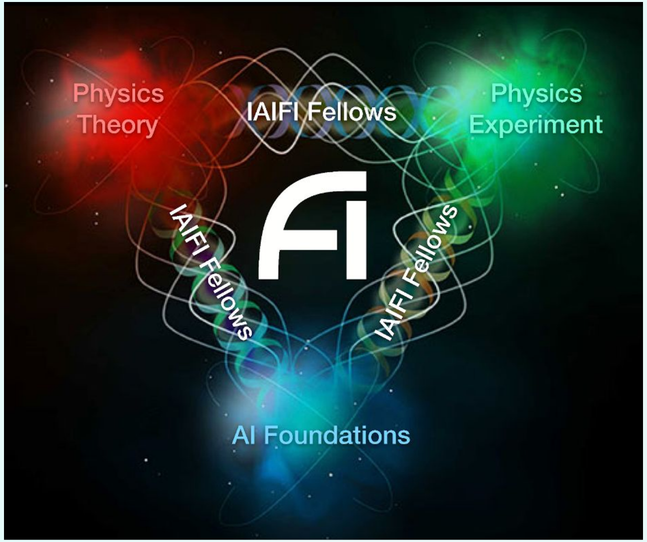
Intense Neutrino Reco: MLReco3D for DUNE's Near Detector

Jessie Micallef
on behalf of the DUNE Collaboration
IAIFI Postdoc Fellow
jessiem@mit.edu

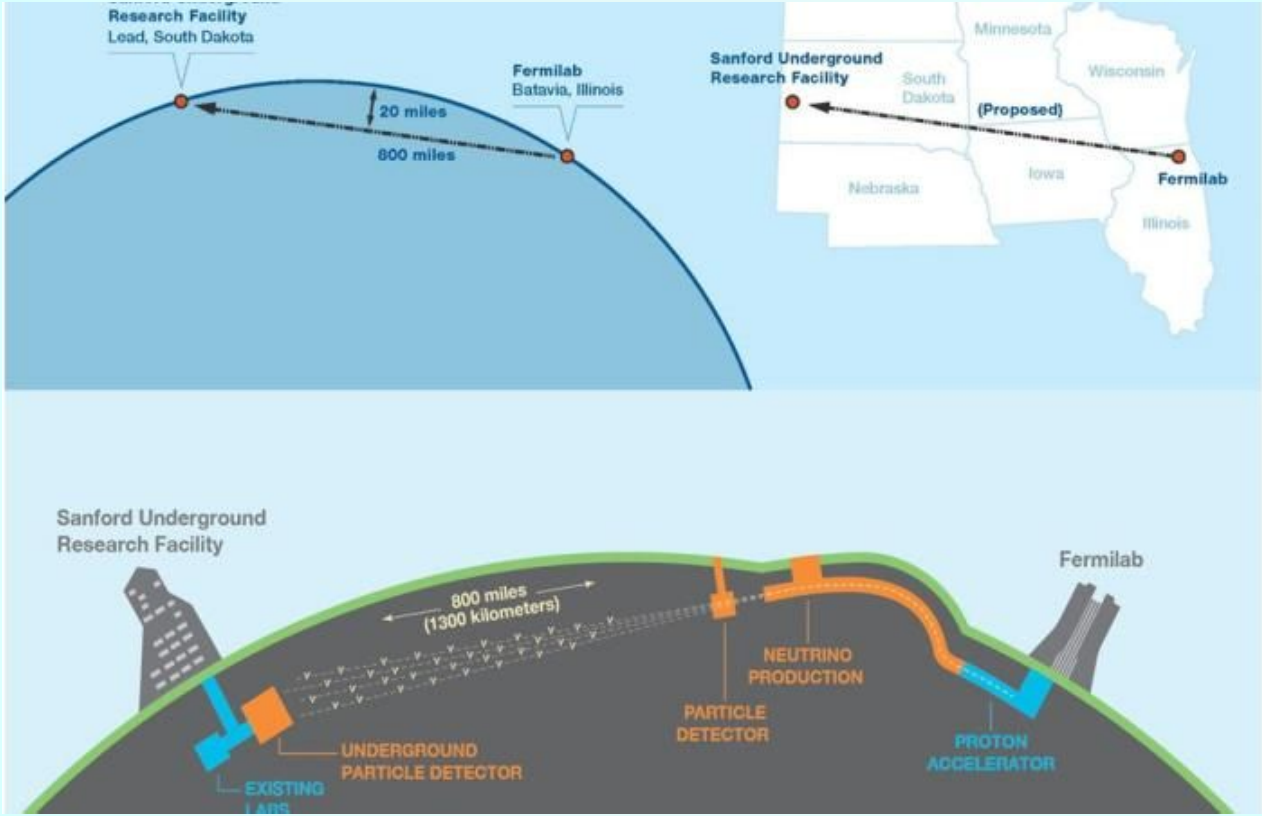
Neutrinos & Machine Learning

Institute for Artificial Intelligence and Fundamental Interactions



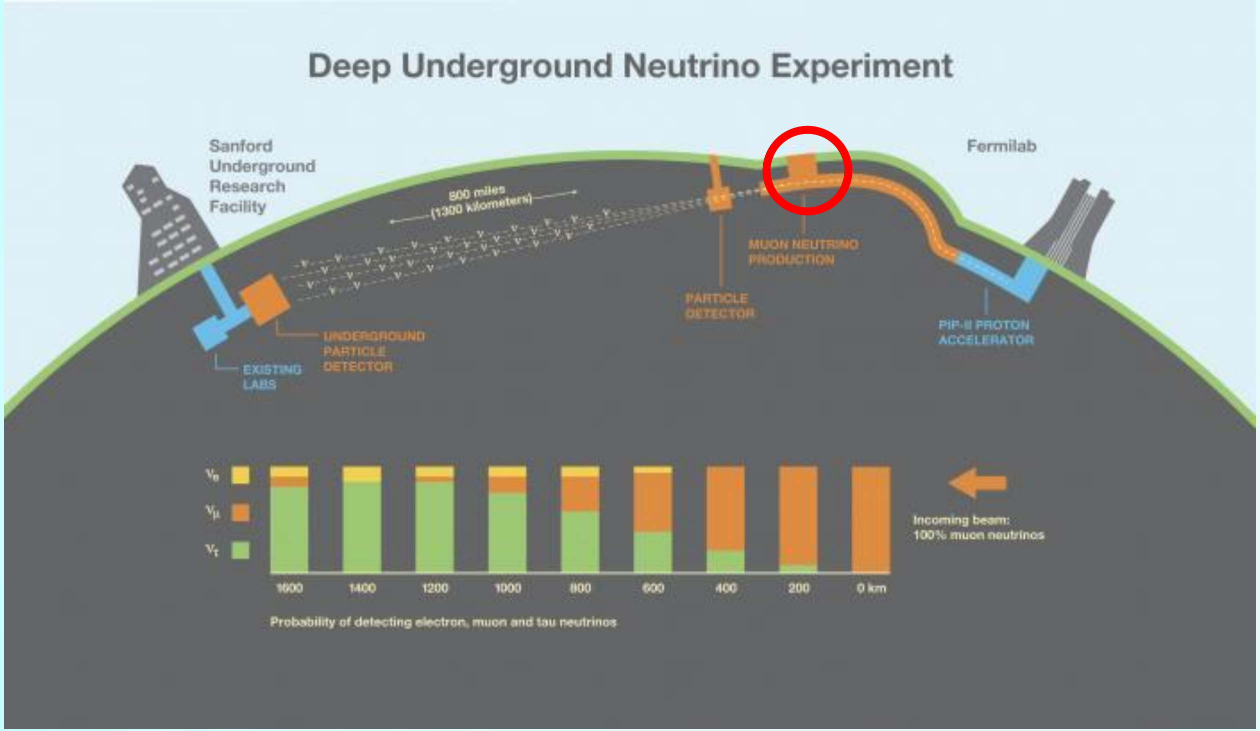
https://jessimic.github.io/tech-portfolio/

DUNE: Deep Underground Neutrino Experiment



https://sciencebusiness.net/network-news/uk-pledges-ps65million-deep-underground-neutrino-experiment

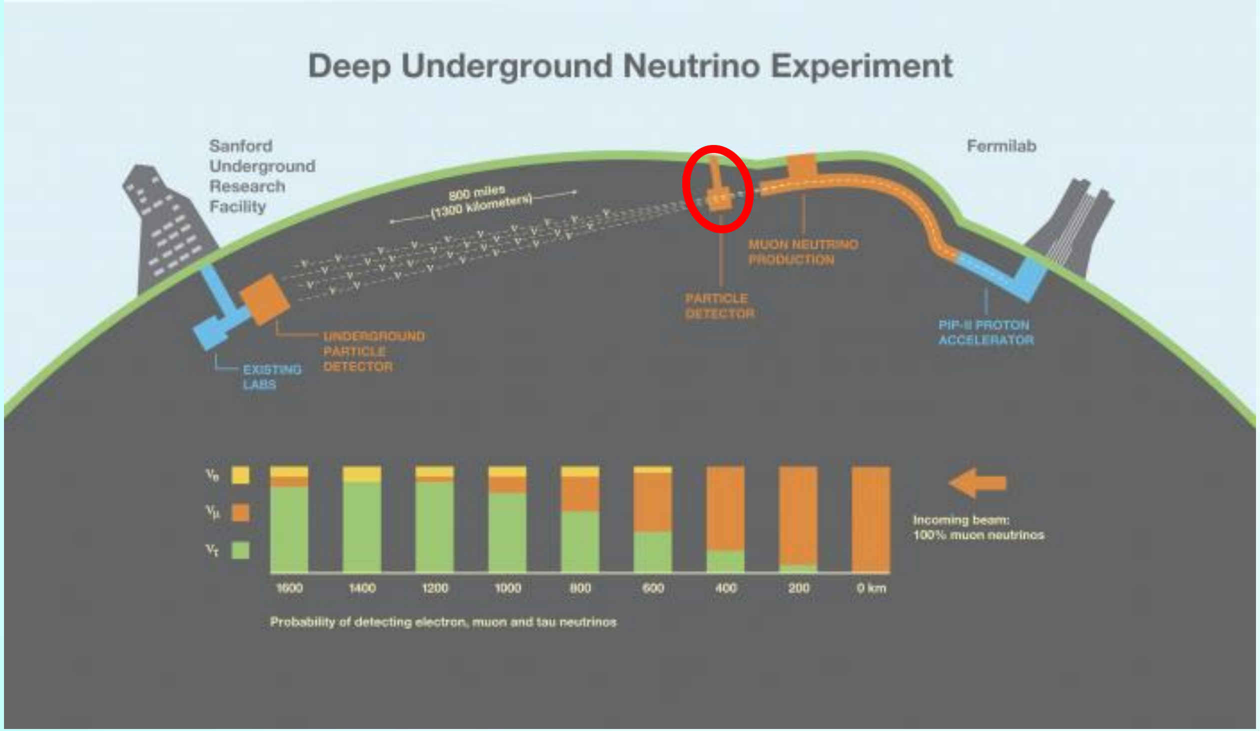
DUNE: Frontier Measurements of Neutrino Physics



- PIP-II = world's most intense neutrino beam

https://www.fzu.cz/en/research/research-topics/deep-underground-neutrino-experiment-dune

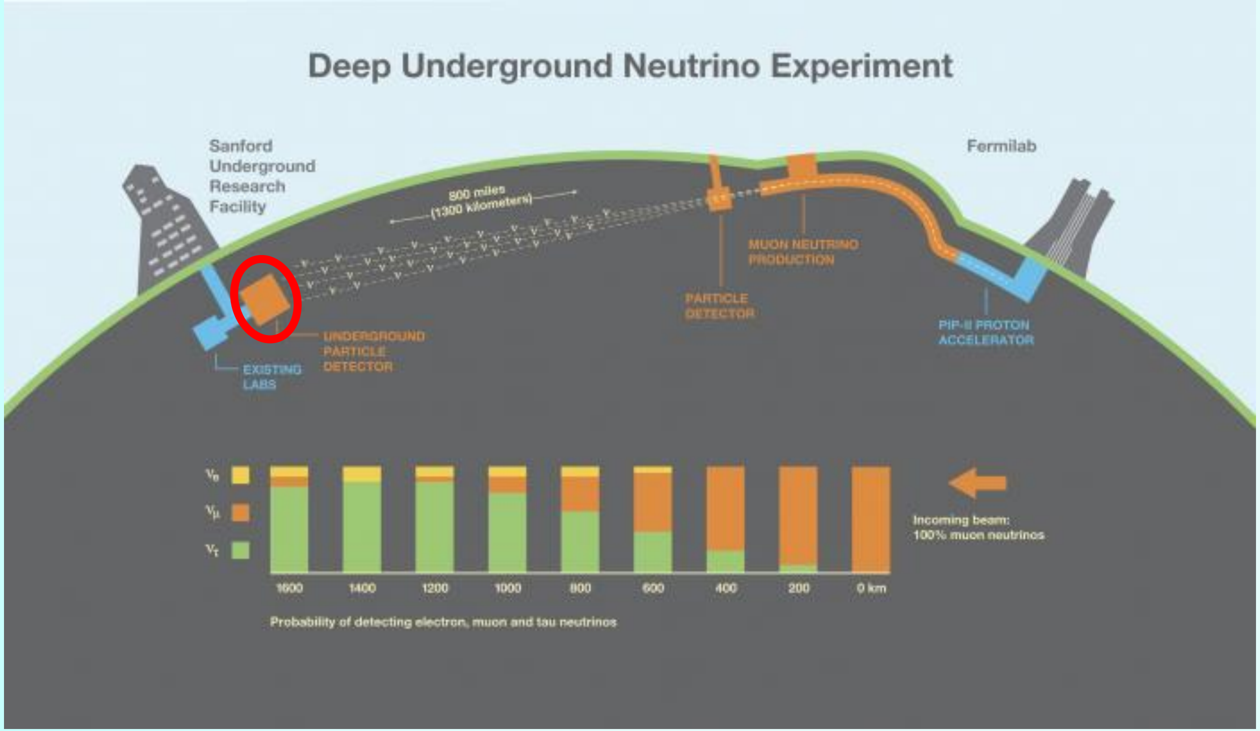
DUNE: Frontier Measurements of Neutrino Physics



- PIP-II = world's most intense neutrino beam
- Near detectors at Ferilab

https://www.fzu.cz/en/research/research-topics/deep-underground-neutrino-experiment-dune

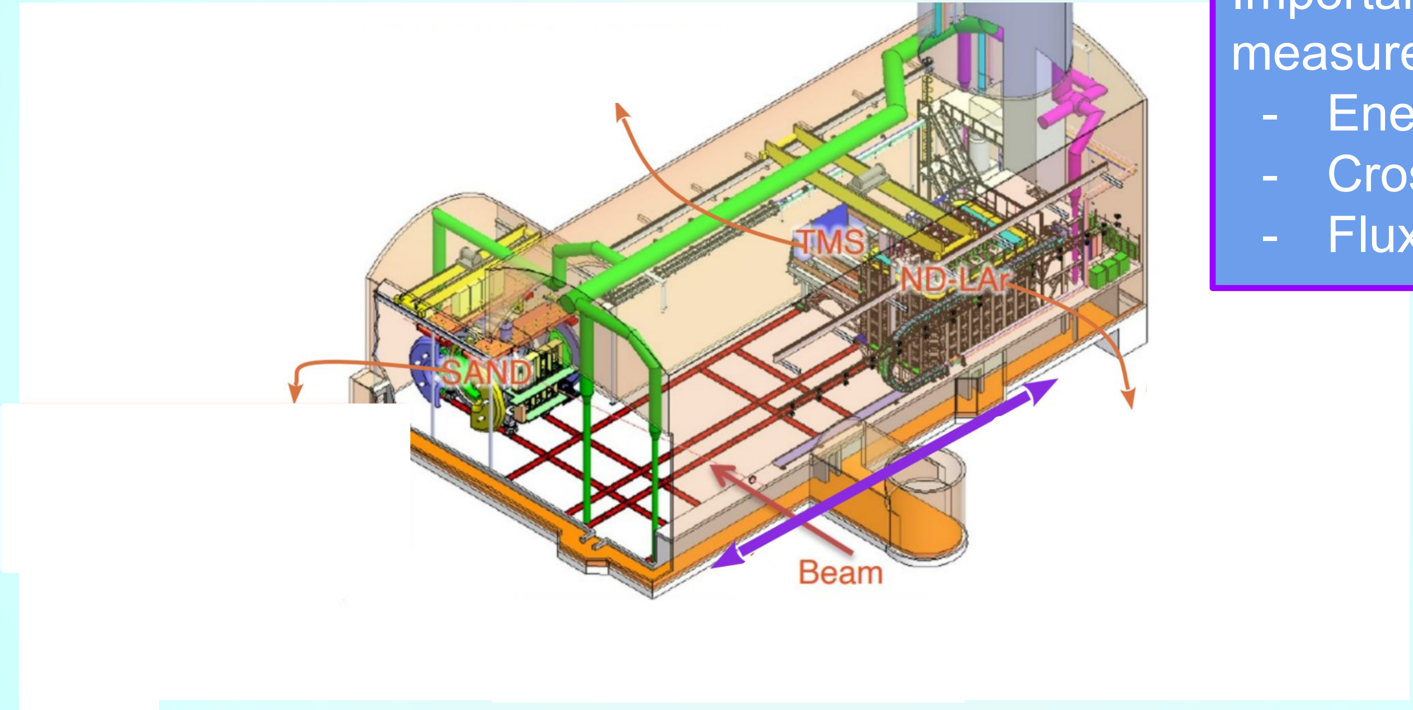
DUNE: Frontier Measurements of Neutrino Physics



https://www.fzu.cz/en/research/research-topics/deep-underground-neutrino-experiment-dune

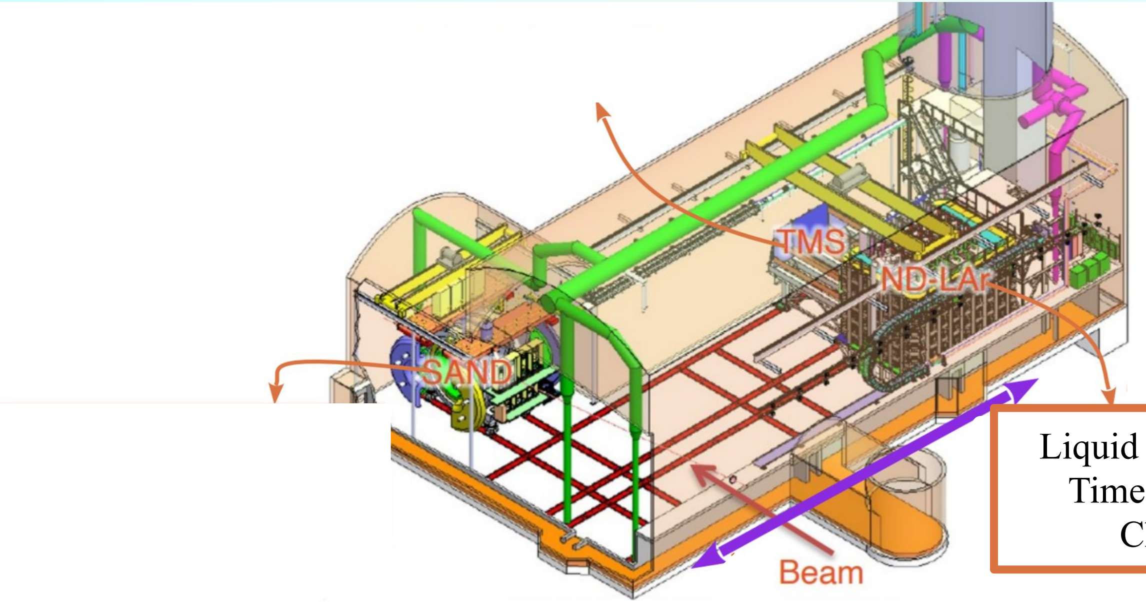
- PIP-II = world's most intense neutrino beam
- Near detectors at Ferilab
- Far detector at SURF

