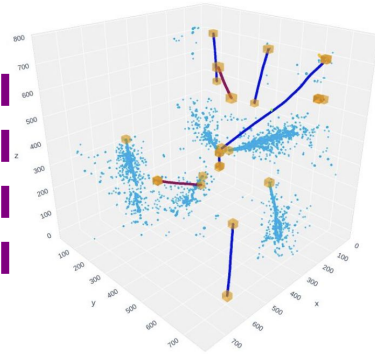


Pixel Features: Points of Interest

Pixel feature extraction at low resolution (PPN1)



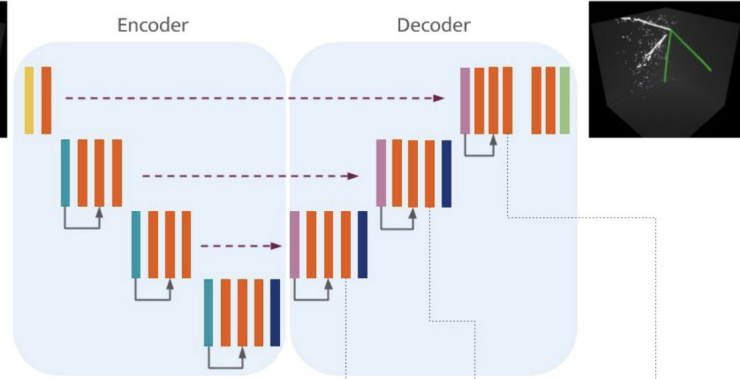
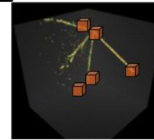
Pixel feature extraction at higher resolution (PPN2)



PPN1 attention mask



PPN2 attention mask



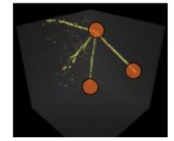
PPN1

PPN2

- input
- conv
- conv-s2-fnc
- tconv-s2-fdec
- conv-fdec
- softmax

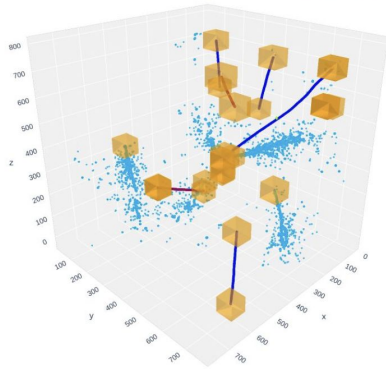
- Residual connections
- Concatenation

- score threshold
- unpool
- add labels @ train
- Multiplying by attention mask
- post-processing

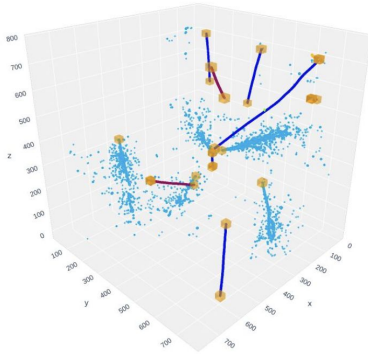


Pixel Features: Points of Interest

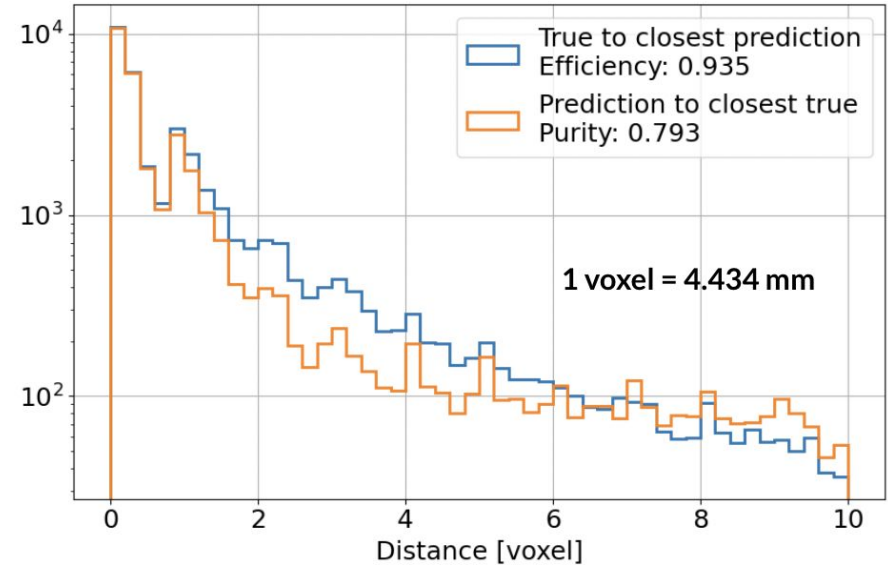
Pixel feature extraction at low resolution (PPN1)



Pixel feature extraction at higher resolution (PPN2)



Current Performance on 2x2 Near Detector Prototype

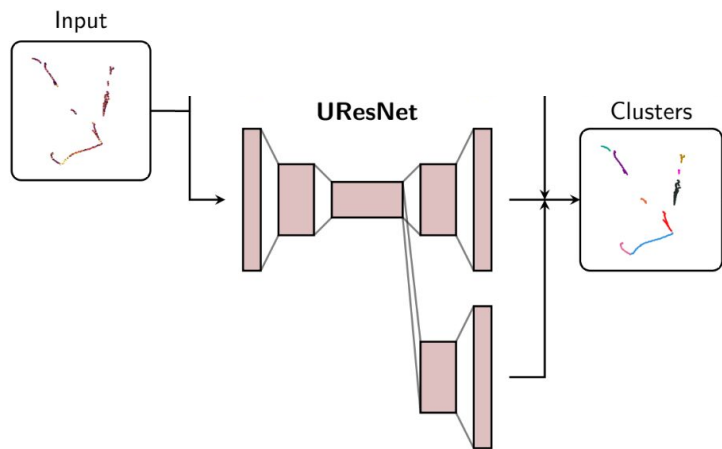


[Phys Rev D \(104\) 032004](#)

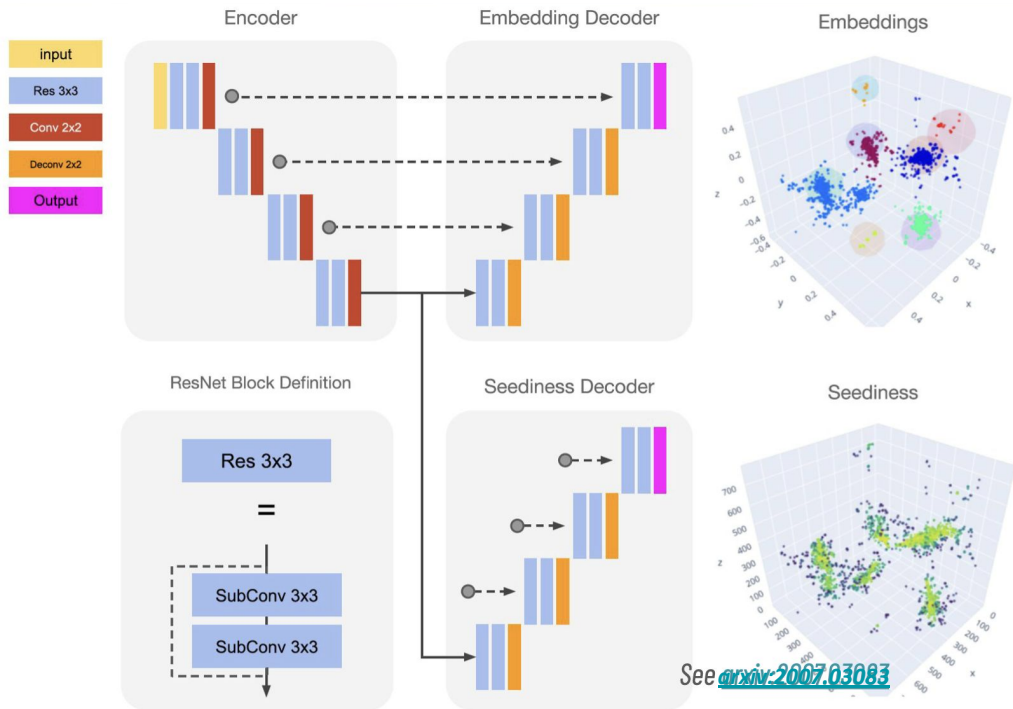
Pixel Features: SPICE Clustering

Scalable Particle Instance Clustering using Embedding

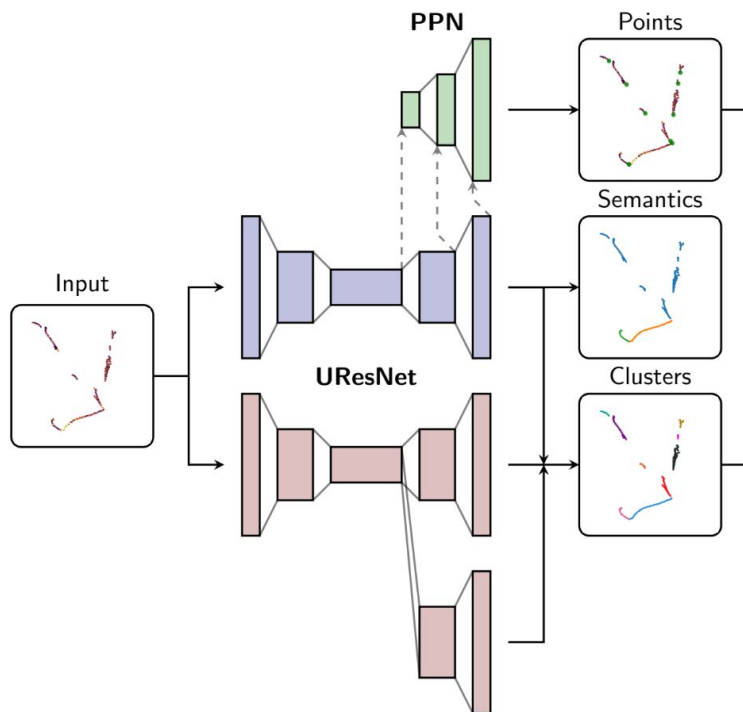
→ Points in cluster flow normal distribution, loss uses this



