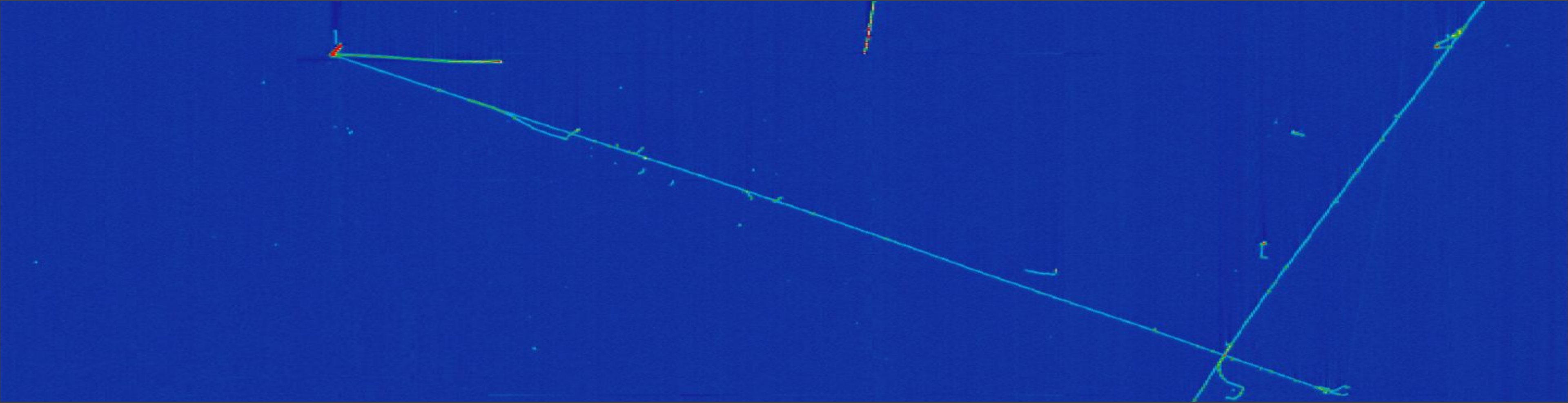


Machine Learning for Particle Imaging Detectors in Experimental Neutrino Physics

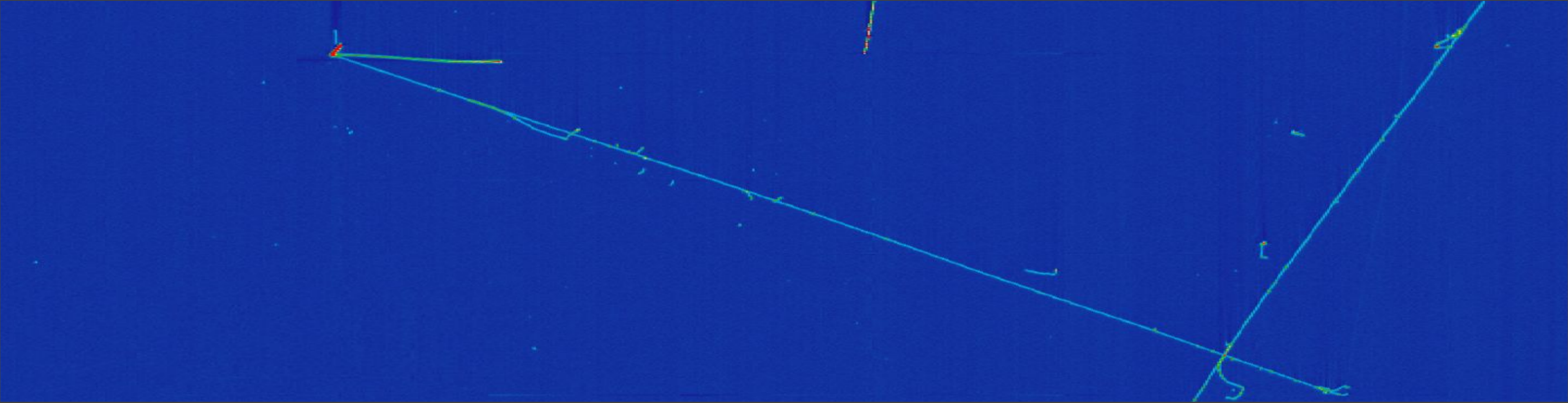
Kazuhiro Terao

SLAC National Accelerator Lab.

Deep learning and Physics 2020 Seminar Series

U.S. DEPARTMENT OF ENERGY Office of Science

SLAC NATIONAL ACCELERATOR LABORATORY



Outline

1. Neutrino detectors
2. Machine Learning & Computer Vision Applications
3. ML-based Neutrino Data Reconstruction Chain
4. Summary

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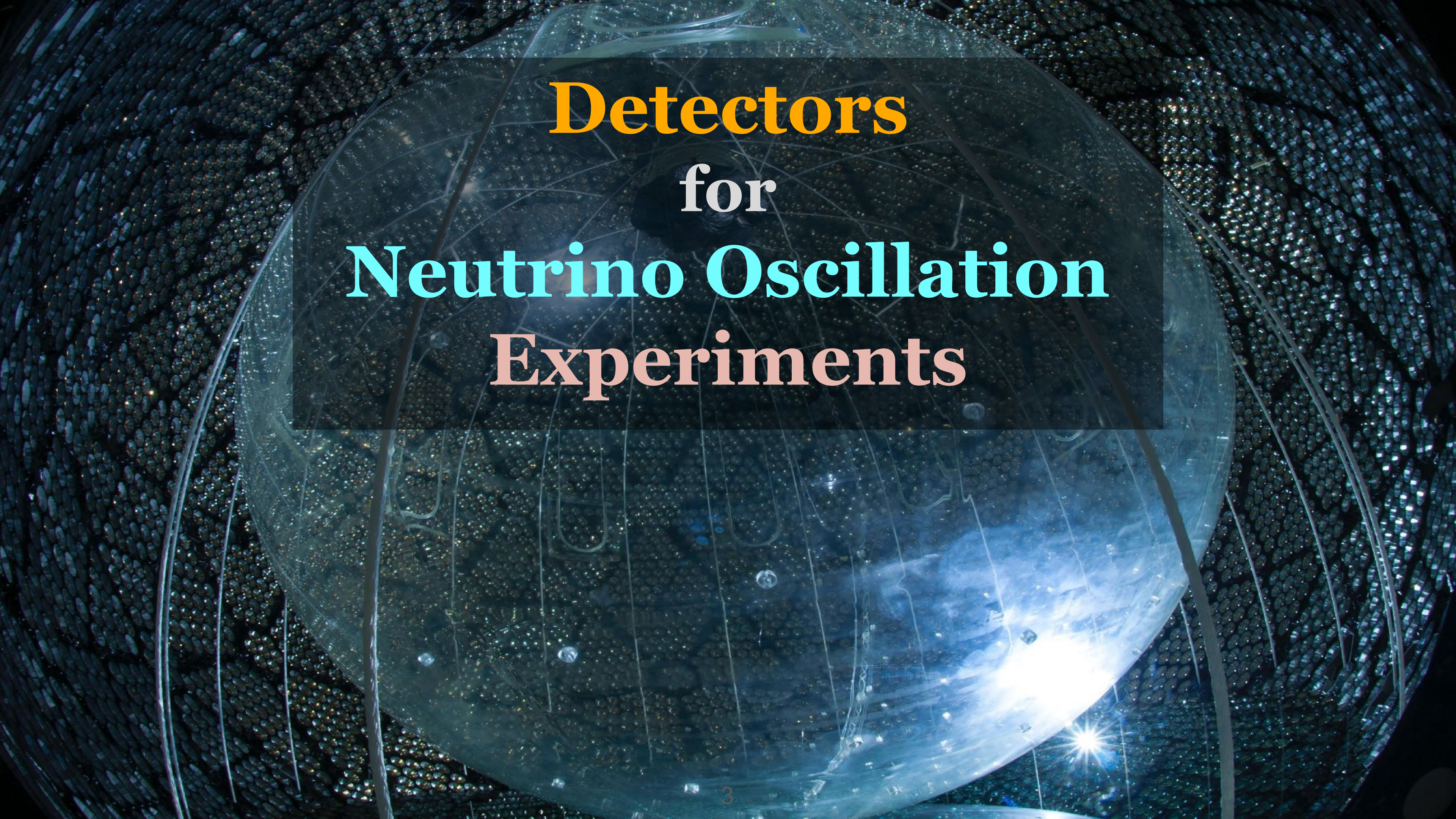
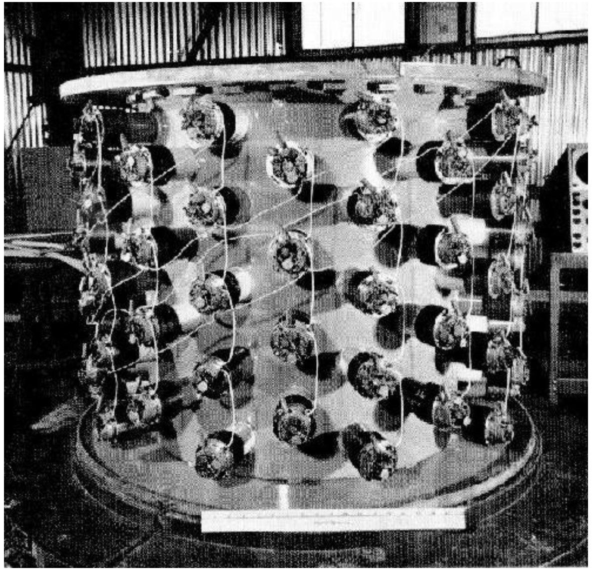
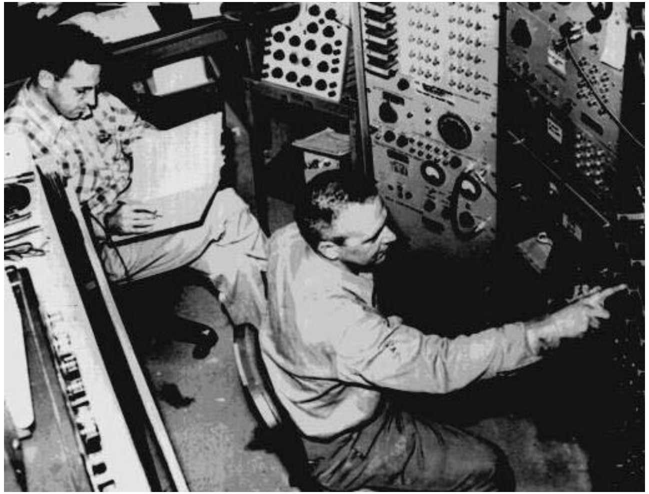


Detectors
for
Neutrino Oscillation
Experiments

Neutrino Detectors: Early Days

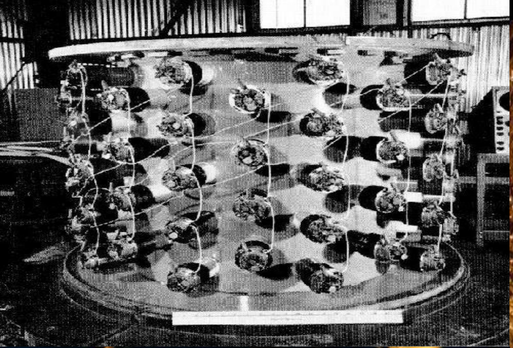


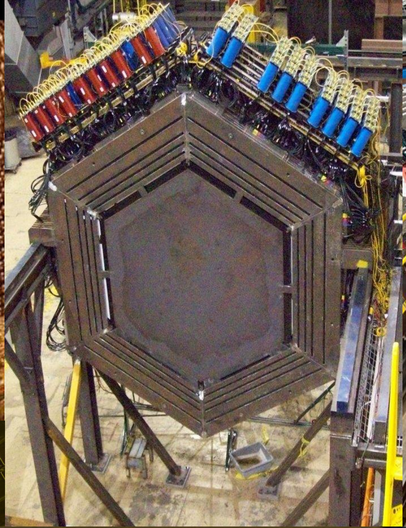
Cd-doped water
0.4 ton, 100 PMTs
(1956)

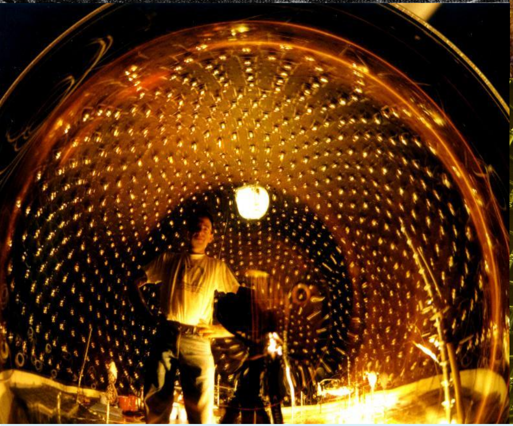
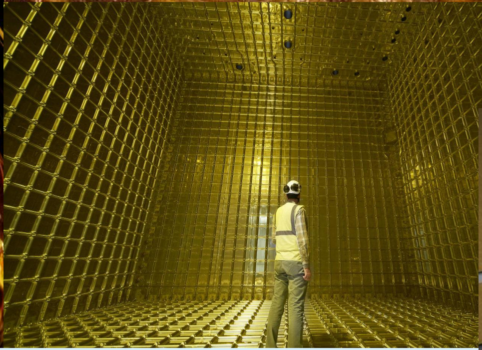
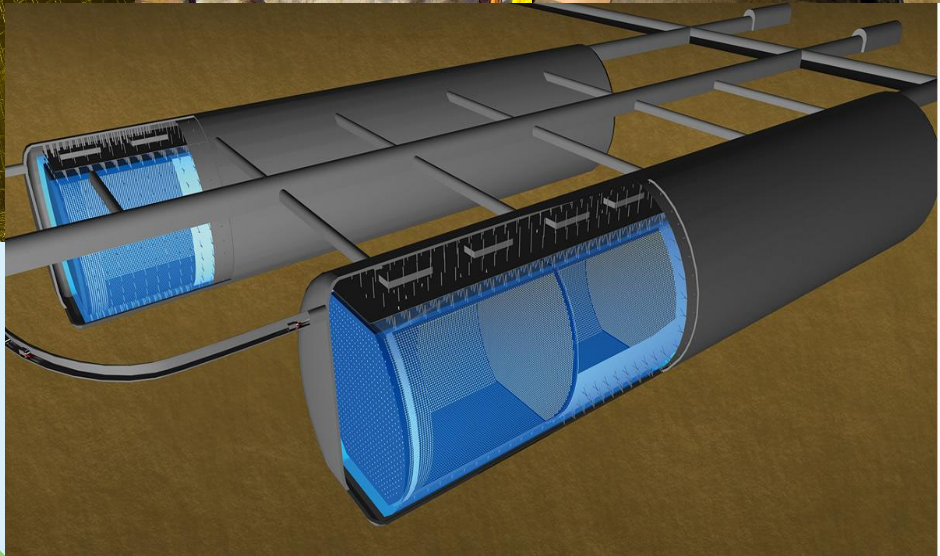
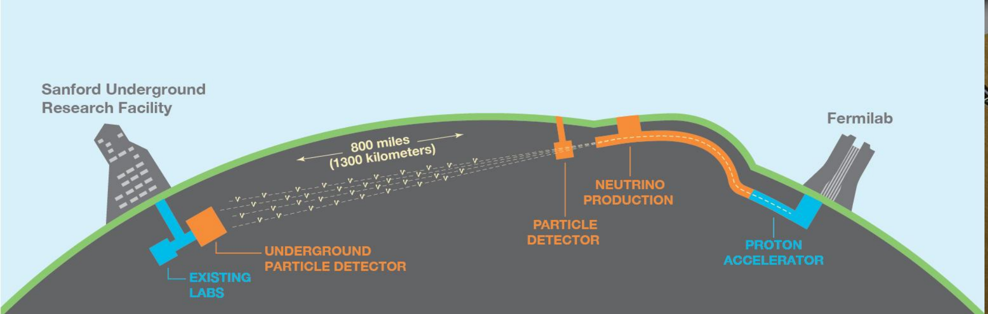


Inverse Beta Decay (IBD)
$\overline{\nu}_e + p \rightarrow e^+ + n$
by Reines & Cowan (Nobel Prize 1995)

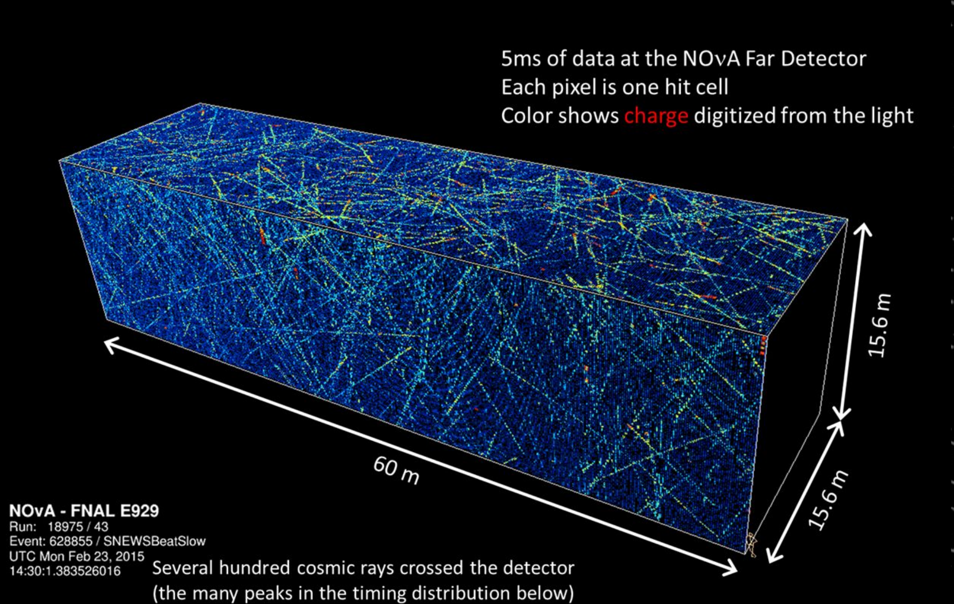
First neutrino detection

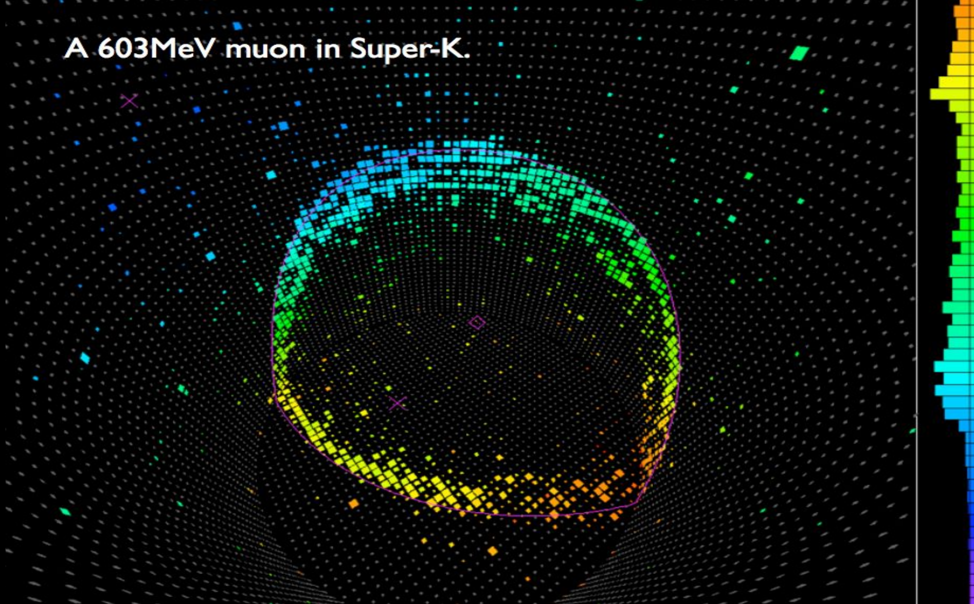


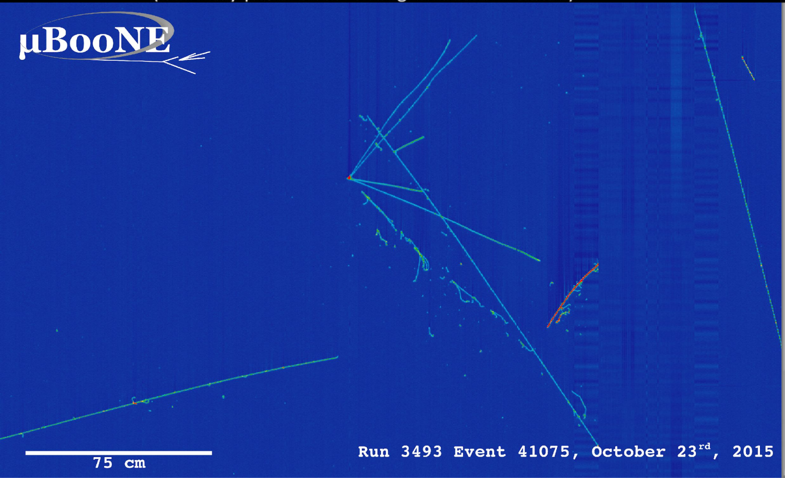


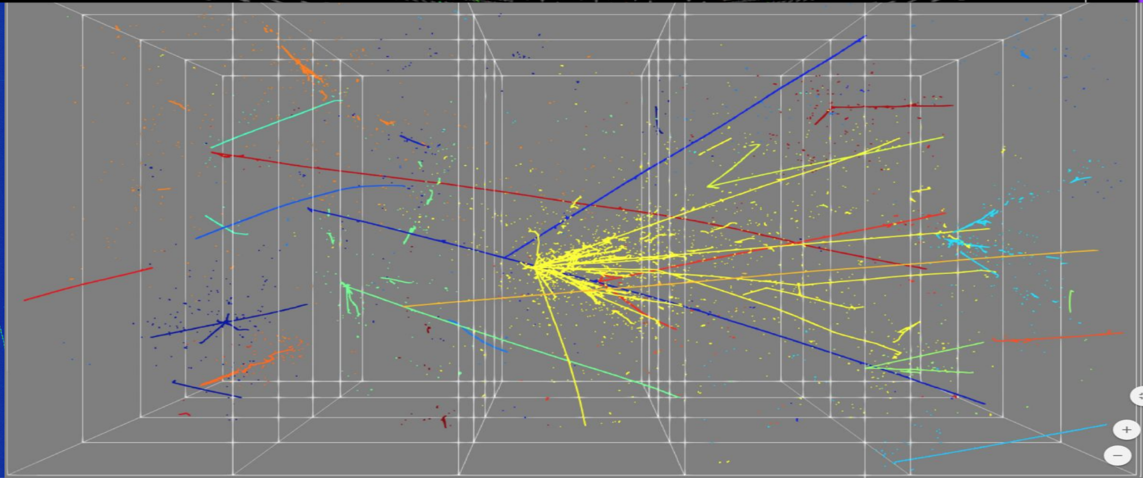





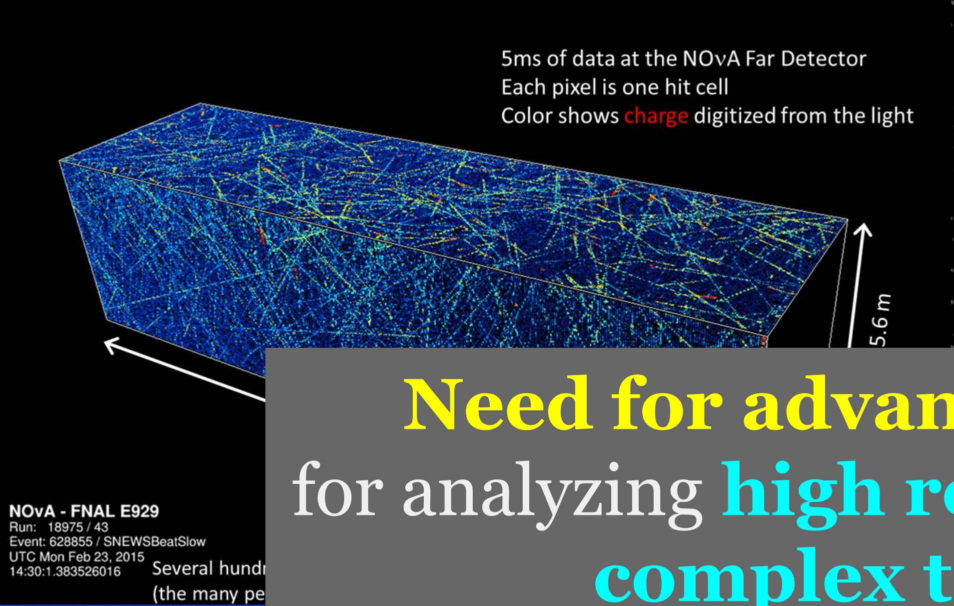
Sanford Underground
Research Facility
800 miles
(1300 kilometers)
Fermilab
NEUTRINO
PRODUCTION
PARTICLE
DETECTOR
UNDERGROUND
PARTICLE DETECTOR
PROTON
ACCELERATOR
EXISTING
LABS