Near Detector Hall



Important to measure ν…
- Energy
- Cross section
- Flux

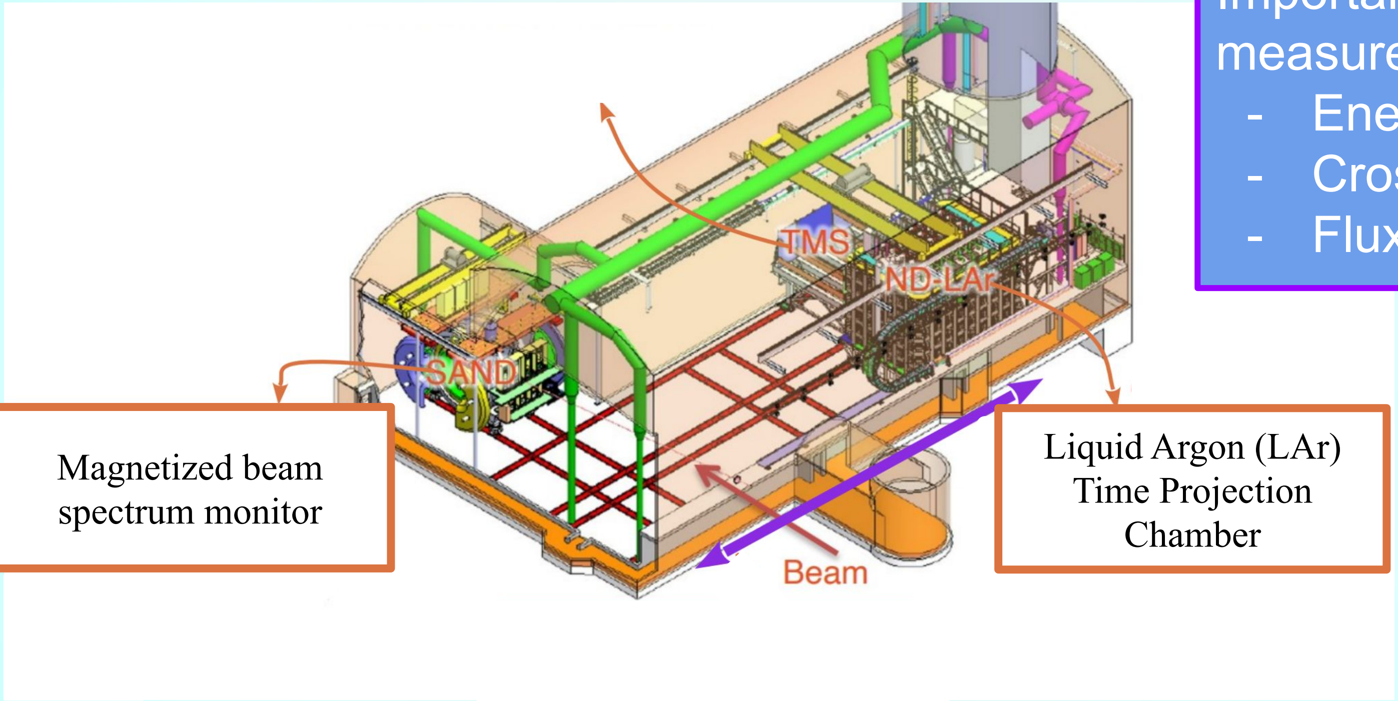
Near Detector Hall



Liquid Argon (LAr) Time Projection Chamber

Important to measure ν…
- Energy
- Cross section
- Flux

Near Detector Hall

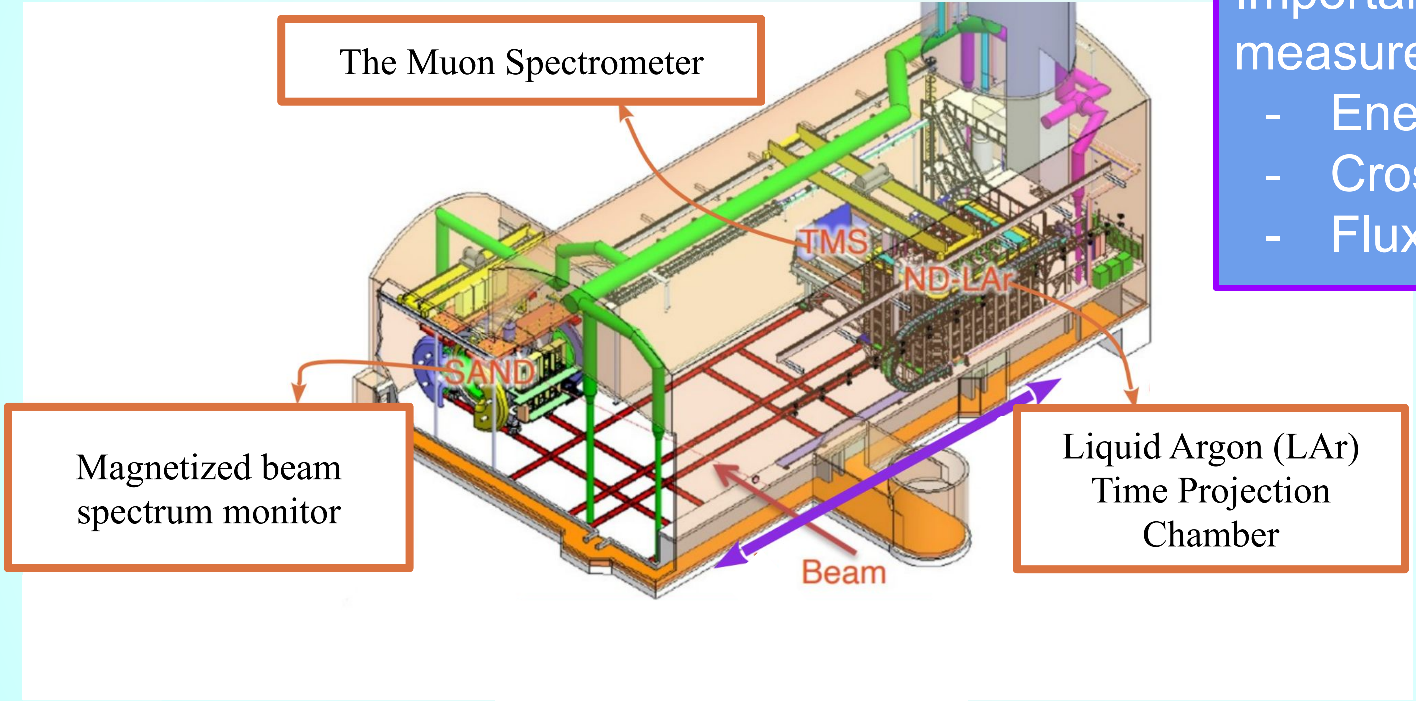


Magnetized beam spectrum monitor

Liquid Argon (LAr) Time Projection Chamber

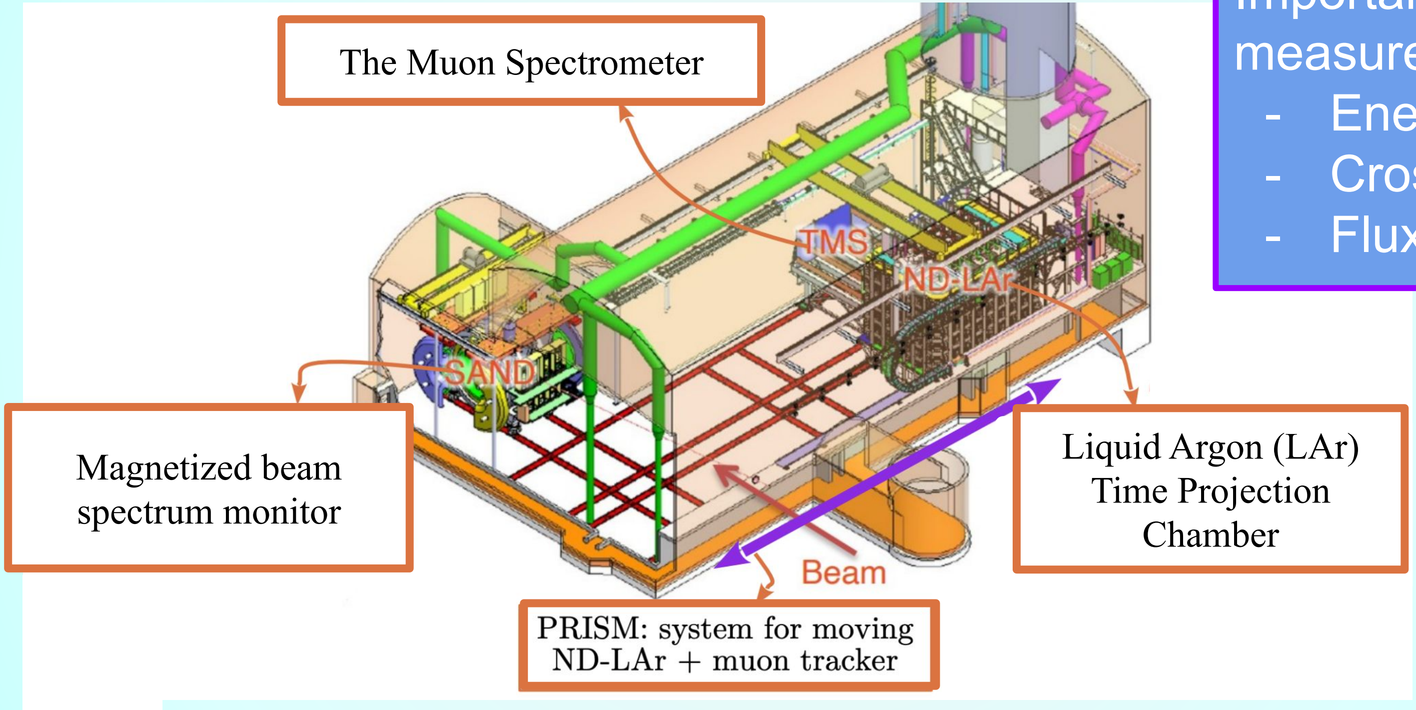
Important to measure ν…
- Energy
- Cross section
- Flux

Near Detector Hall



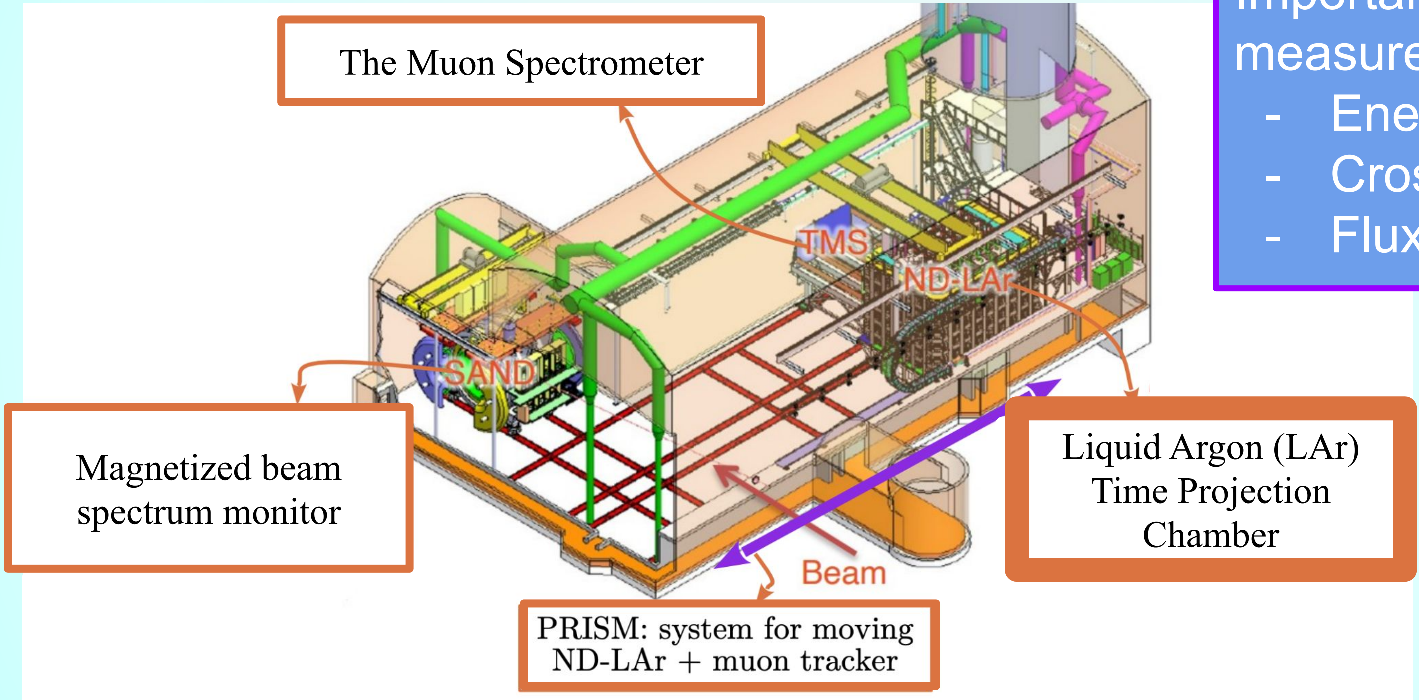
Important to measure ν…
- Energy
- Cross section
- Flux

Near Detector Hall



Important to measure ν…
- Energy
- Cross section
- Flux

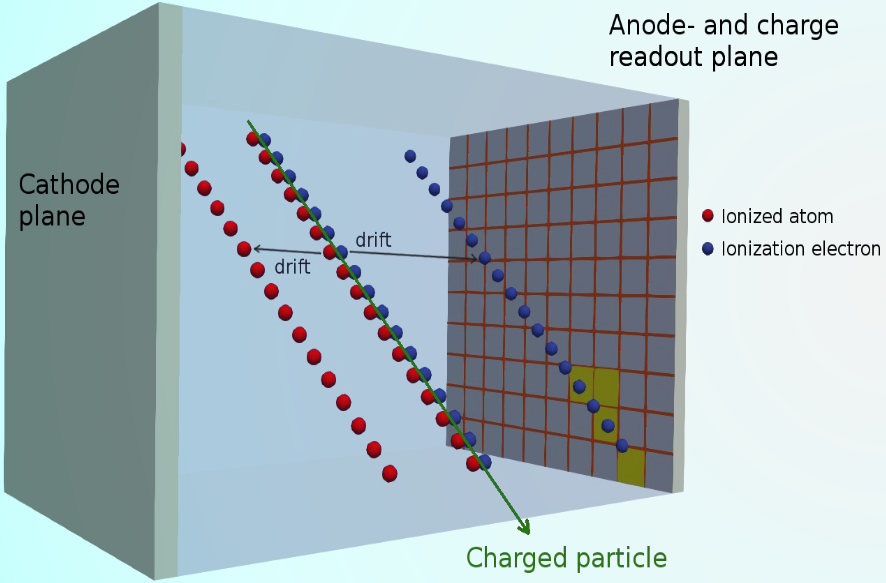
Near Detector Hall



Important to measure ν…

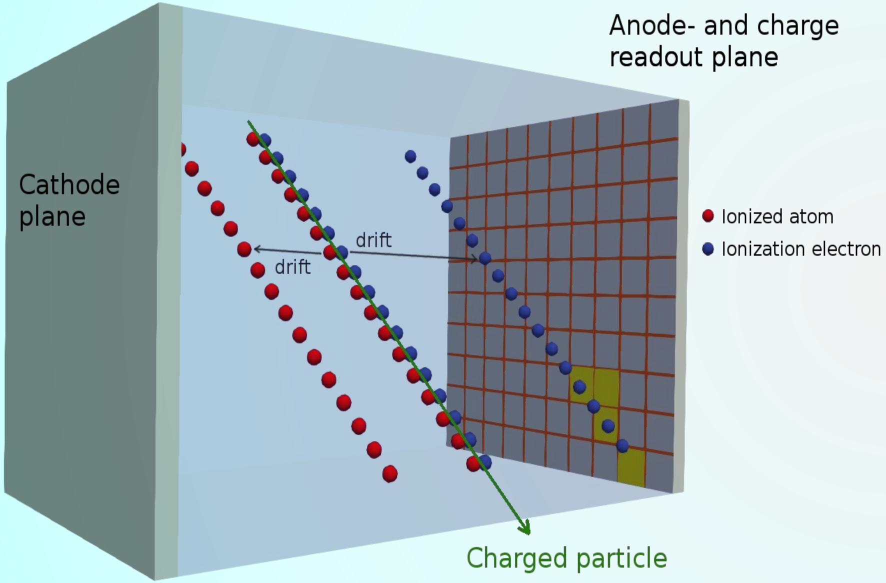
- Energy
- Cross section
- Flux

Liquid Argon (LAr) Time Projection Chamber (TPC)

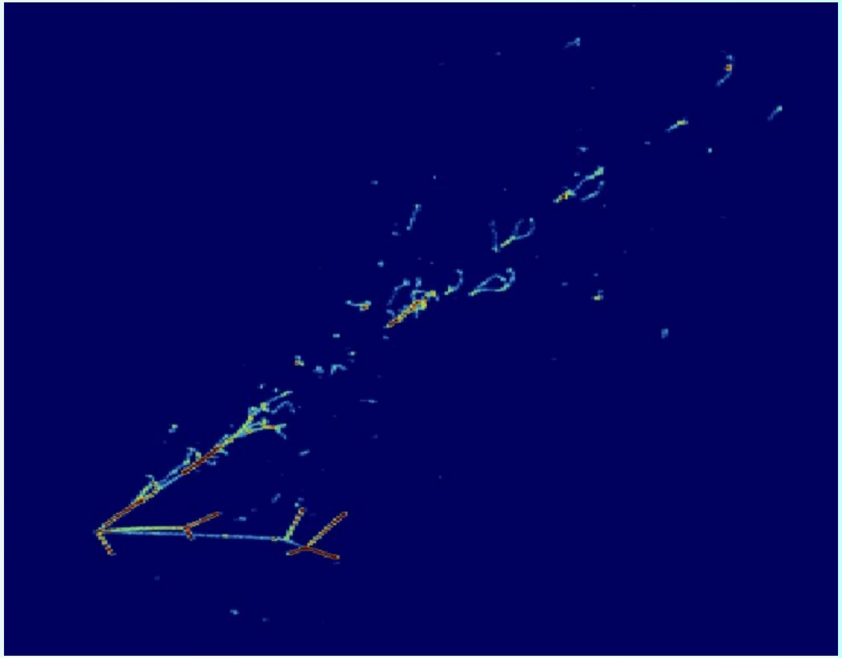


https://argoncube.org/LArTPCs.html

Liquid Argon (LAr) Time Projection Chamber (TPC)

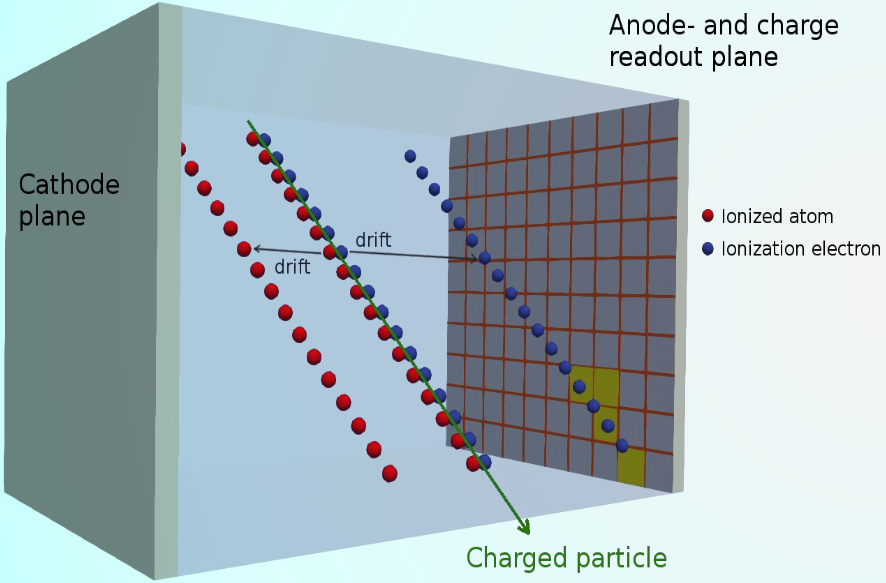


https://argoncube.org/LArTPCs.html



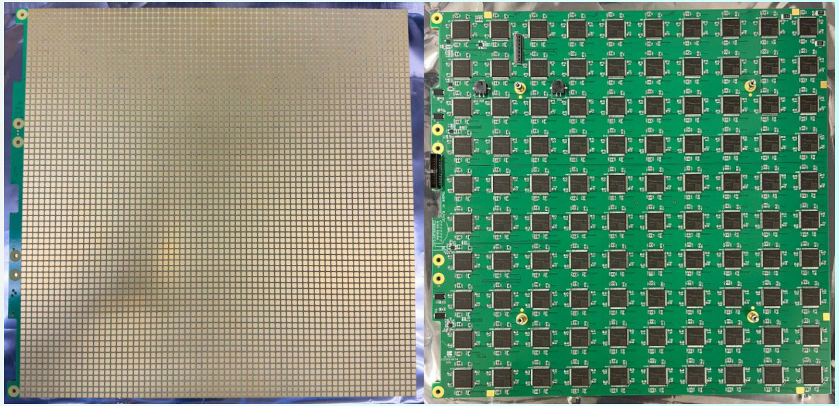
Color = charge deposition
Output: pion and two protons

Liquid Argon (LAr) Time Projection Chamber (TPC)



https://argoncube.org/LArTPCs.html

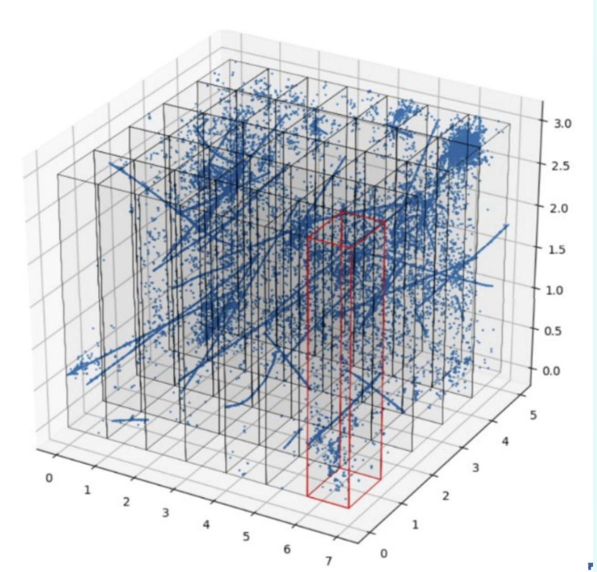
But we're using a 2D pixel plane readout! So we get a 3D image!



Both sides of a 1,000 square cm LArPix tile with 4900 pixels (left) and 100 LArPix ASICs (right). (Credit: Andrew Lambert)
https://physicalsciences.lbl.gov/2023/06/22/larpix-berkeley-labs-new-3d-pixel-tile-detection-system-for-dune/

Intense Near Detector Beam

- Expect ~20 ν interactions!