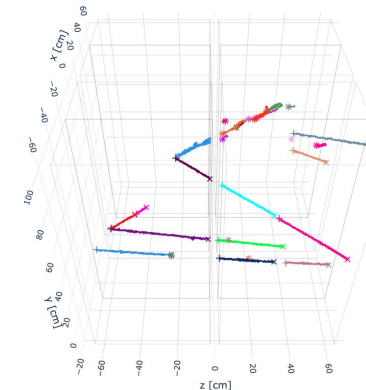
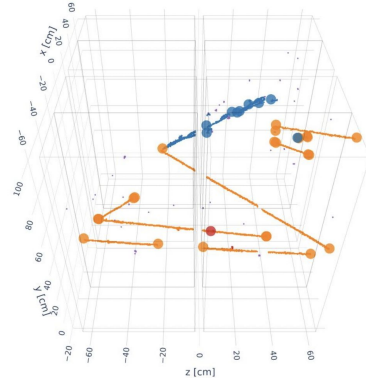
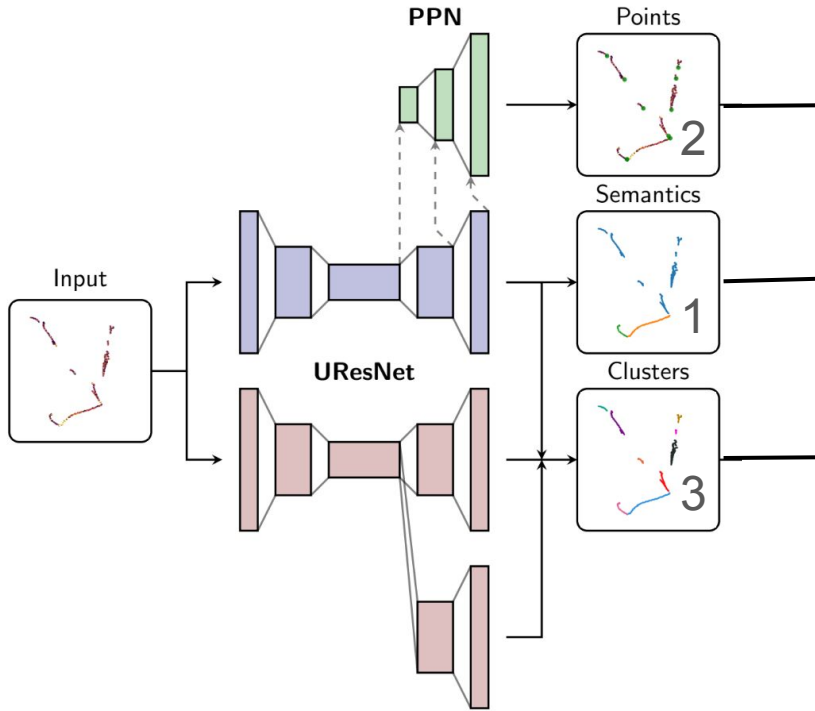
Embedding decoder	Transformation
Seediness decoder	Centroids



Pixel Features: Output



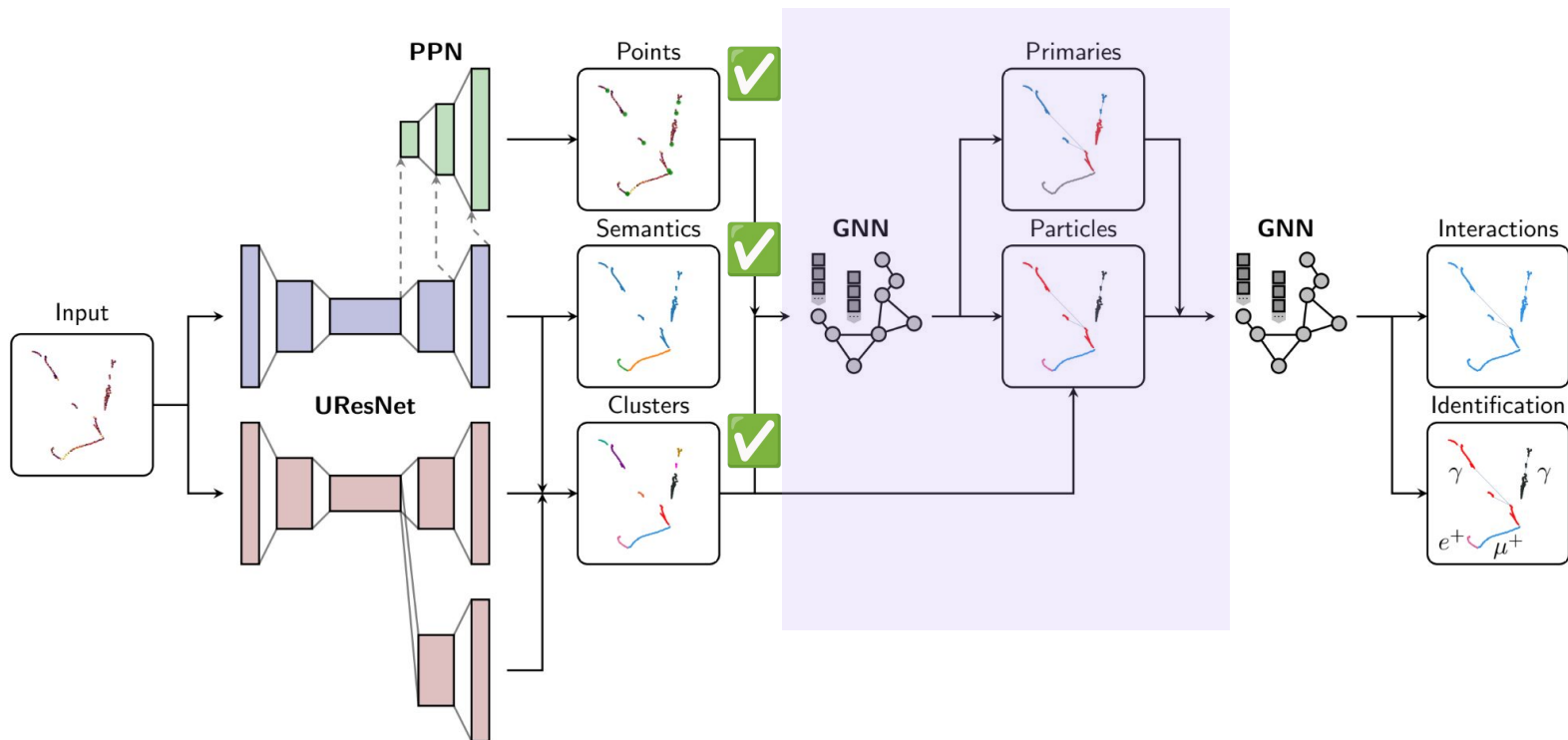
Pixel Features: Output



Track
Shower
Michel electron
Delta rays
Low energy scatters

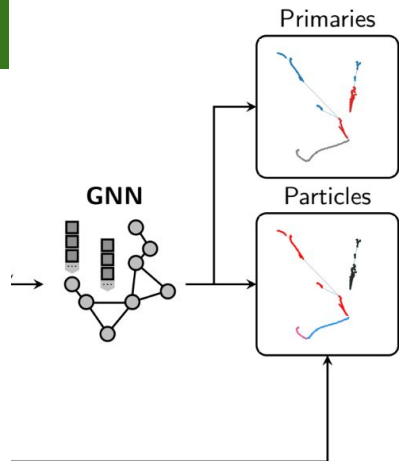
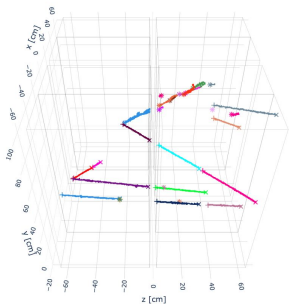
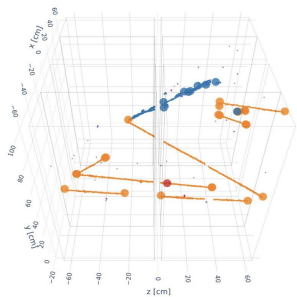
1. Pixel “signature” of particle interaction type
2. Points of interest
 - a. Start of tracks & showers
 - b. End track
3. Pixel clusters
 - a. Including centroids

3D LAr TPC: ML Reco 3D

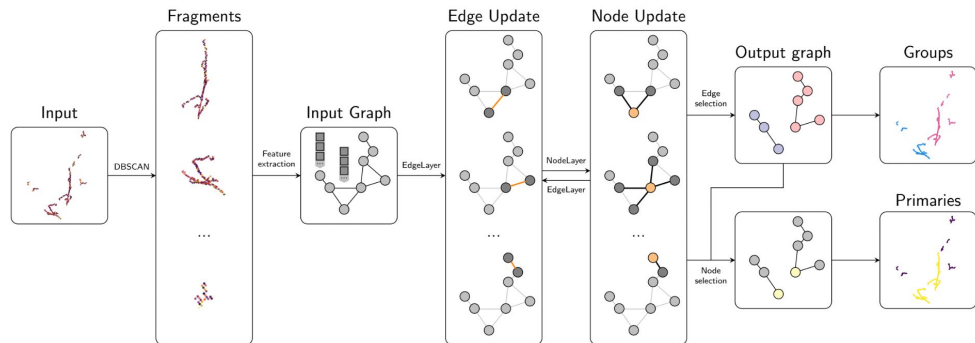


Cluster Clustering

Pixel Features



Use Graph Neural Network

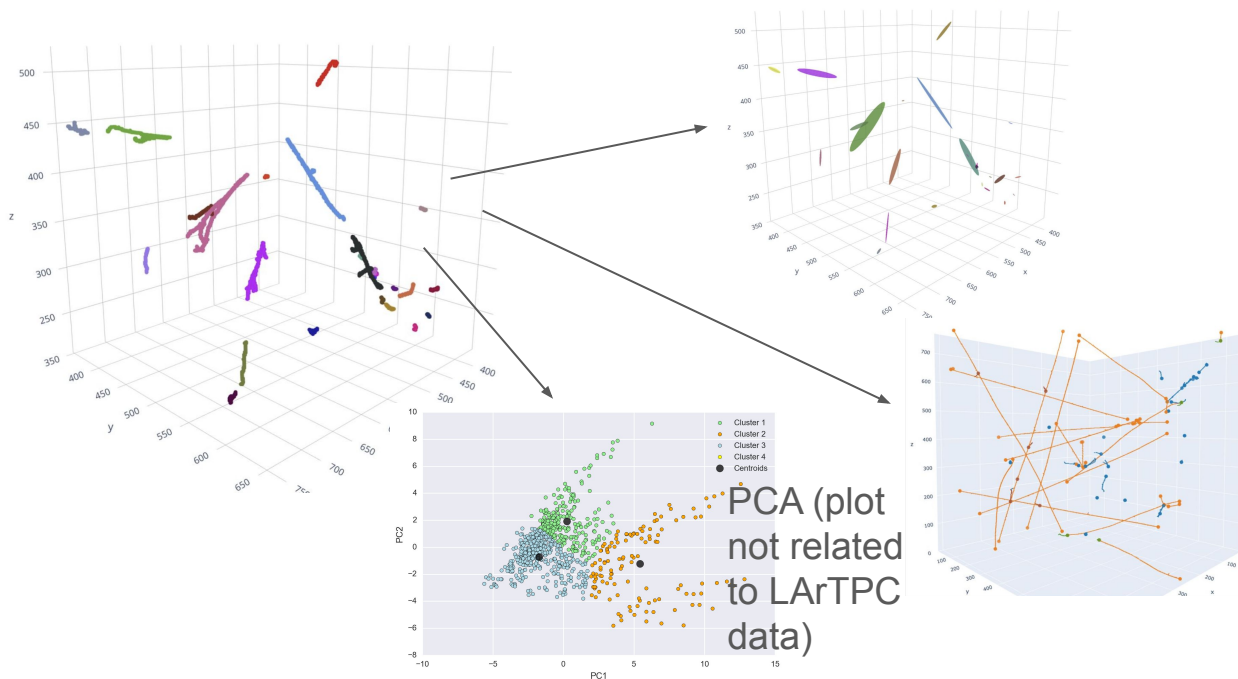


GrapPA: Graph Particle Aggregator

[arxiv 2020](#)