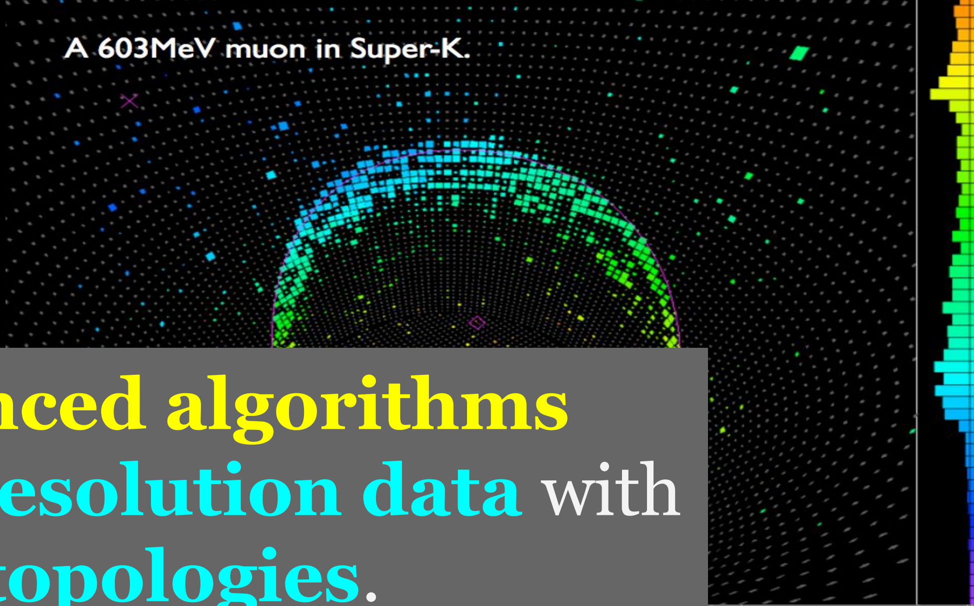

5ms of data at the NOνA Far Detector
Each pixel is one hit cell
Color shows charge digitized from the light
15.6 m
60 m
15.6 m
NOvA - FNAL E929
Run: 18975 / 43
Event: 628855 / SNEWSBeatSlow
UTC Mon Feb 23, 2015
14:30:1.383526016
Several hundred cosmic rays crossed the detector
(the many peaks in the timing distribution below)


A 603MeV muon in Super-K.

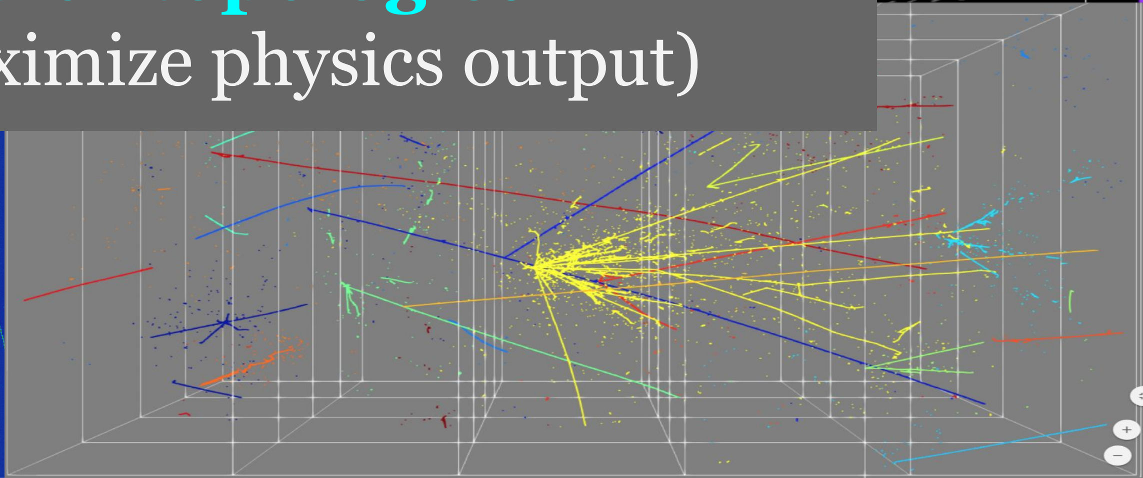

μBooNE
75 cm
Run 3493 Event 41075, October 23rd, 2015







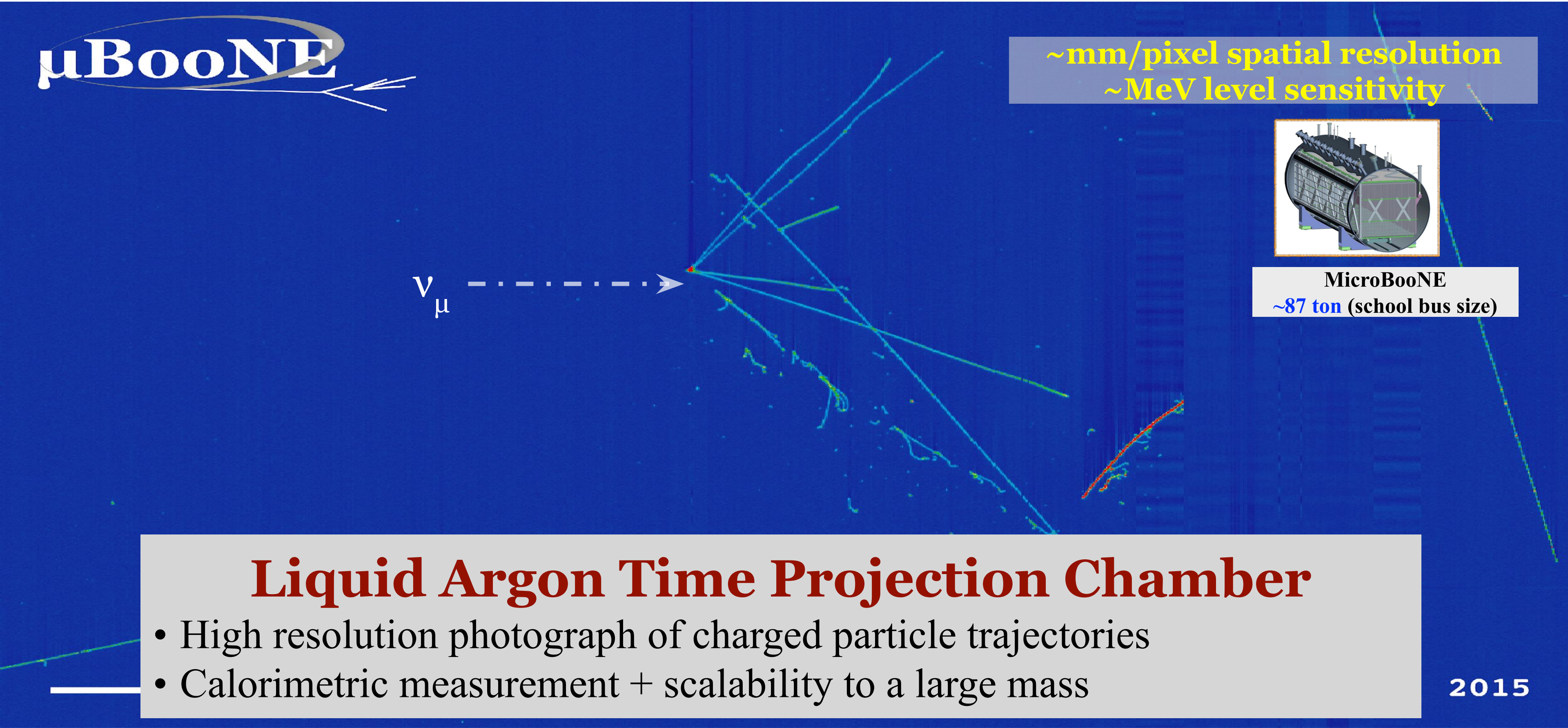
Need for advanced algorithms
for analyzing **high resolution data** with **complex topologies**.
(**goal**: maximize physics output)



Machine Learning & Computer Vision in Neutrino Physics
Time Projection Chambers

SLAC

µBooNE



~mm/pixel spatial resolution
~MeV level sensitivity

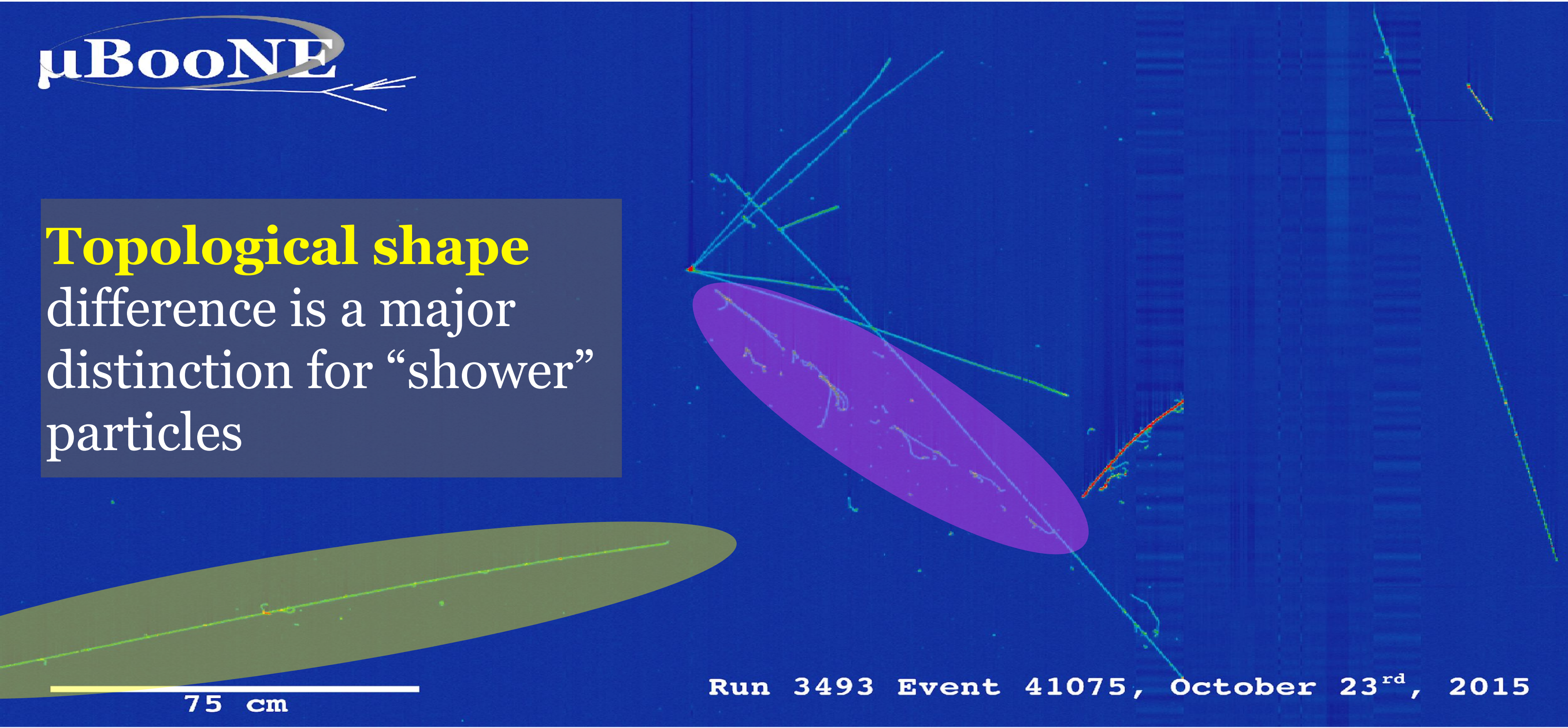
MicroBooNE
~87 ton (school bus size)

Liquid Argon Time Projection Chamber

- High resolution photograph of charged particle trajectories
- Calorimetric measurement + scalability to a large mass

Machine Learning & Computer Vision in Neutrino Physics

Time Projection Chambers



Machine Learning & Computer Vision in Neutrino Physics

Time Projection Chambers

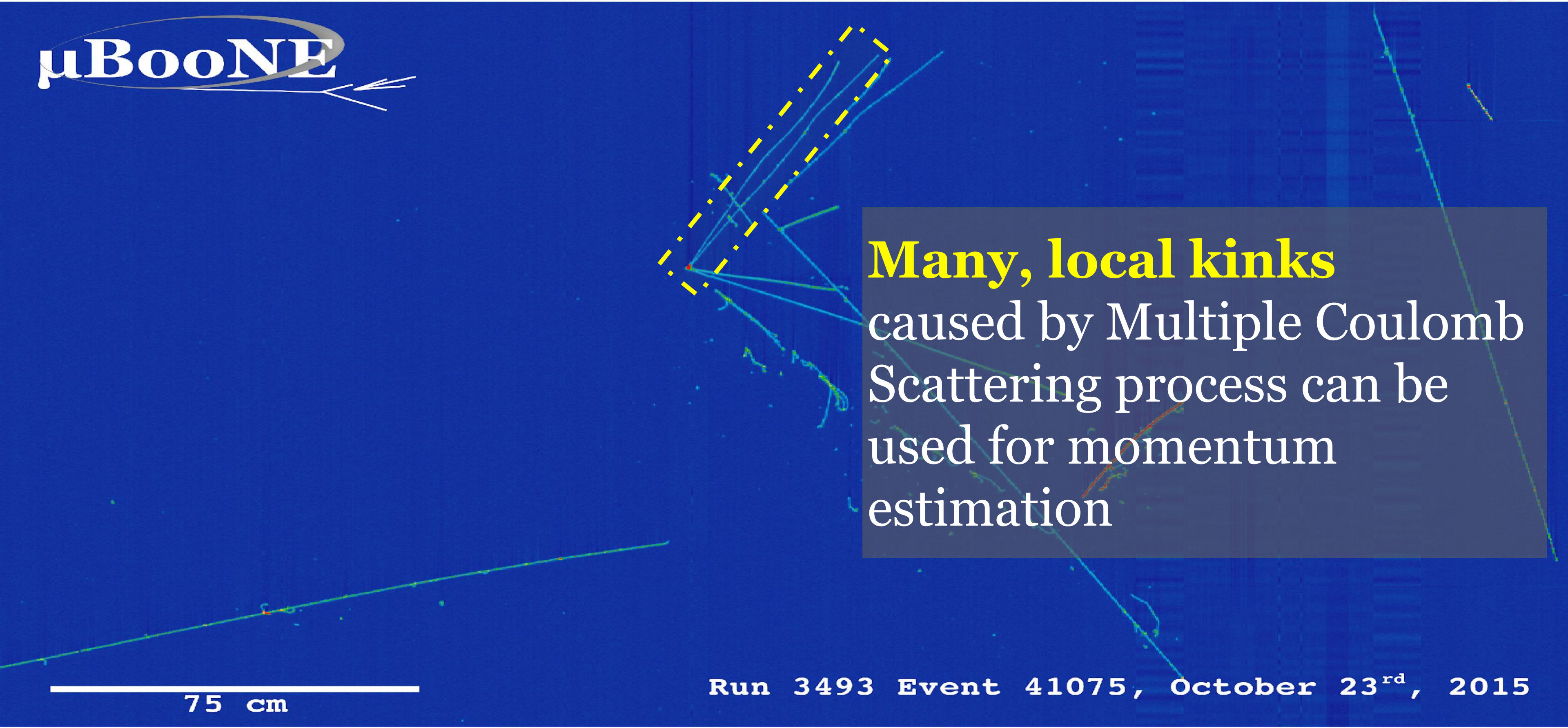
SLAC

Trajectory ends are distinct, and useful for seeding particle clustering and trajectory fitting

Machine Learning & Computer Vision in Neutrino Physics

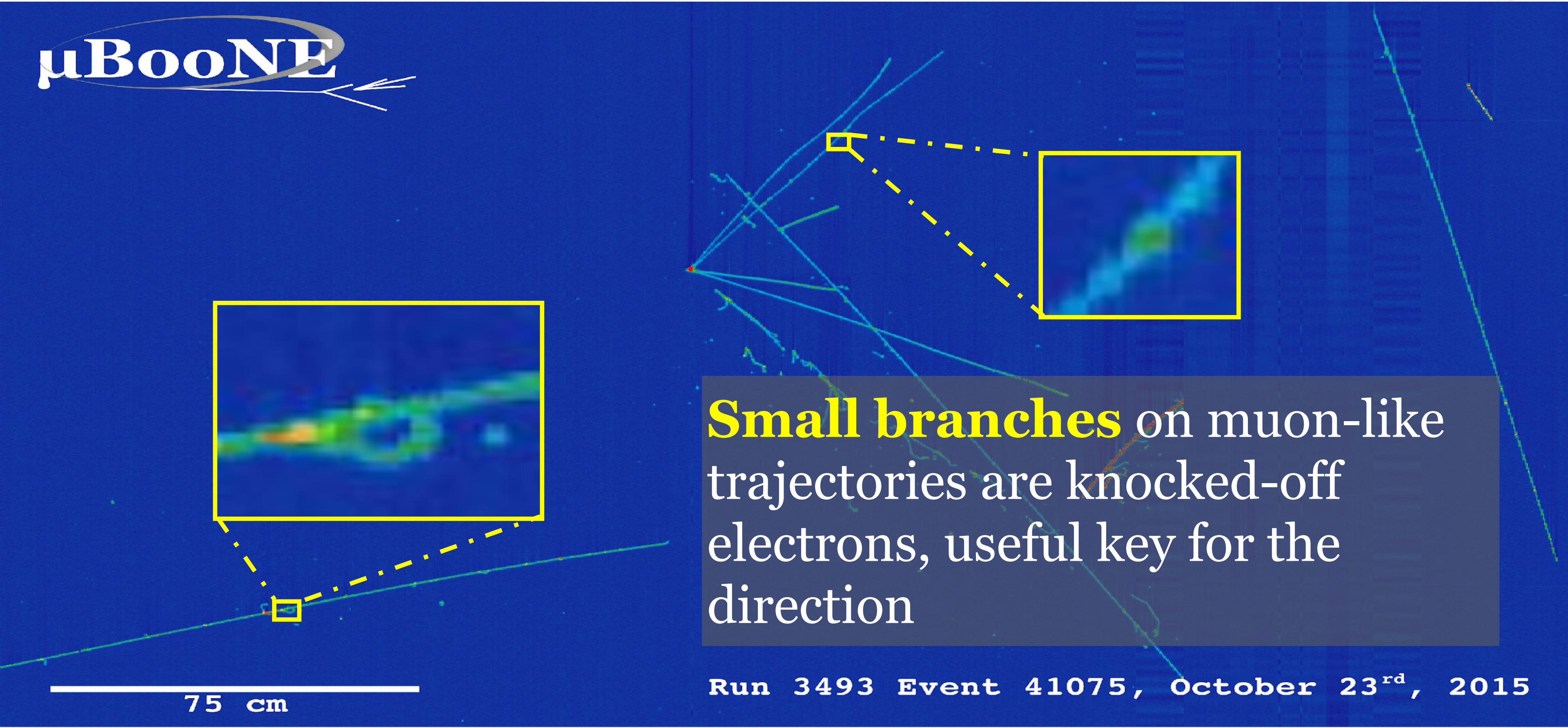
Time Projection Chambers

SLAC



Many, local kinks caused by Multiple Coulomb Scattering process can be used for momentum estimation

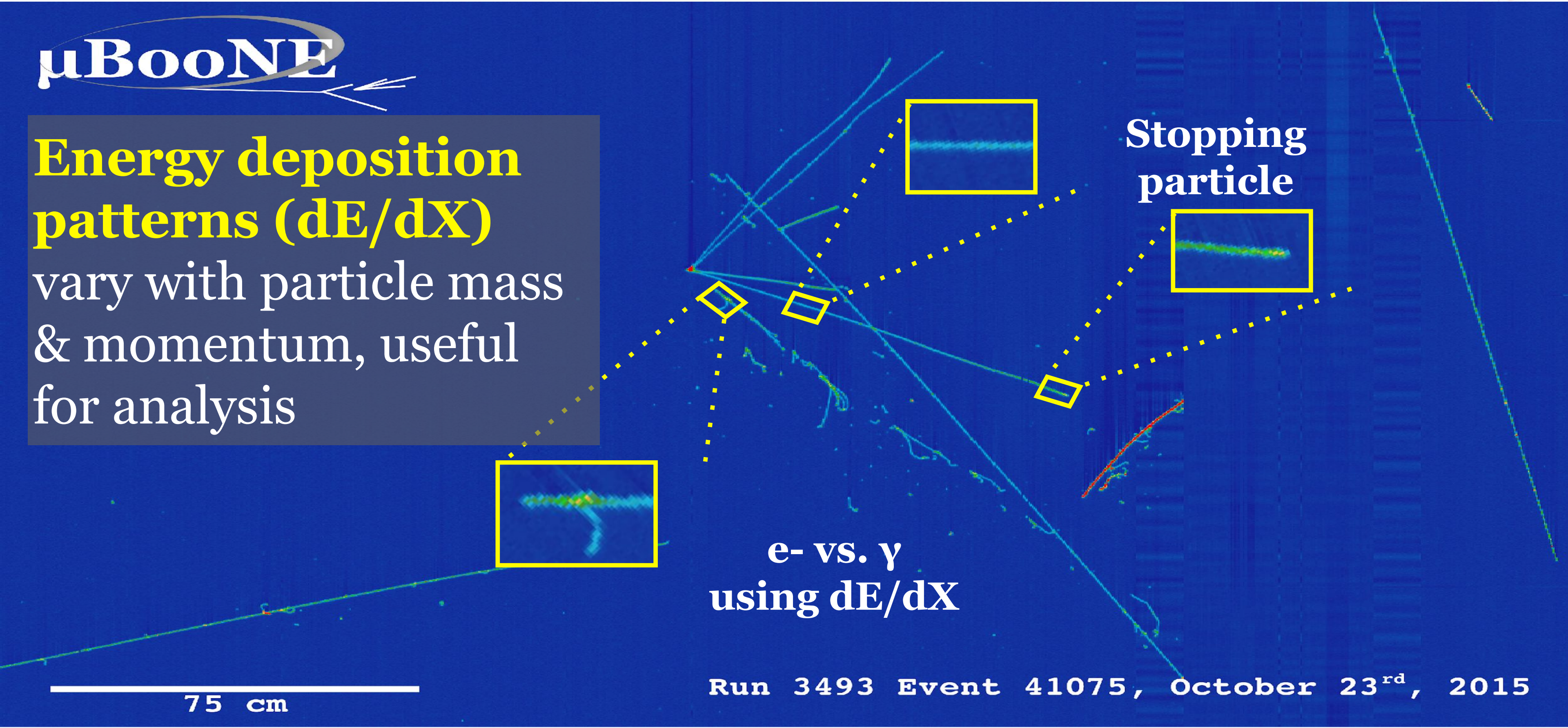
Machine Learning & Computer Vision in Neutrino Physics
Time Projection Chambers