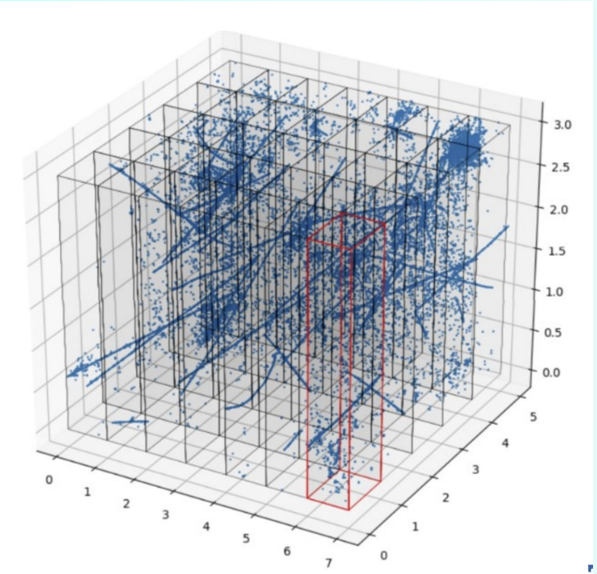


Simulation of ND LAr beam spill (10μs)

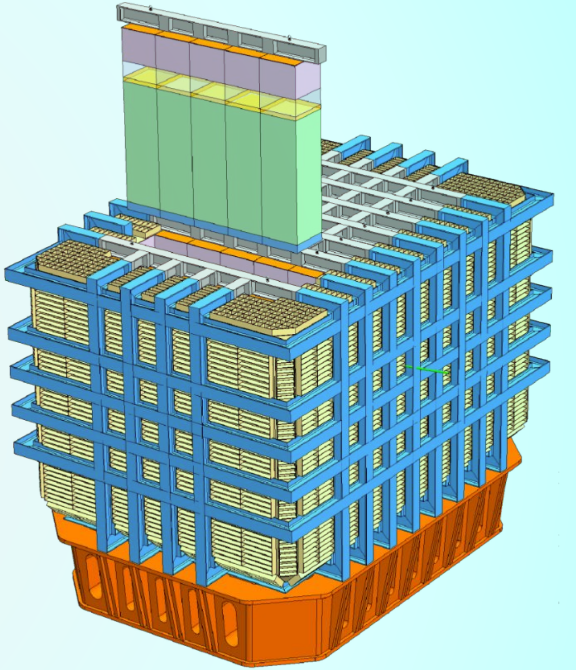
https://argoncube.org/LArTPCs.html

DUNE: Near Detector LAr TPCs

- Expect ~20 ν interactions!
- Need new technology:
  - Modularized detector



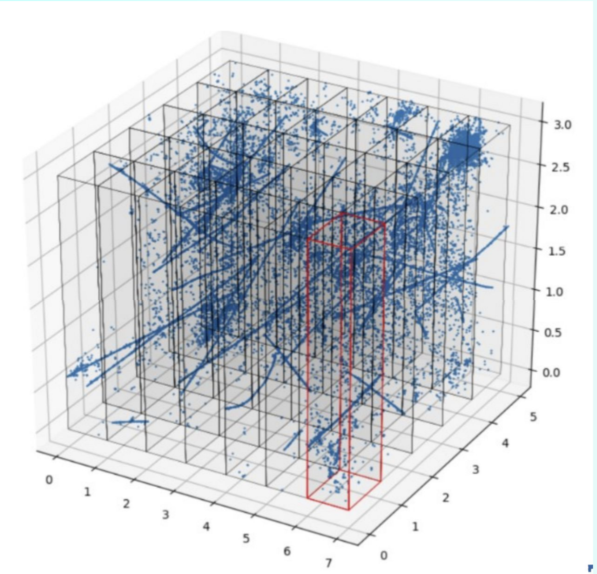
Simulation of ND LAr beam spill (10μs)



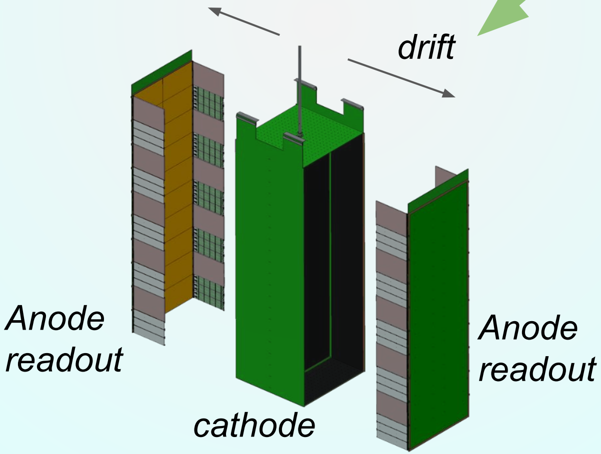
https://argoncube.org/duneND.html

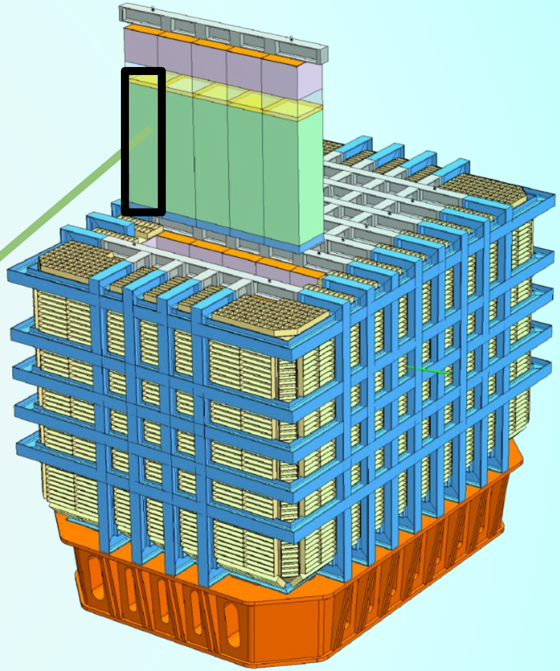
DUNE: Near Detector LAr TPCs

- Expect ~20 ν interactions!
- Need new technology:
  - Modularized detector
- TPC with central cathode



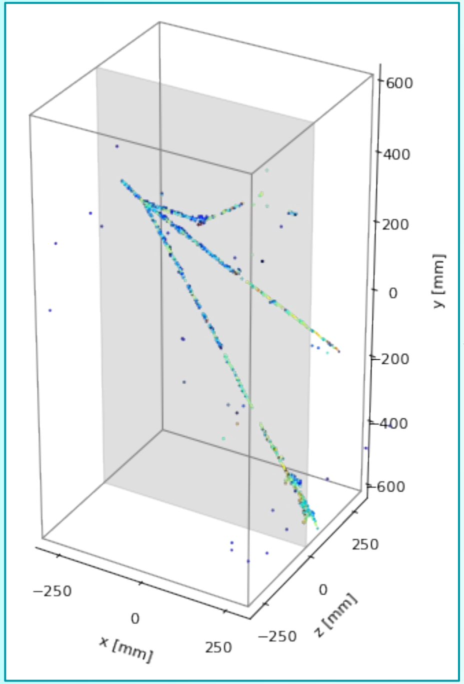
Simulation of ND LAr beam spill ($10\mu s$)





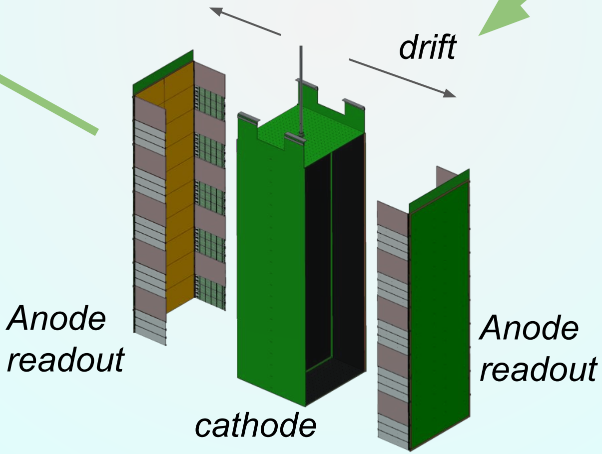
https://argoncube.org/duneND.html

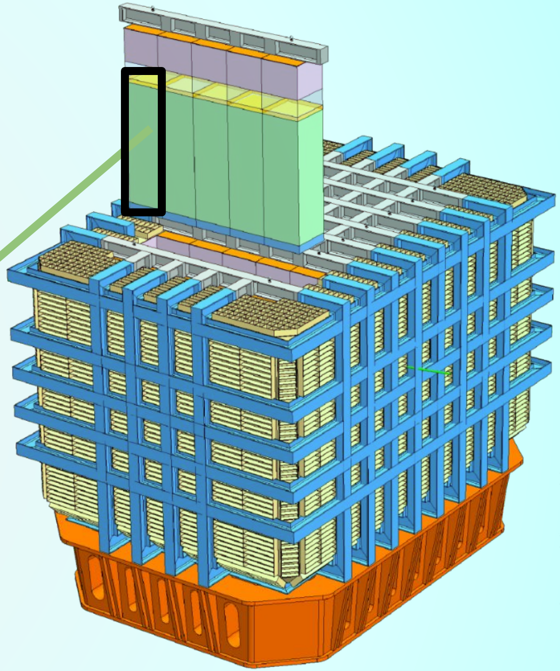
DUNE: Near Detector LAr TPCs



Simulation of 1 ND LAr TPC module

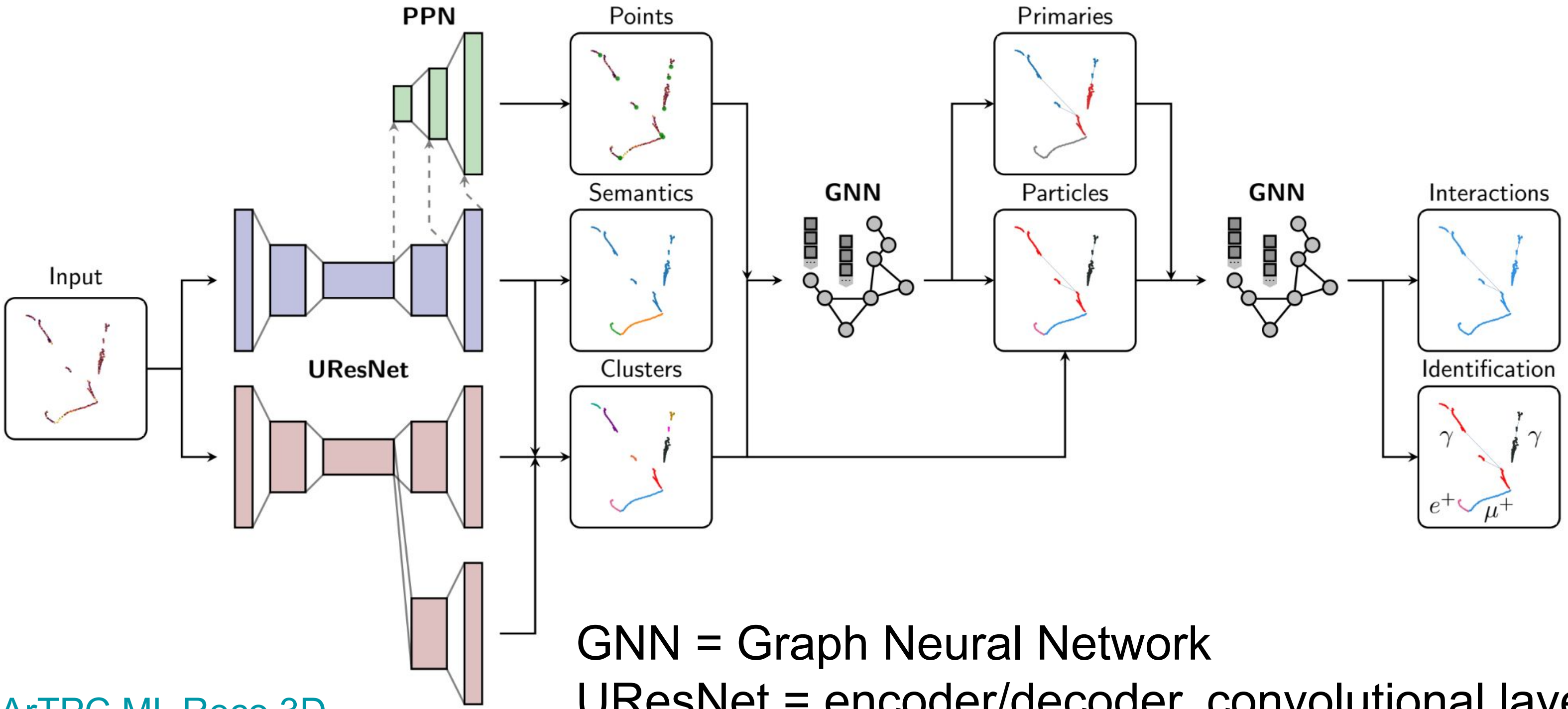
- Expect ~20 ν interactions!
- Need new technology:
  - Modularized detector
- TPC with central cathode





https://argoncube.org/duneND.html

3D LAr TPC: ML Reco 3D

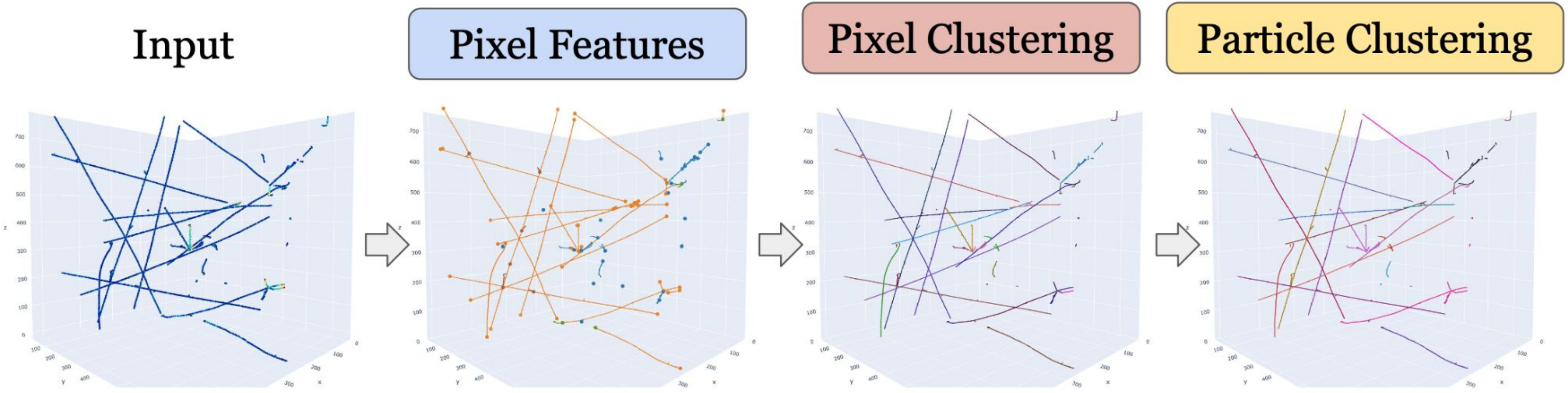


[LArTPC ML Reco 3D]

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

3D LAr TPC: ML Reco 3D

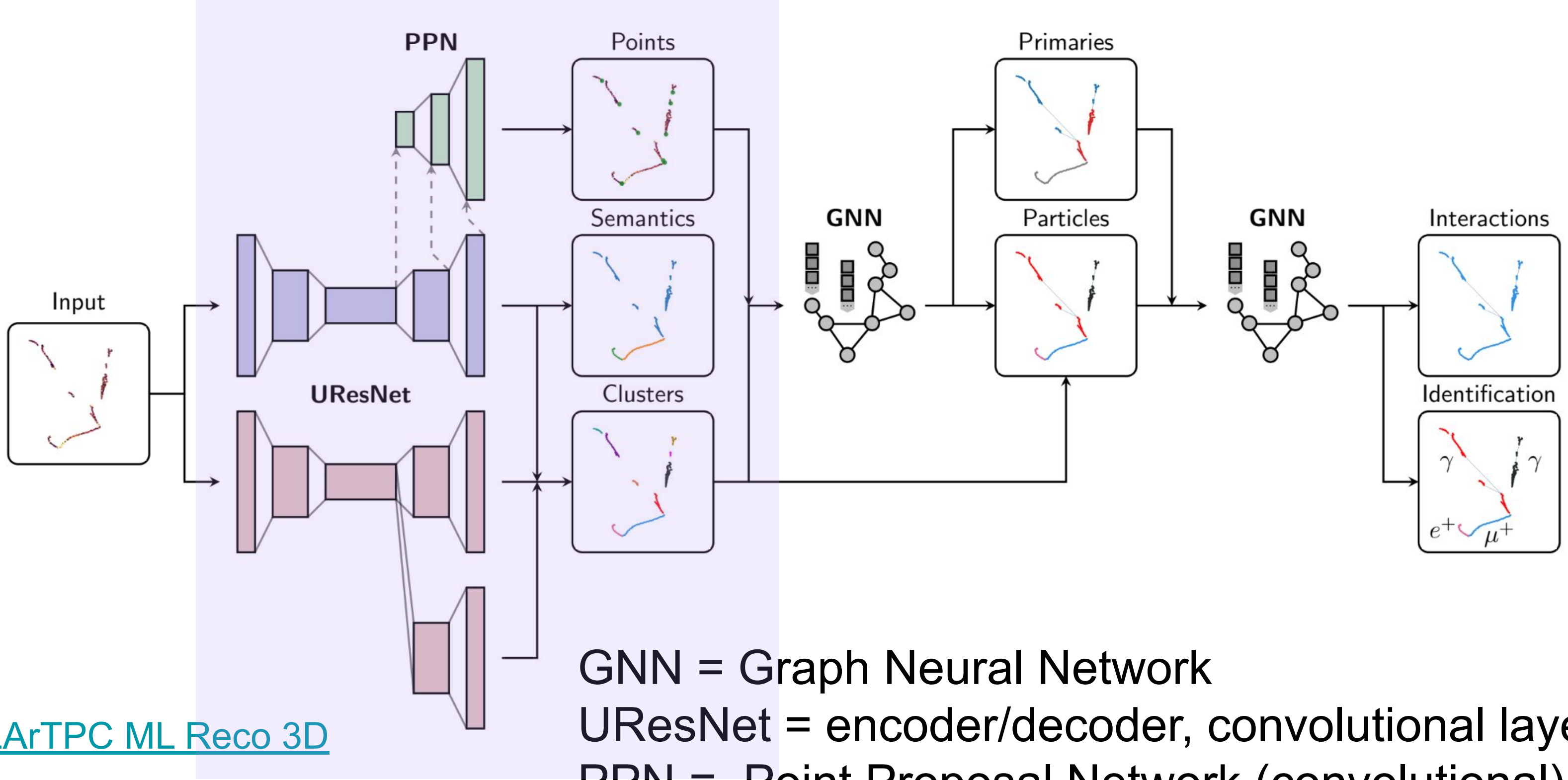
→ Starts by labeling pixels & features
→ End goal of chain: identifies particles in the input image



LArTPC ML Reco 3D

Graphic credit: Kazuhiro Terao

3D LAr TPC: ML Reco 3D

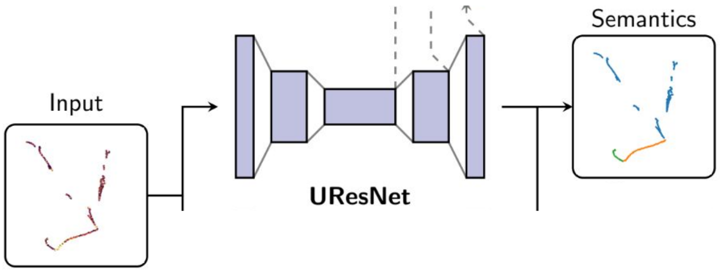


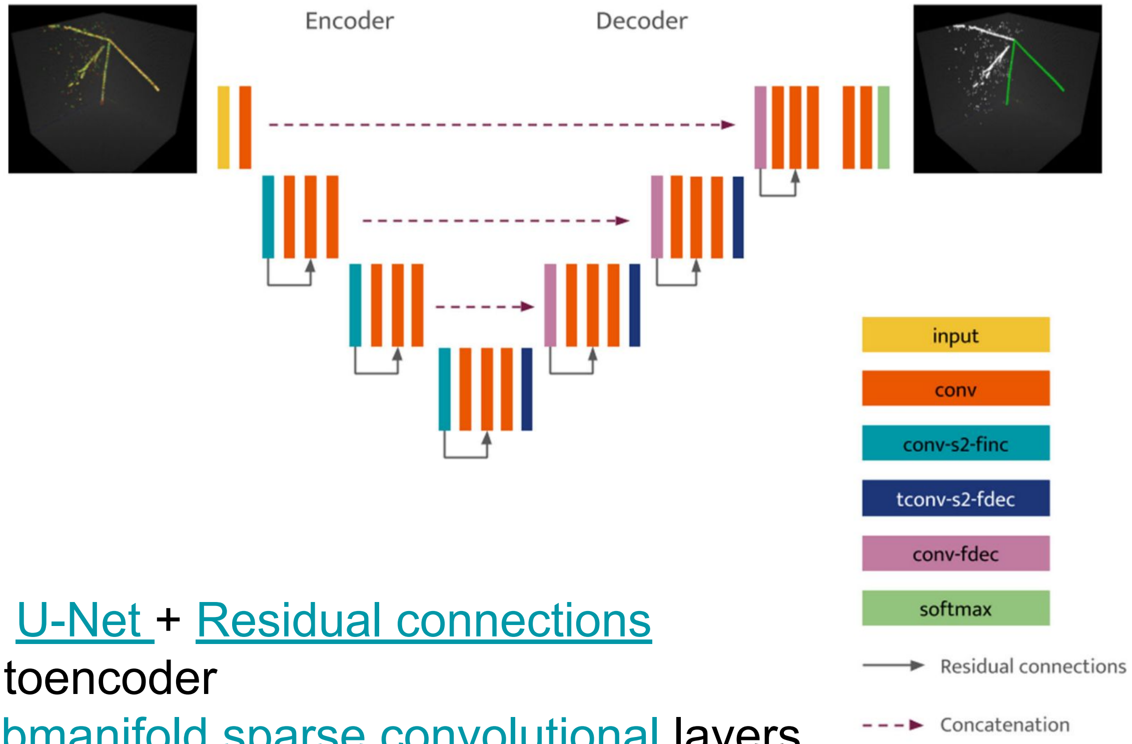
GNN = Graph Neural Network
UResNet = encoder/decoder, convolutional layers
PPN = Point Proposal Network (convolutional)