Cluster Clustering: Inputs

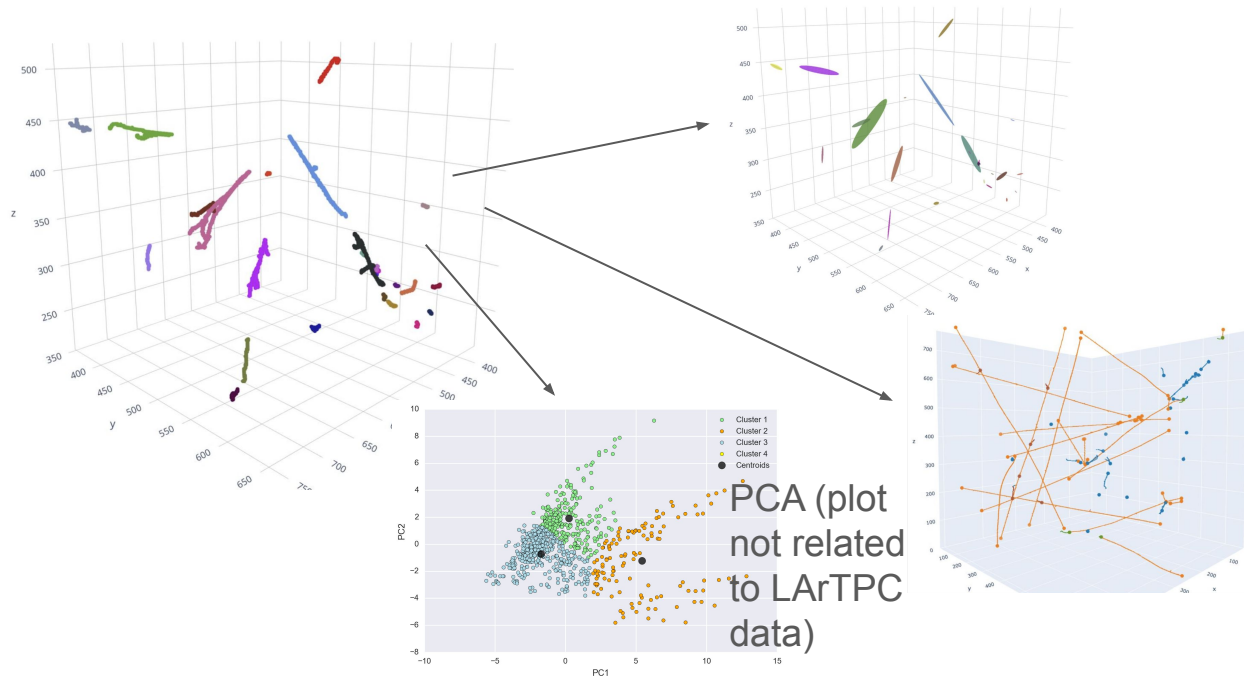
Input: Encode Fragments into set of node features



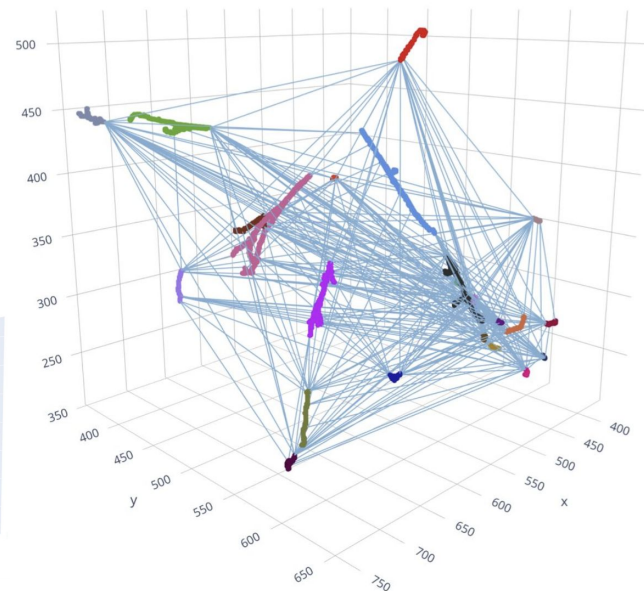
Fragment Summary	# Features
Number of voxels	1
Initial Point	3
Normalized initial direction	3
Normalized covariance matrix	9
Normalized principal axis	3
Centroid	3

Cluster Clustering: Inputs

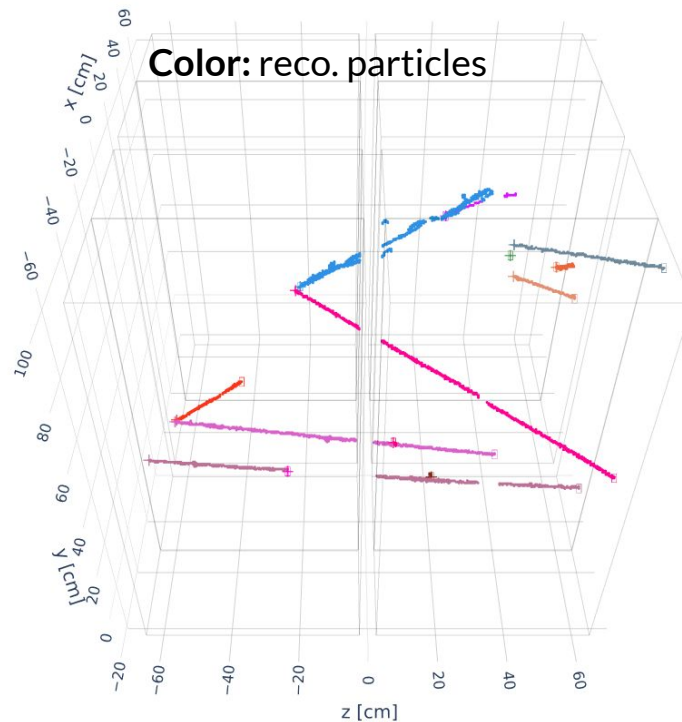
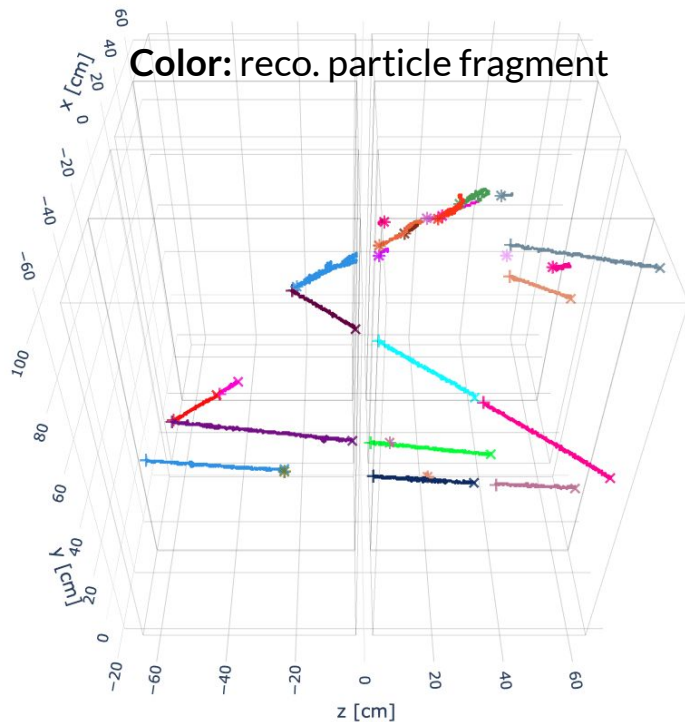
Input: Encode Fragments into set of node features