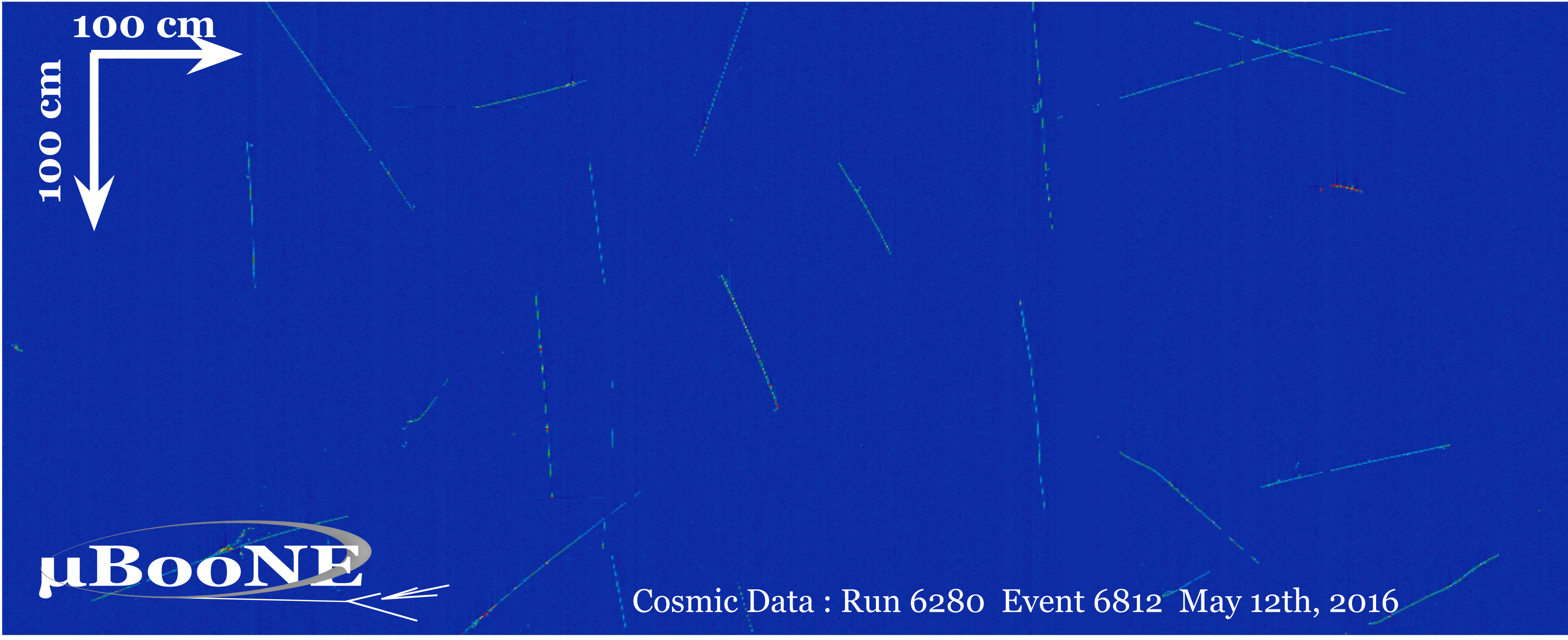
Machine Learning & Computer Vision in Neutrino Physics
Time Projection Chambers

SLAC

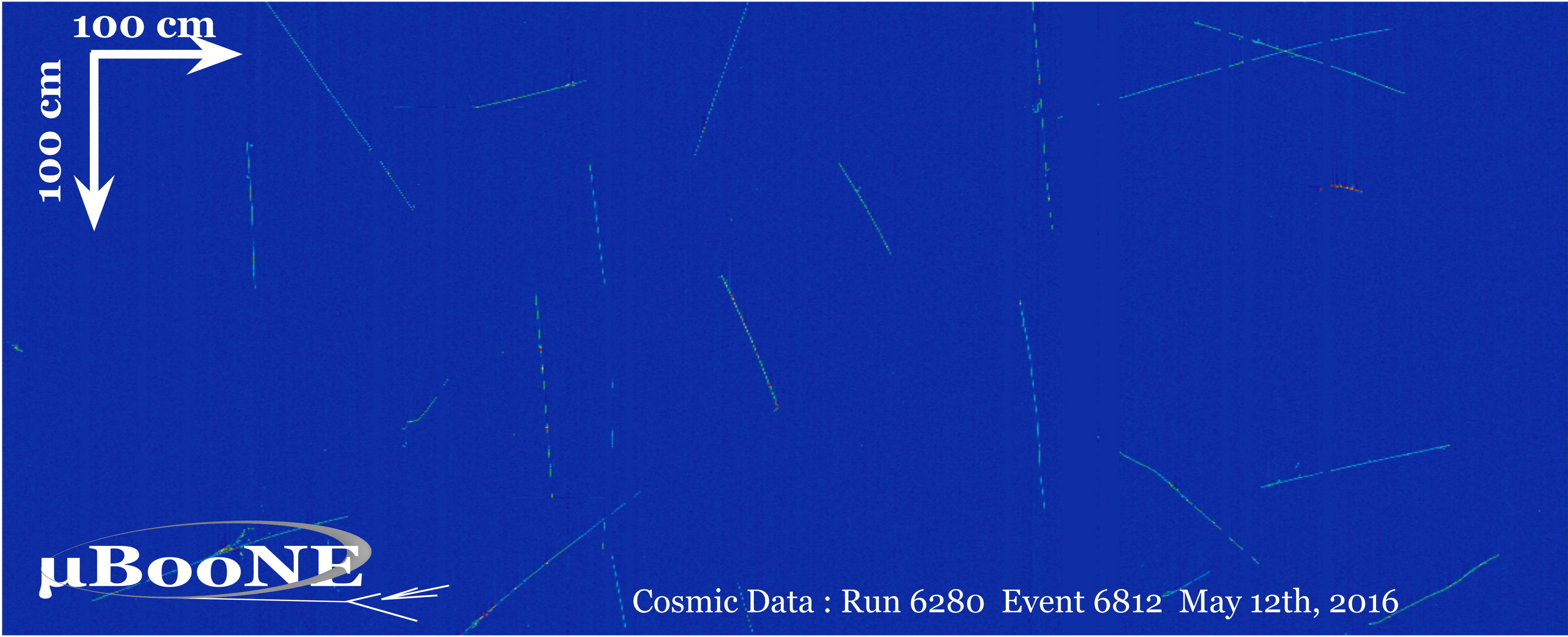
Energy deposition patterns (dE/dX) vary with particle mass & momentum, useful for analysis



Do you see neutrino interaction here?

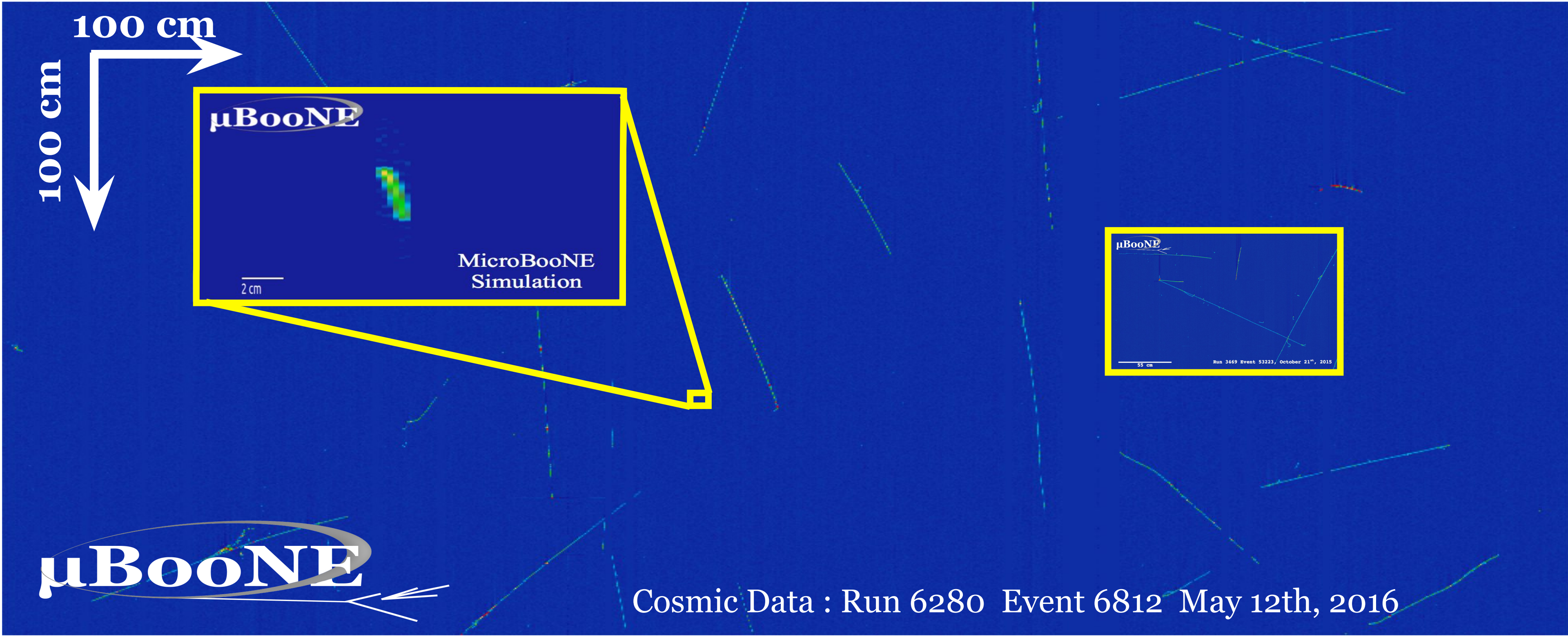


Nope :) In this detector, only ~1/700 beam neutrino interacts



Time Projection Chambers

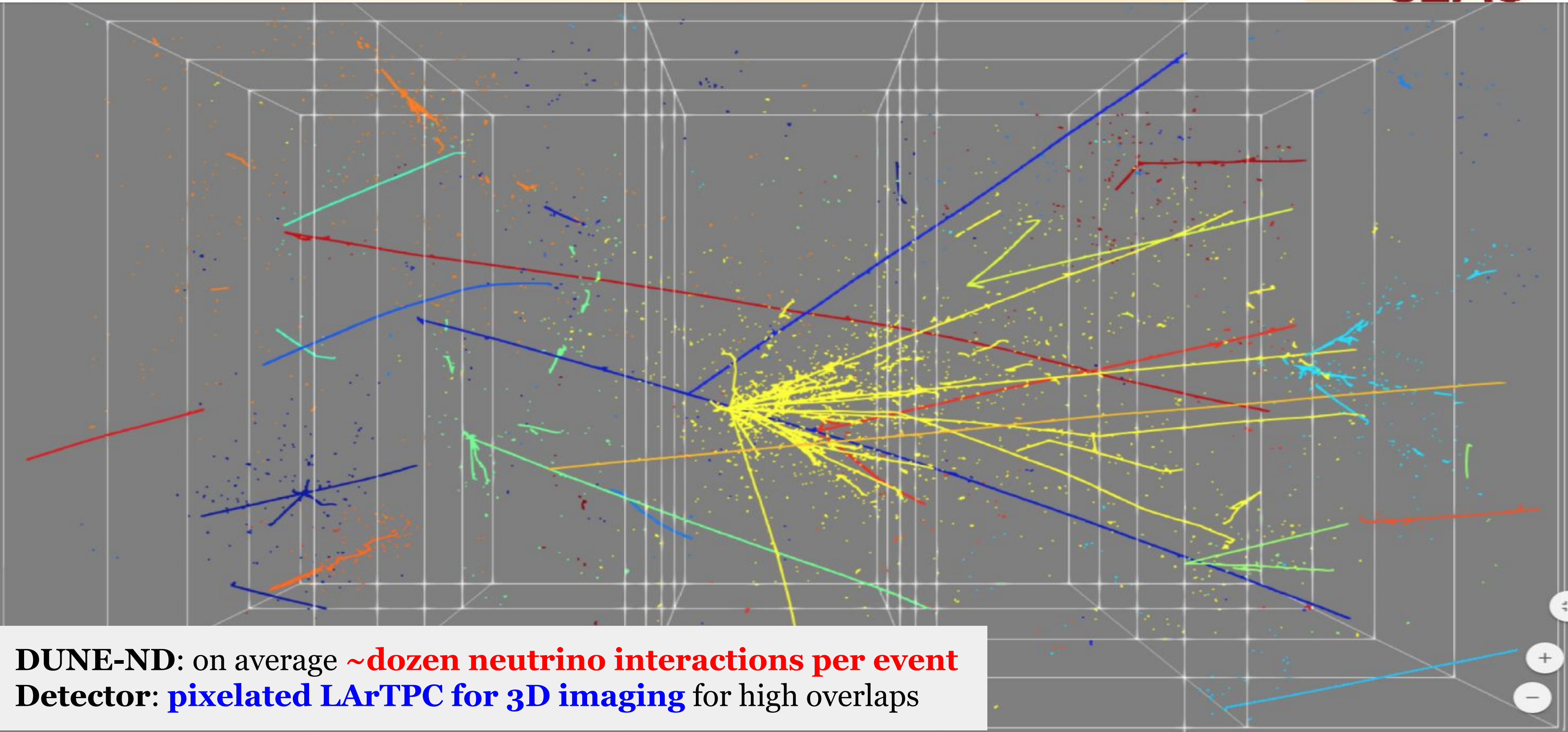
… and 1/700 have many variations in hi-resolution imaging…



Machine Learning & Computer Vision in Neutrino Physics

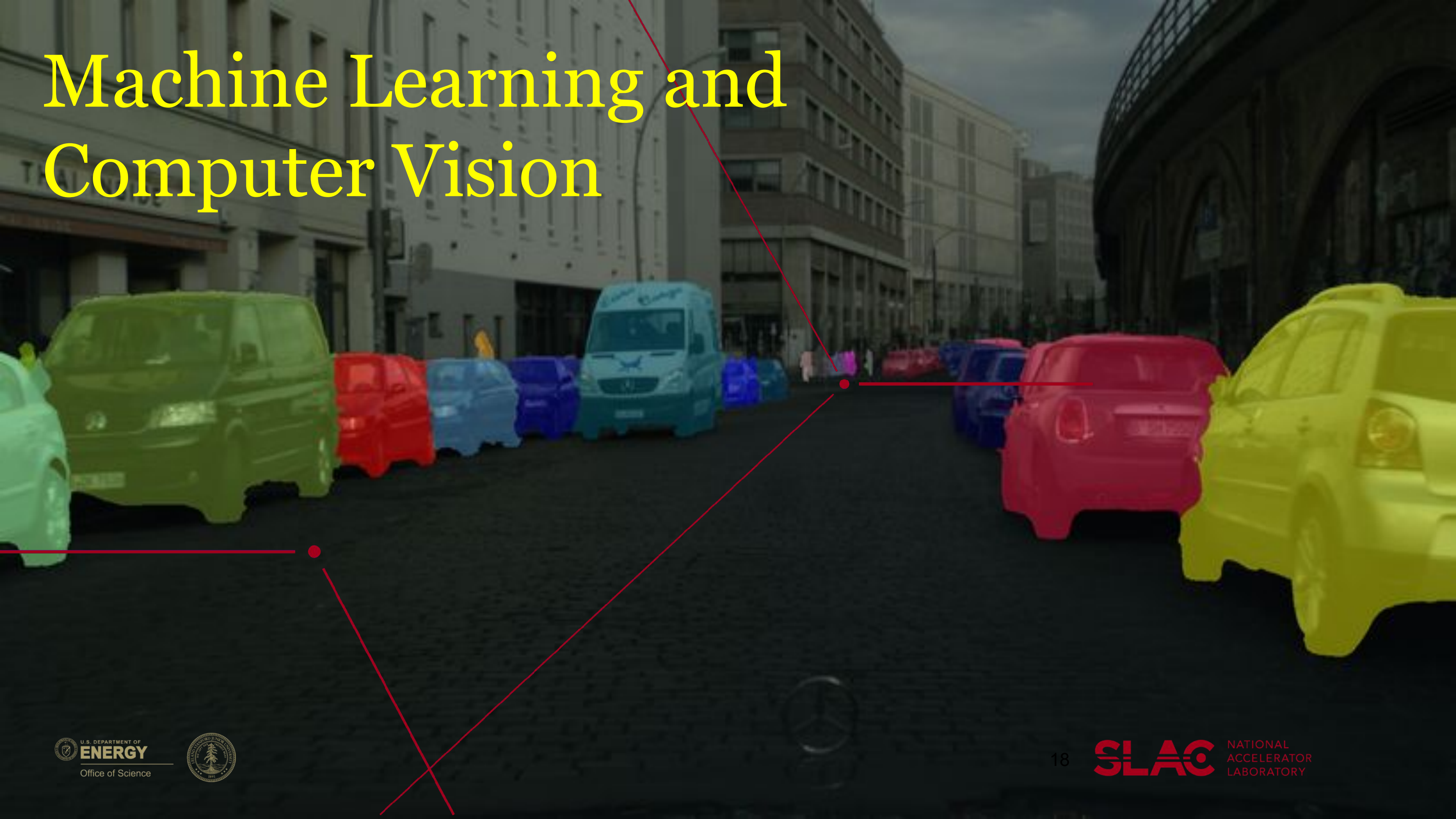
Time Projection Chambers (3D ones)

SLAC



DUNE-ND: on average **~dozen neutrino interactions per event**
Detector: **pixelated LArTPC for 3D imaging** for high overlaps

Machine Learning and Computer Vision



You can find a cat? You can find a neutrino!

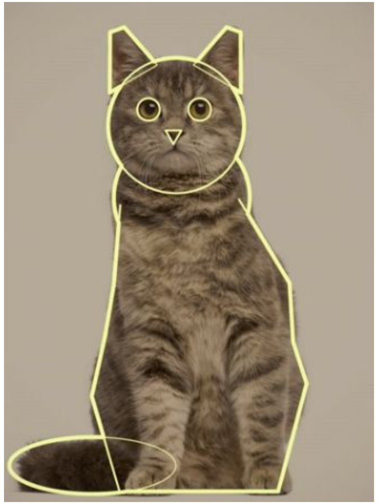
How to write an algorithm to identify a cat?

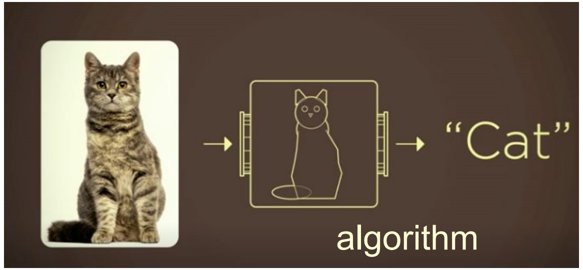
… very hard task …

16	08	67	15	83	09
37	52	77	23	22	74
35	42	48	72	85	27
68	36	43	54	21	33
79	60	10	25	54	71
18	55	38	73	50	47

Development Workflow for non-ML reconstruction

1. Write an algorithm based on physics principles





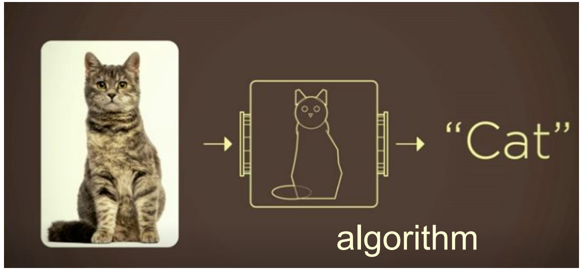
A cat (or, a neutrino) = collection of certain shapes

Development Workflow for non-ML reconstruction

1. Write an algorithm based on physics principles
2. Run on simulation and data samples
3. Observe failure cases, implement fixes/heuristics
4. Iterate over 2 & 3 till a satisfactory level is achieved
5. Chain multiple algorithms as one algorithm, repeat 2, 3, and 4.

Partial cat
(escaping the detector)

Stretching cat (Nuclear FSI)



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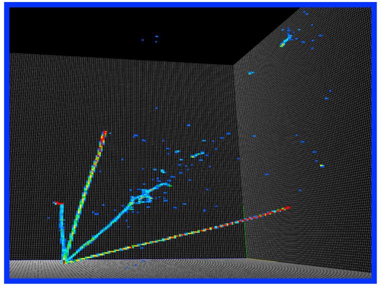
"Machine learning"

- Automatization of step 2, 3, and 4.
- Well-defined error propagation (step 5).
- Can optimize the whole chain for physics.

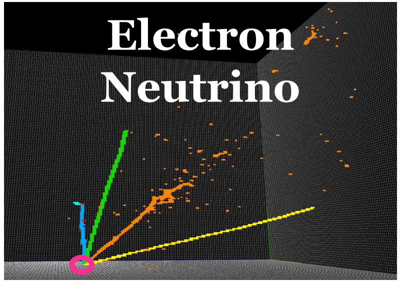
Next: what kind of ML algorithms?