[LArTPC ML Reco 3D]

Pixel Features: Semantics

Pixel feature extraction



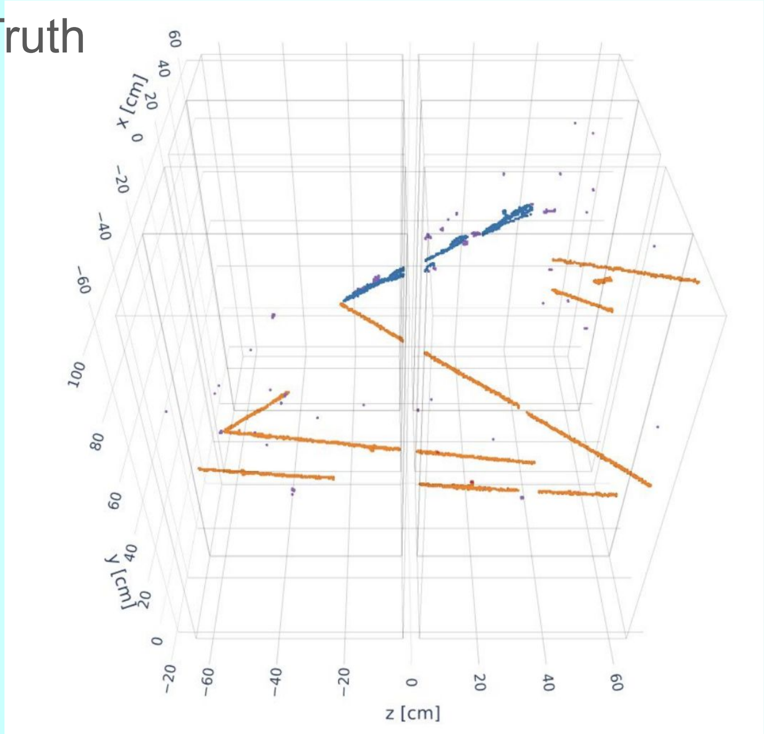


UResNet = U-Net + Residual connections
→ Uses autoencoder
→ Uses submanifold sparse convolutional layers

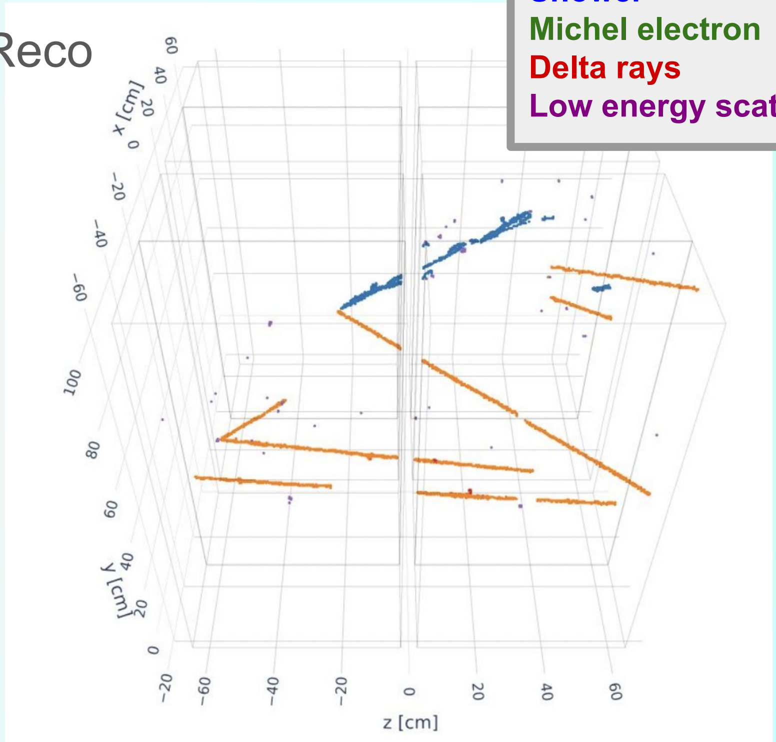
LArTPC ML Reco 3D
Phys Rev D (102) 012005

Assign Each Pixel To Label

Truth



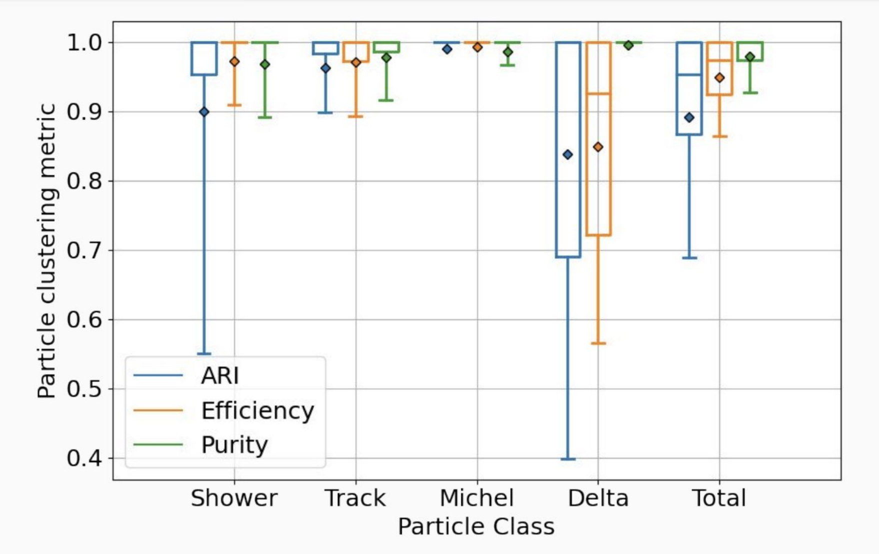
Reco



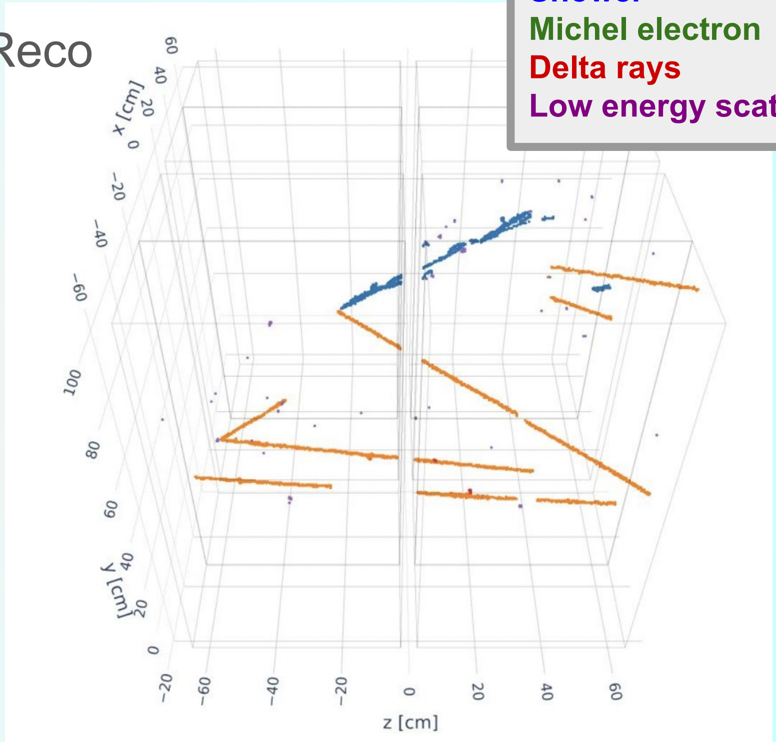
Track
Shower
Michel electron
Delta rays
Low energy scatters

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

Assign Each Pixel To Label



Reco

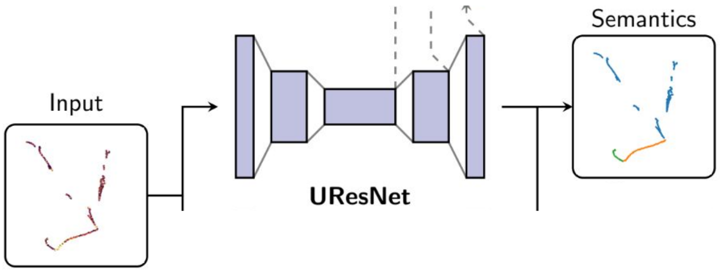


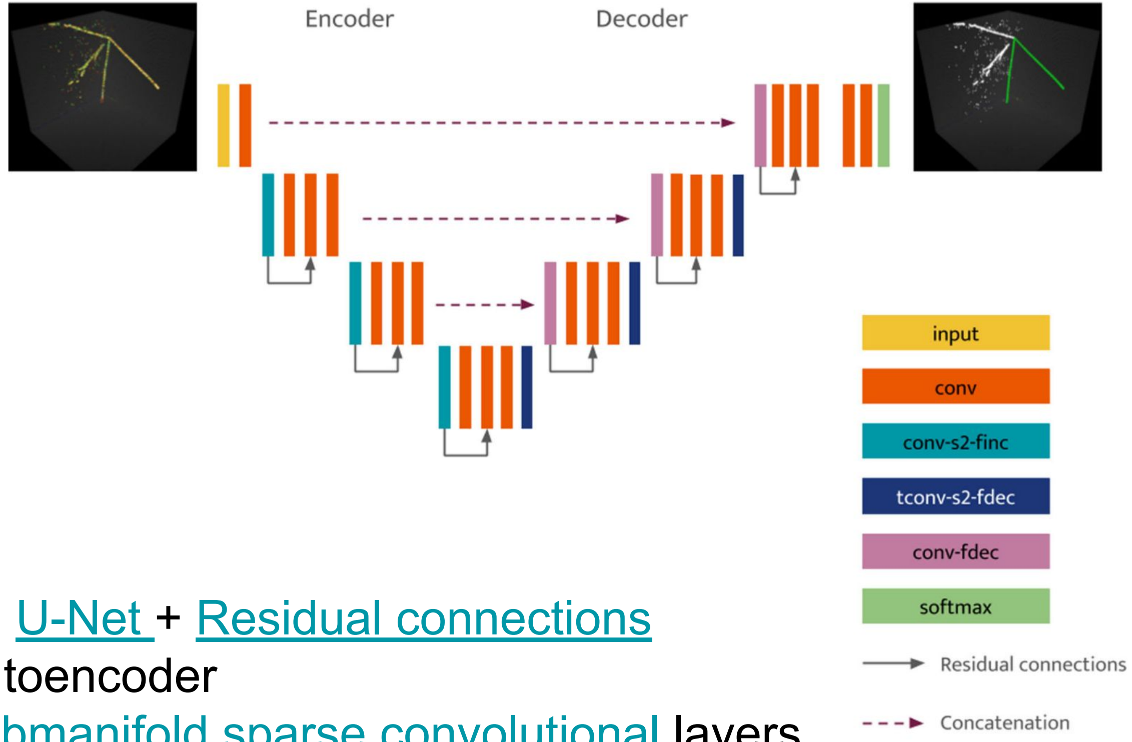
Track
Shower
Michel electron
Delta rays
Low energy scatters

PhysRevD (102) 012005 & PhysRevD (104) 032004

Pixel Features: Semantics

Pixel feature extraction



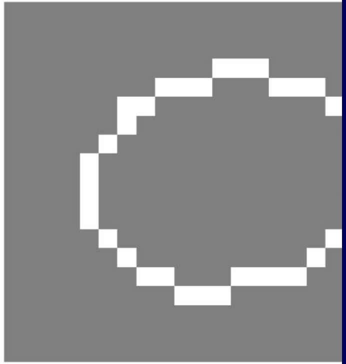


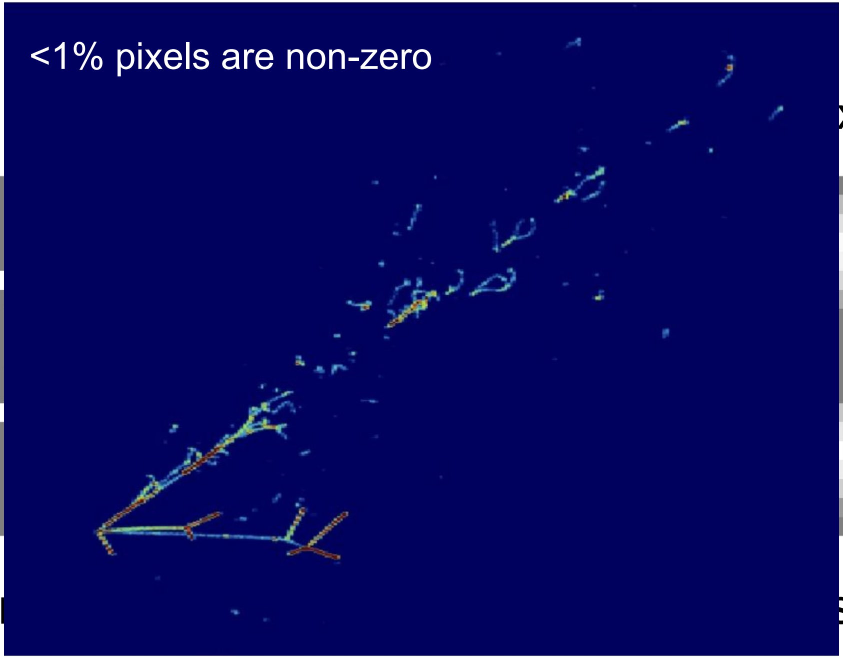
UResNet = [U-Net](#) + [Residual connections](#)
→ Uses autoencoder
→ Uses [submanifold sparse convolutional](#) layers

[LArTPC ML Reco 3D](#)
[Phys Rev D (102) 012005](#)

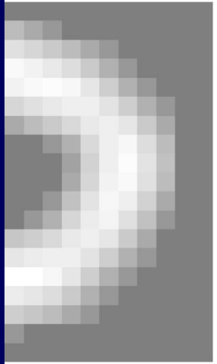
Submanifold Sparse Convolutions

Original





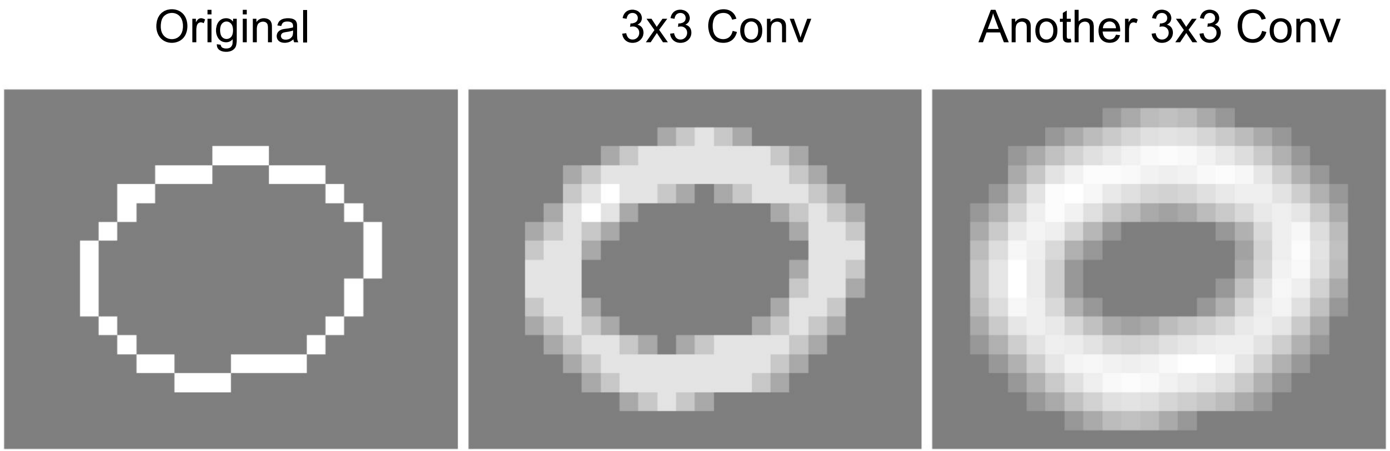
x3 Conv



❗ Applyi sity

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

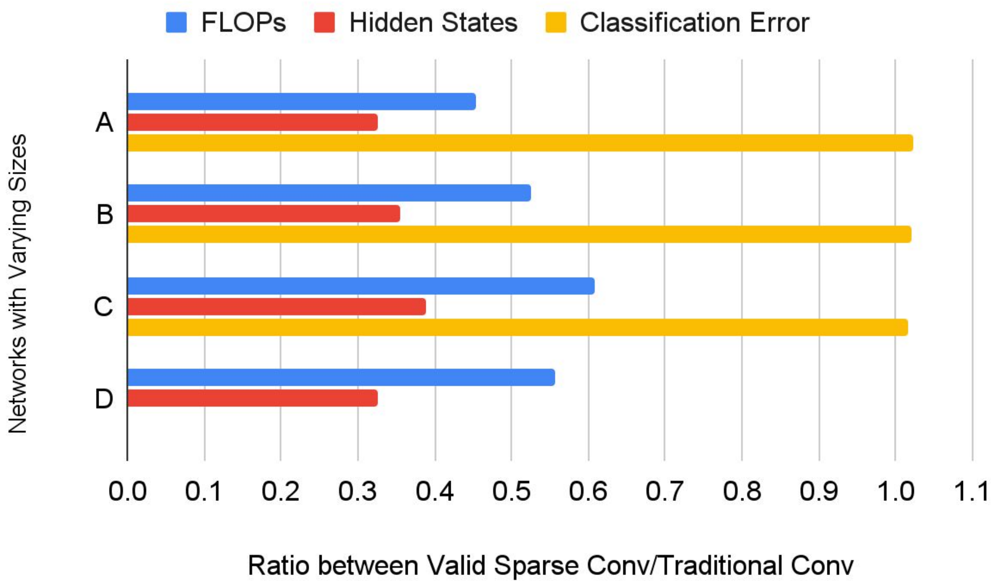
Submanifold Sparse Convolutions



❗ Applying regular convolutions reduces sparsity

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

Submanifold Sparse Convolutions



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

Advantage of sparse conv:

✓ Classification error ~equal

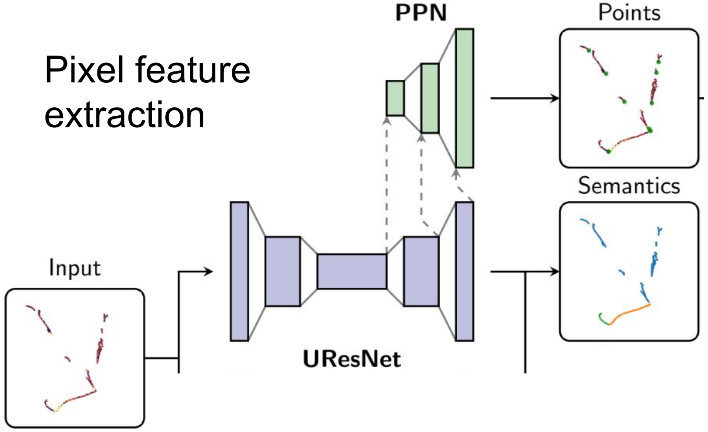
✓ Uses ~½ FLOPs

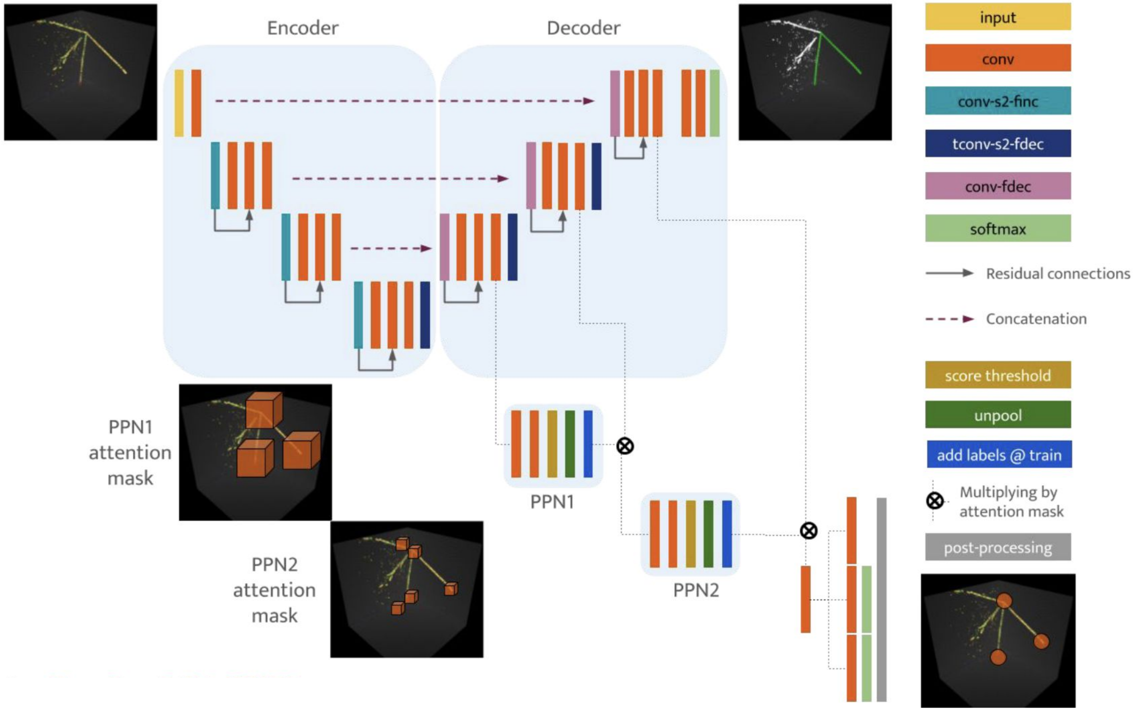
✓ Uses ~⅓ hidden states

Example Application:
*On MicroBooNE, gives capability to train on **entire** LArTPC image, instead of 64 crops (ref Ran's Talk at NPML 2020)!*