Fully connect nodes

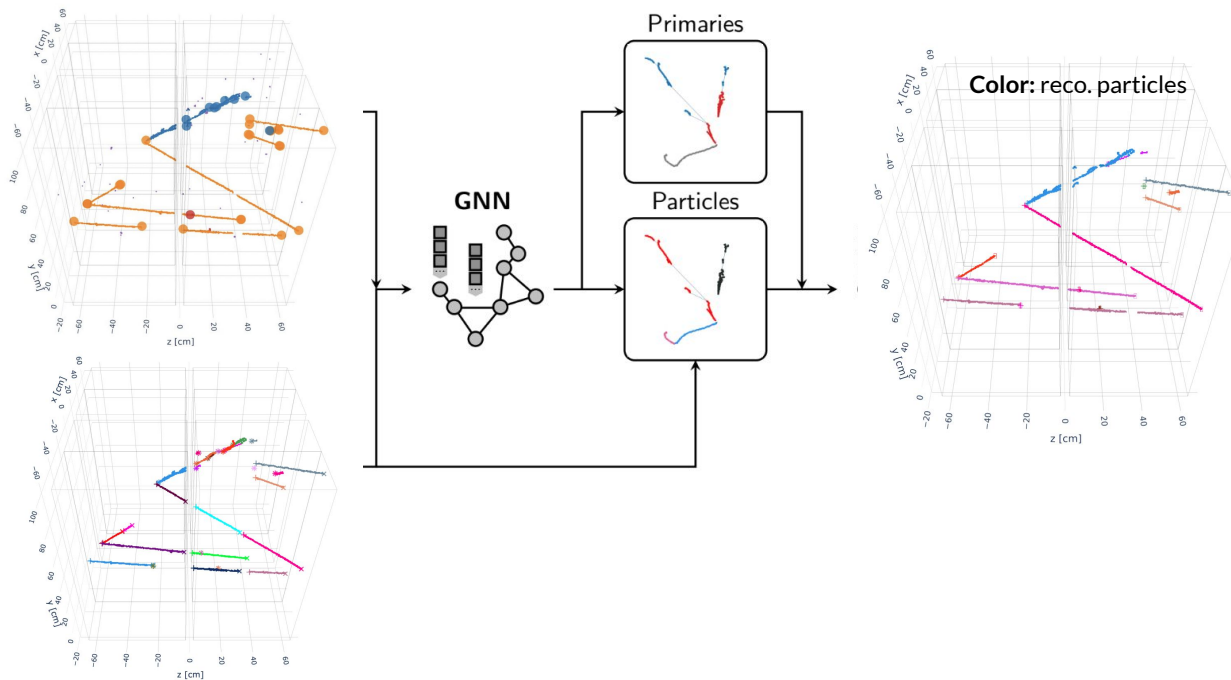


Cluster Clustering: Particle Clustering



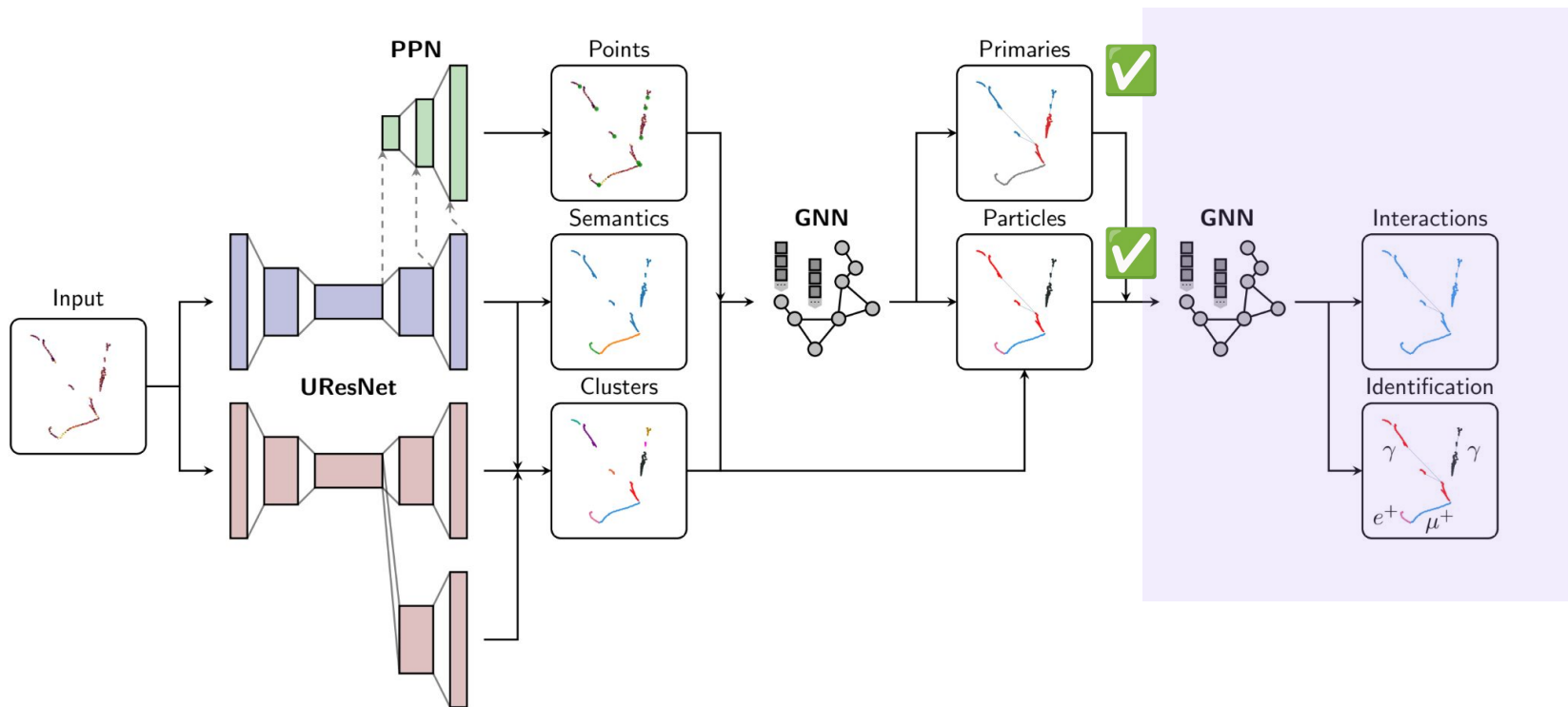
Output: Primaries & Particles

Pixel Features



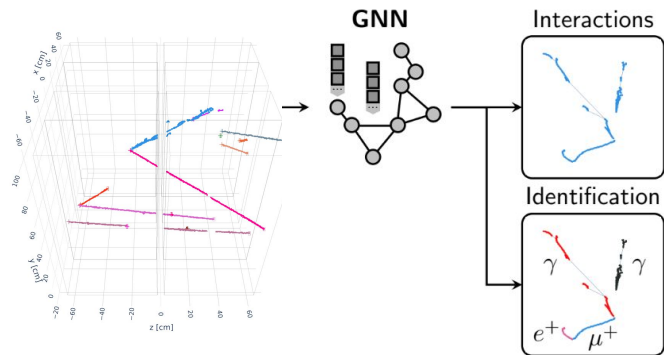
Fragment Features

3D LAr TPC: ML Reco 3D

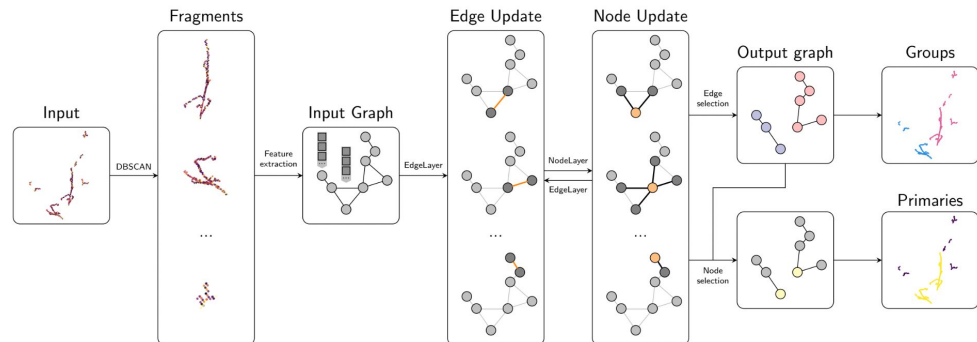


Interactions & Identification

Fragment Features



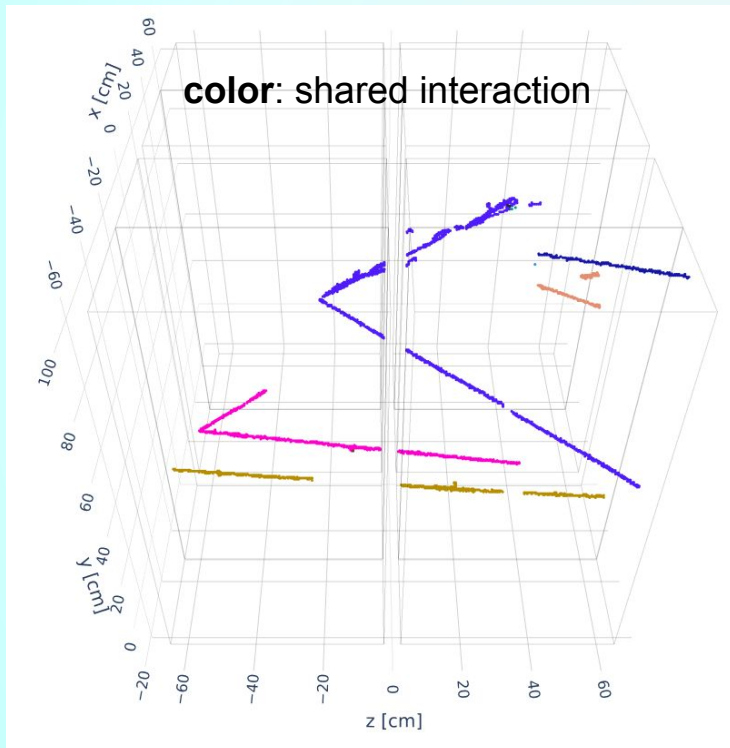
Re-use GrapPA



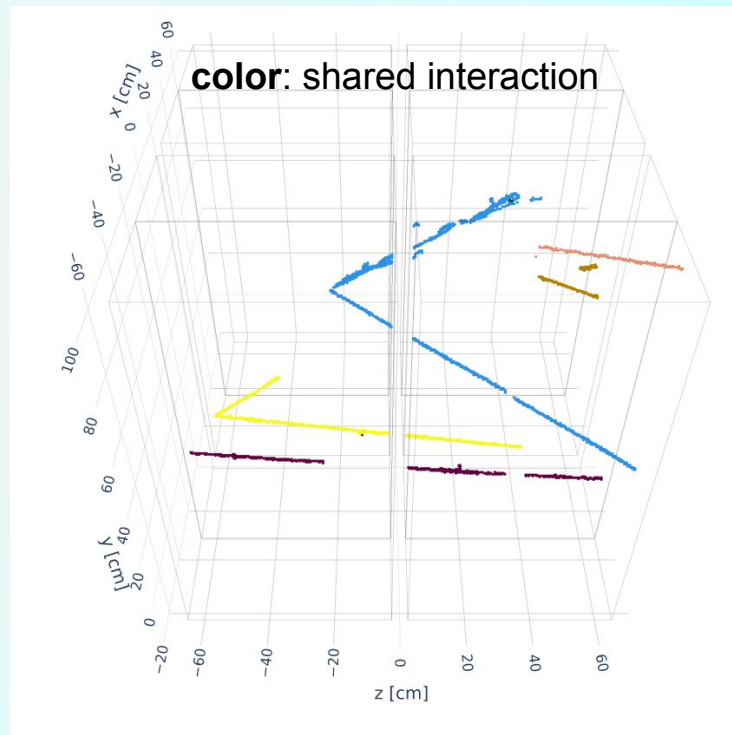
Interactions = find same neutrino source
+ Edges classification for interactions
+ Nodes classification for identification