Machine Learning for Data Reconstruction

- **Goal**: high level abstract information (like image classification)



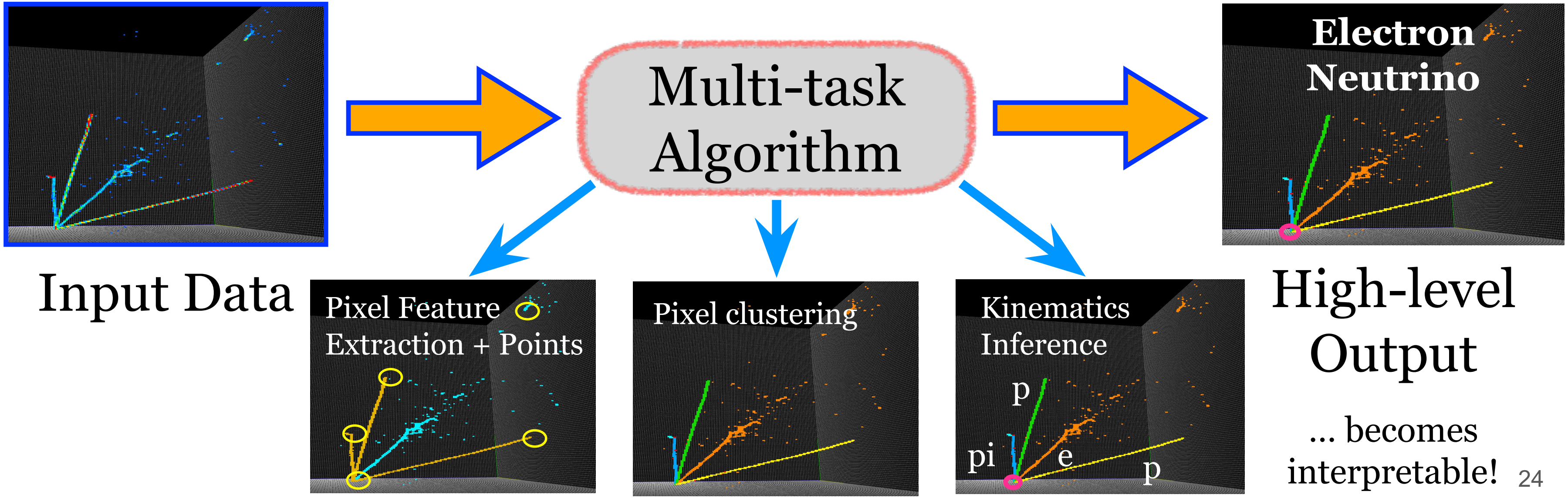
Input Data



High-level Output

Machine Learning for Data Reconstruction

- **Goal**: high level abstract information (like image classification)
- **How**: design the algorithm = data transformation architecture that extracts a hierarchy of physically meaningful features (evidences)



Machine Learning for Data Reconstruction

- **Goal**: high level abstract information (like image classification)
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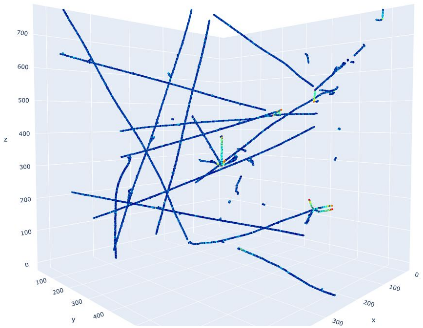
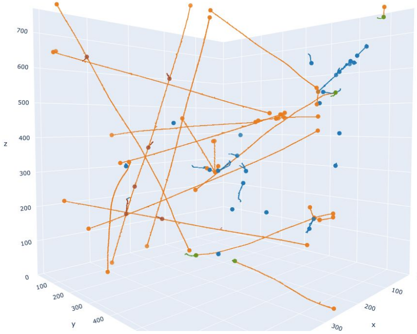
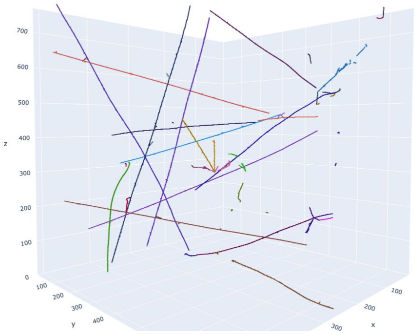
Input



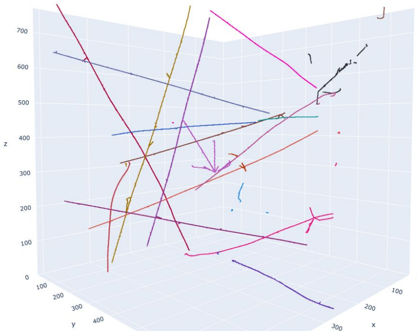
Pixel Feature



Pixel Clustering



Particle Clustering



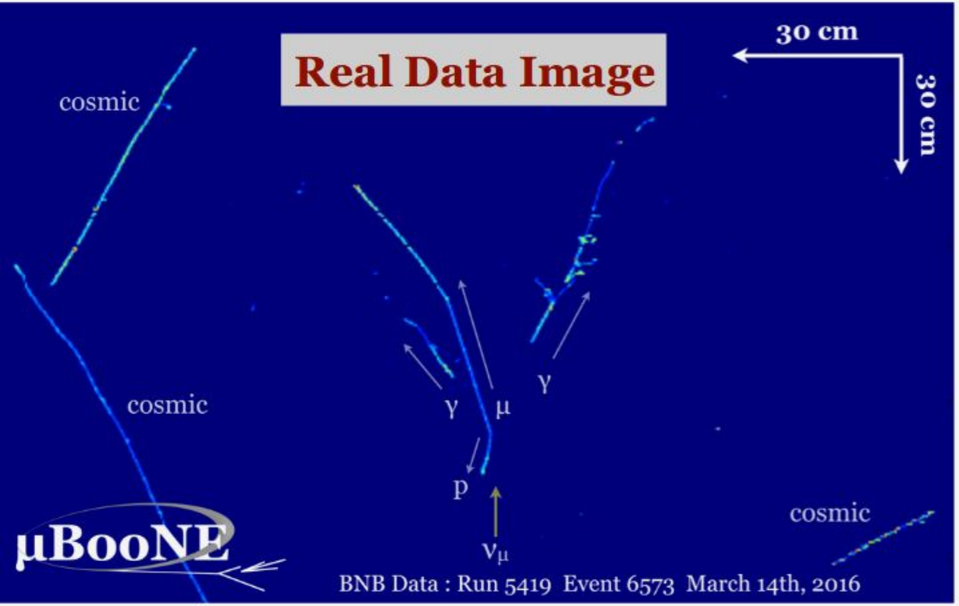
The Rest: describe the chain

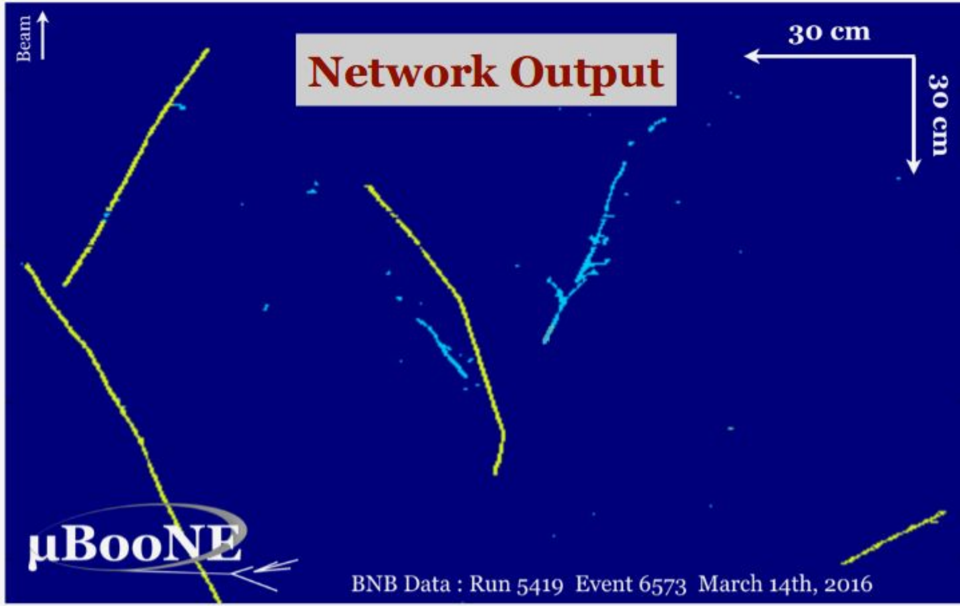
ML-Based LArTPC Data Reconstruction

ML-based Neutrino Data Reconstruction Chain
Stage 1-a: Pixel Feature Extraction + Scalablility

Distinguish 2 distinct particle topologies: **showers** **v.s.** **tracks**

Critical to deploy different algorithms for clustering pixels in the next stage.





Network Input

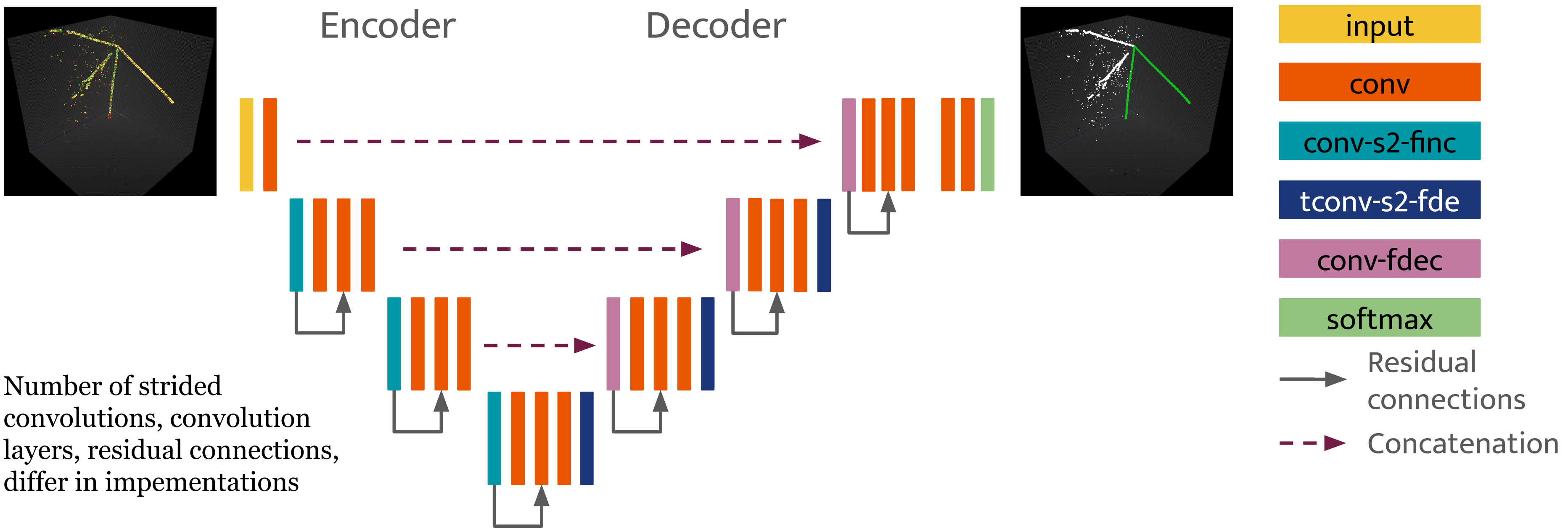
PRD 99 092001
arXiv:1808.07269

Network Output

ML-based Neutrino Data Reconstruction Chain

Stage 1-a: Pixel Feature Extraction + Scalablility

Architecture: **U-Net + Residual Connections**



Number of strided convolutions, convolution layers, residual connections, differ in impementations

Image credit: Laura Domine @ Stanford

Stage 1-a: Pixel Feature Extraction + Scalablility

"Applying CNN" is simple, but **is it scalable for us?**

CNN applies **dense matrix operations**

In photographs, **all pixels are meaningful**

grey pixels = dolphins,
blue pixels = water, etc...

Stage 1-a: Pixel Feature Extraction + Scalablility

"Applying CNN" is simple, but **is it scalable for us?**

LArTPC data is generally sparse, but locally dense

CNN applies **dense matrix operations**

In photographs, **all pixels are meaningful**

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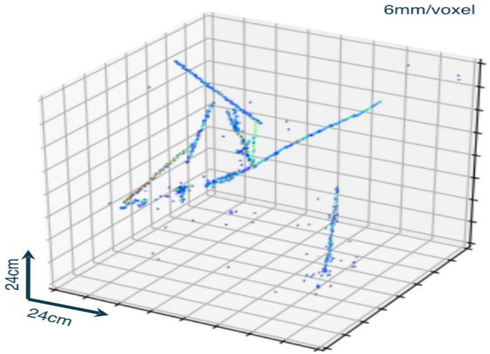

Empty pixels = no energy

<1% of pixels are non-zero in LArTPC data

Zero pixels are meaningless!

Figures/Texts: courtesy of Laura Domine @ Stanford

Figure credit: Laura Domine @ Stanford

ML-based Neutrino Data Reconstruction Chain
Stage 1-a: Pixel Feature Extraction + Scalablility

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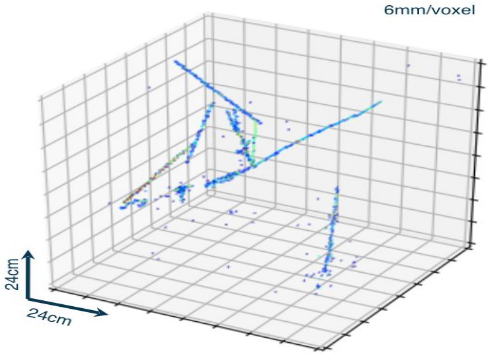


<1% of pixels are non-zero in LArTPC data

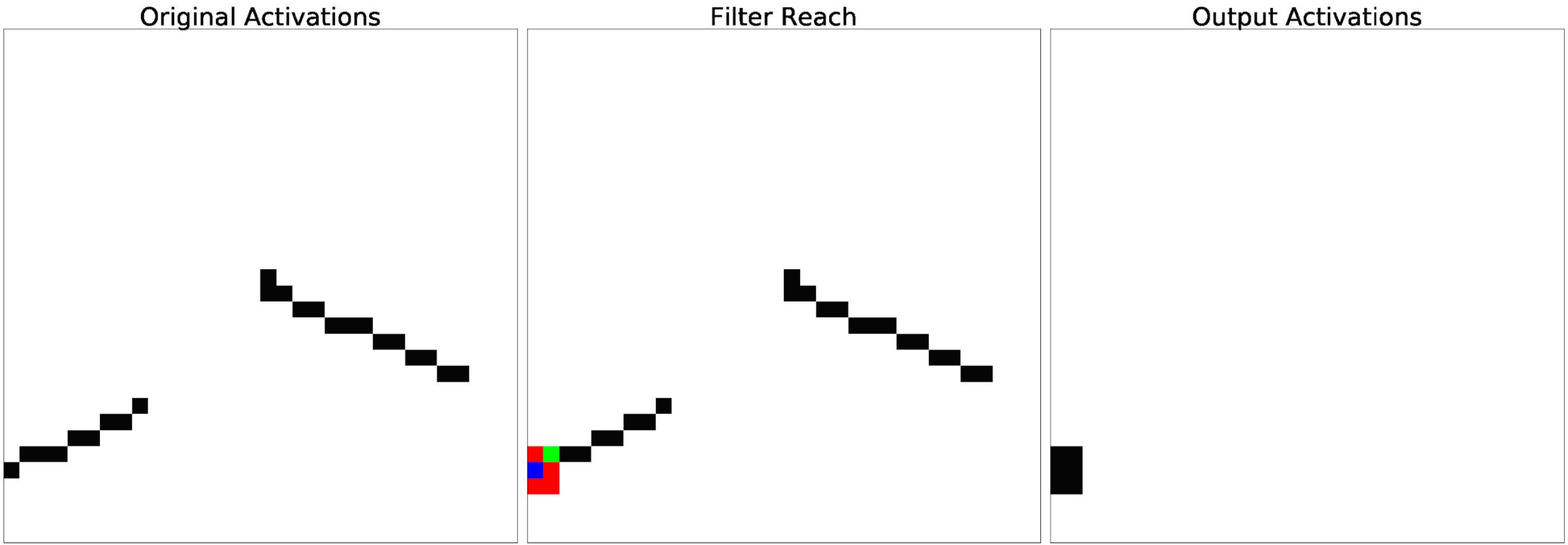
Zero pixels are meaningless!

Figures/Texts: courtesy of Laura Domine @ Stanford

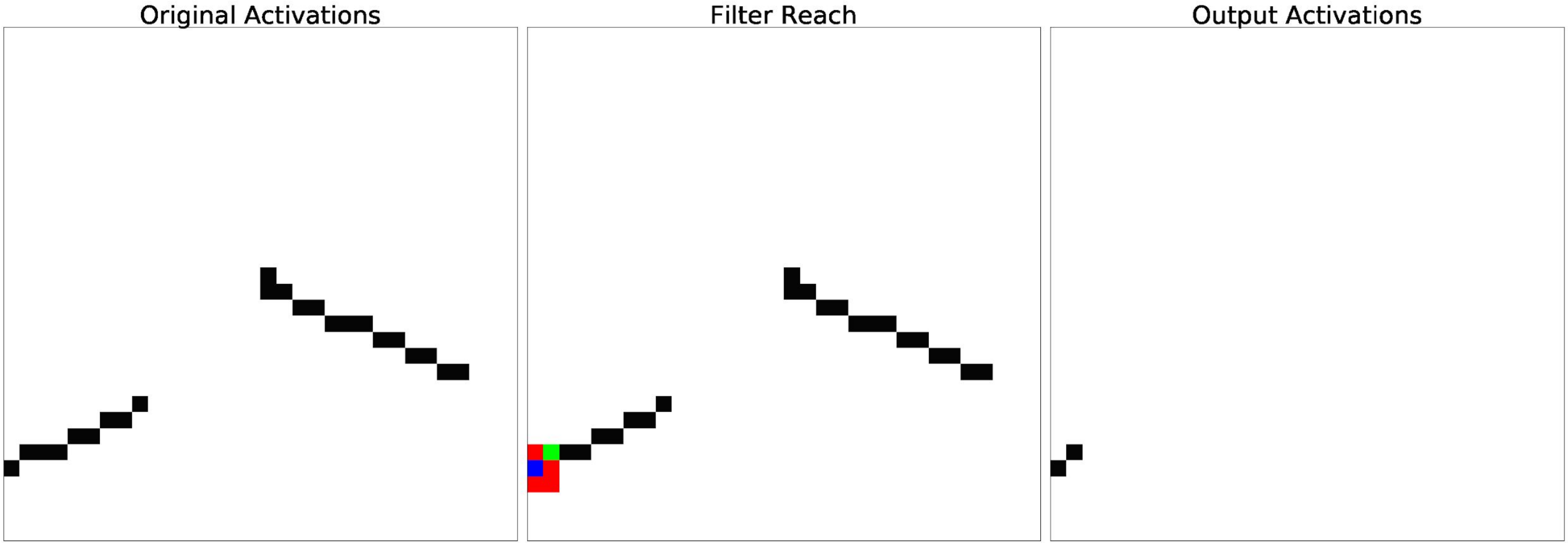
- **Scalability for larger detectors**
  - Computation cost increases linearly with the volume
  - But the number of non-zero pixels does not

Figure credit: Laura Domine @ Stanford

Sparse Submanifold Convolutions



Sparse Submanifold Convolutions



ML-based Neutrino Data Reconstruction Chain

Stage 1-a: Pixel Feature Extraction + Scalablility

Our data is locally much more dense than ShapeNet 3D dataset

... which makes convolution filter more effective on our data as long as the sparsity issue is handled

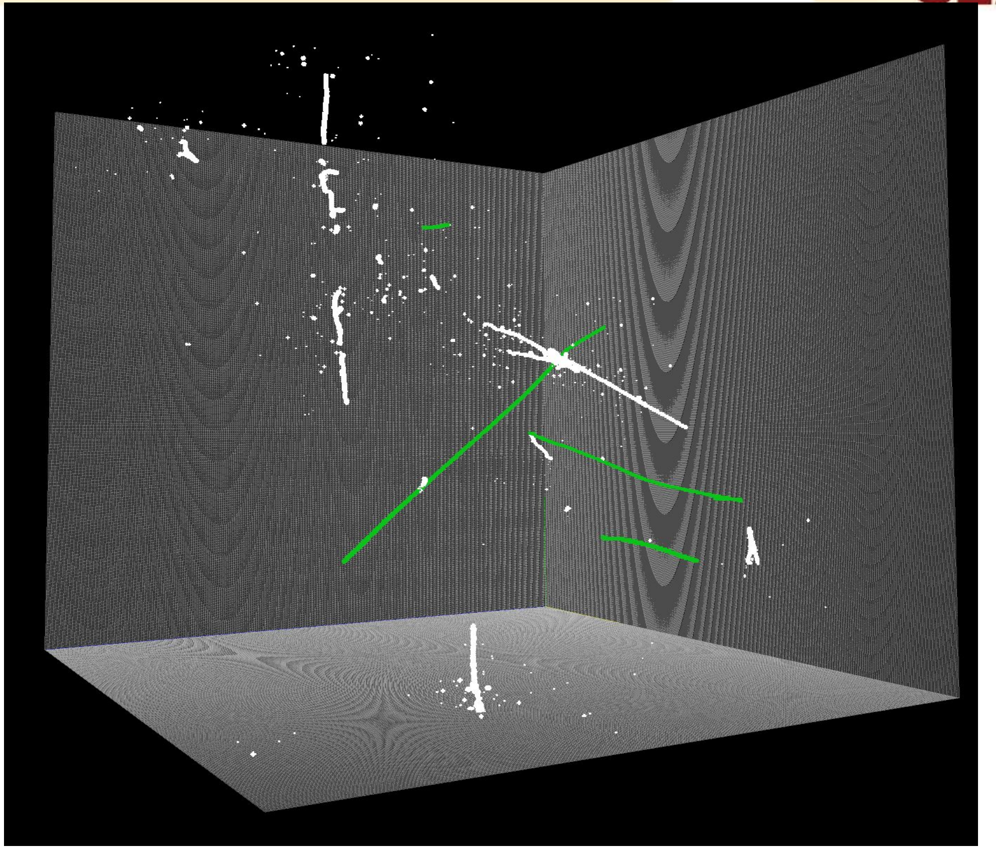
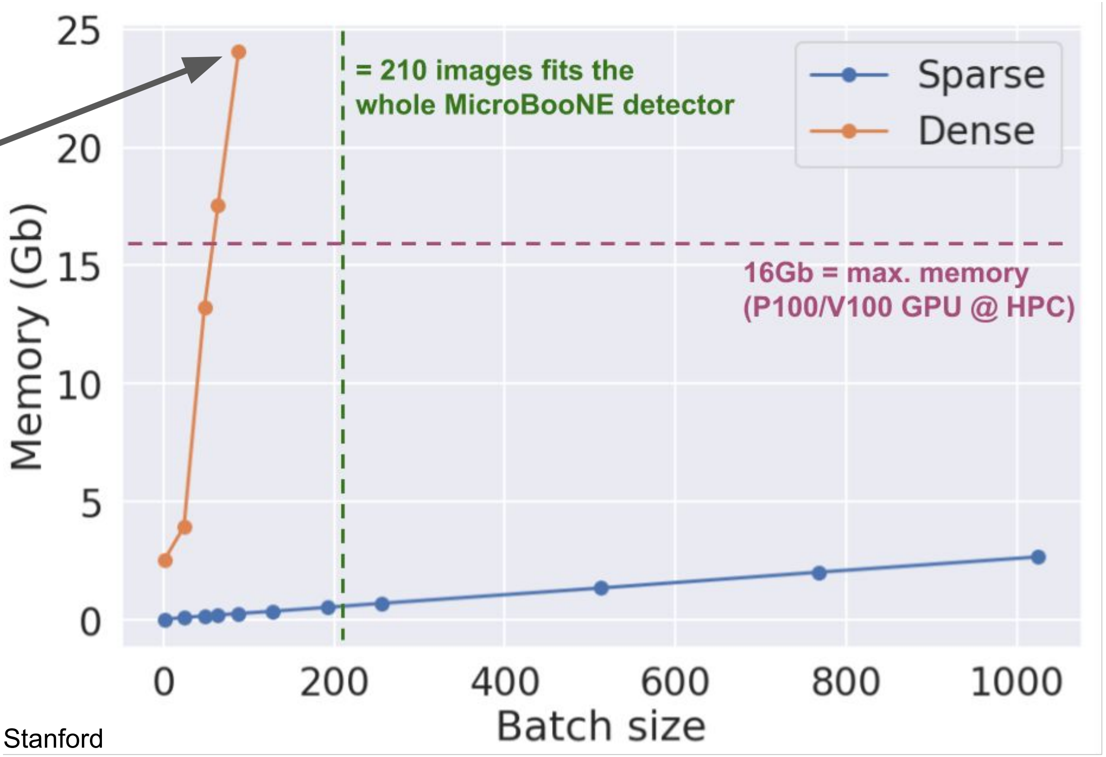


Image credit: Laura Domine @ Stanford

ML-based Neutrino Data Reconstruction Chain
Stage 1-a: Pixel Feature Extraction + Scalablility

Sparse U-ResNet fits more data in GPU + good scalability

@batch size 88
sparse uses
93x less memory
than dense and
computation is
3x faster



Can handle easily the whole ICARUS detector which is x6 larger than MicroBooNE.