Pixel Features: Points of Interest

Pixel feature extraction

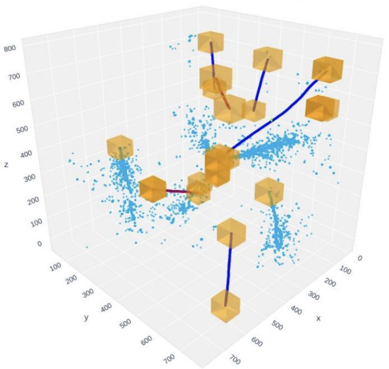


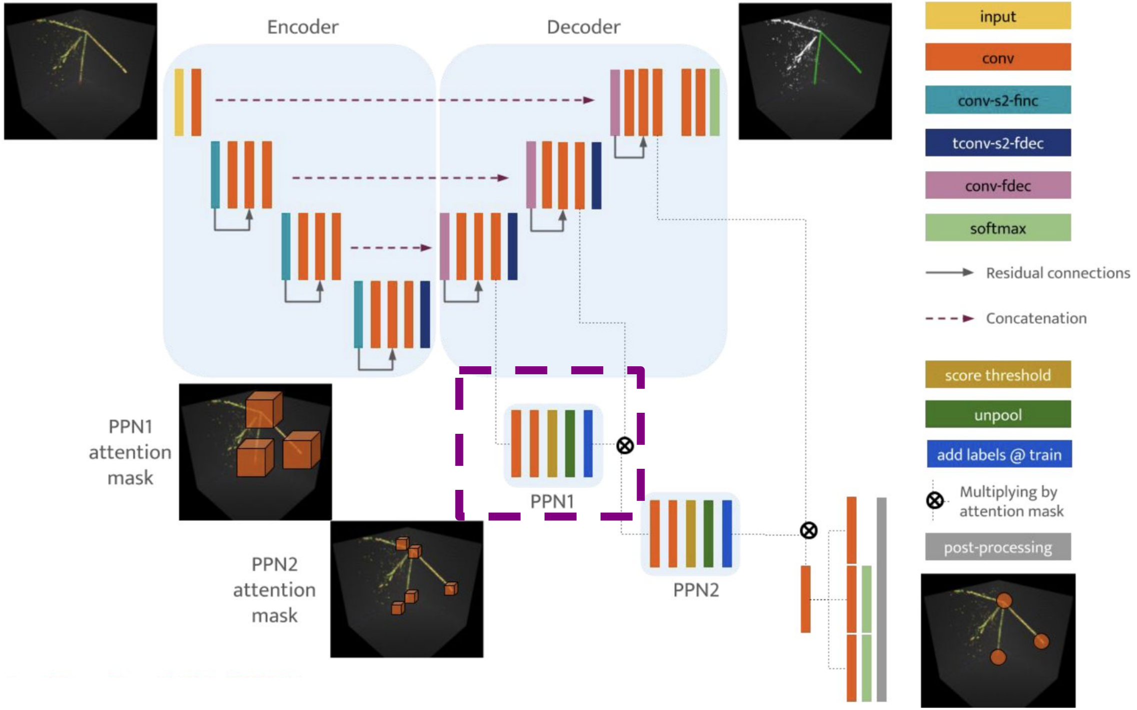


[LArTPC ML Reco 3D](#)
[Phys Rev D (104) 032004](#)

Pixel Features: Points of Interest

Pixel feature extraction at low resolution (PPN1)



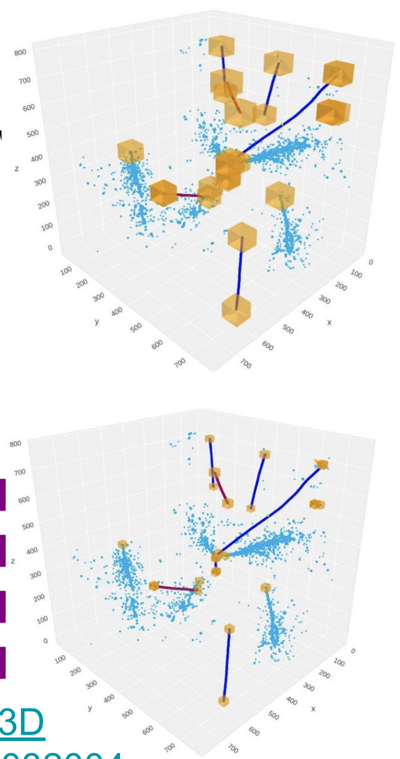


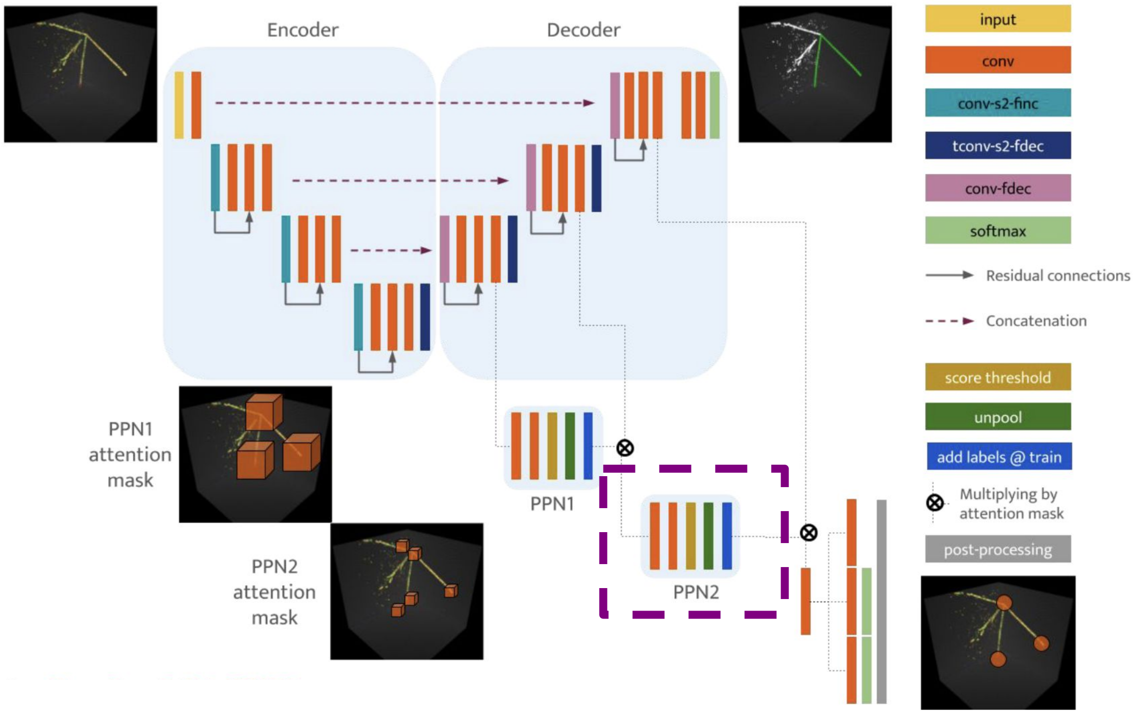
[LArTPC ML Reco 3D](#)
[Phys Rev D (104) 032004](#)

Pixel Features: Points of Interest

Pixel feature extraction at low resolution (PPN1)

Pixel feature extraction at higher resolution (PPN2)

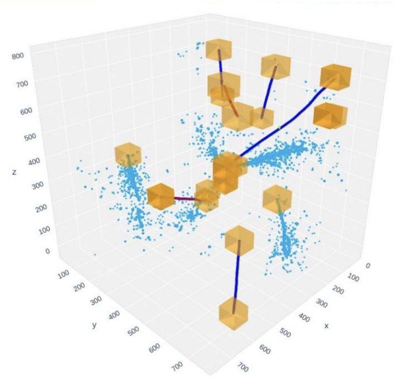




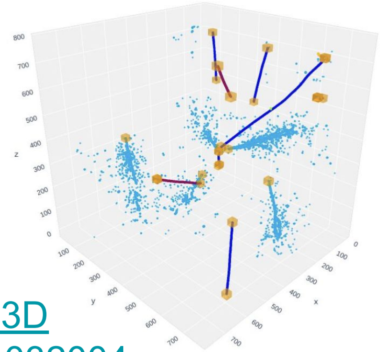
[LArTPC ML Reco 3D](#)
[Phys Rev D (104) 032004](#)

Pixel Features: Points of Interest

Pixel feature extraction at low resolution (PPN1)

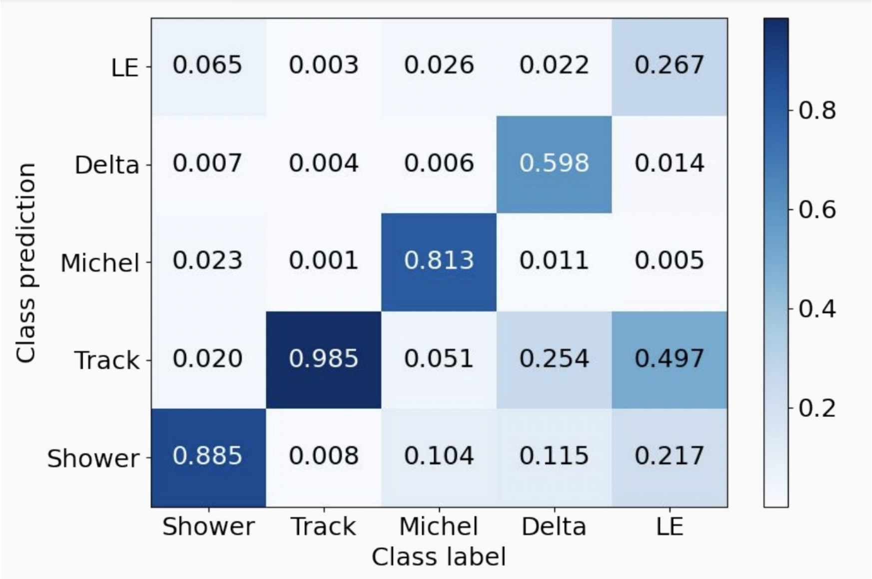


Pixel feature extraction at higher resolution (PPN2)



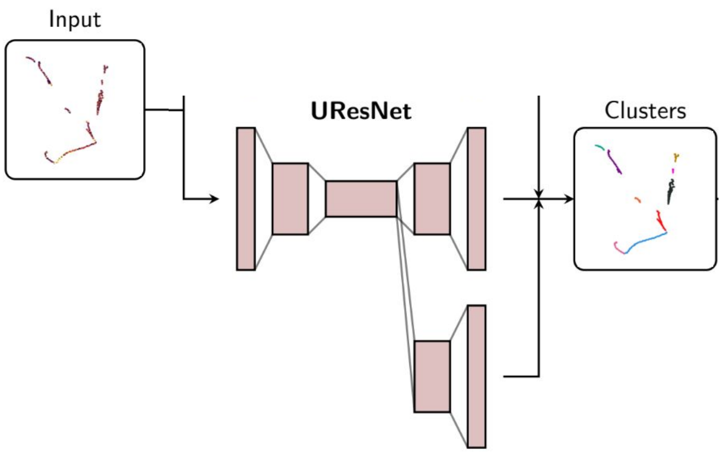
[LArTPC ML Reco 3D](#)
[Phys Rev D (104) 032004](#)

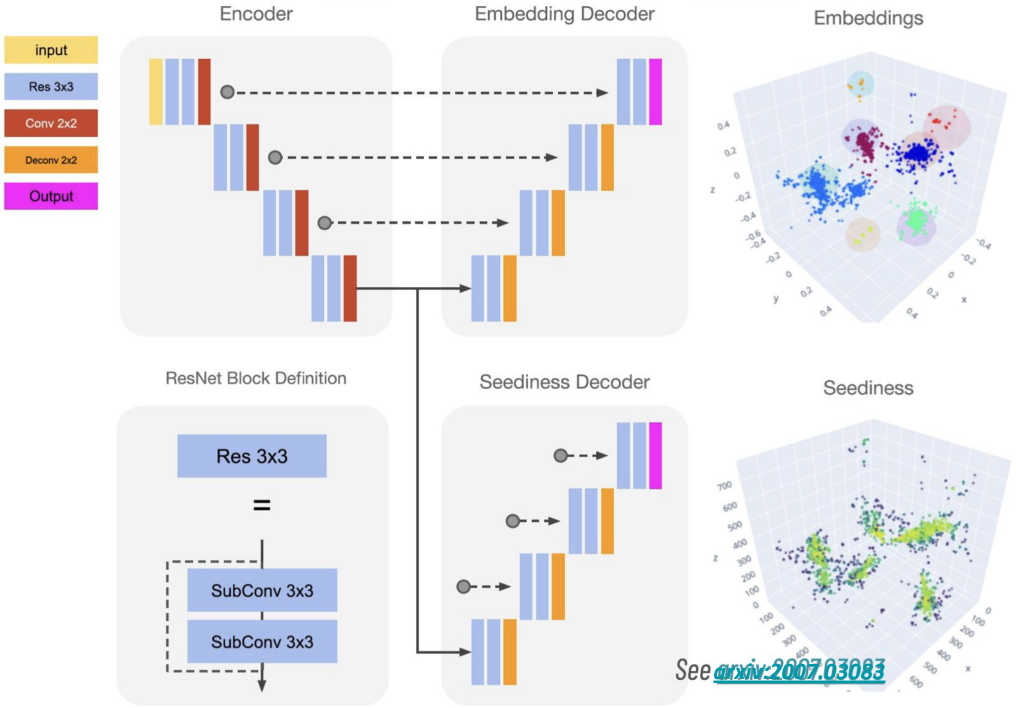
Current Performance on 2x2 Near Detector Prototype



Pixel Features: SPICE Clustering

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

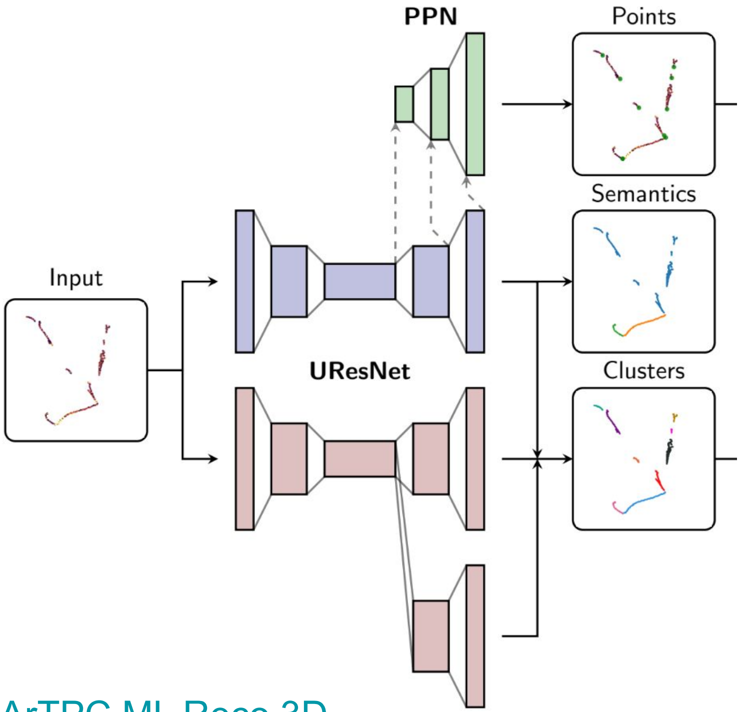




See arxiv:2007.03083

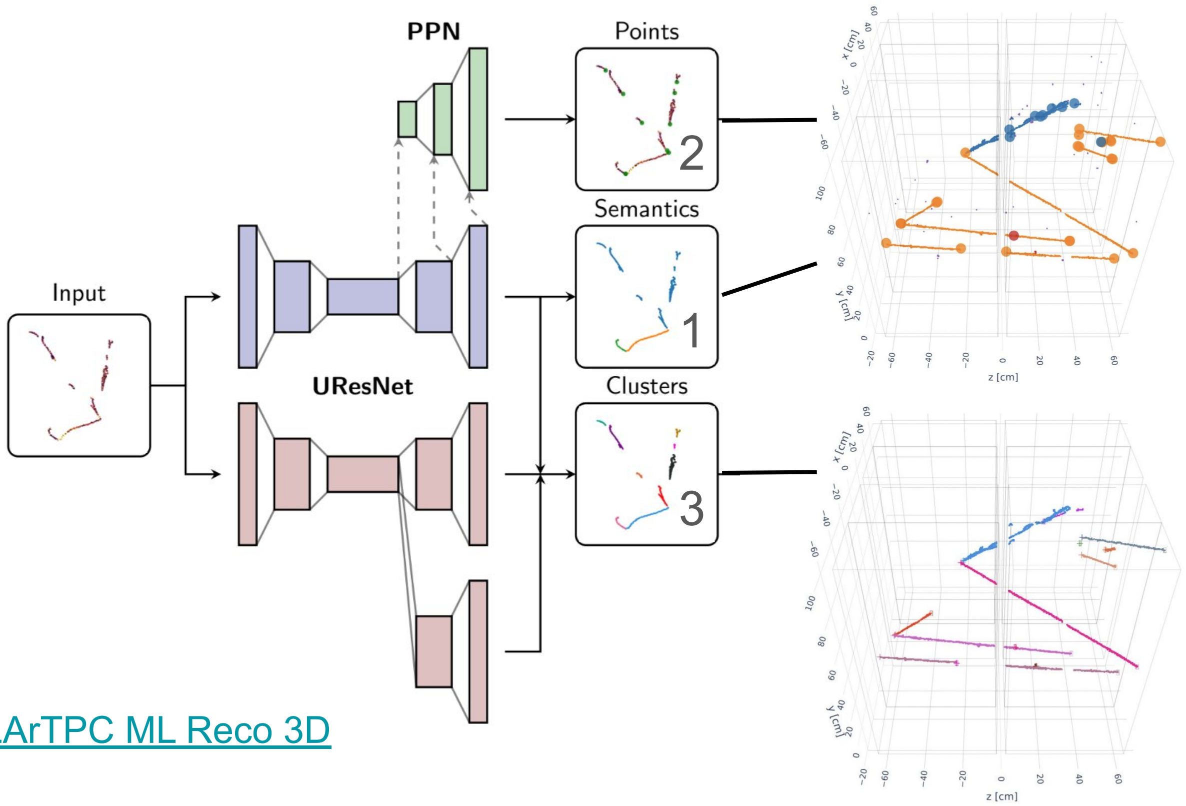
Embedding decoder	Transformation
Seediness decoder	Centroids

Pixel Features: Output



LArTPC ML Reco 3D

Pixel Features: Output

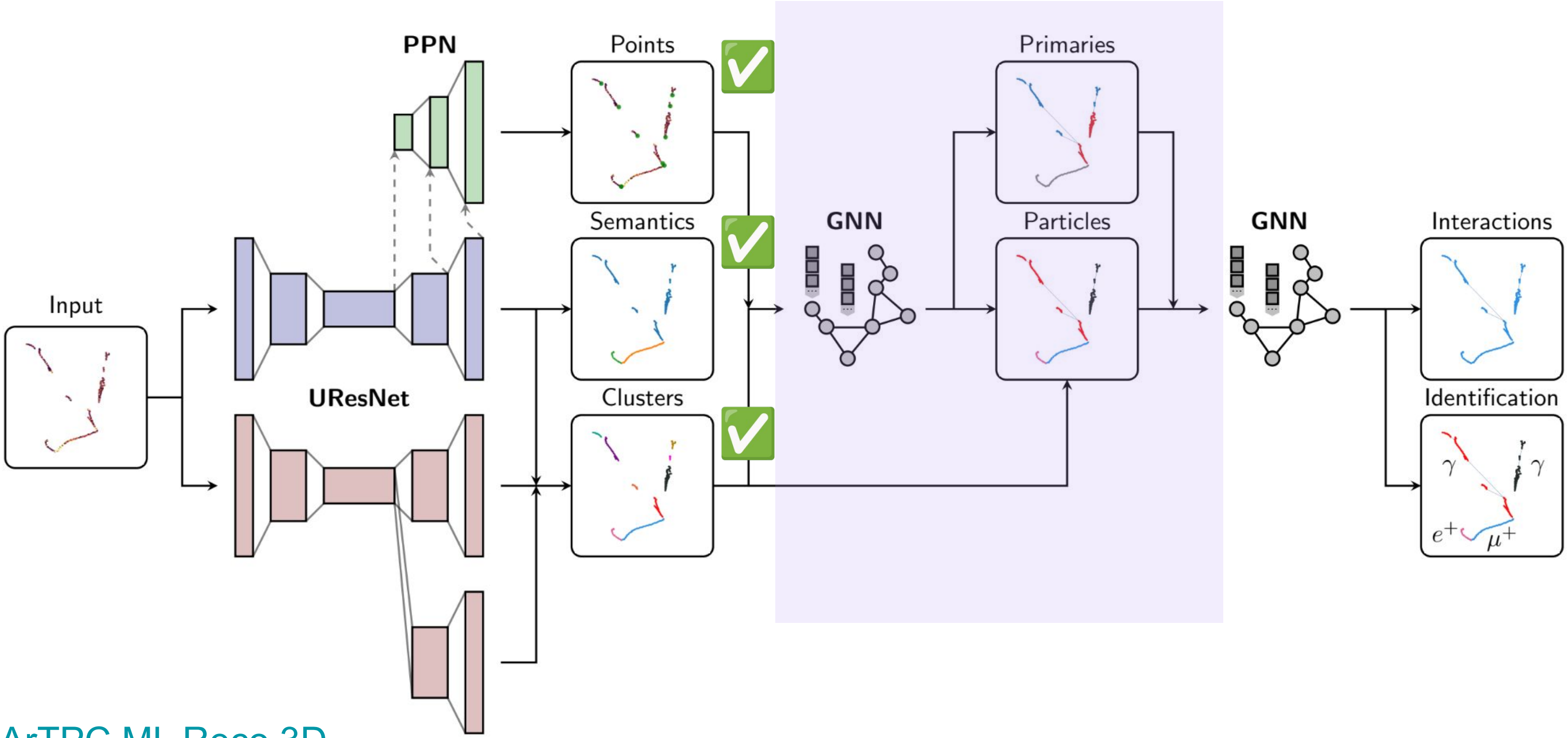


[LArTPC ML Reco 3D]