Performance Shared Interaction

Truth

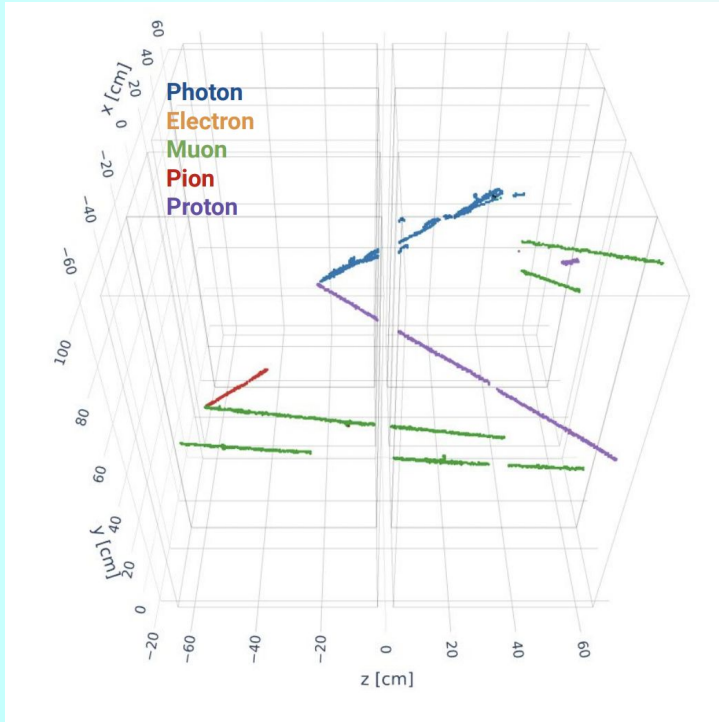


Reco

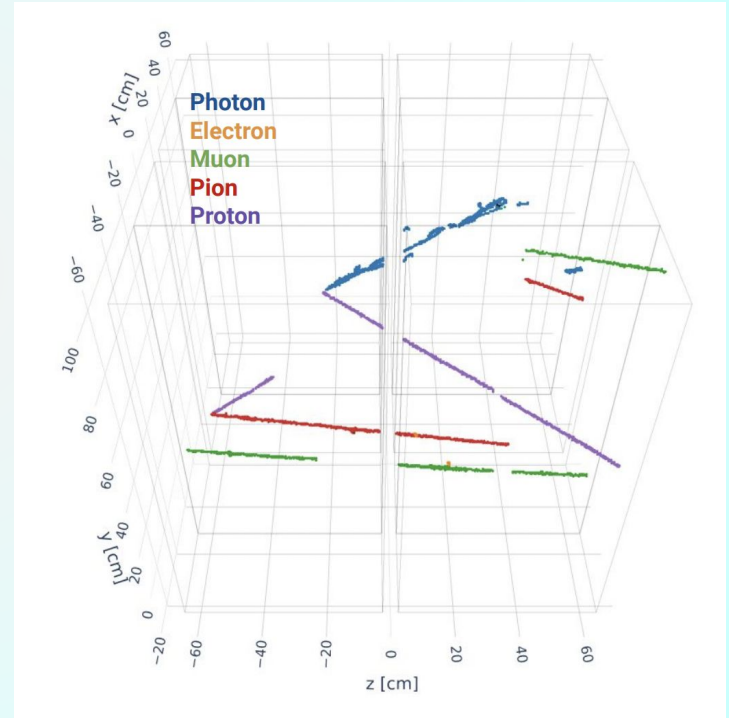


Performance: Example for Prototype ND

Truth

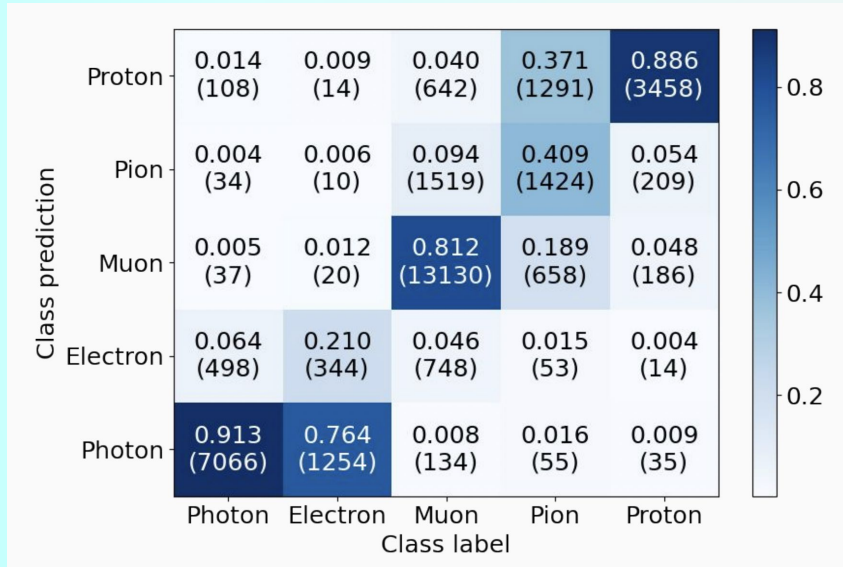


Reco

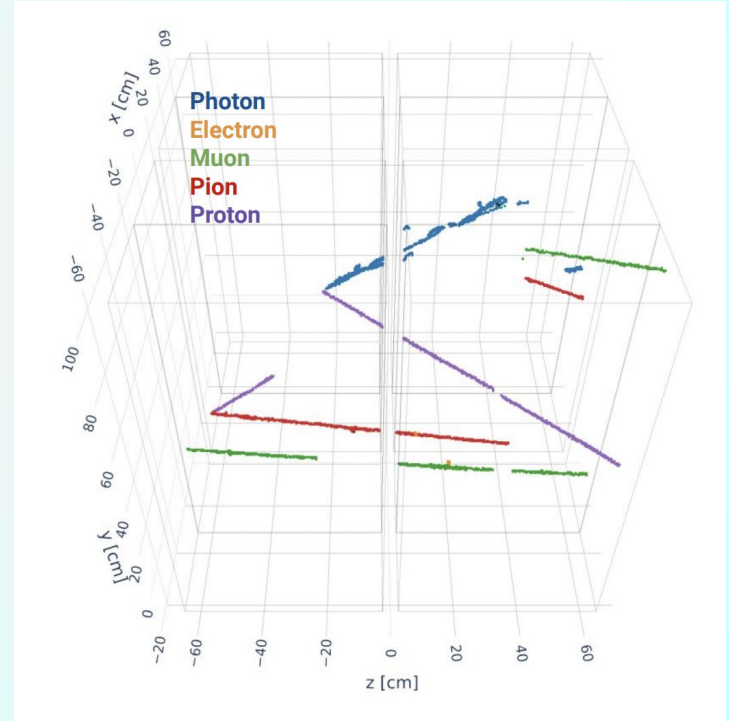


Performance: Metrics

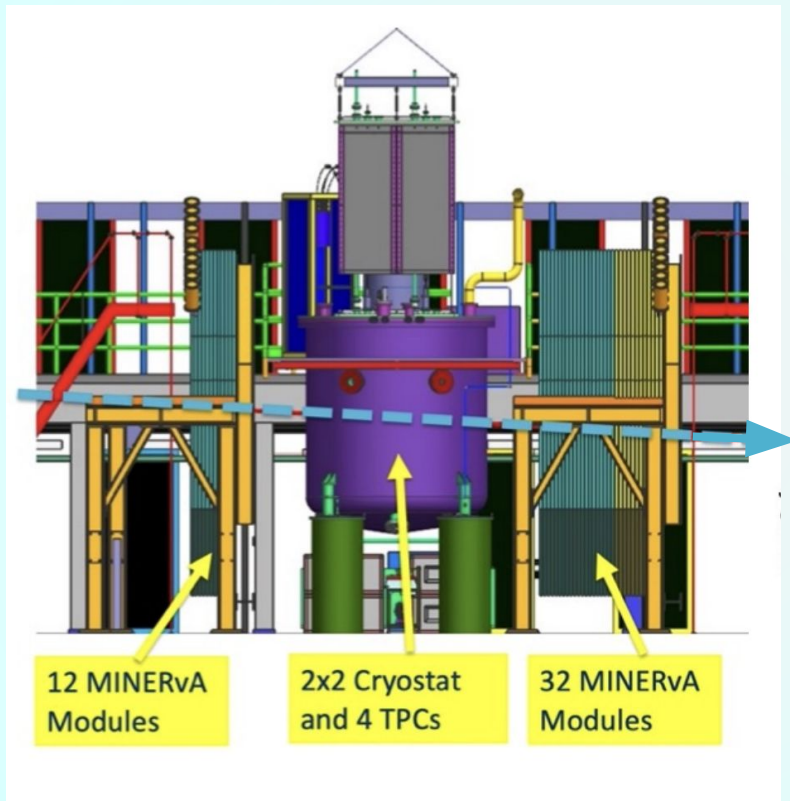
Performance



Reco



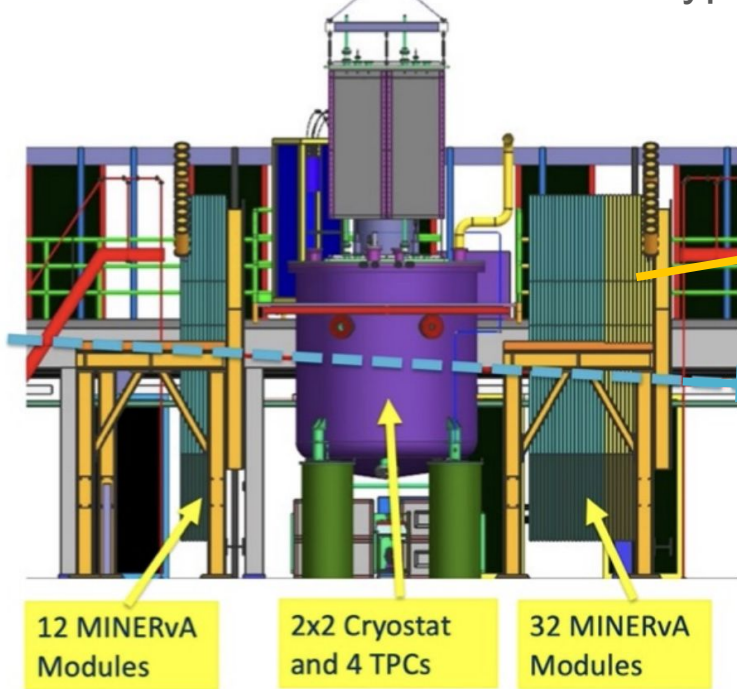
DUNE Near Detector 2x2 Prototype



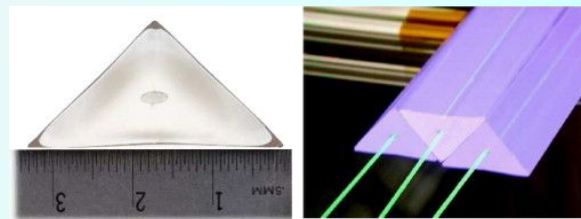
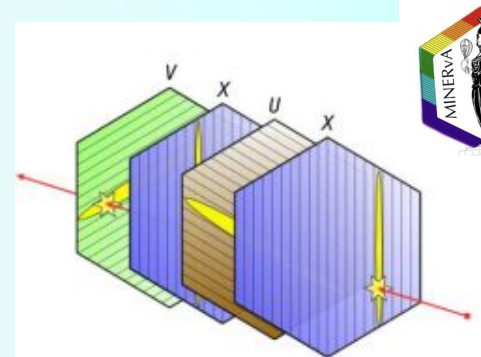
See Brooke's [ND-LAr Overview](#) from Thursday afternoon!

MINERvA uses Solid Scintillator Planes

DUNE Near Detector 2x2 Prototype



MINERvA: Solid scintillation particle detector with 3 orientations

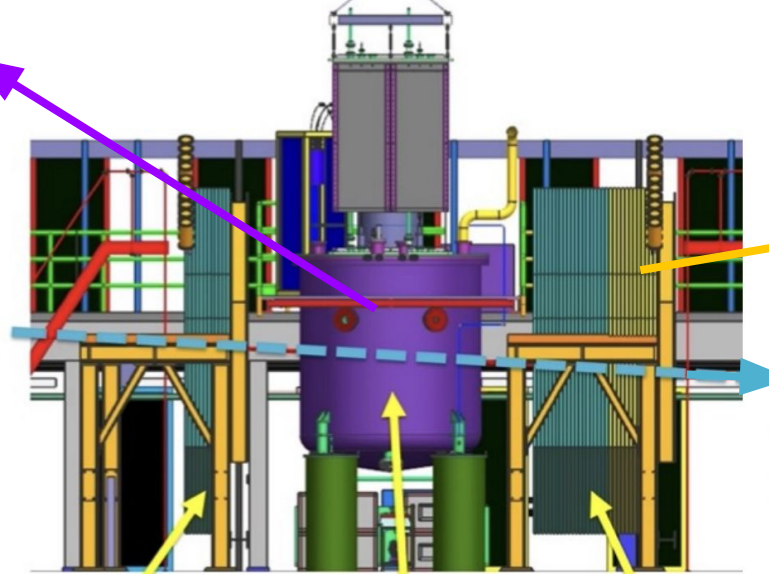
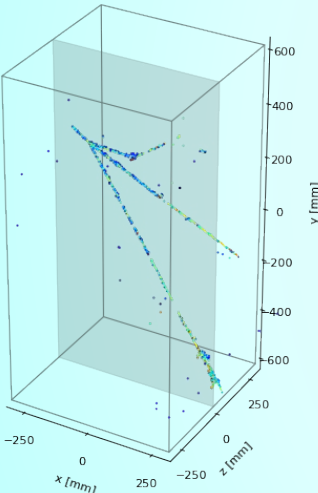


DUNE 2x2 uses Liquid Argon TPCs

4 LArTPCs with 3D pixel readout

DUNE Near Detector 2x2 Prototype

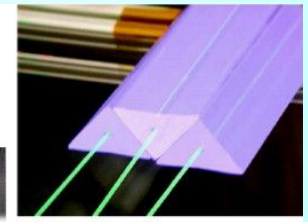
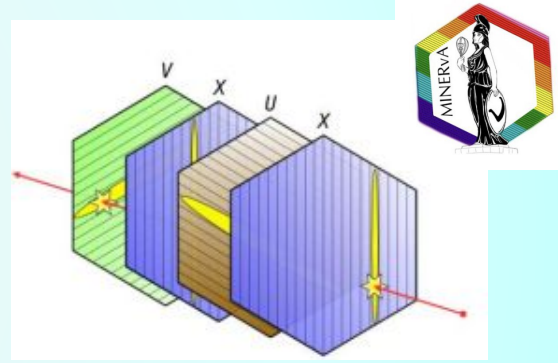
MINERvA: Solid scintillation particle detector with 3 orientations