DUNE-FD is piece of cake (larger volume but less non-zero pixels)

Figure credit: Laura Domine @ Stanford

ML-based Neutrino Data Reconstruction Chain
Stage 1-a: Pixel Feature Extraction + Scalablility

Sparse Sub-manifold Convolutional NN

Type	Proton	Mu/Pi	Shower	Delta	Michel
Acc.	0.99	0.98	0.99	0.97	0.96

- **Public LArTPC simulation**
  - Particle tracking (Geant4) + diffusion, no noise, true energy

Computer Science > Computer Vision and Pattern Recognition

Scalable Deep Convolutional Neural Networks for Sparse, Locally Dense Liquid Argon Time Projection Chamber Data

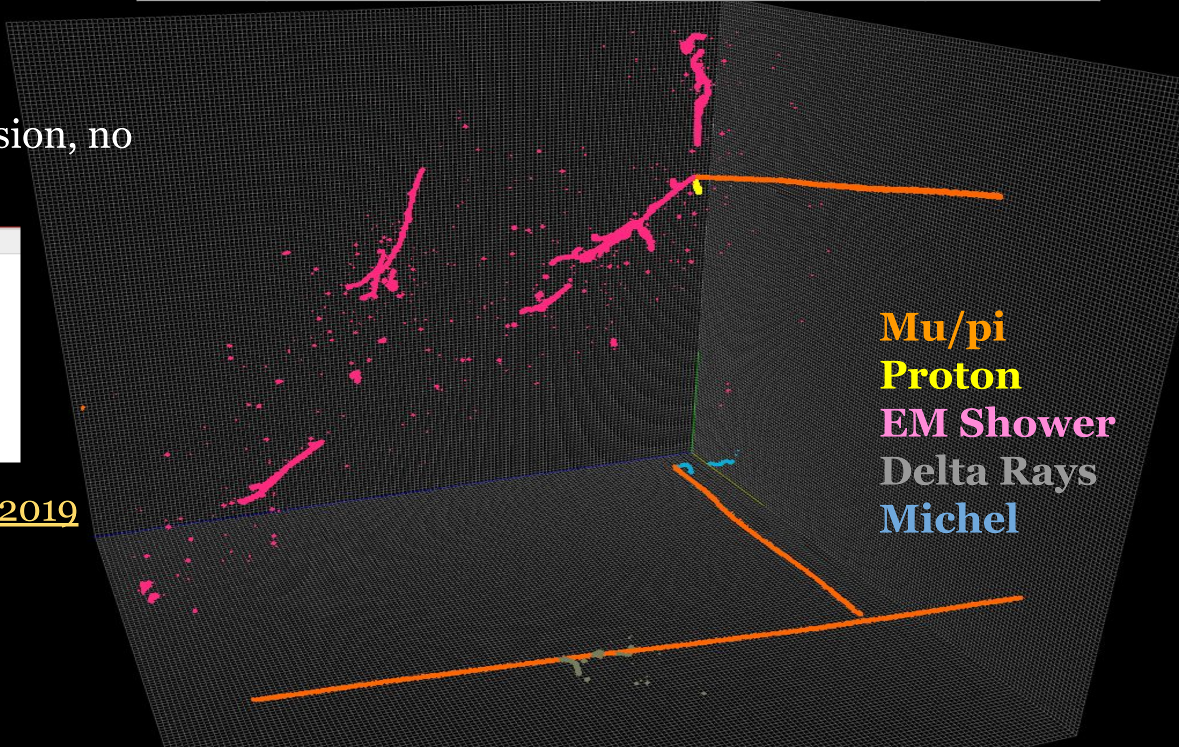
Laura Dominé, Kazuhiro Terao

(Submitted on 13 Mar 2019 (v1), last revised 15 Mar 2019 (this version, v2))

Deep convolutional neural networks (CNNs) show strong promise for analyzing scientific data in many domains including particle imaging detectors such as a liquid argon time projection chamber (LArTPC). Yet the high sparsity of LArTPC data challenges traditional CNNs which were designed for dense data such as photographs. A naive application of CNNs on LArTPC data results in inefficient computations and a poor scalability to large LArTPC detectors such as the Short Baseline

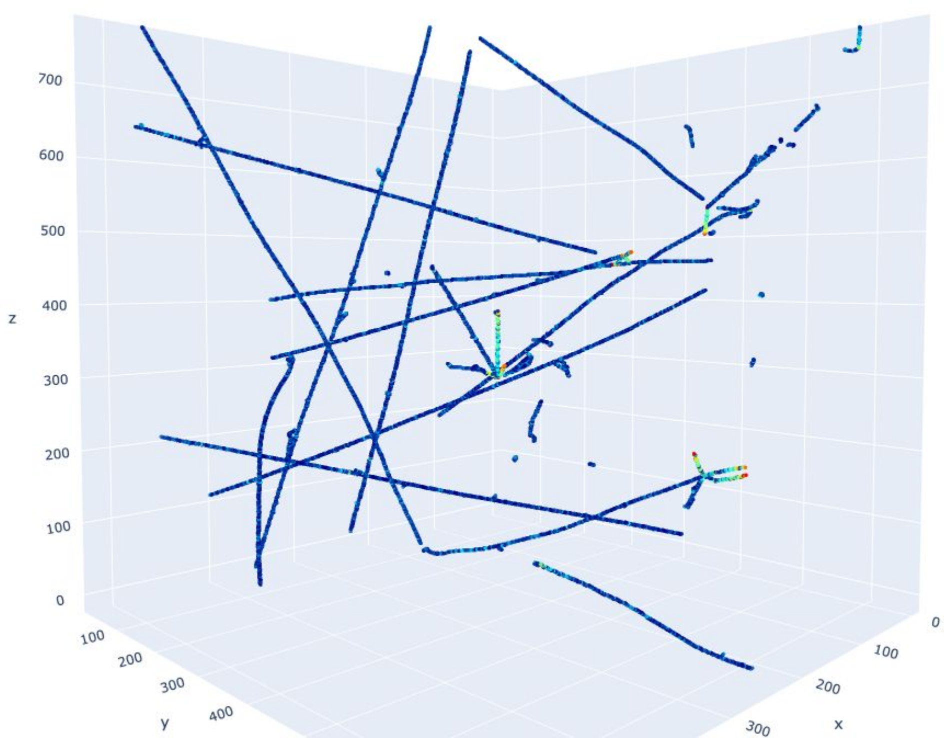
PhysRevD.102.012005 presented @ ACAT 2019

- Memory reduction ~ 1/360
- Compute time ~ 1/30
- Handles large future detectors

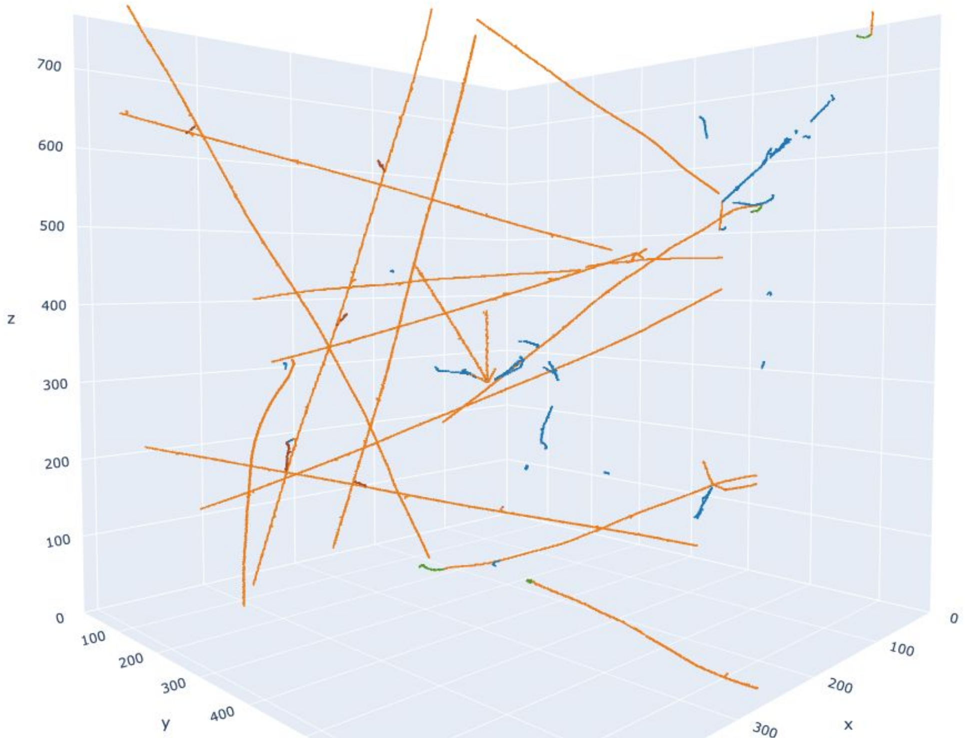


ML-based Neutrino Data Reconstruction Chain
Stage 1-a: input & output

Stage 1-a Input

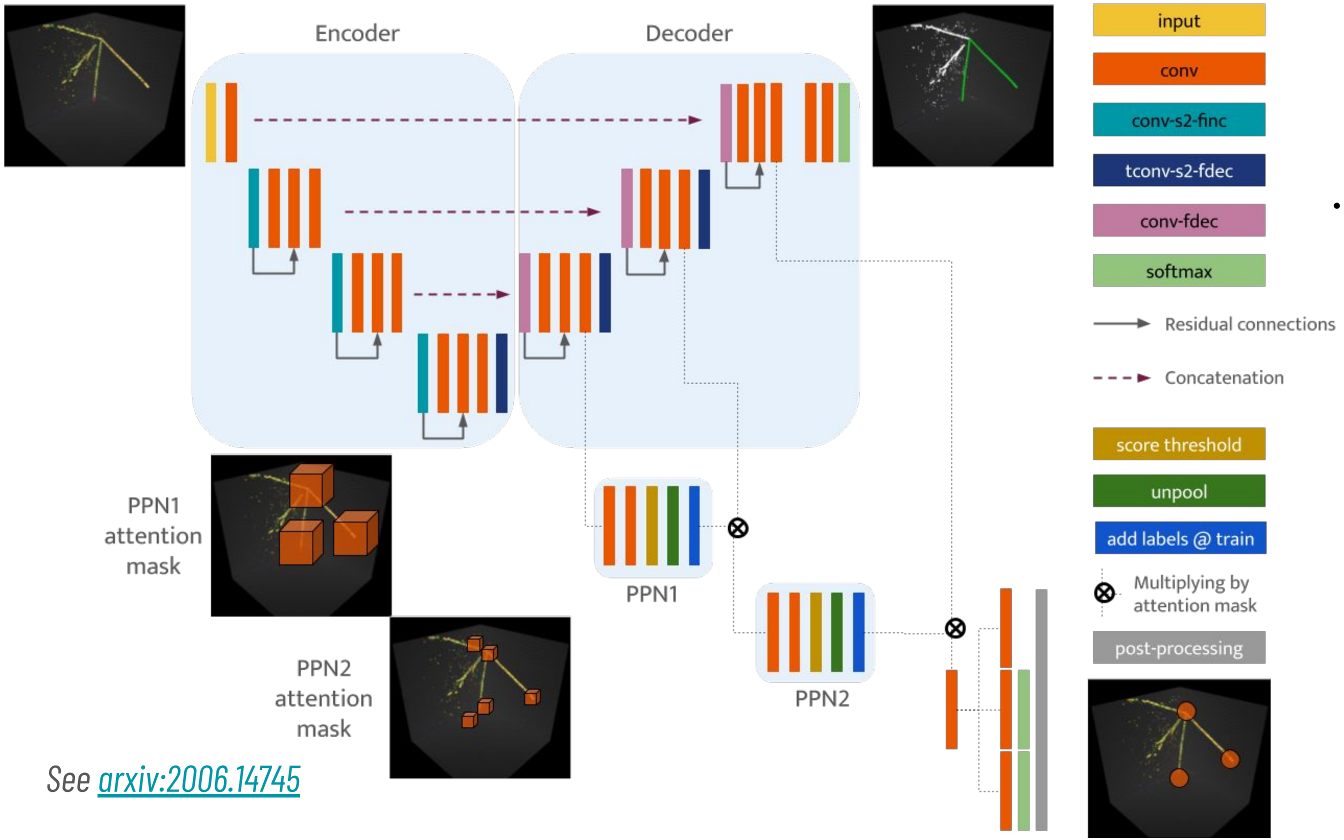


Stage 1-a Output



ML-based Neutrino Data Reconstruction Chain

Stage 1-b: Particle Endpoint Prediction

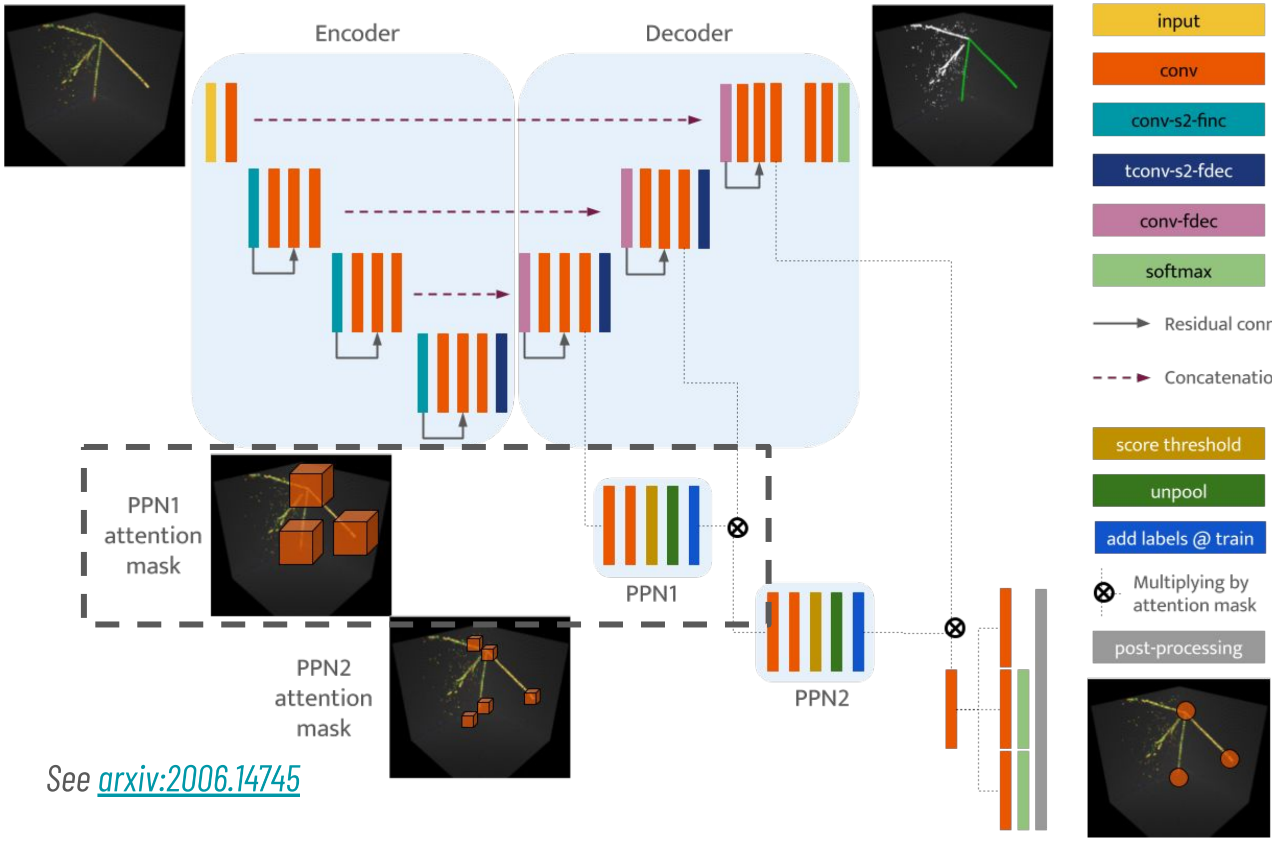


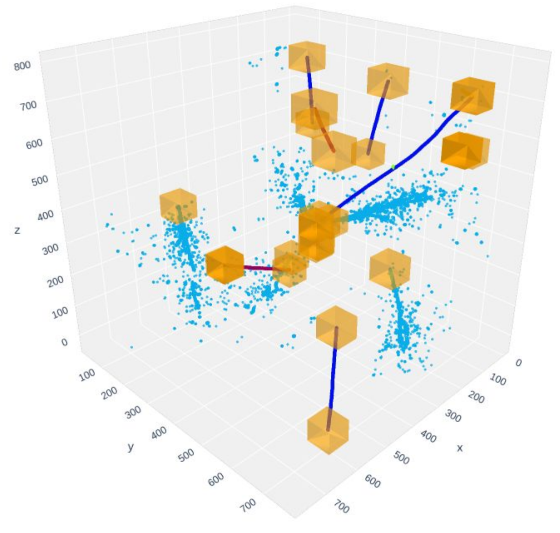
Point Proposal Network (PPN)

… extension of U-ResNet with 3 CNN blocks

See arxiv:2006.14745

ML-based Neutrino Data Reconstruction Chain
Stage 1-b: Particle Endpoint Prediction

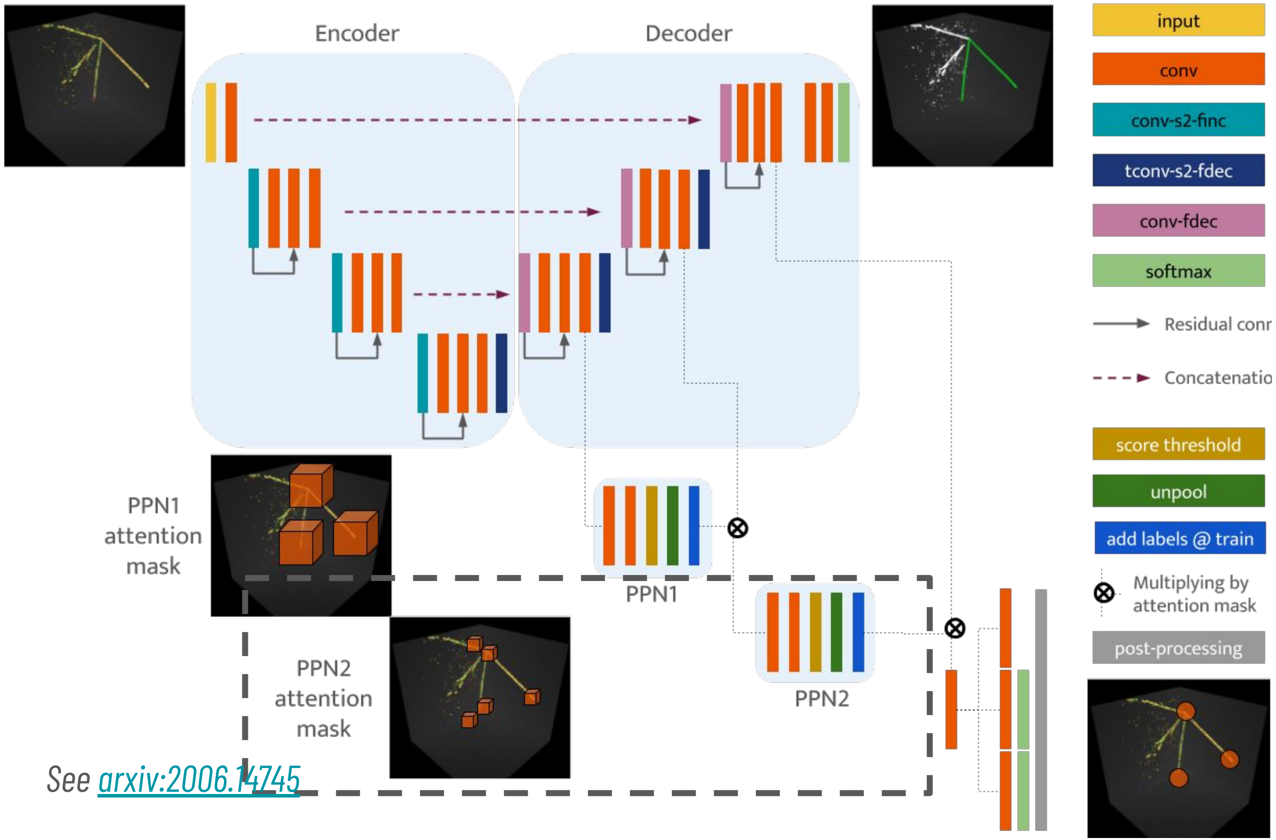




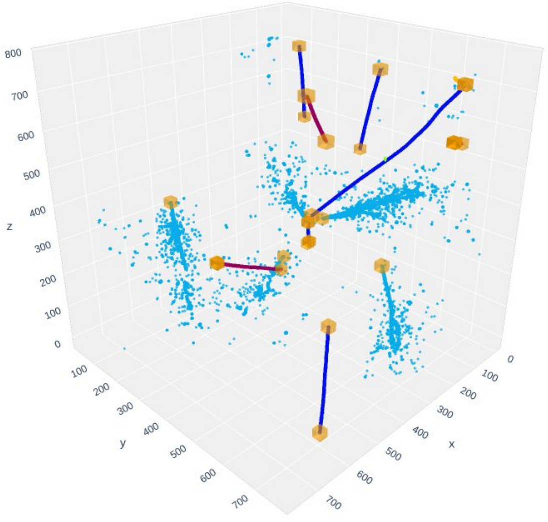
PPN1 generates an attention mask at the lowest resolution

See [arxiv:2006.14745](https://arxiv.org/abs/2006.14745)

ML-based Neutrino Data Reconstruction Chain
Stage 1-b: Particle Endpoint Prediction