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

Color-coded by cluster

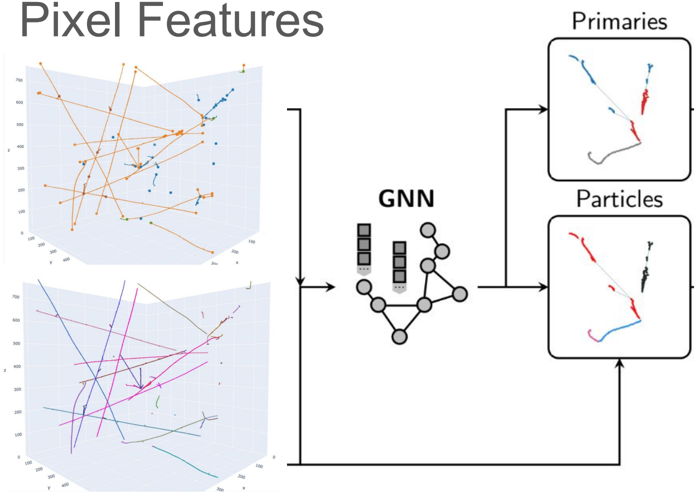
3D LAr TPC: ML Reco 3D



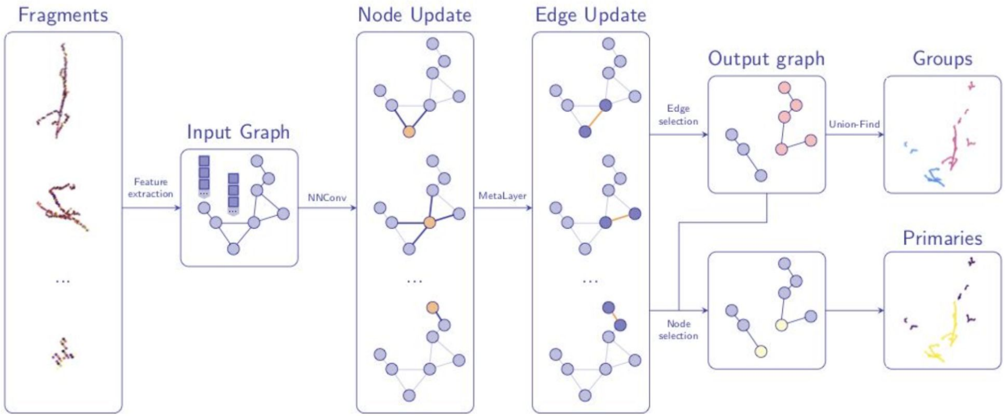
[LArTPC ML Reco 3D]

Fragment Clustering

Pixel Features



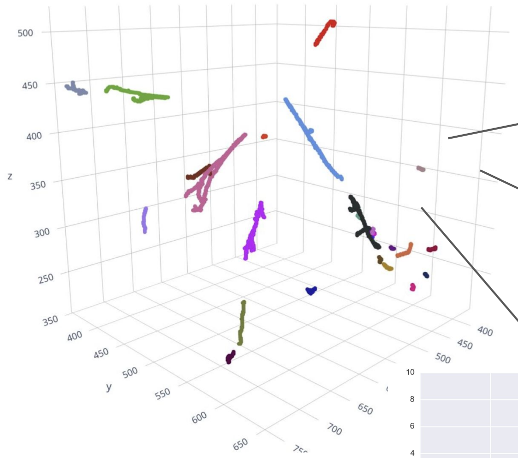
GraphPA

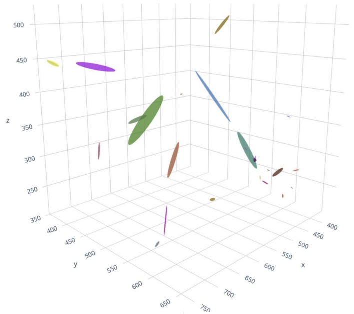


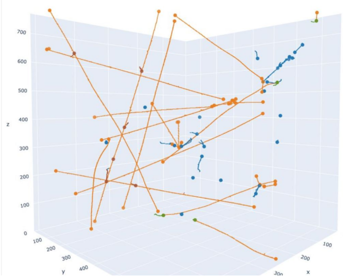
[LArTPC ML Reco 3D]

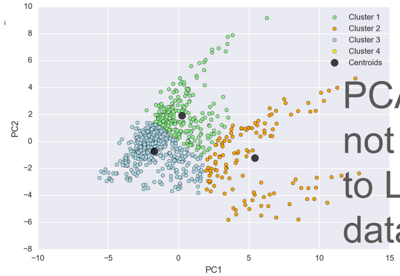
Fragment Clustering: Inputs

Input: Encode Fragments into set of node features









PCA (plot not related to LArTPC data)

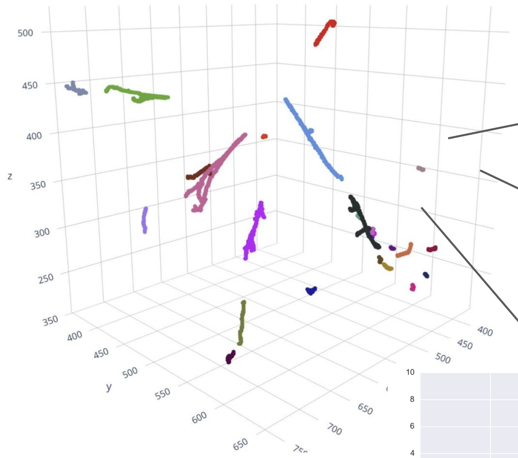
[LArTPC ML Reco 3D]

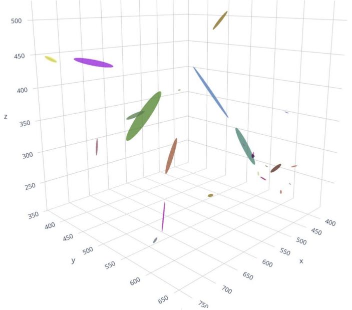
Fragment Summary	# Features
Number of voxels	1
Initial Point	3
Normalized initial direction	3
Normalized covariance matrix	9
Normalized principal axis	3
Centroid	3

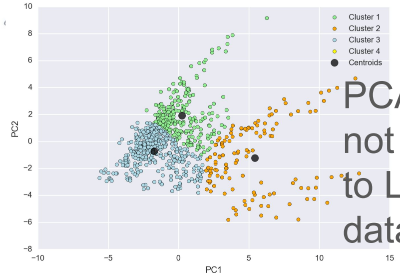
Fragment Clustering: Inputs

Input: Encode Fragments into set of node features

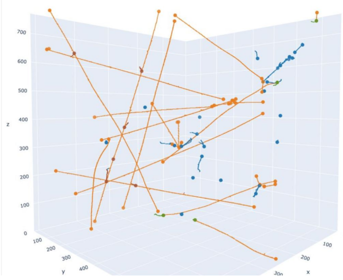
Fully connect nodes

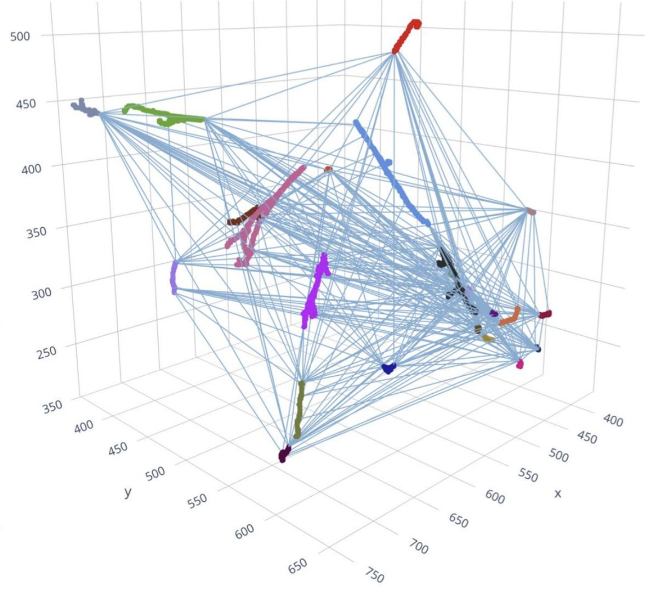






PCA (plot not related to LArTPC data)

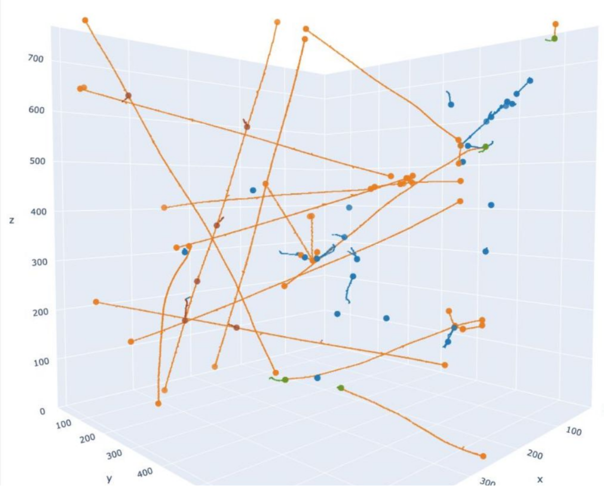


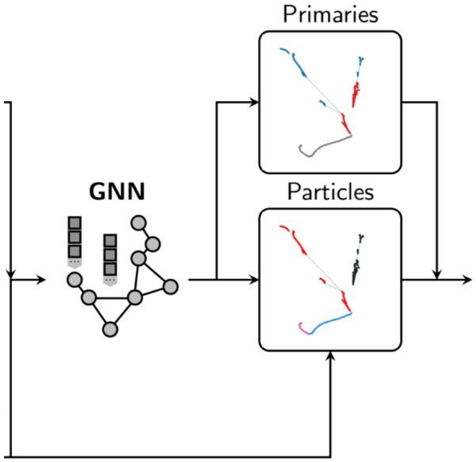


[LArTPC ML Reco 3D]

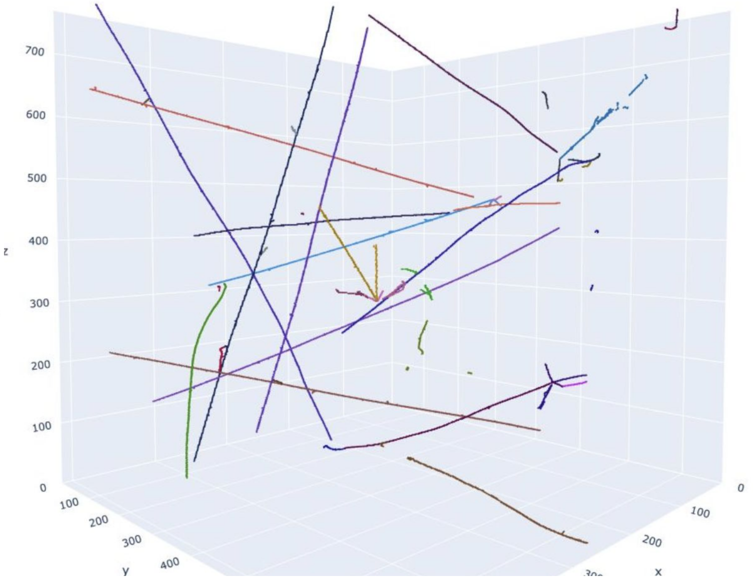
Output: Fragment Clustering

Pixel Features



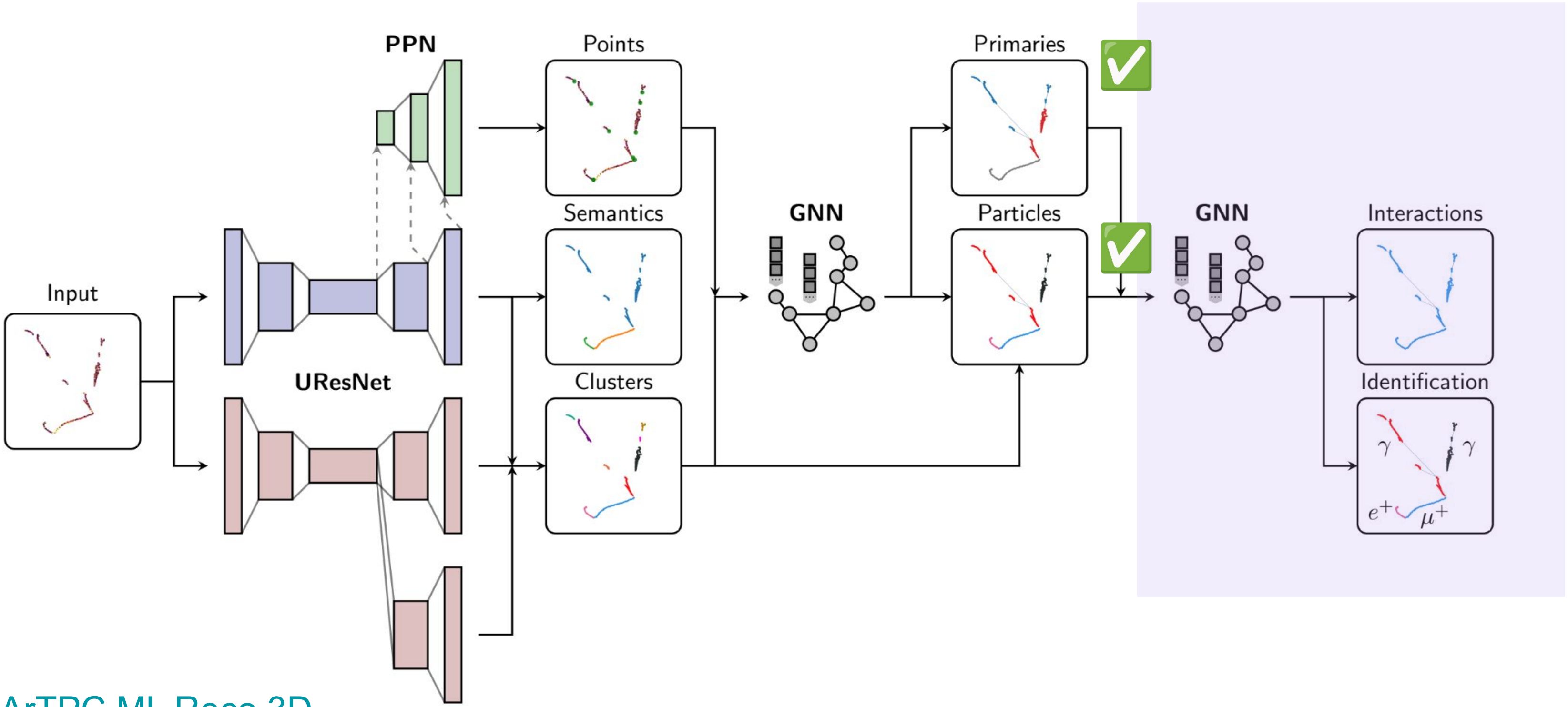


Fragment Features



[LArTPC ML Reco 3D]

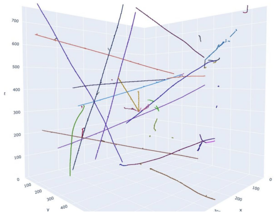
3D LAr TPC: ML Reco 3D

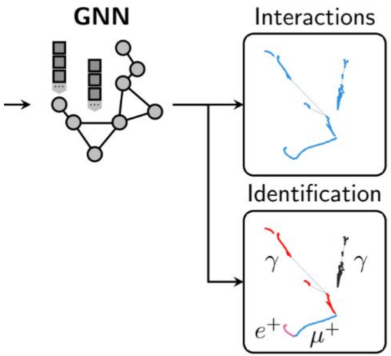


[LArTPC ML Reco 3D]

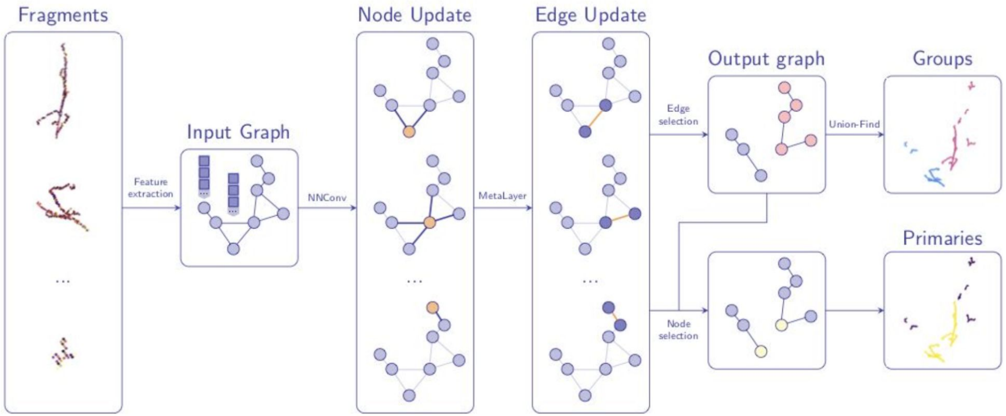
Interactions & Identification

Fragment Features





Re-use the GraphPA



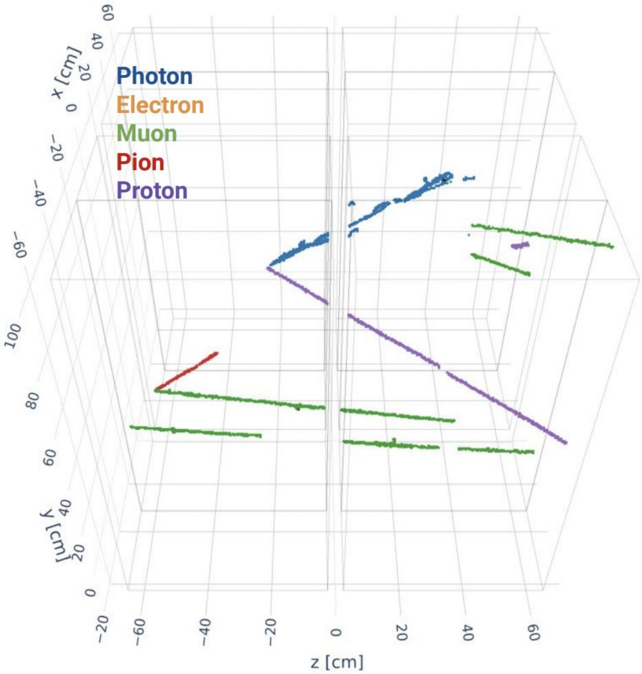
[LArTPC ML Reco 3D]

Interactions = find same neutrino source

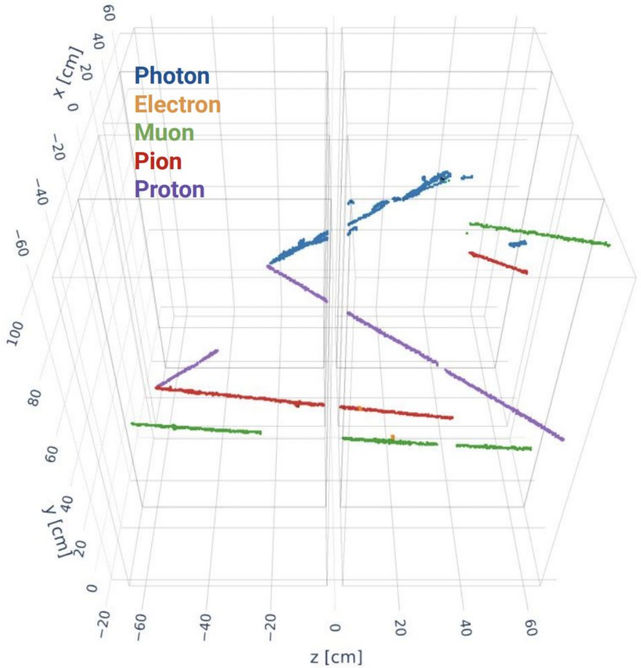
- \+ Edges classification for interactions
- \+ Nodes classification for identification