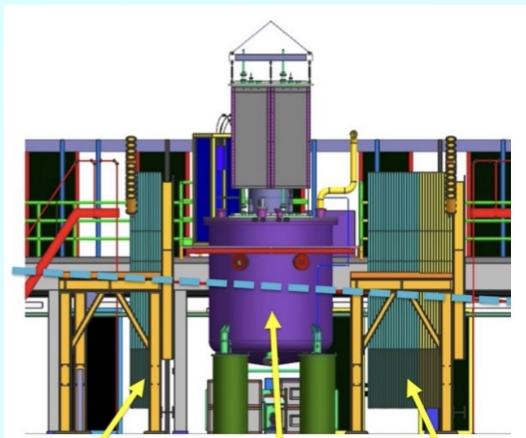


12 MINERvA Modules

2x2 Cryostat and 4 TPCs

32 MINERvA Modules

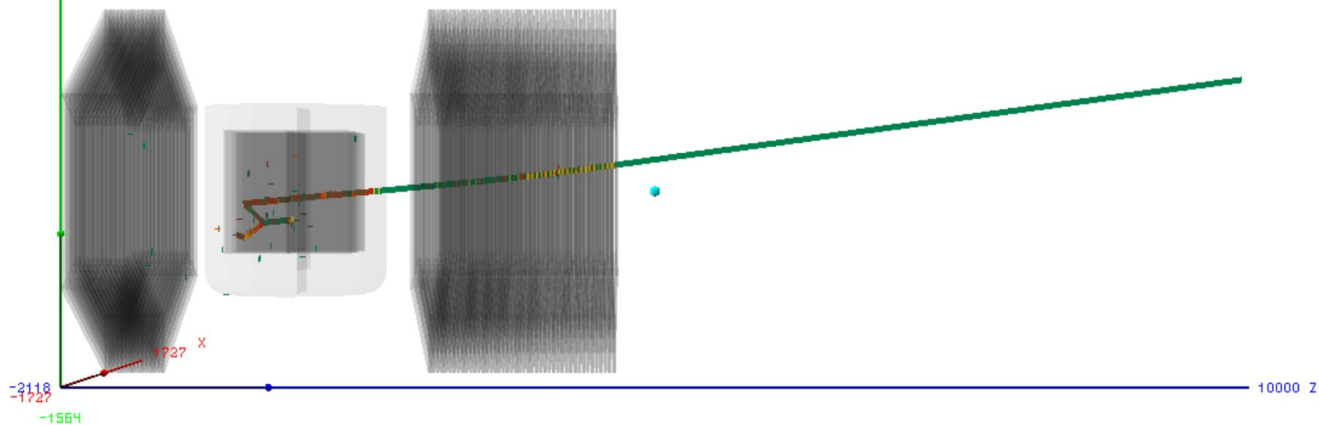




2
12 MINERvA
Modules

2x2 Cryostat
and 4 TPCs

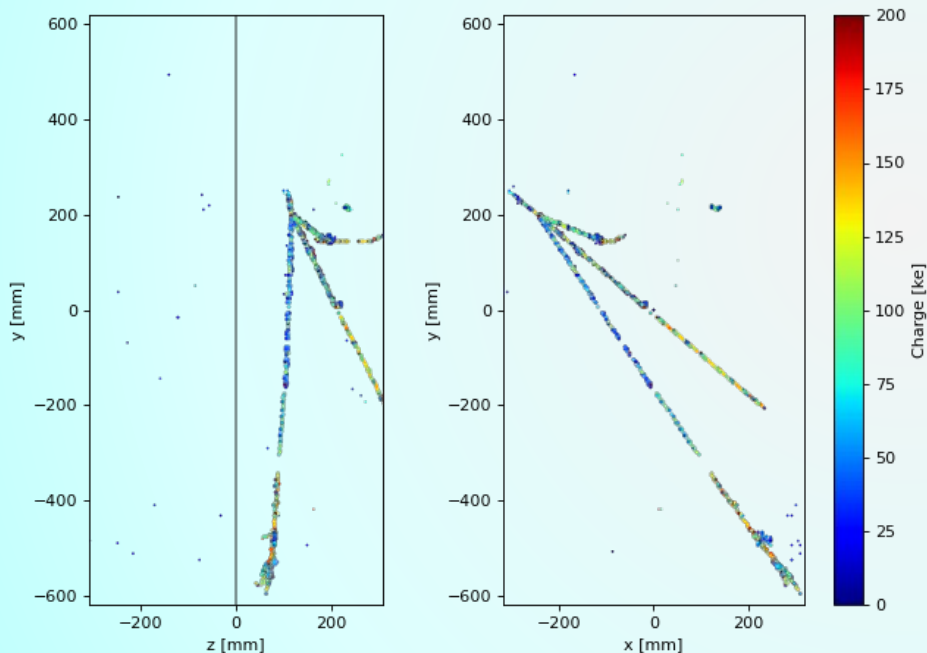
32 MINERvA
Modules



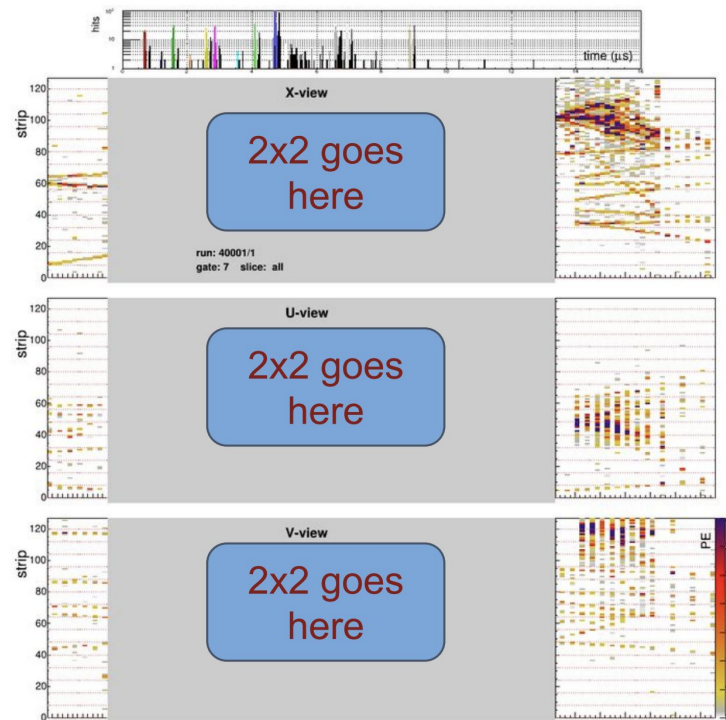
Wait! MINERvA has different detection resolution