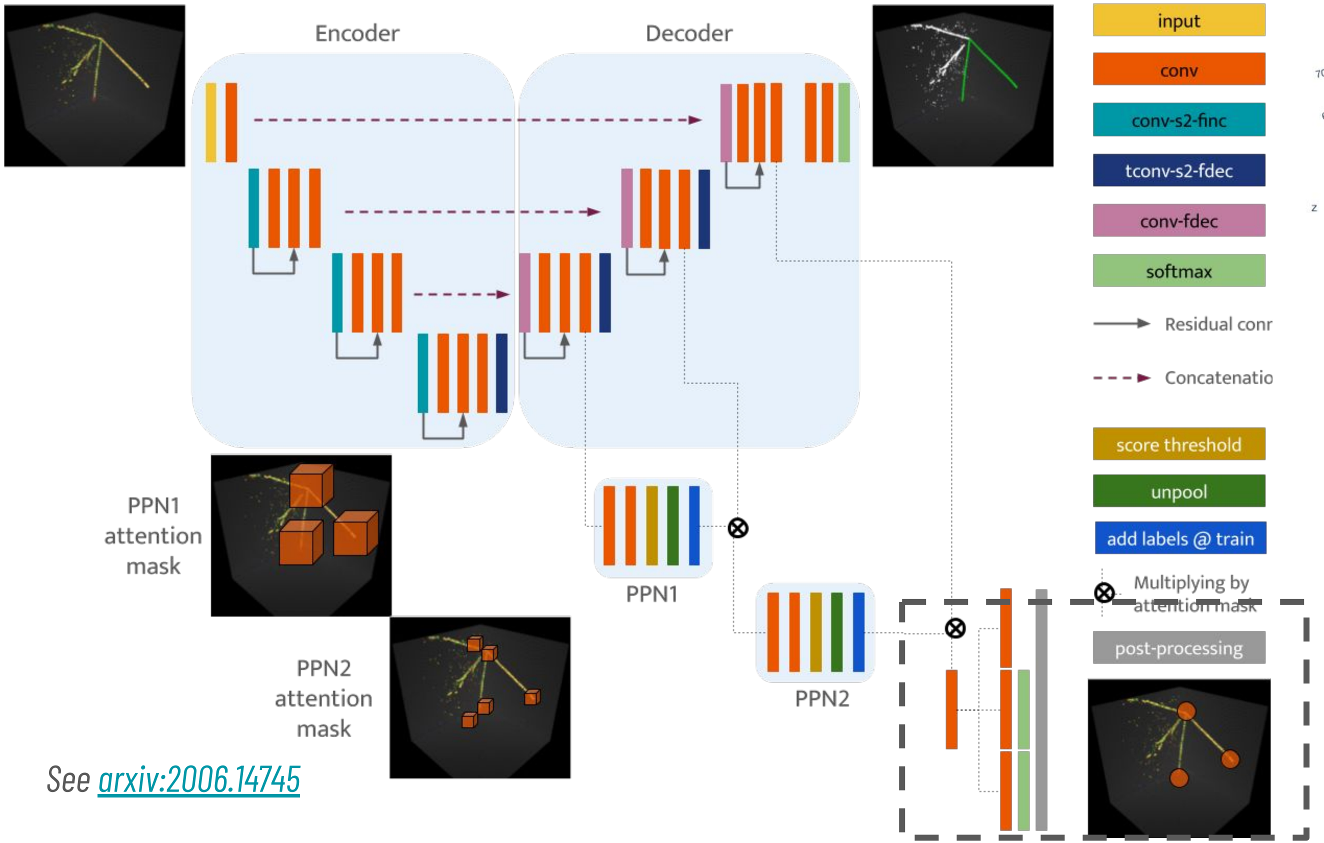
See [arxiv:2006.14745](https://arxiv.org/abs/2006.14745)

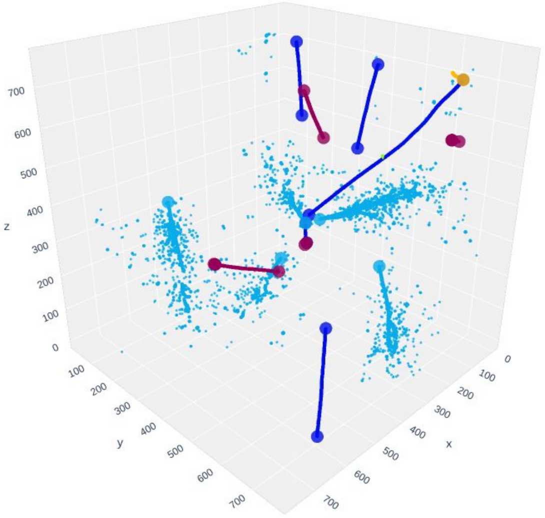


PPN2 generates an attention mask at the intermediate resolution

ML-based Neutrino Data Reconstruction Chain

Stage 1-b: Particle Endpoint Prediction





PPN makes the final prediction (point type + coordinate regression)

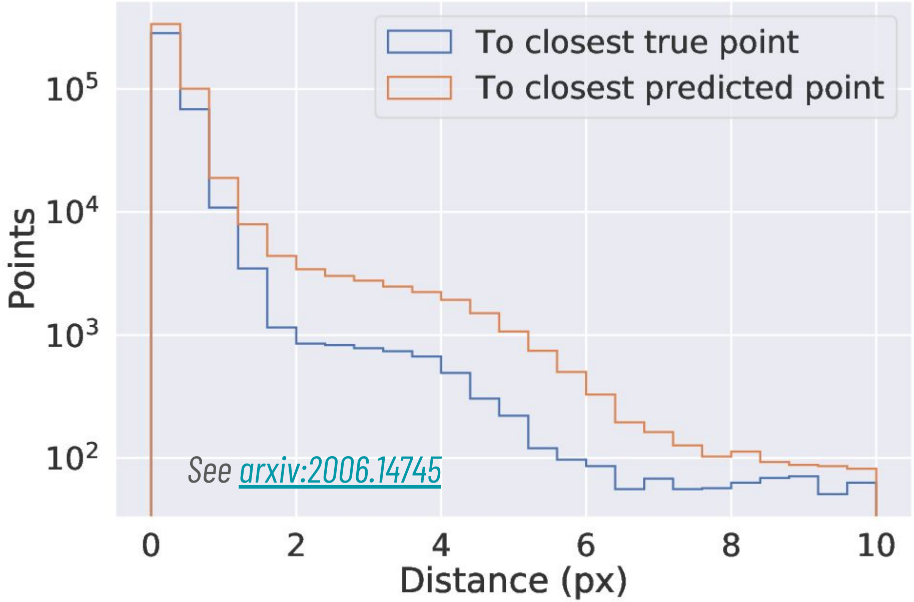
See [arxiv:2006.14745](https://arxiv.org/abs/2006.14745)

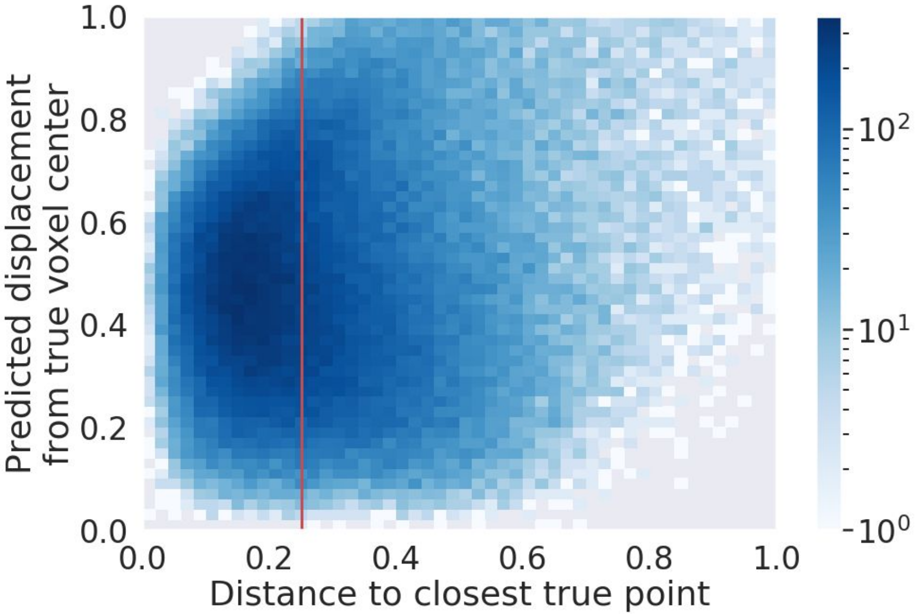
ML-based Neutrino Data Reconstruction Chain
Stage 1-b: Particle Endpoint Prediction

SLAC

96.8% of predicted points within 3 voxels of a true point

- 68% of true points found within the radius of 0.12 cm
- Traditional (nominal) reconstruction method finds 90% of predicted points within 17 voxels, and 68% of true points found within the radius of 0.74cm

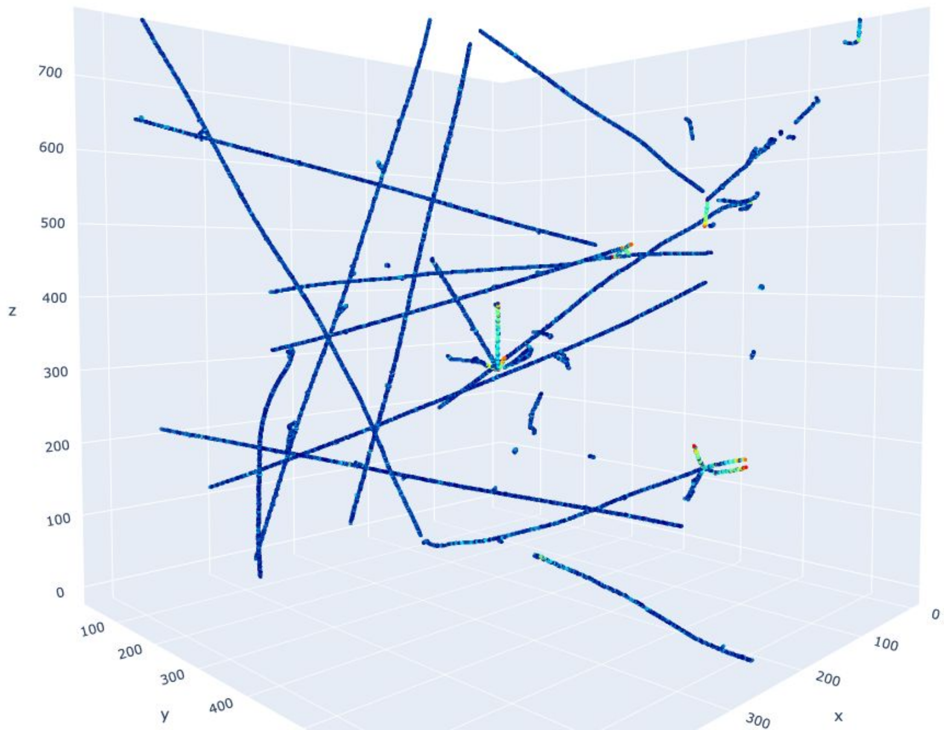




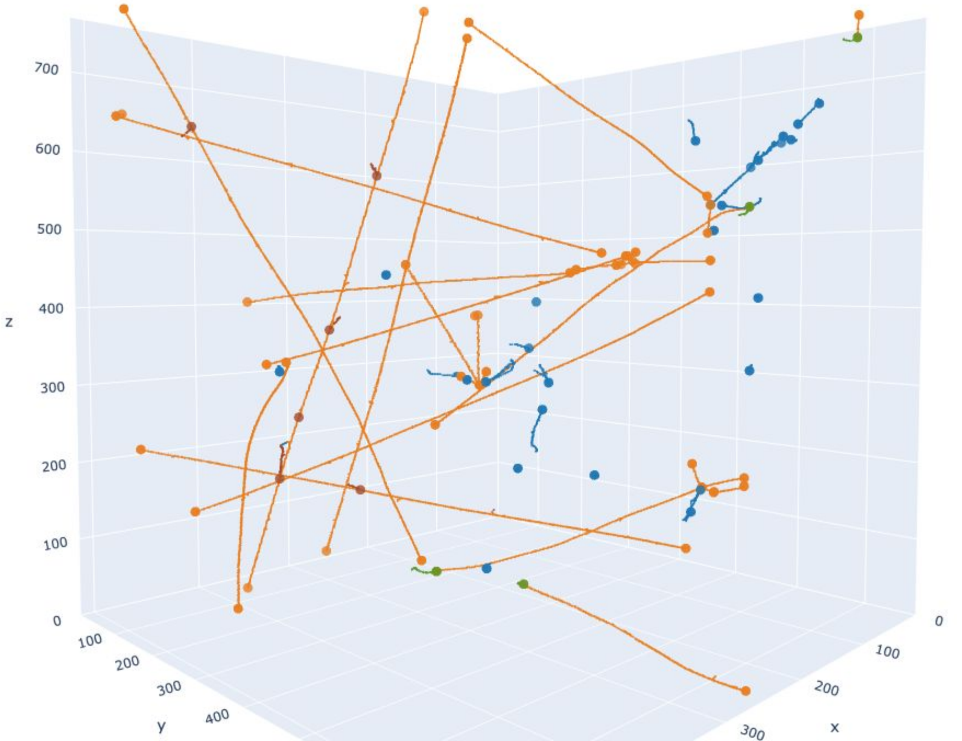
ML-based Neutrino Data Reconstruction Chain

Stage 1: input & output

Stage 1 Input



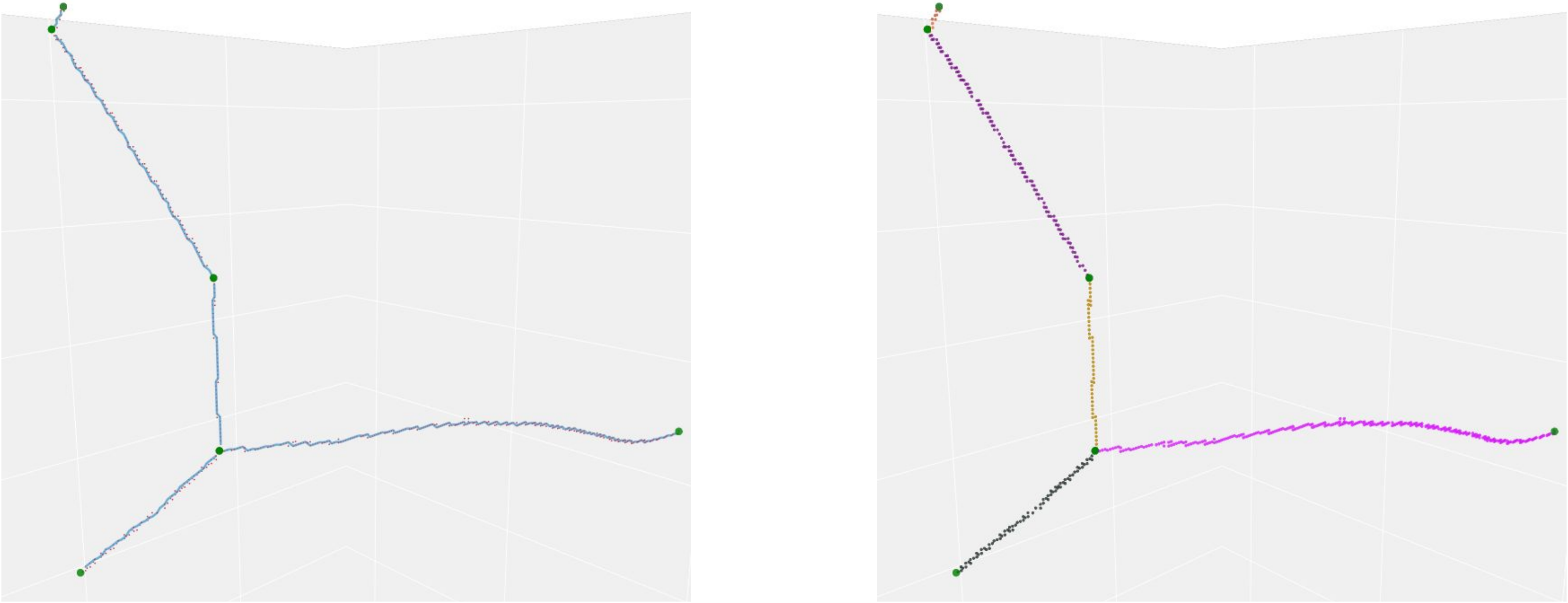
Stage 1 Output



Stage 2-a: Dense Pixel Clustering

Simple approach: path-finding between PPN points

- MST to find the "shortest" path between PPN points to cluster pixels
- **Works well! BUT** it depends on PPN performance directly + not learnable



ML-based Neutrino Data Reconstruction Chain
Stage 2: Particle & Interaction Clustering

Learnable approach: clustering in the embedding space

- Use CNN to learn a transformation function from the 3D voxels to the embedding space where clustering can be performed in a simple manner

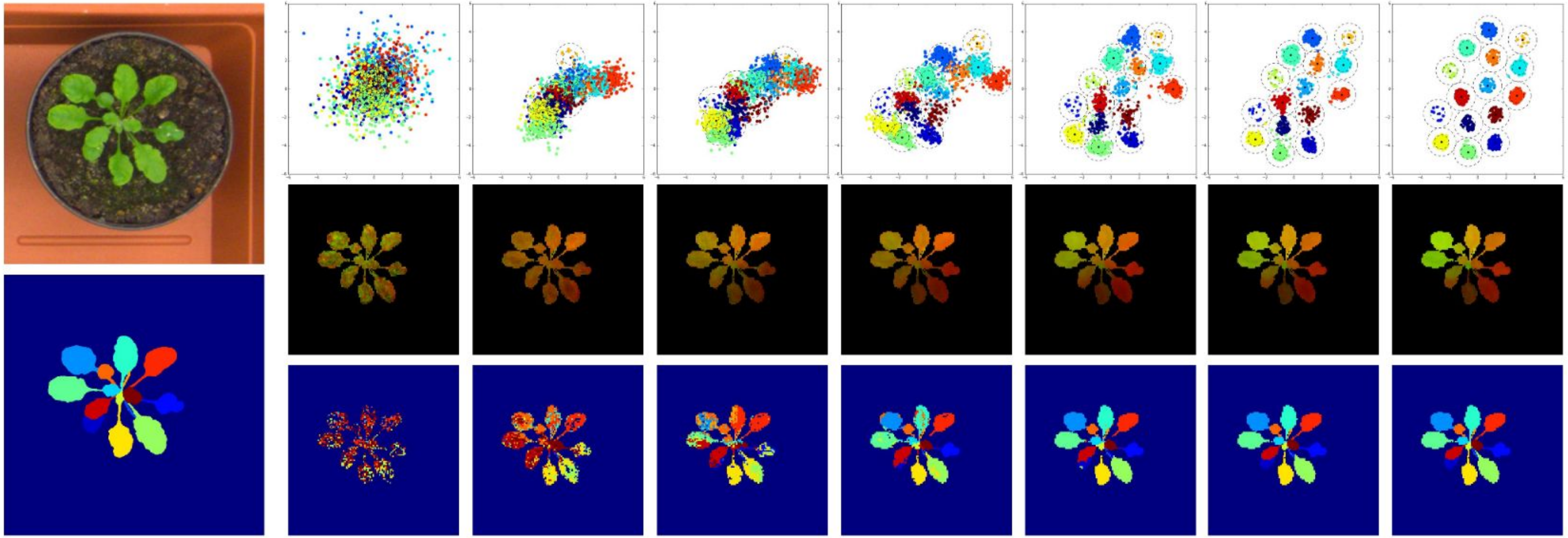
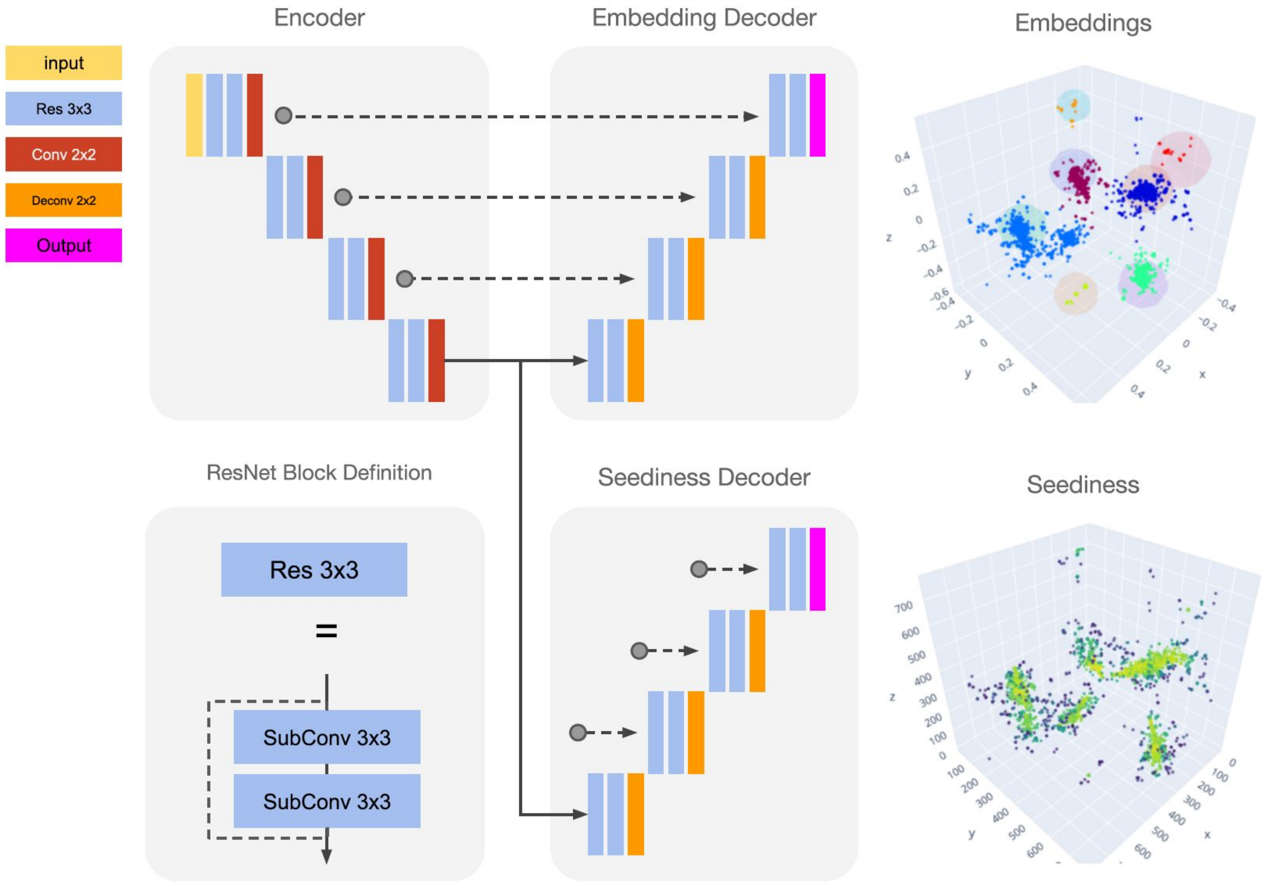


Image credit: [arXiv 1708.02551]