Performance: Example for Prototype ND

Truth

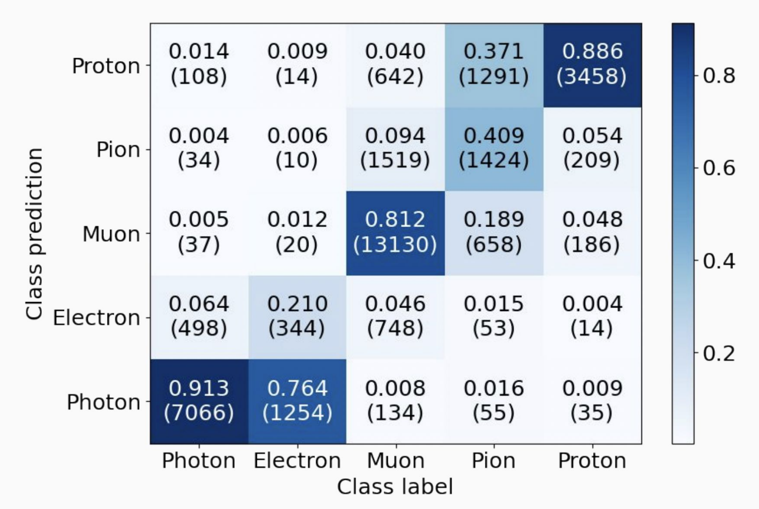


Reco



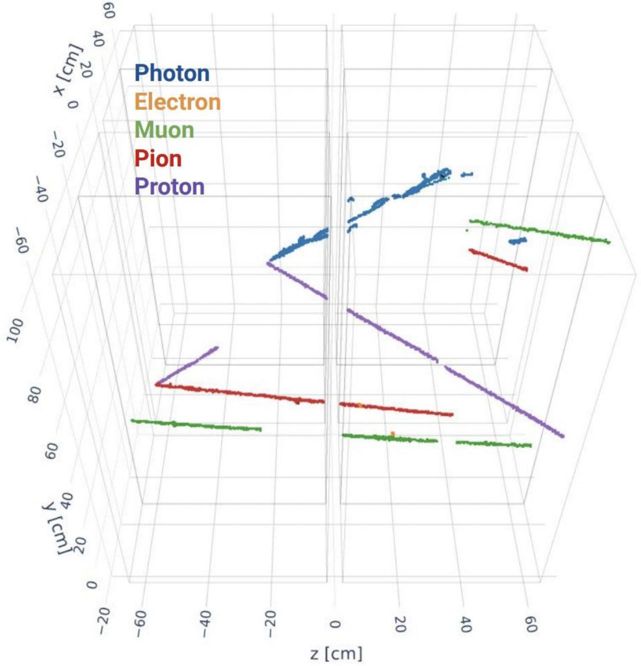
Performance: Metrics

Performance

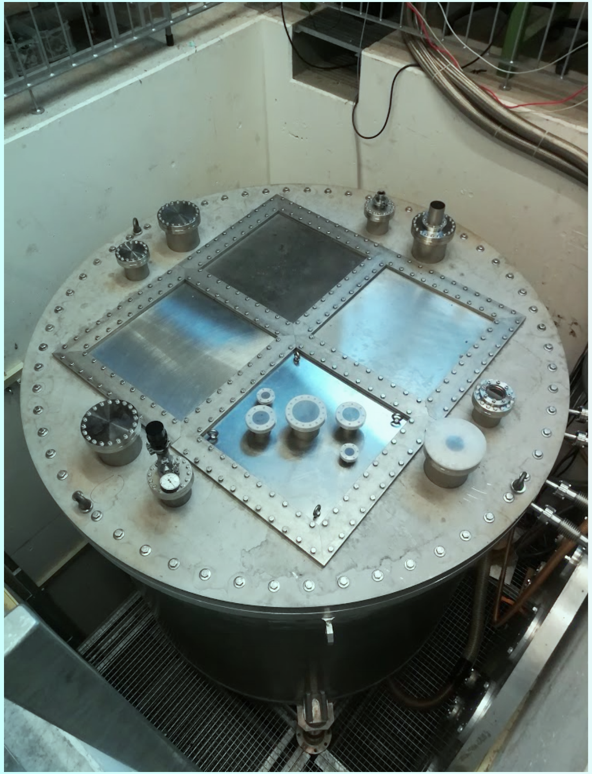


[LArTPC ML Reco 3D]

Reco



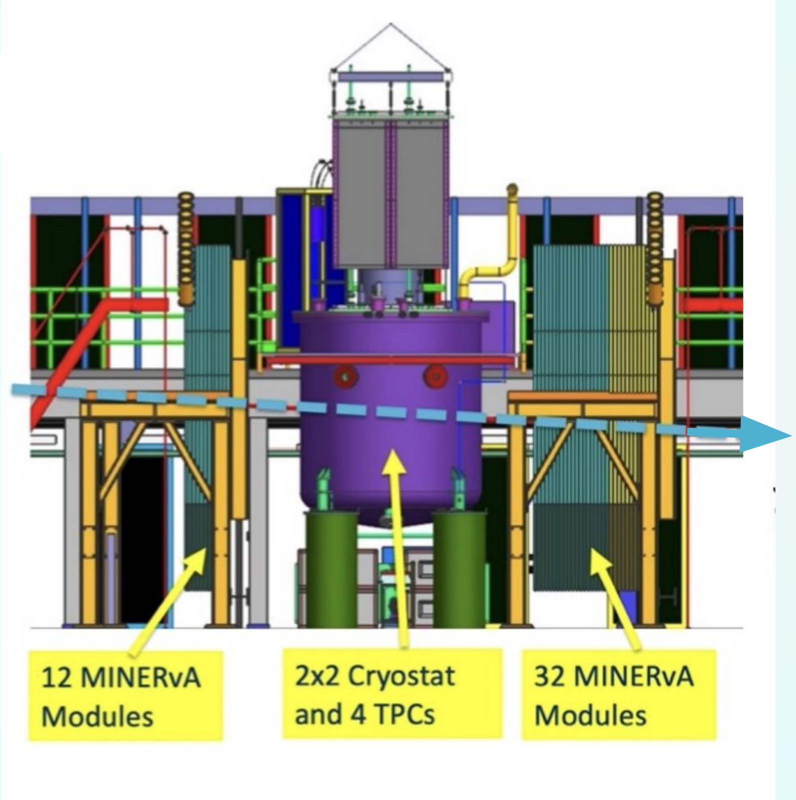
2x2 Prototype Near Detector



- Start with 4 ND-LAr modules (slightly smaller)
- Tested at University of Bern using cosmic rays
- Underground at Fermilab now to test in NuMI neutrino beam

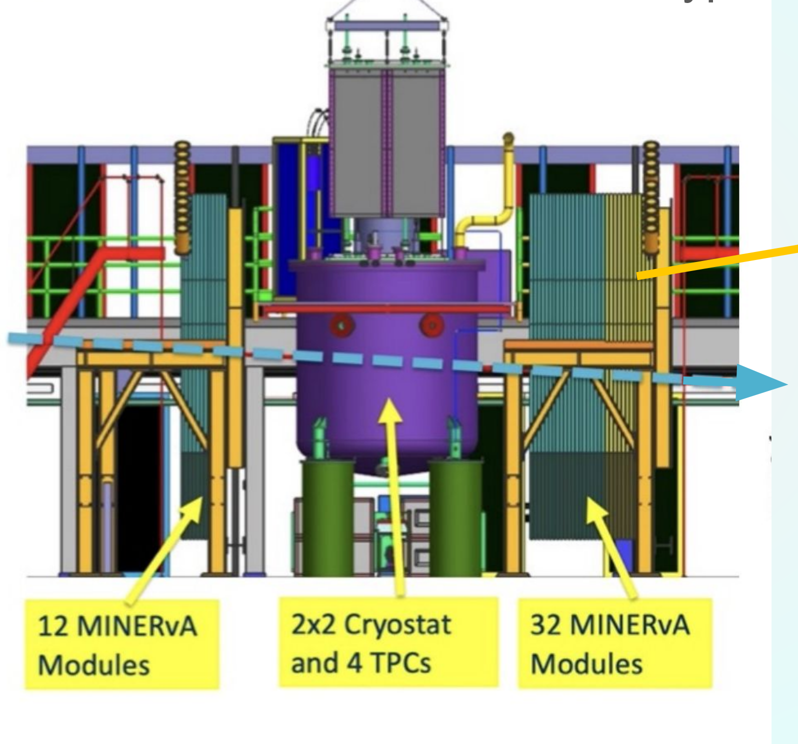
https://argoncube.org/LArTPCs.html

DUNE Near Detector 2x2 Prototype

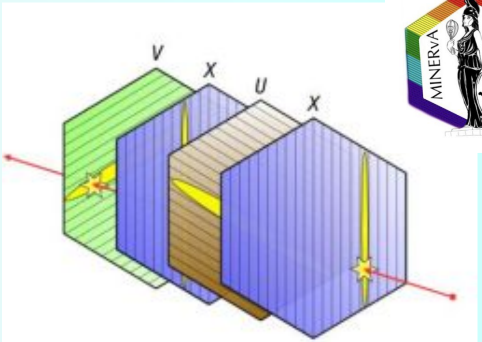


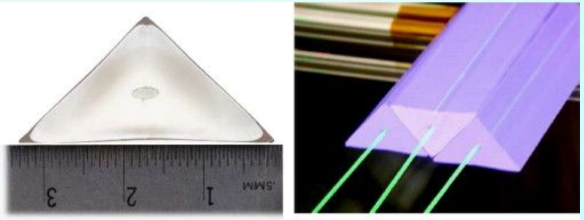
MINERvA uses Solid Scintillator Planes

DUNE Near Detector 2x2 Prototype



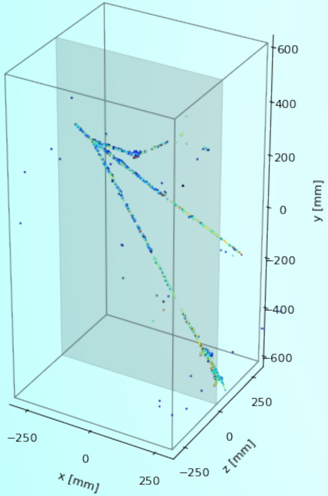
MINERvA: Solid scintillation particle detector with 3 orientations

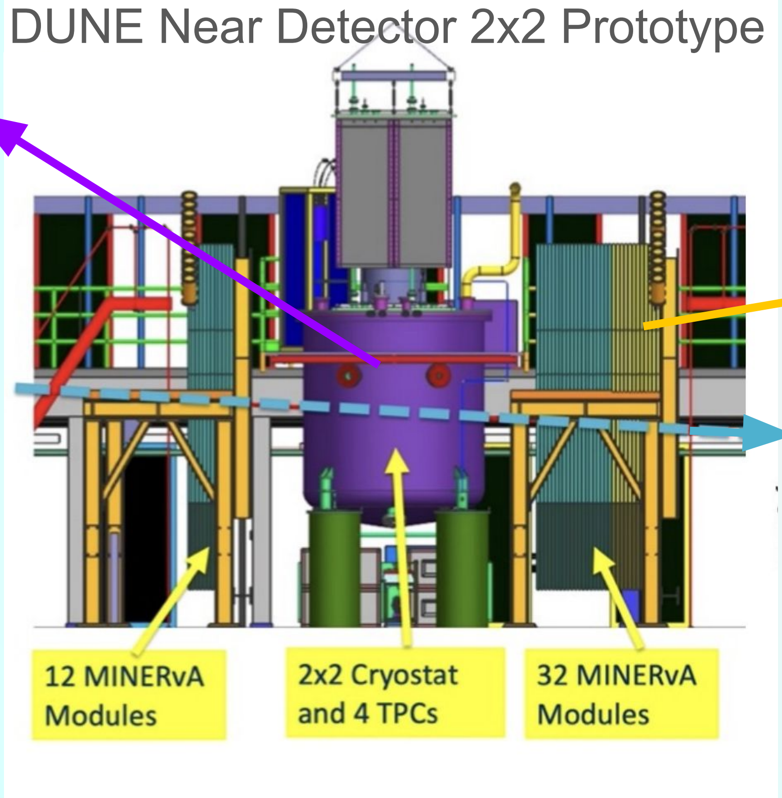




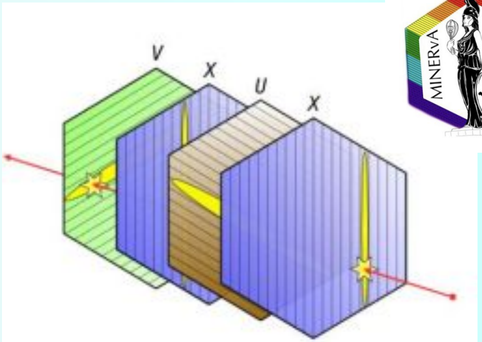
DUNE 2x2 uses Liquid Argon TPCs

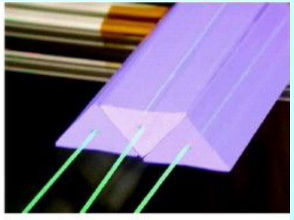
4 LArTPCs with 3D pixel readout

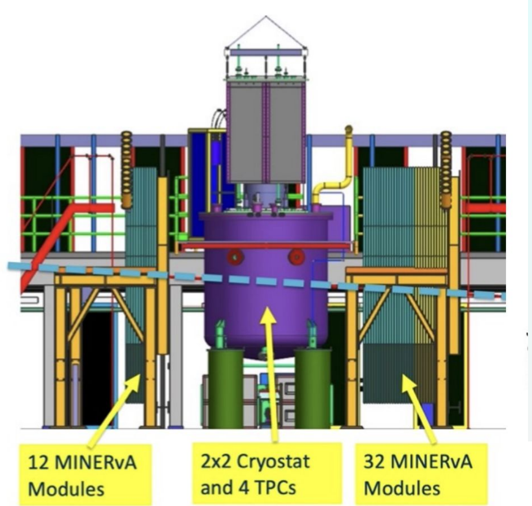


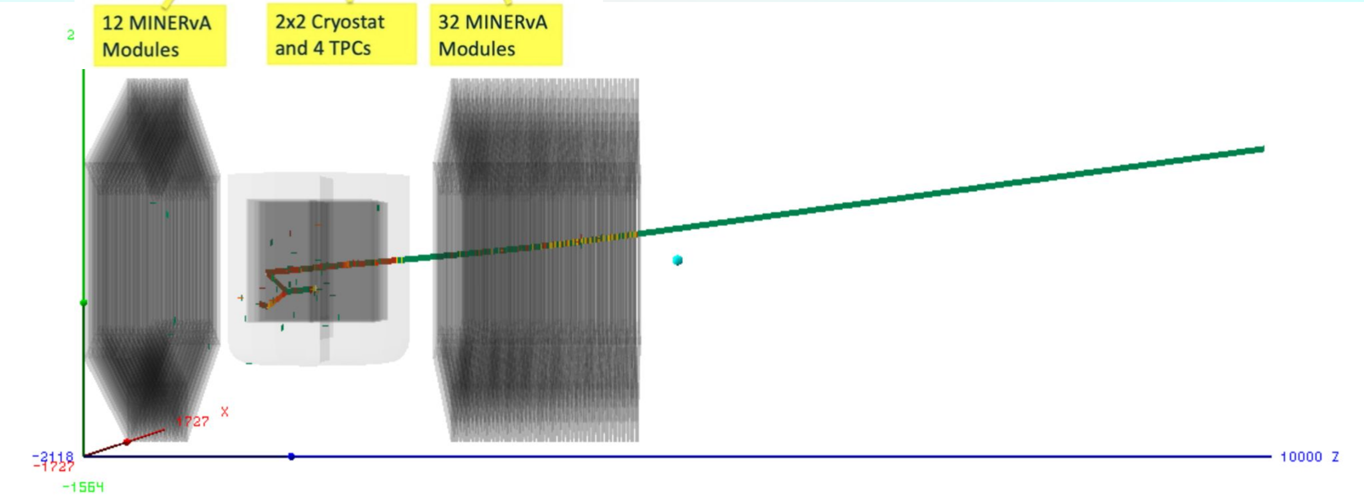


MINERvA: Solid scintillation particle detector with 3 orientations





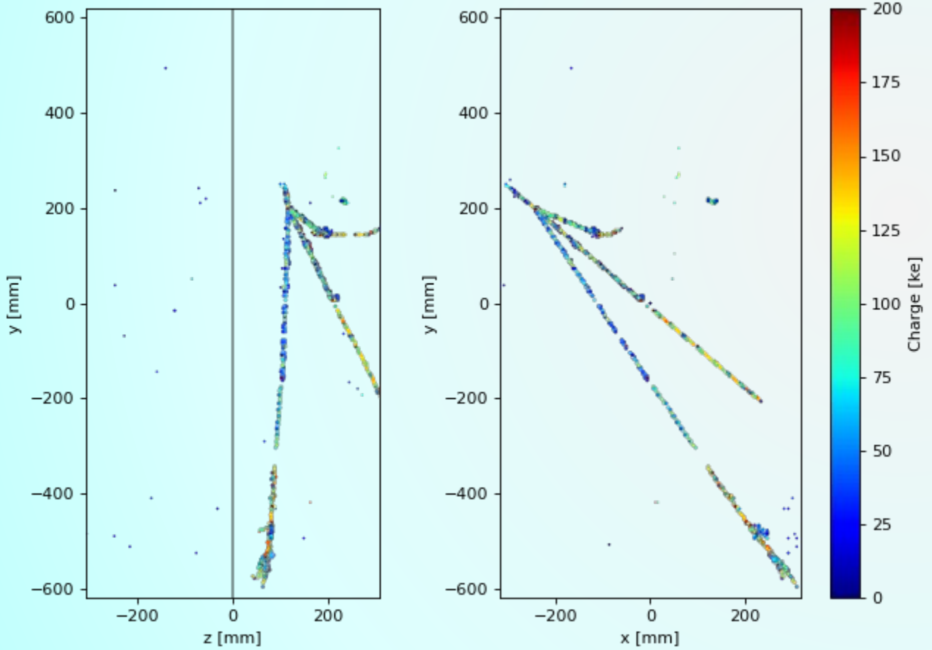

12 MINERvA Modules
2x2 Cryostat and 4 TPCs
32 MINERvA Modules


2
X
1727
-2118
-1727
-1564
10000 Z

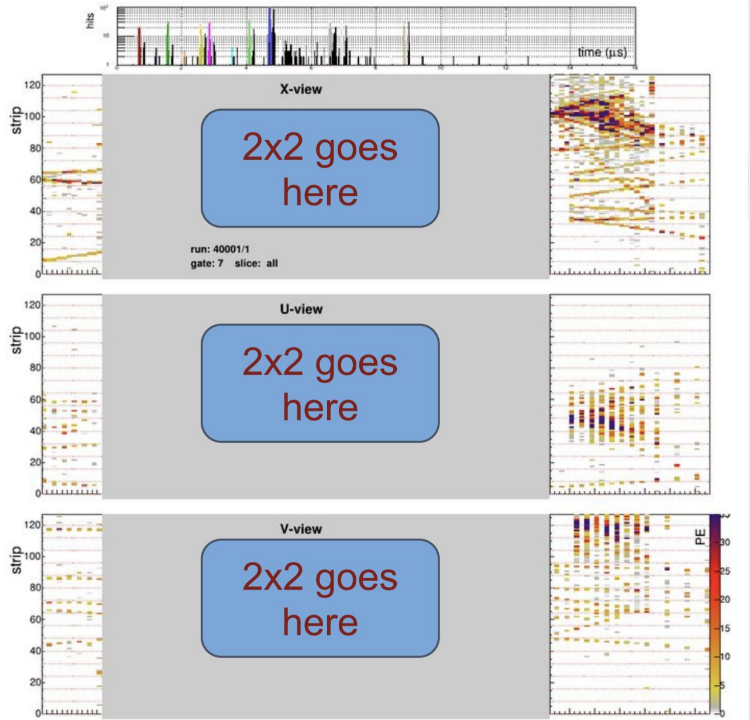
Wait! MINERvA has different detection resolution