→ *CNN would be affected by this*

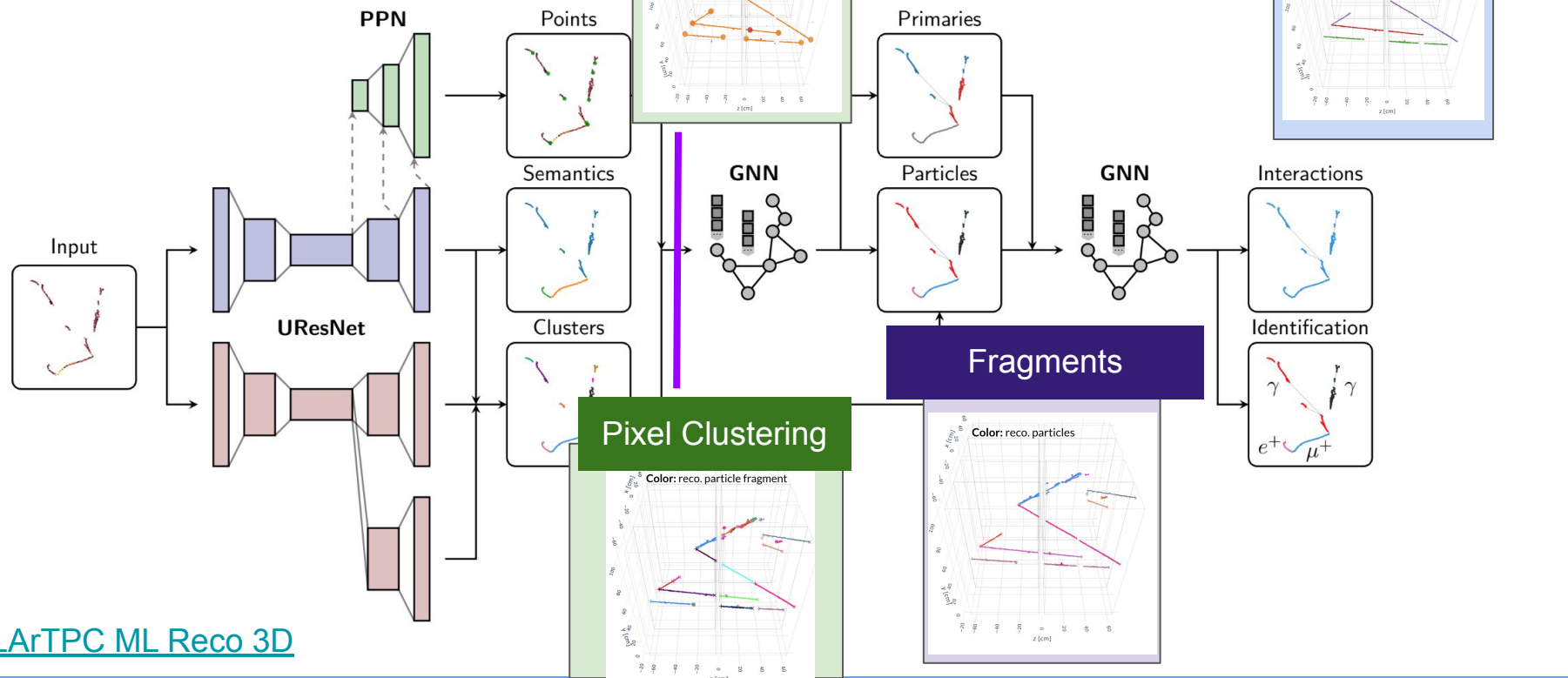
2x2 in 2D projection simulation



Preliminary DUNE ND-LAr 2x2 MINERvA data

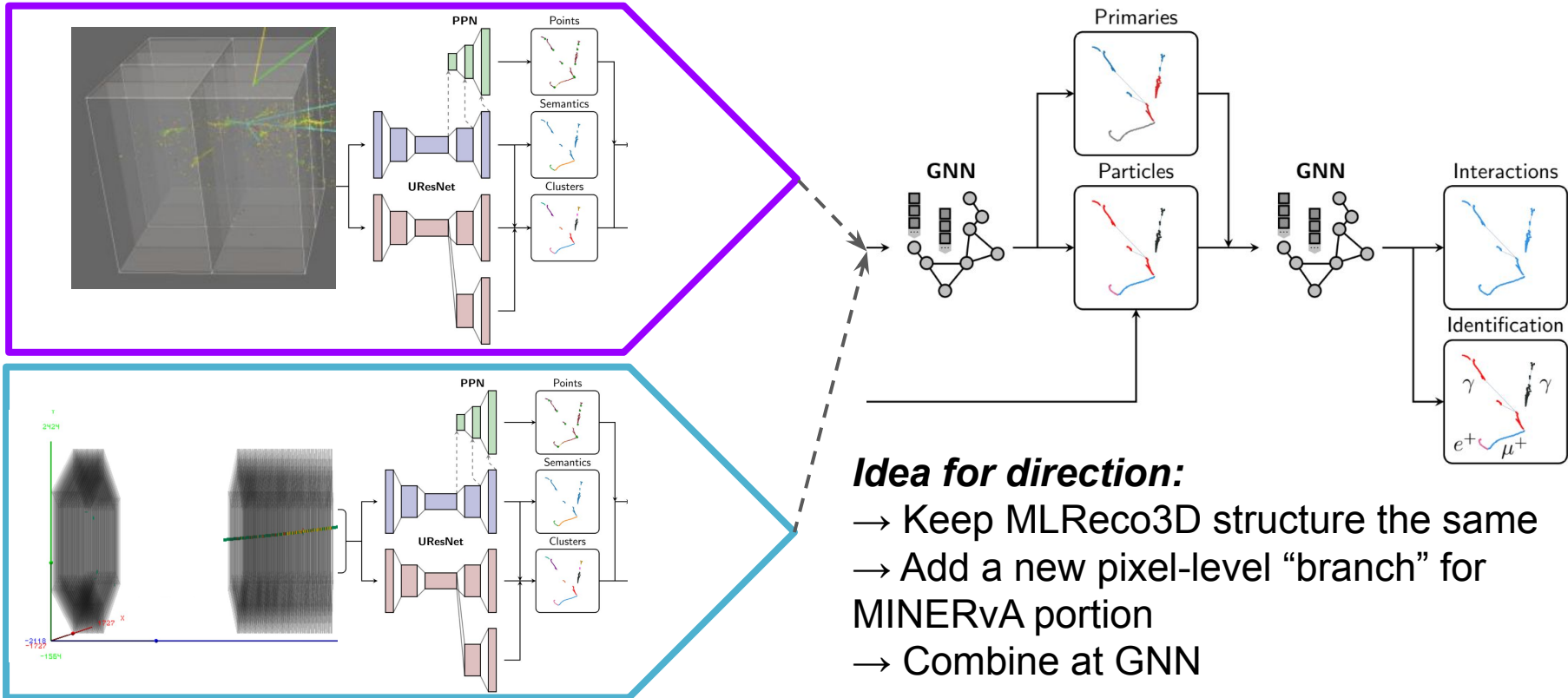


2x2 ML Framework



[LArTPC ML Reco 3D](#)

ML Reco 3D: Adding MINERvA



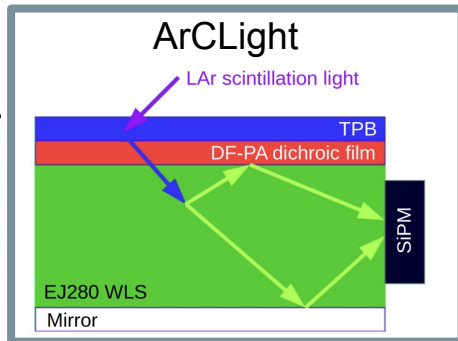
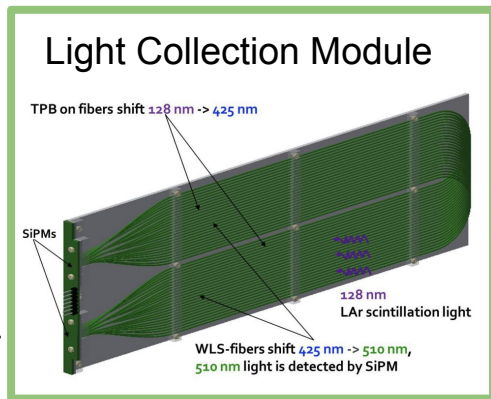
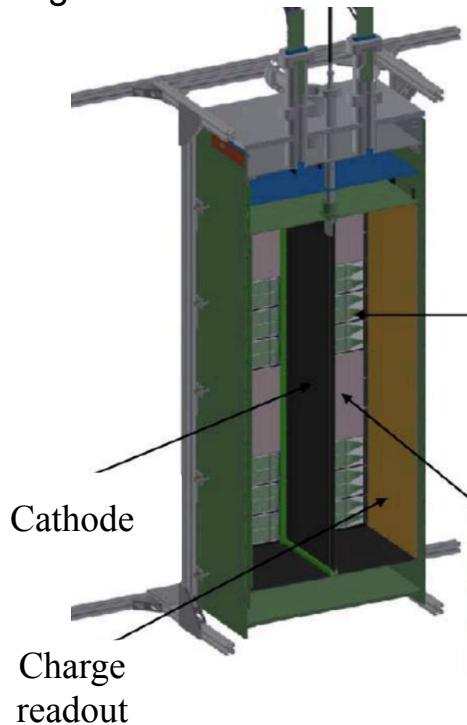
Idea for direction:

- Keep MLReco3D structure the same
- Add a new pixel-level “branch” for MINERvA portion
- Combine at GNN

Future Applications

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

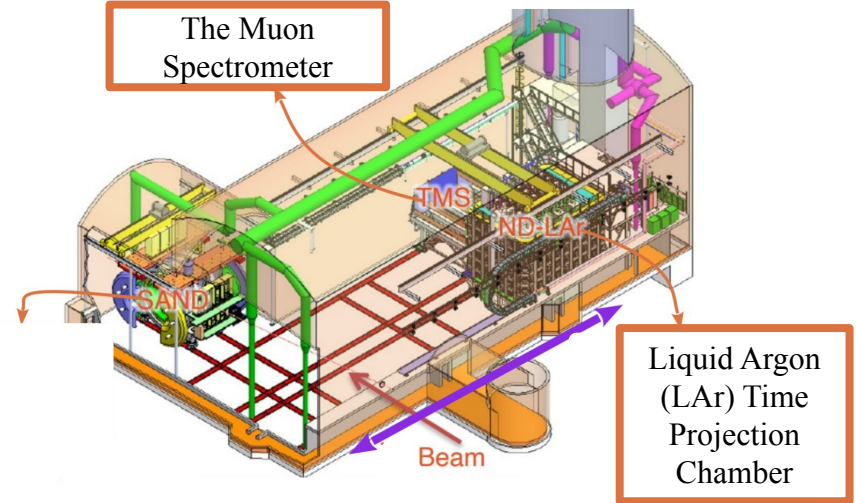
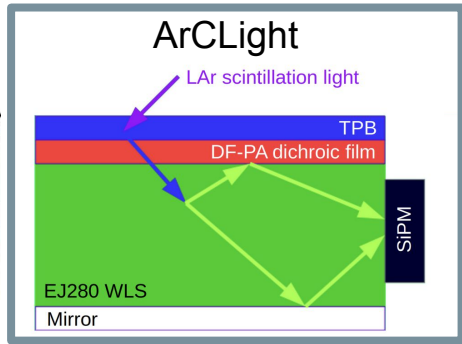
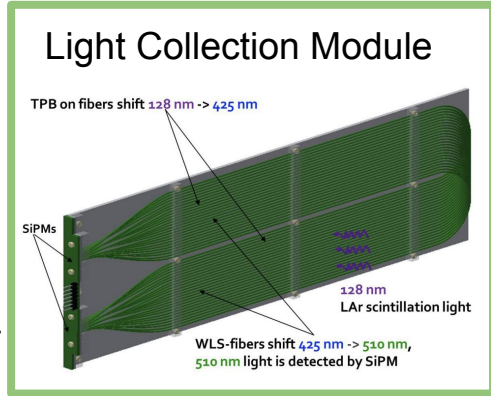
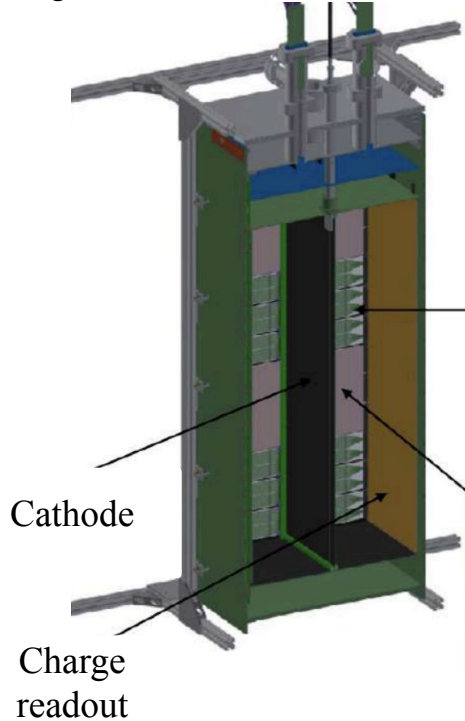
Single ND-LAr Module