ML-based Neutrino Data Reconstruction Chain

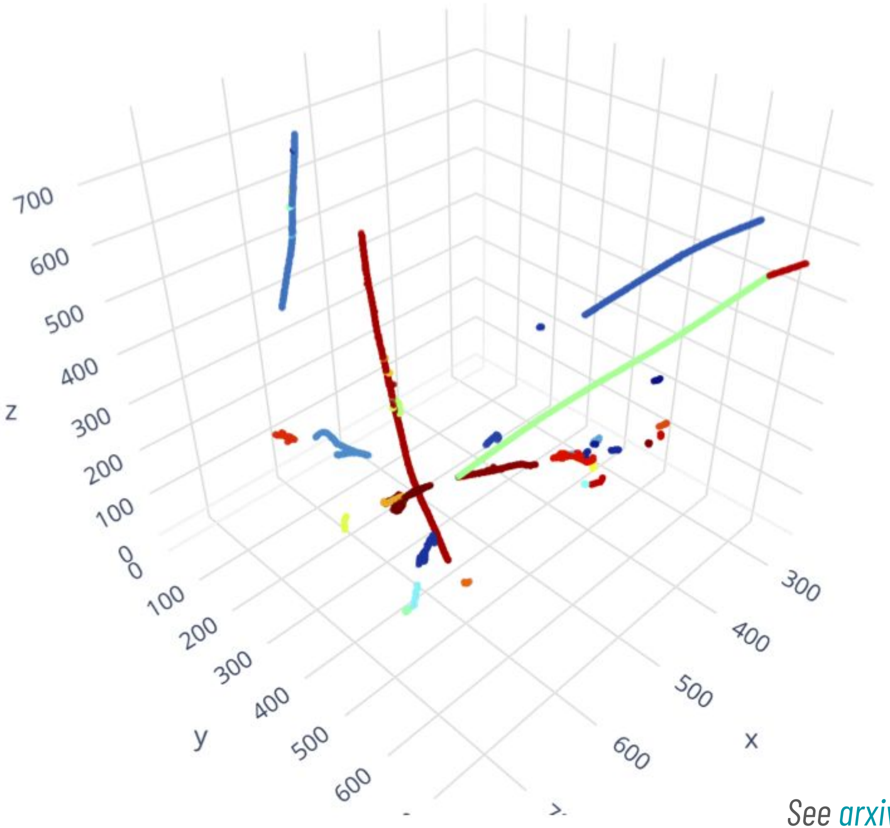
Stage 2-a: Dense Pixel Clustering

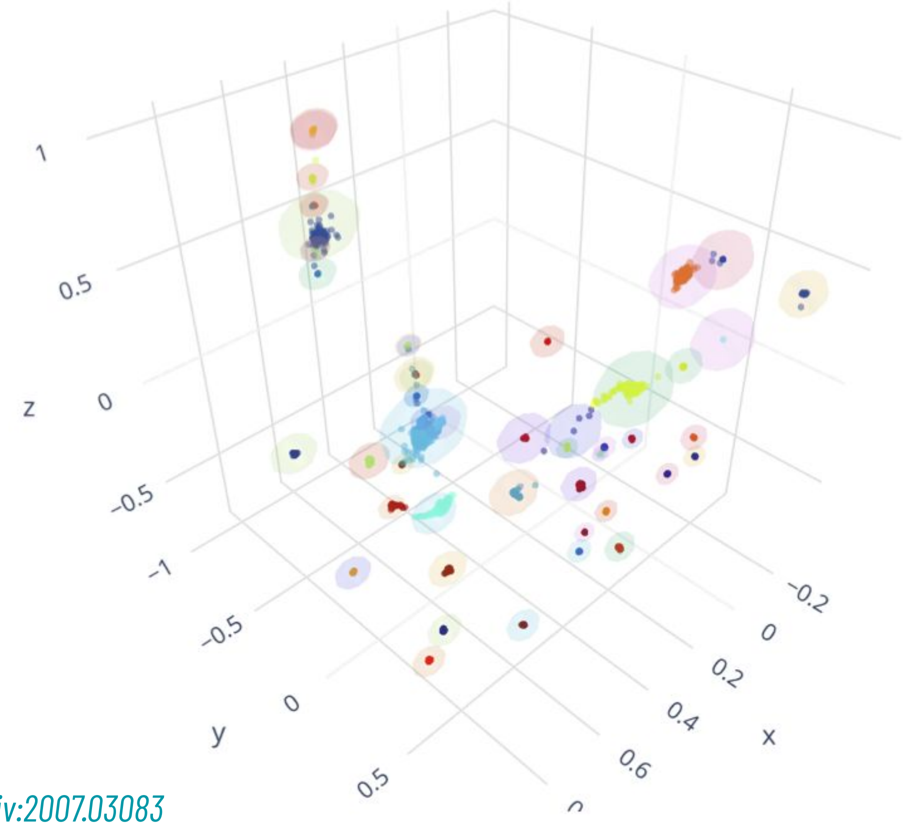


Scalable Particle Instance Clustering using Embedding (SPICE)

- Embedding decoder learns transformation
- Seediness decoder identifies the centroids
- During training, loss is conditioned so that the points that belong to the same cluster follow a normal distribution

ML-based Neutrino Data Reconstruction Chain
Stage 2-a: Dense Pixel Clustering

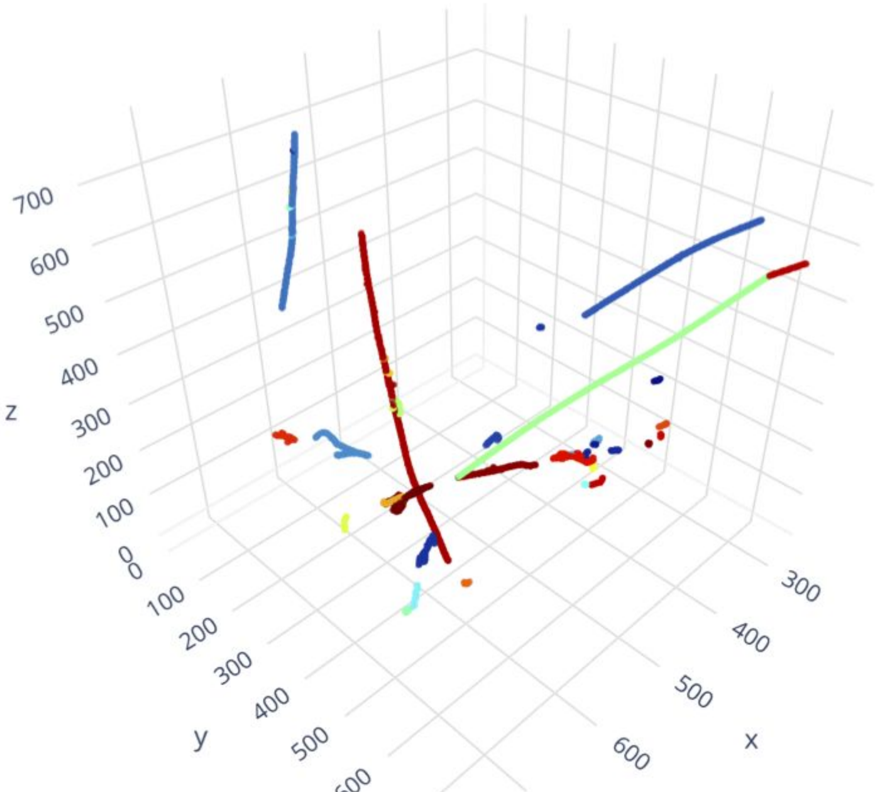


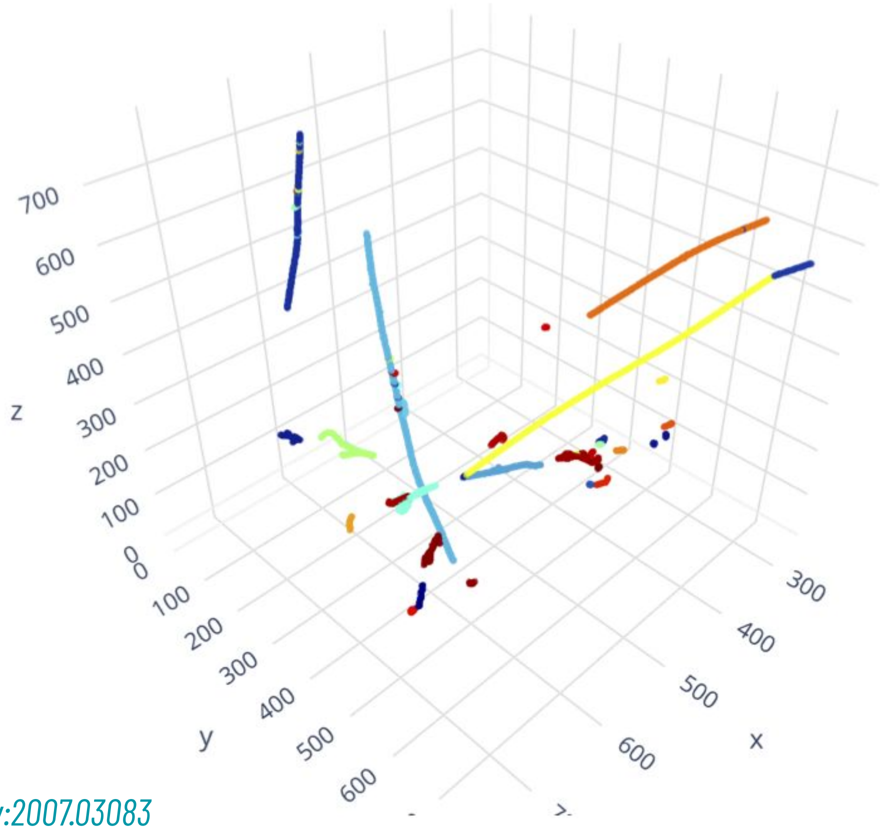


See arxiv:2007.03083

ML-based Neutrino Data Reconstruction Chain

Stage 2-a: Dense Pixel Clustering

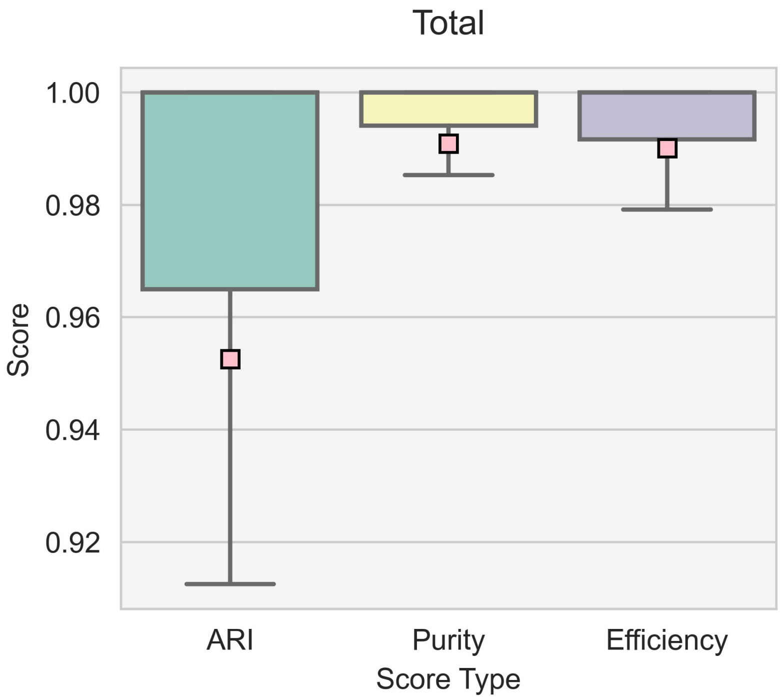


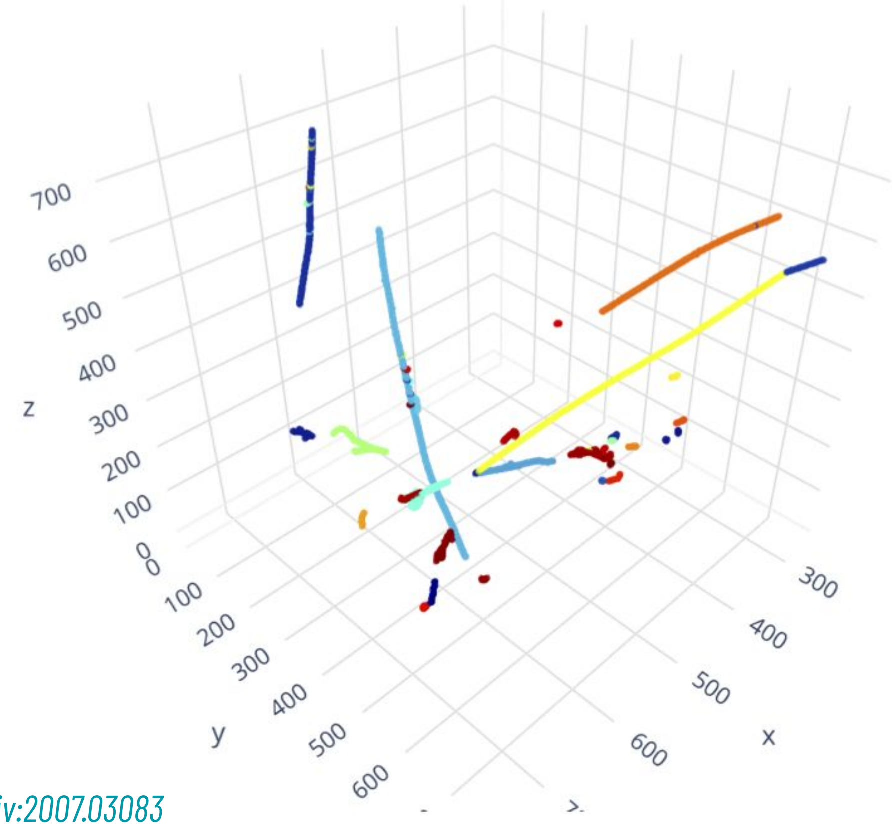


See arxiv:2007.03083

ML-based Neutrino Data Reconstruction Chain
Stage 2-a: Dense Pixel Clustering

Pixels clustered into trajectory fragments using SPICE



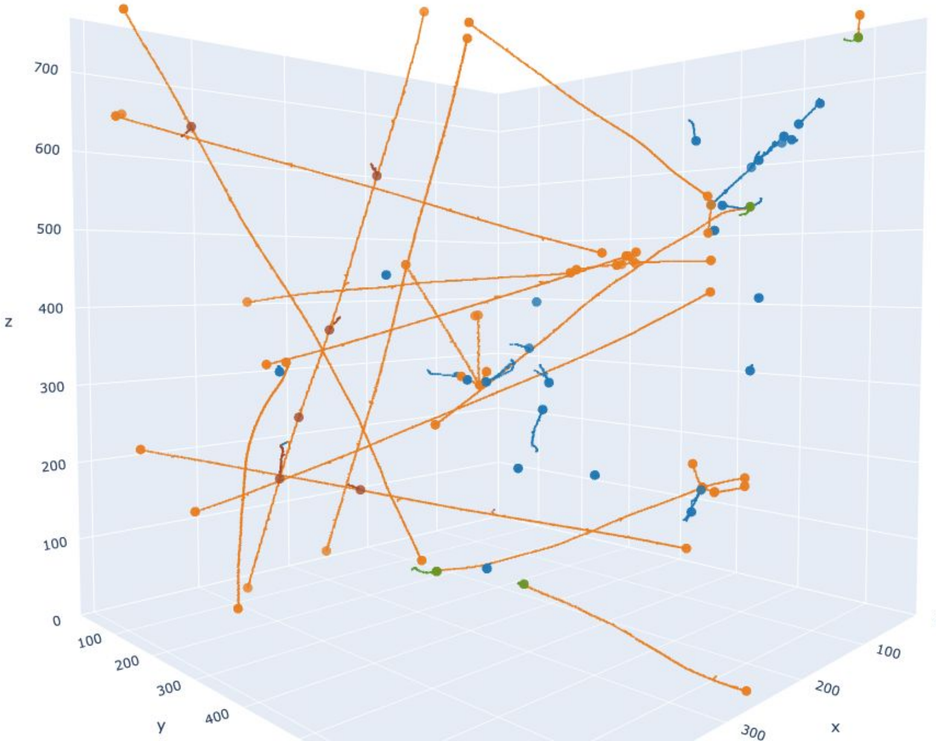


See arxiv:2007.03083

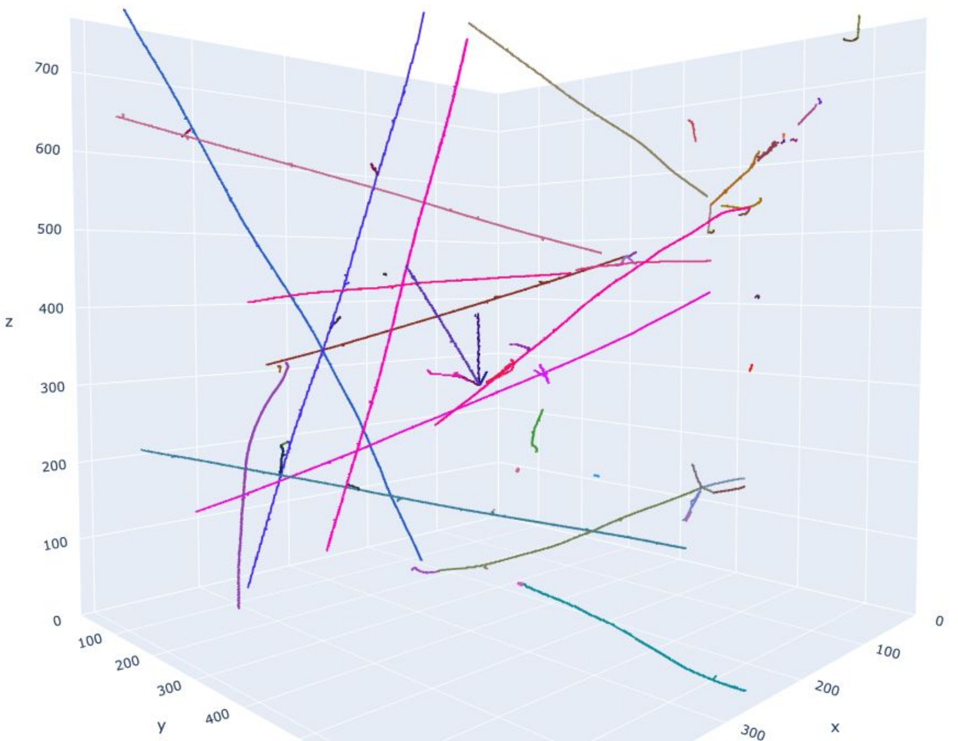
ML-based Neutrino Data Reconstruction Chain

Stage 2-a: input & output

Stage 2-a Input

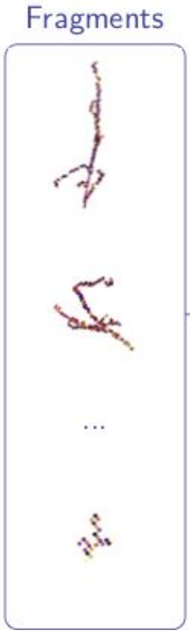


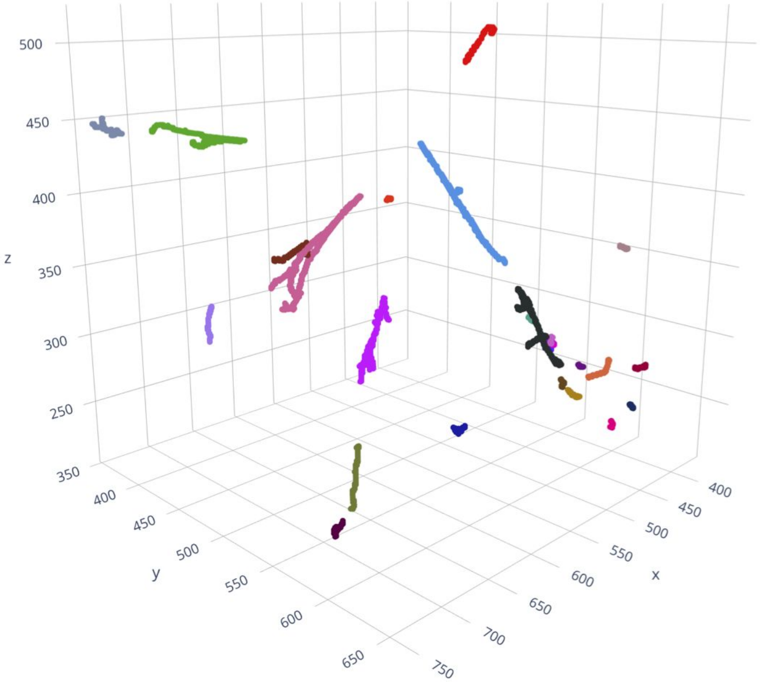
Stage 2-a Output



ML-based Neutrino Data Reconstruction Chain
Stage 2-b: Sparse Fragment Clustering

Identifying 1 shower … which consists of **many fragments**

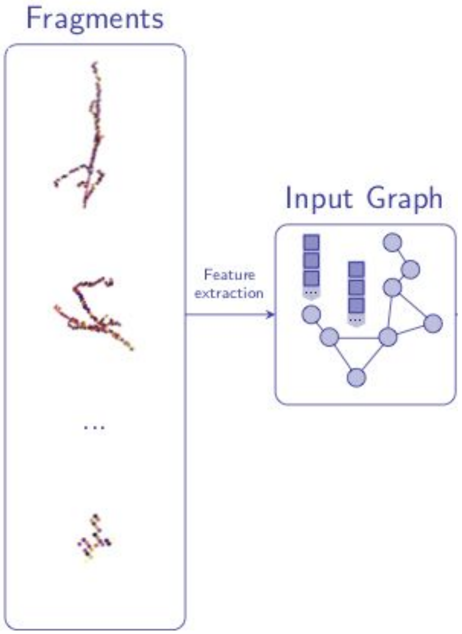


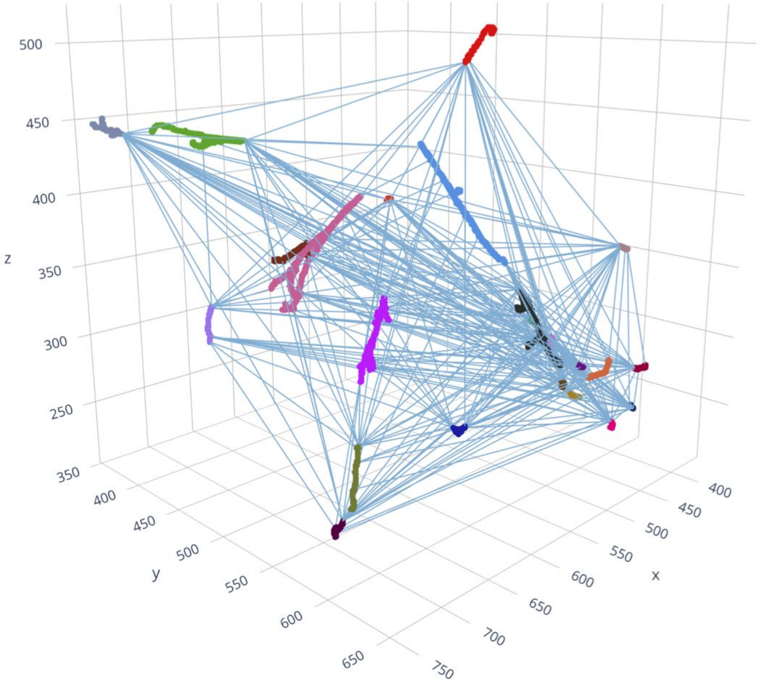


ML-based Neutrino Data Reconstruction Chain
Stage 2-b: Sparse Fragment Clustering

Identifying 1 shower ... which consists of **many fragments**

- Interpret each fragment as a graph node + edges connect nodes in the same cluster