→ ***CNN would be affected by this***

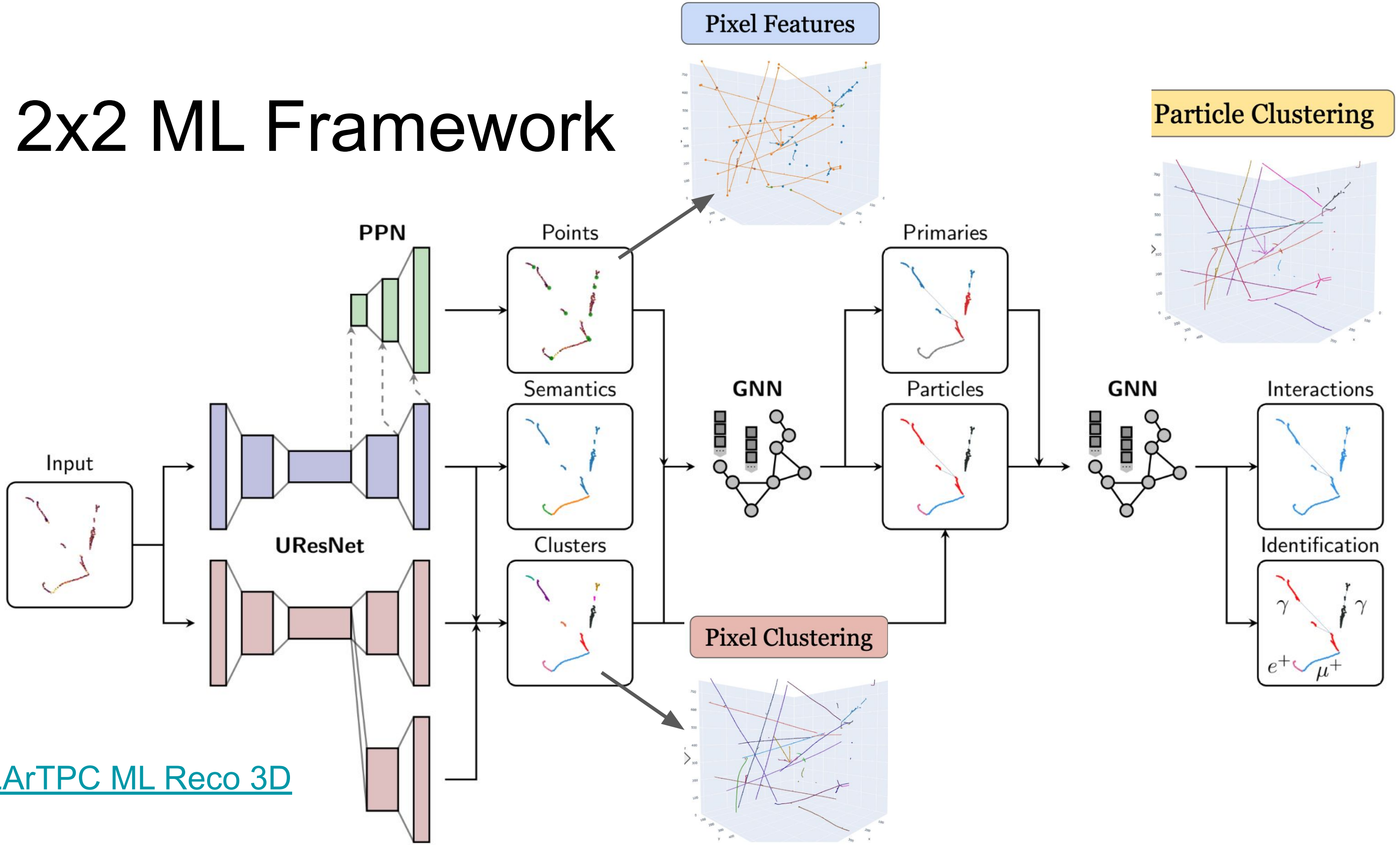
2x2 in 2D projection simulation



Preliminary
DUNE ND-LAr 2x2 MINERvA data

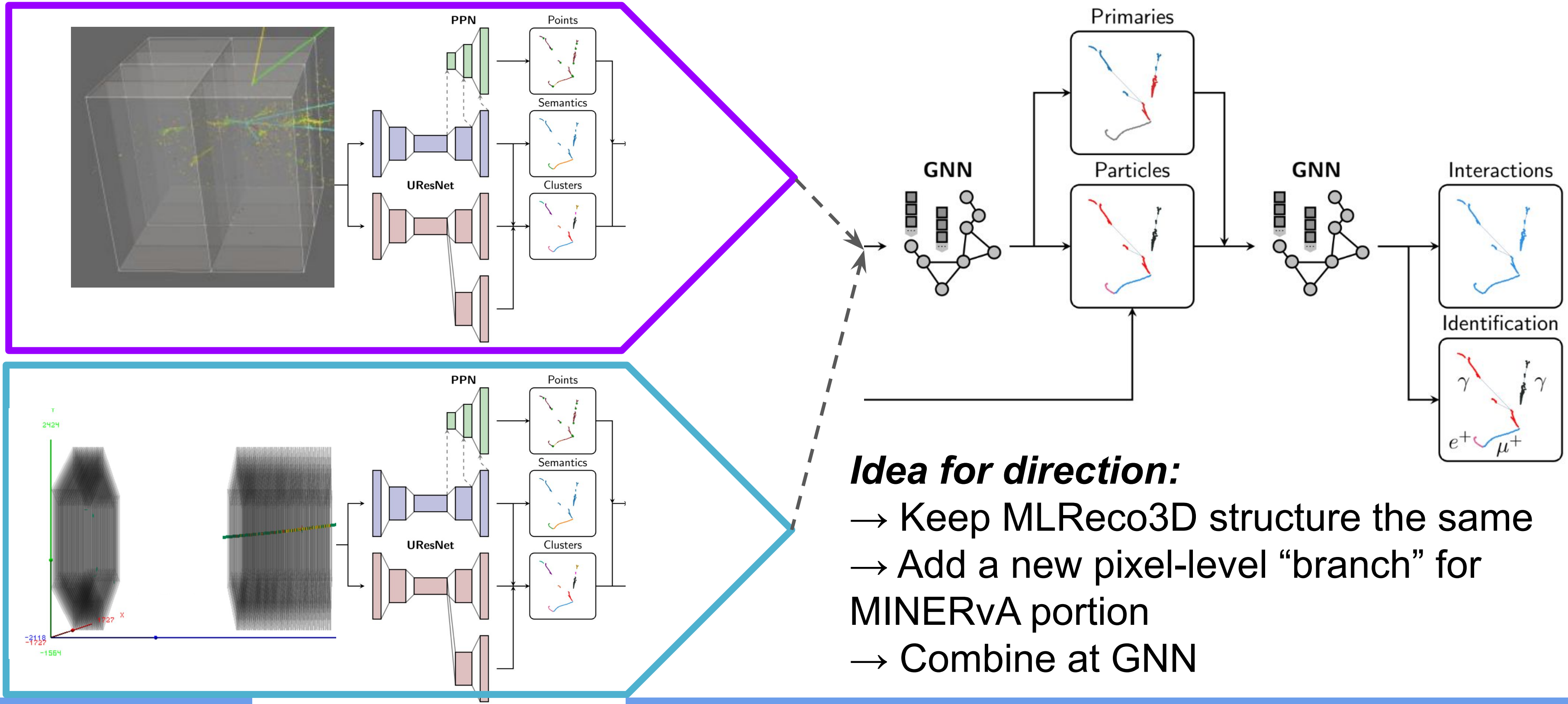


2x2 ML Framework



LArTPC ML Reco 3D

ML Reco 3D: Adding MINERvA



Idea for direction:

→ Keep MLReco3D structure the same

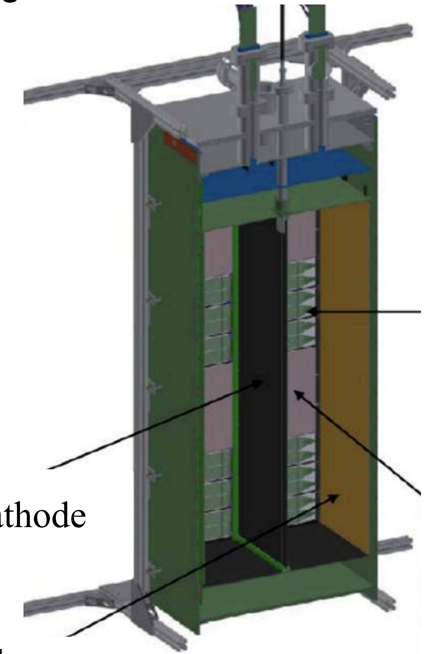
→ Add a new pixel-level “branch” for MINERvA portion

→ Combine at GNN

Future Applications

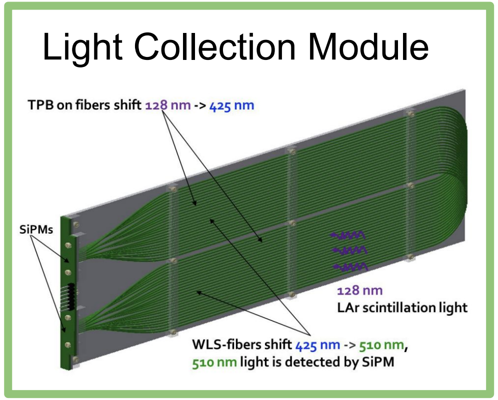
- Integrating detection from multiple detectors into single network
  - Light & Charge

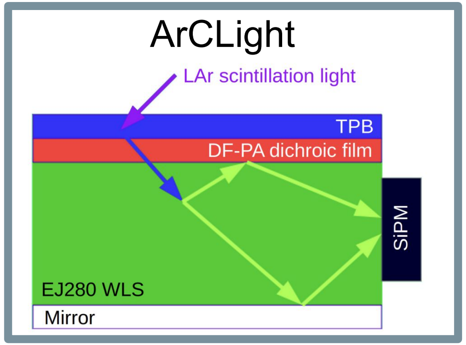
Single ND-LAr Module



Cathode

Charge readout

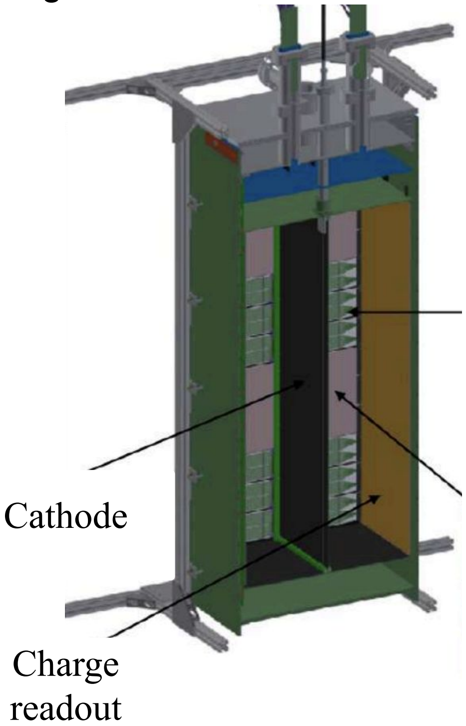


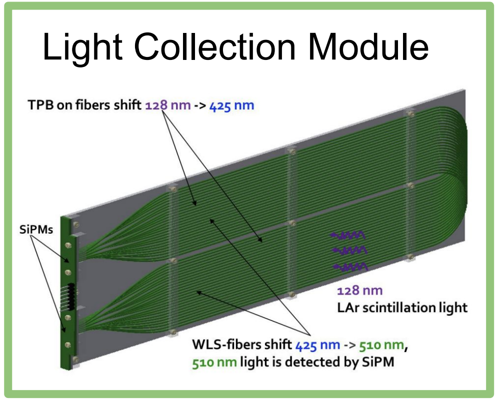


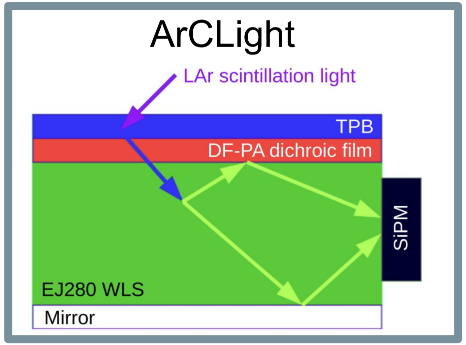
Future Applications

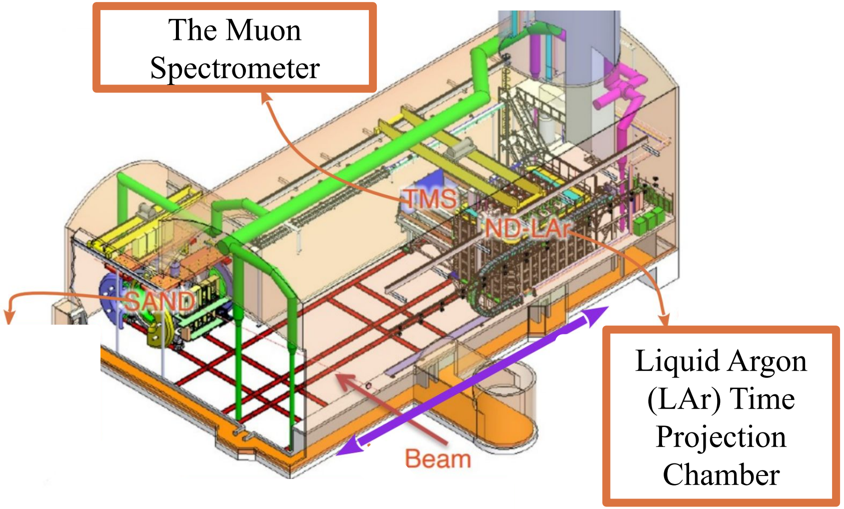
- Integrating detection from multiple detectors into single network
  - Light & Charge
  - ND-LAr & TMS

Single ND-LAr Module









Thank you for your attention!

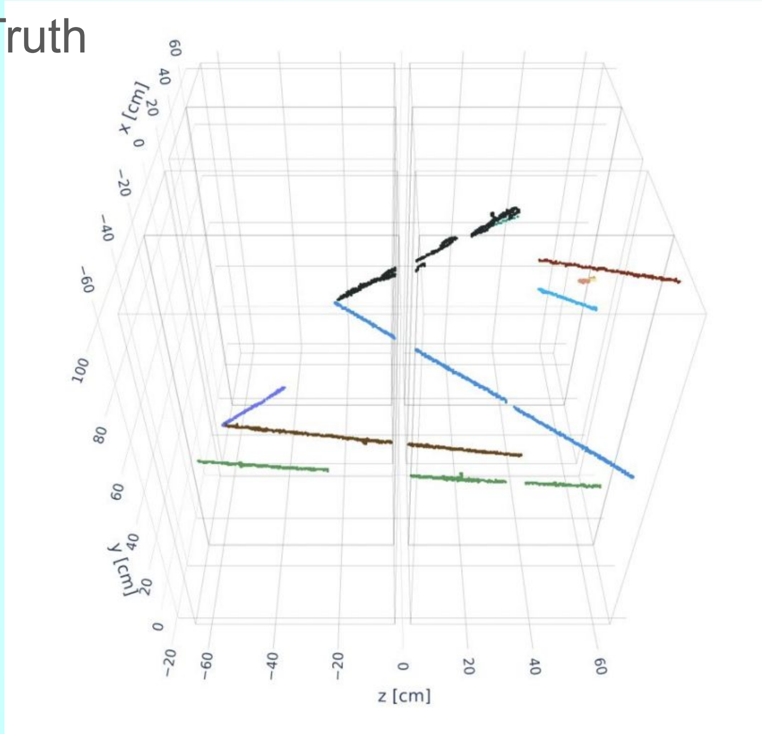
U.S. DEPARTMENT OF ENERGY | Office of Science

2x2 Analysis Workshop May 2023

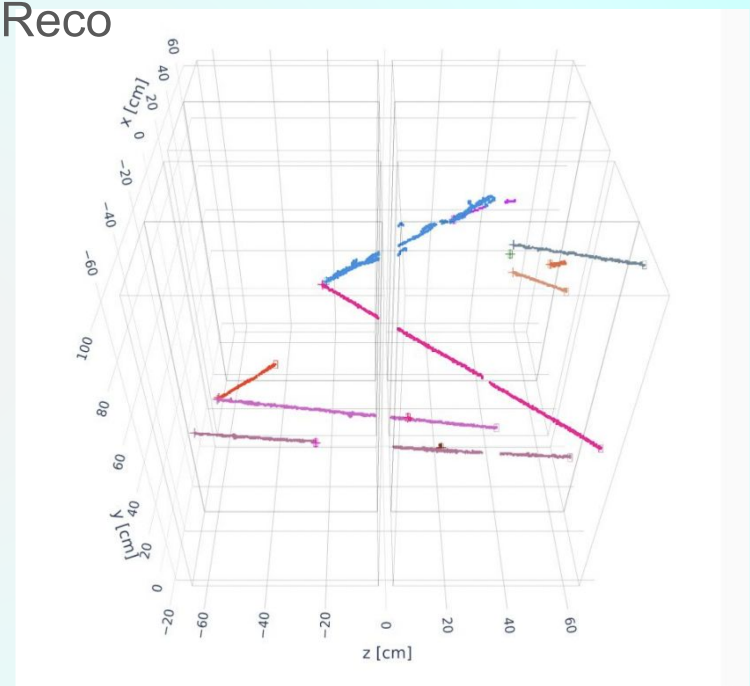
Backup

Pixel Features: Output

Truth



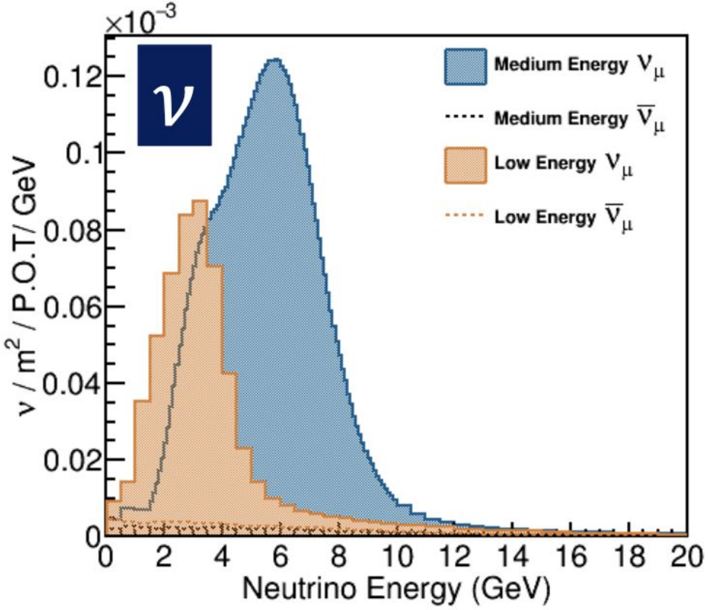
Reco



[Phys Rev D (102) 012005]

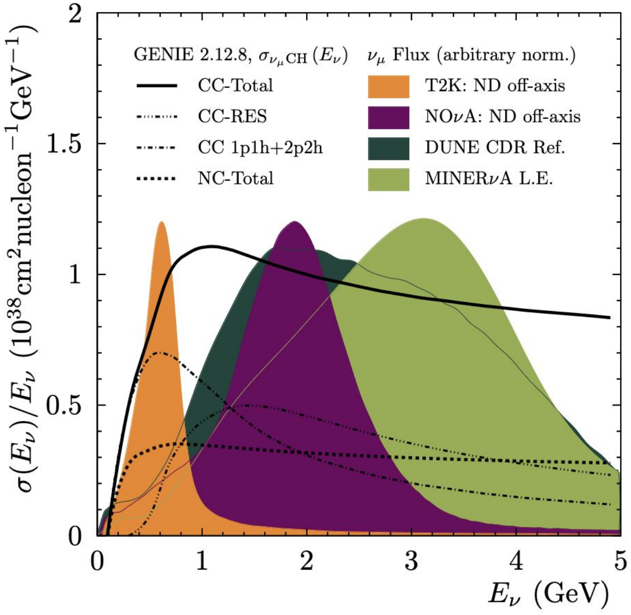
2x2 Prototype Beam vs DUNE Beam

NuMI



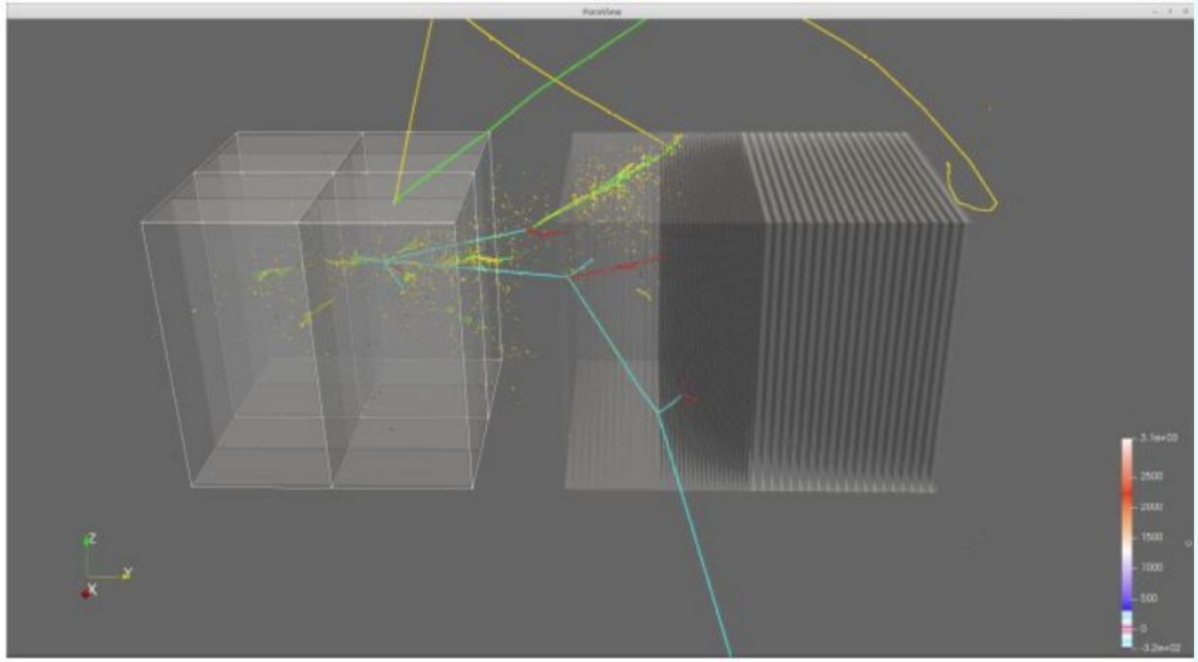
https://indico.cern.ch/event/881216/contributions/5048756/attachments/2534229/4361050/Klustova_MINERvAFlux_NuINT22.pdf

DUNE (dark green)



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

Thinking About Multi-Detector Training



https://argoncube.org/duneND.html

- Take 2D MINERvA output → 3D hits
- Choose voxel (“pixel”) resolution
  - Different than 2x2
- Extract target input features and training labels
  - Particle ID
  - Points of interest (stop & end points)
  - Parent particle