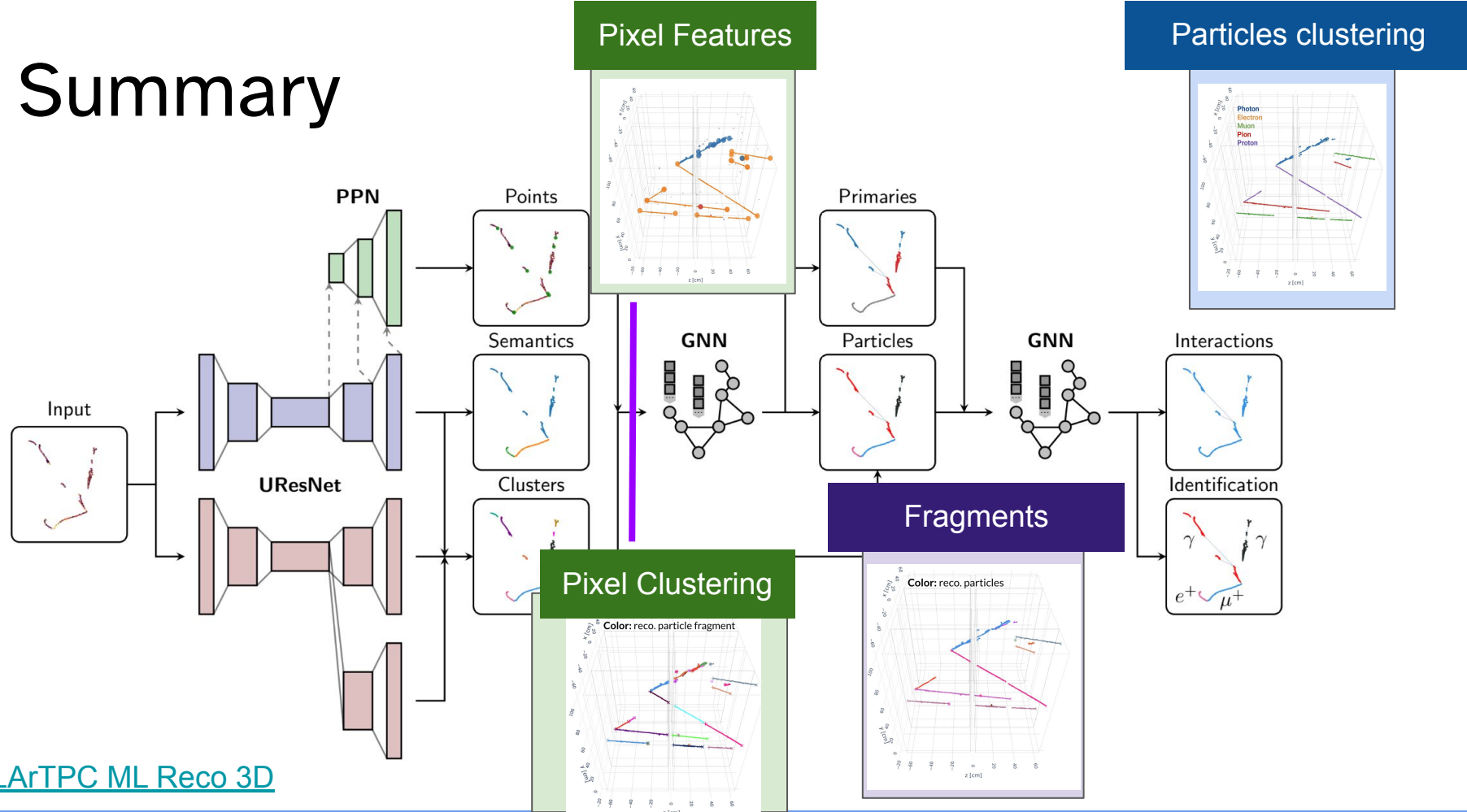
Future Applications

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

Single ND-LAr Module



Summary



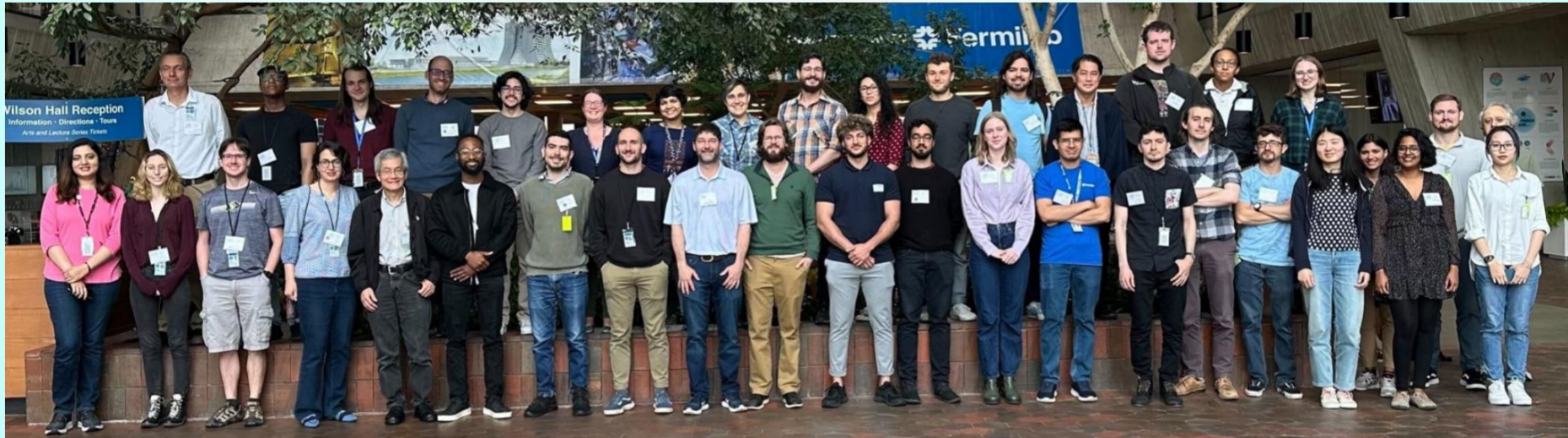
[LArTPC ML Reco 3D](#)

Thank you for your attention!



U.S. DEPARTMENT OF
ENERGY

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Science

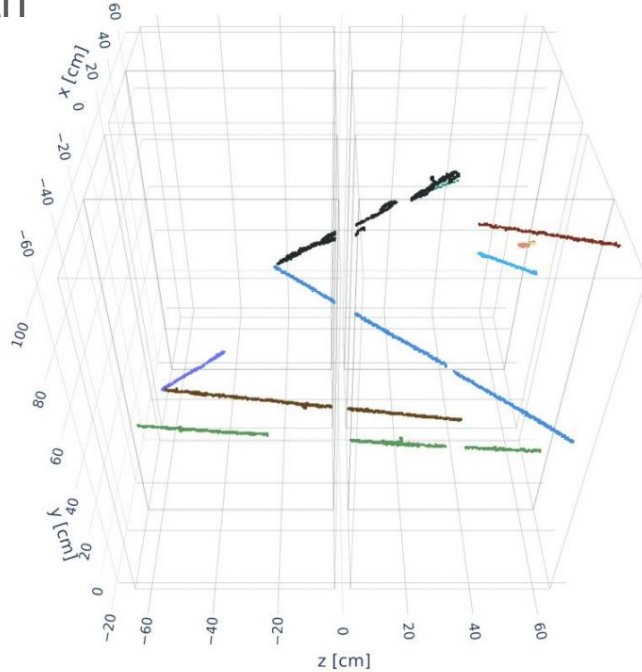


2x2 Analysis Workshop May 2023

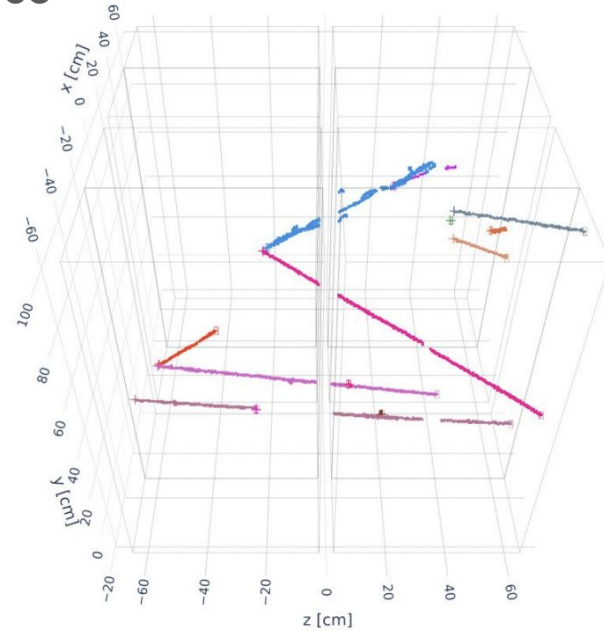
Backup

Pixel Features: Output

Truth

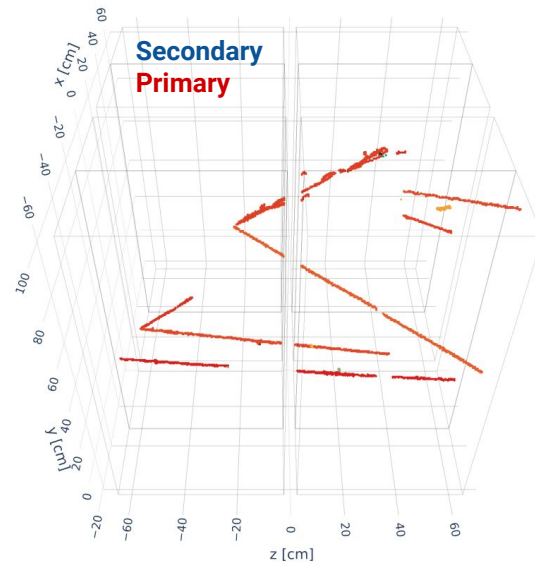
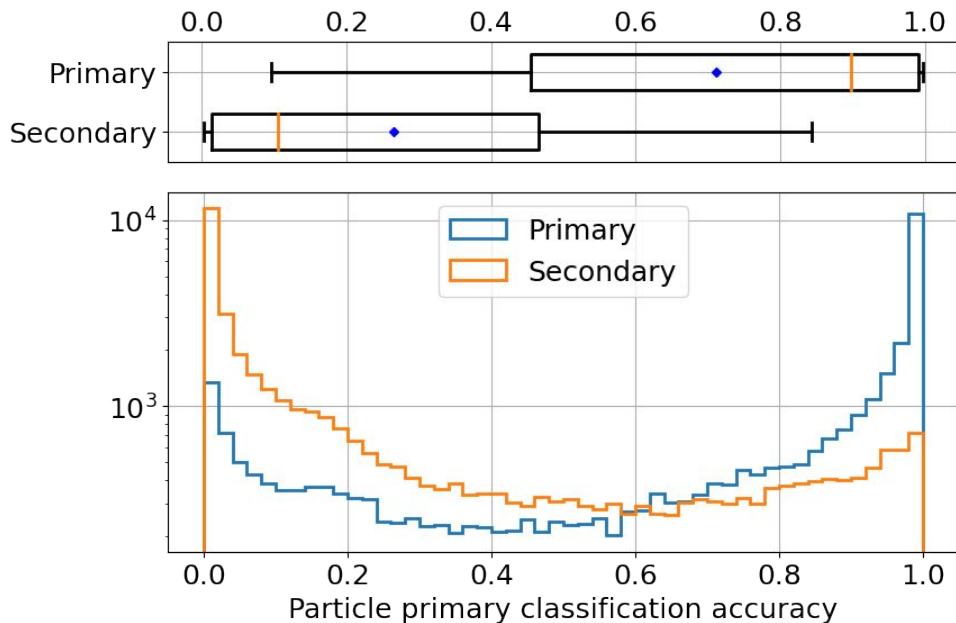


Reco



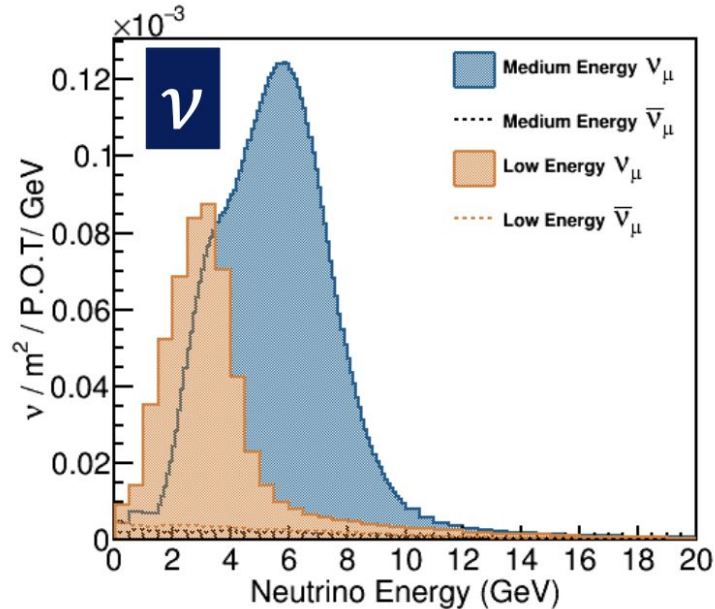
[Phys Rev D \(102\) 012005](#)

Cluster Clustering: Primary Classification



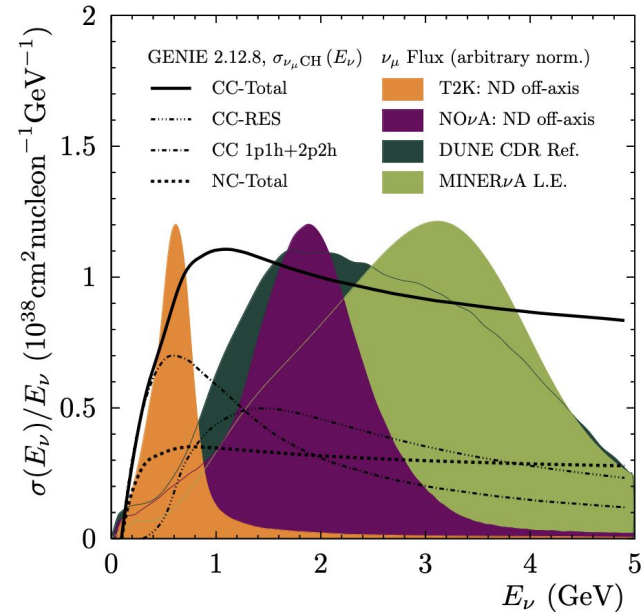
2x2 Prototype Beam vs DUNE Beam

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>