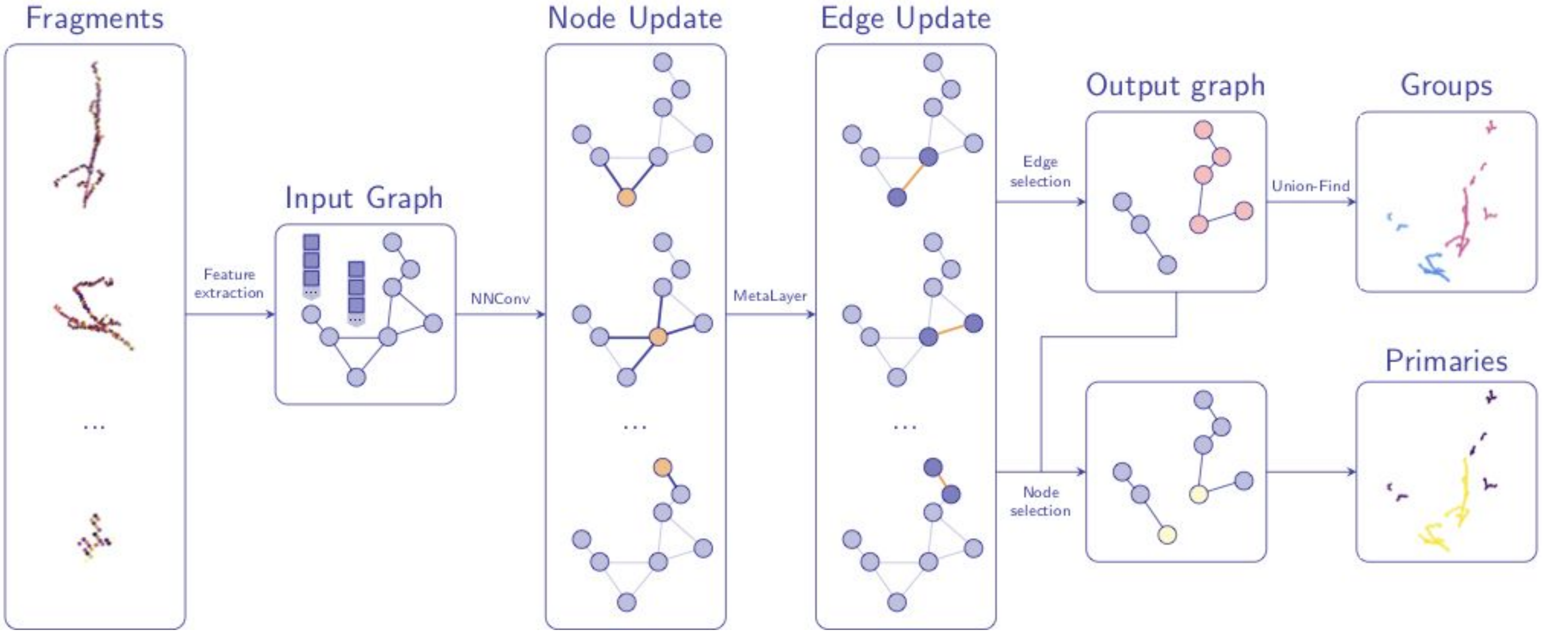




ML-based Neutrino Data Reconstruction Chain
Stage 2-b: Sparse Fragment Clustering

Identifying 1 shower … which consists of **many fragments**

- Interpret each fragment as a graph node + edges connect nodes in the same cluster
- Cast the problem to a classification of node (e.g. particle type) and edge (clustering)

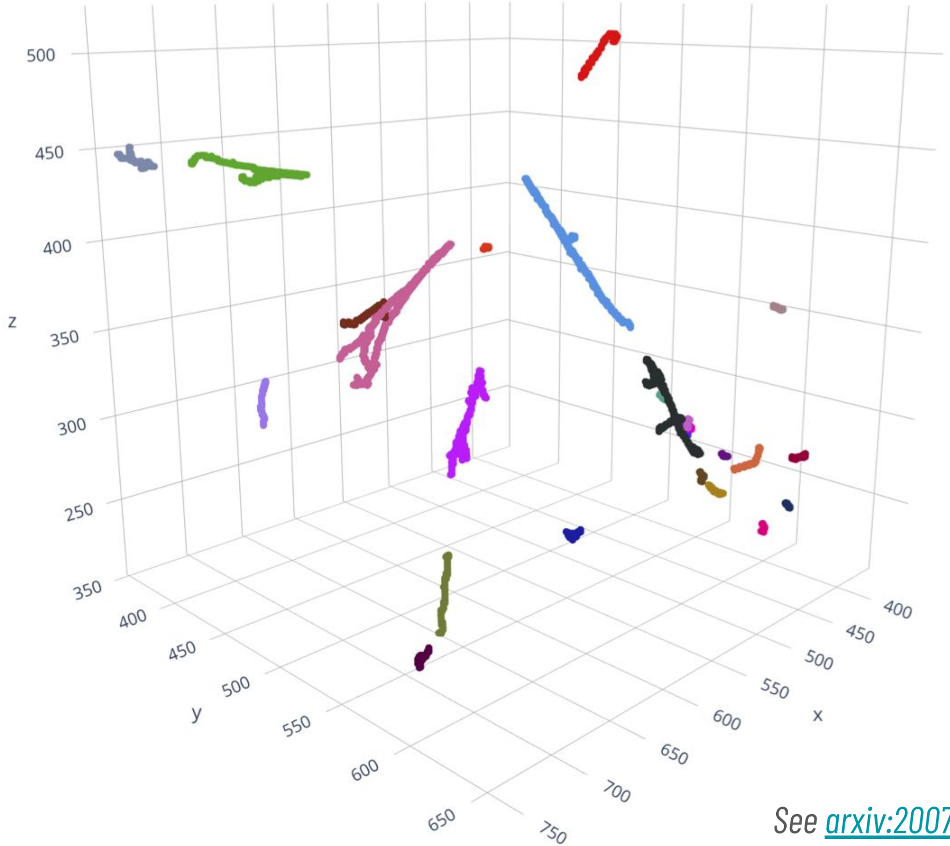


ML-based Neutrino Data Reconstruction Chain
Stage 2-b: Sparse Fragment Clustering

Graph-NN for Particle Aggregation (GrapPA)

Input:

- Fragmented EM showers



See arxiv:2007.01335

ML-based Neutrino Data Reconstruction Chain

Stage 2-b: Sparse Fragment Clustering

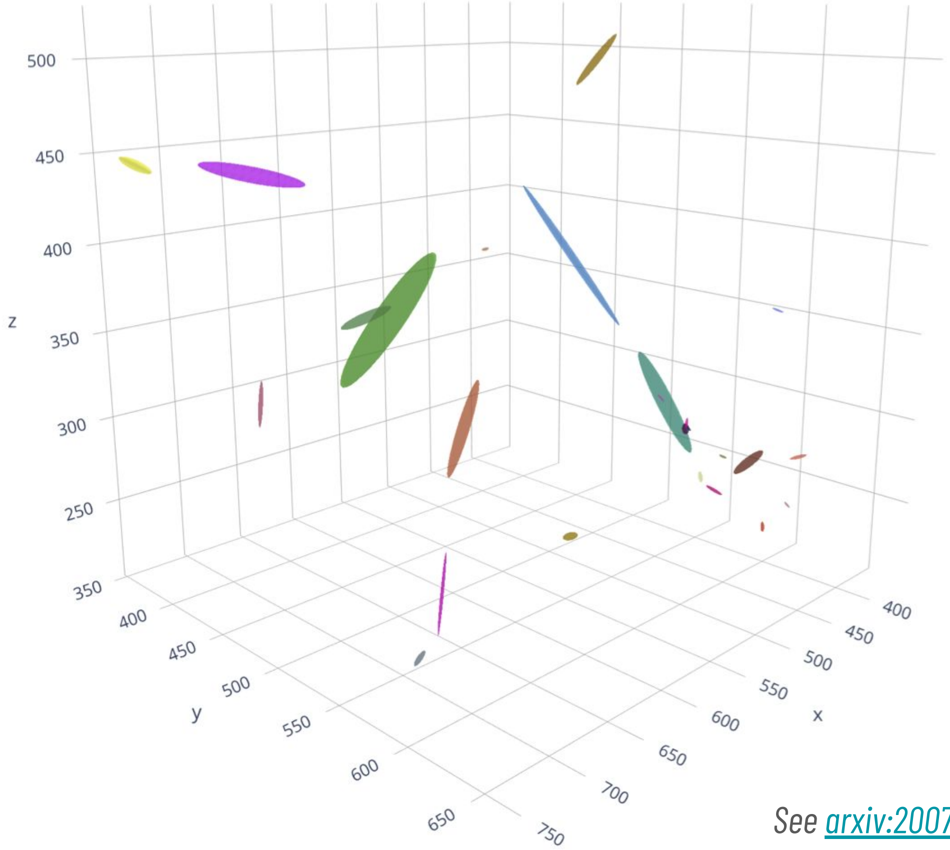
Graph-NN for Particle Aggregation (GrapPA)

Input:

- Fragmented EM showers

Node features:

- Centroid, Covariance matrix, PCA
- Start point, direction (PPN)



See arxiv:2007.01335

ML-based Neutrino Data Reconstruction Chain
Stage 2-b: Sparse Fragment Clustering

SLAC

Graph-NN for Particle Aggregation (GrapPA)

Input:

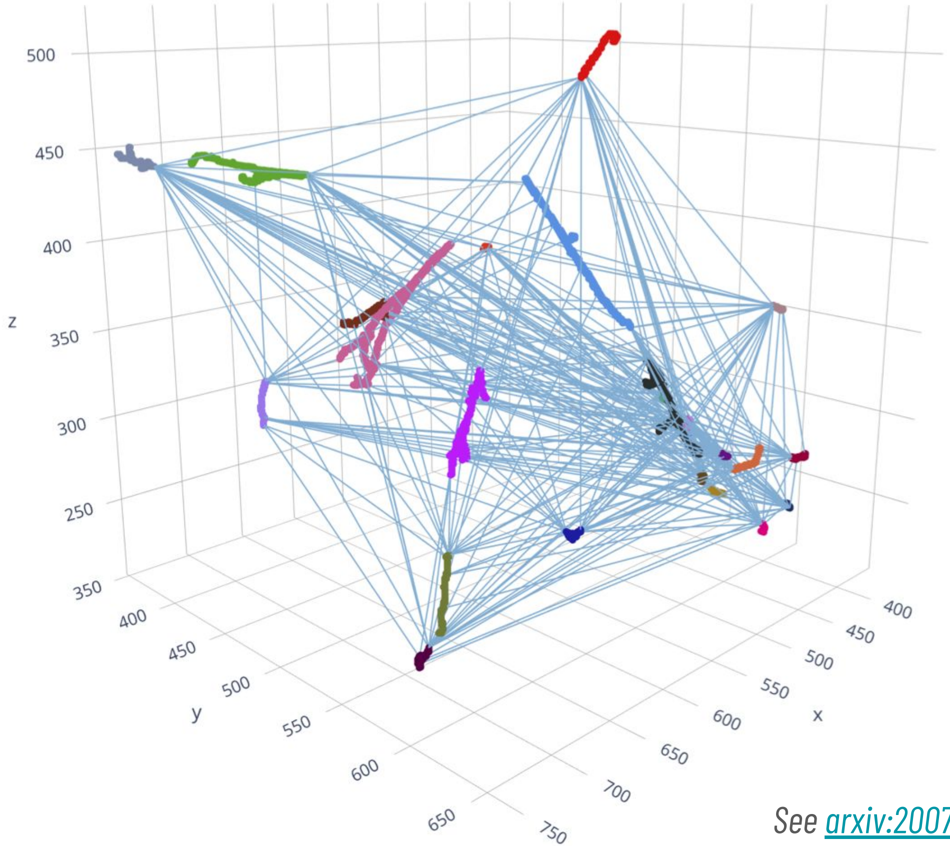
- Fragmented EM showers

Node features:

- Centroid, Covariance matrix, PCA
- Start point, direction (PPN)

Input graph:

- Connect every node with every other node (complete graph)



See arxiv:2007.01335

ML-based Neutrino Data Reconstruction Chain
Stage 2-b: Sparse Fragment Clustering

SLAC

Graph-NN for Particle Aggregation (GrapPA)

Input:

- Fragmented EM showers

Node features:

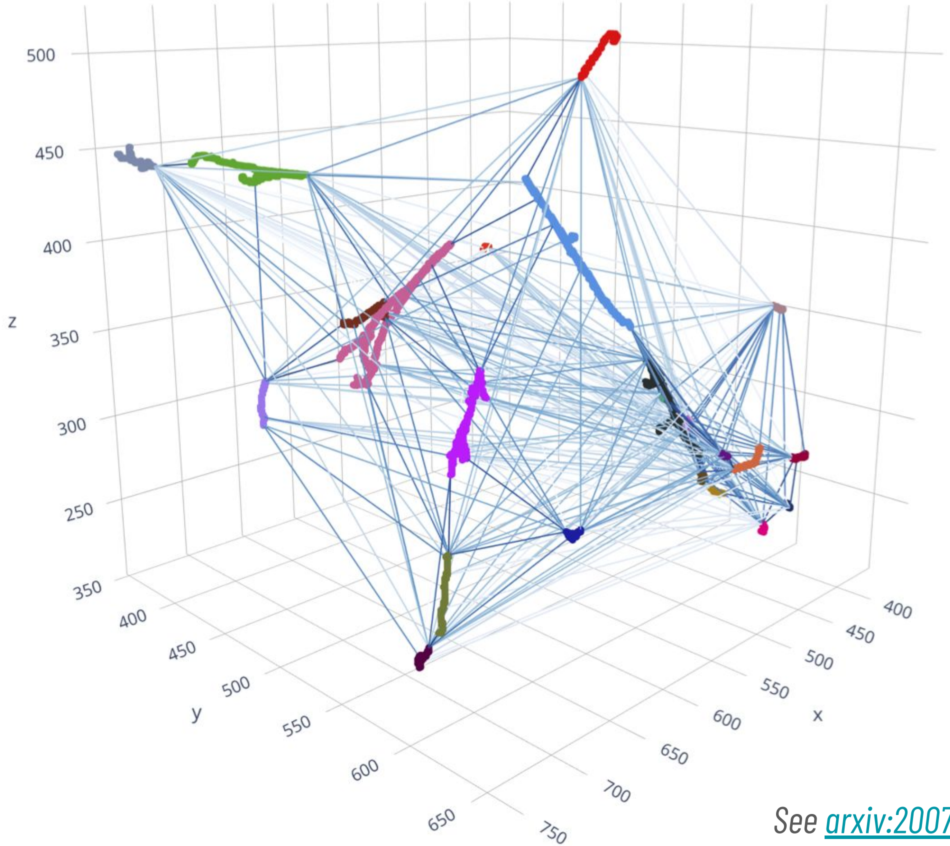
- Centroid, Covariance matrix, PCA
- Start point, direction (PPN)

Input graph:

- Connect every node with every other node (complete graph)

Edge features:

- Displacement vector
- Closest points of approach



See arxiv:2007.01335

ML-based Neutrino Data Reconstruction Chain
Stage 2-b: Sparse Fragment Clustering

SLAC

Graph-NN for Particle Aggregation (GrapPA)

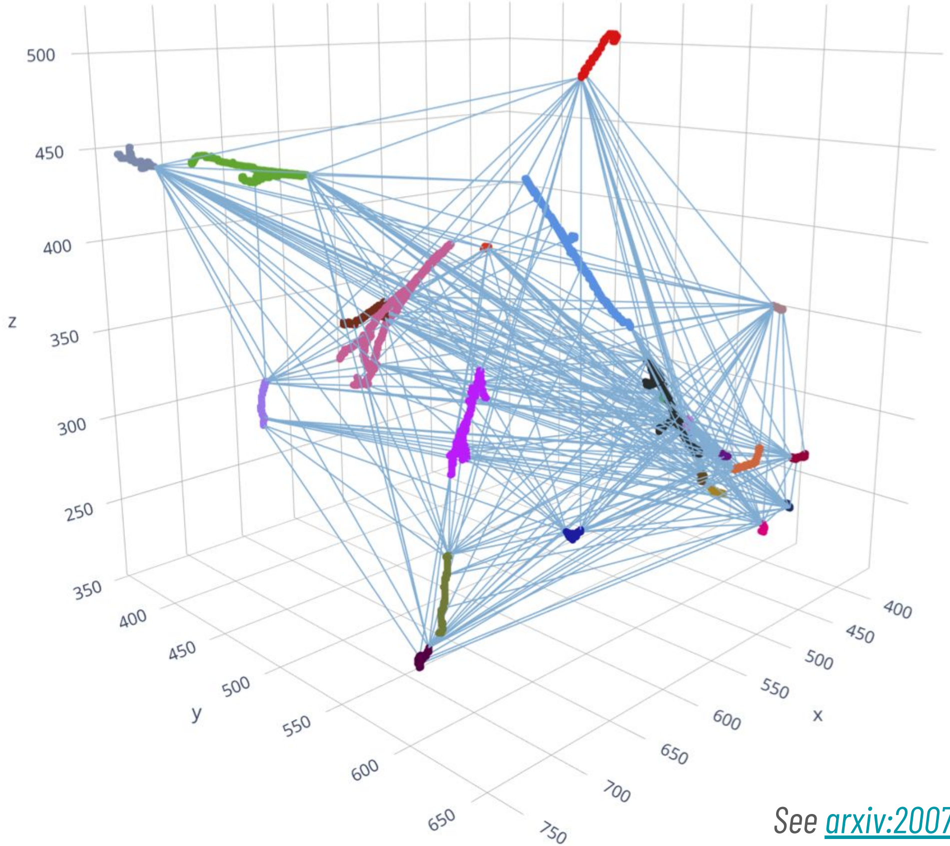
Message passing (MP):

- Meta layer (arxiv:1806.01261)
- Essentially two 3-layer MLPs (BatchNorm + LeakyReLU) for edge feature update and node feature update
- 3 times MP (=Edge+Node feature update)

Target:

- Prediction of adjacency matrix representing valid edges (=true partition)
- Apply cross-entropy loss

For more studies, see our paper

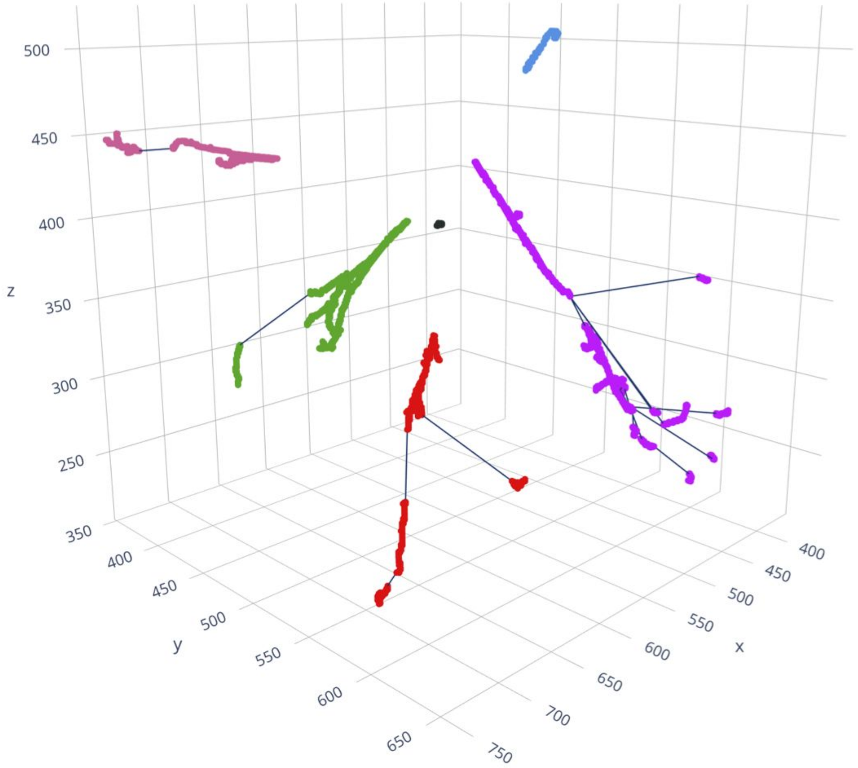


See arxiv:2007.01335

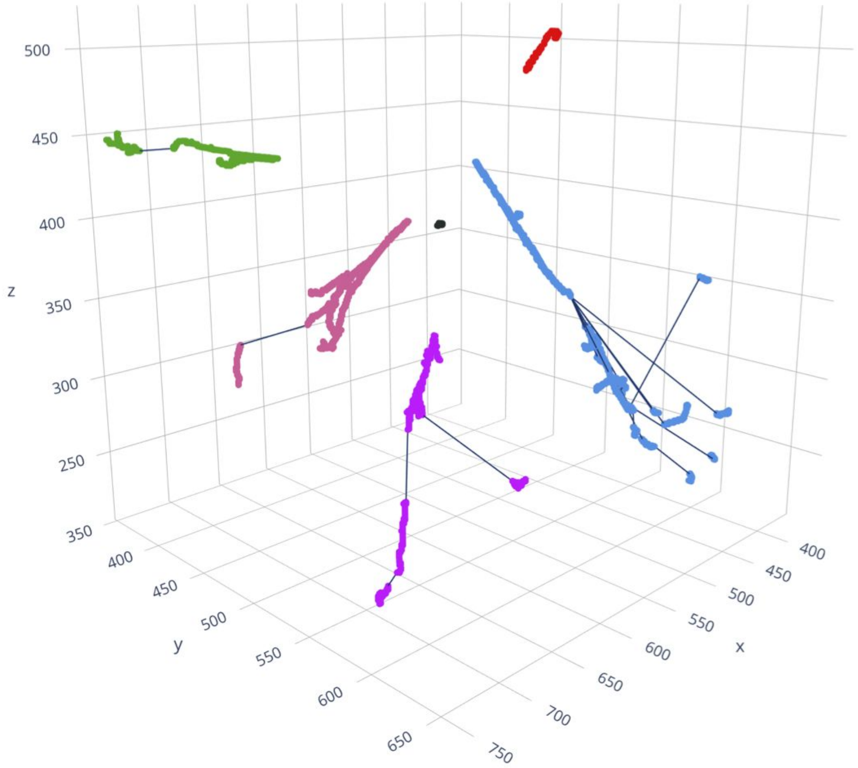
ML-based Neutrino Data Reconstruction Chain

Stage 2-b: Sparse Fragment Clustering

Target Label



Edge Prediction

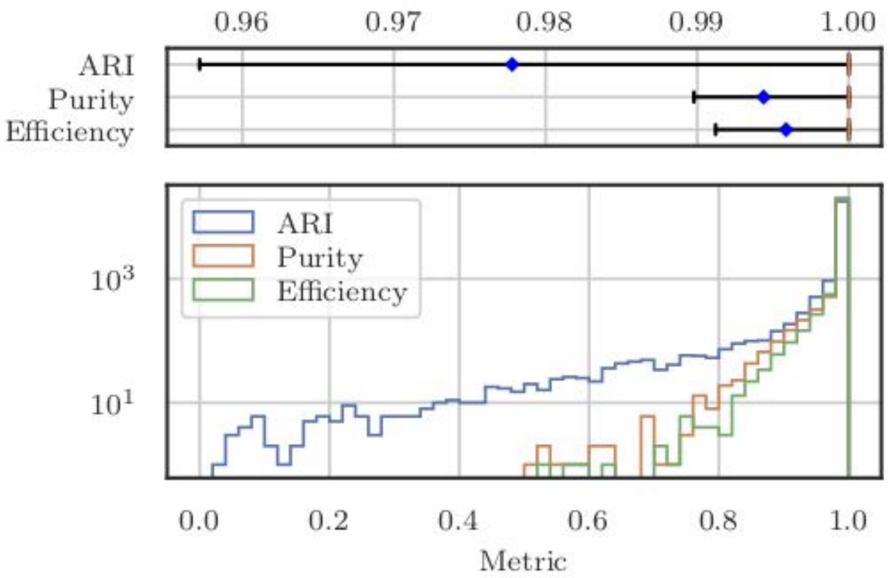


ML-based Neutrino Data Reconstruction Chain

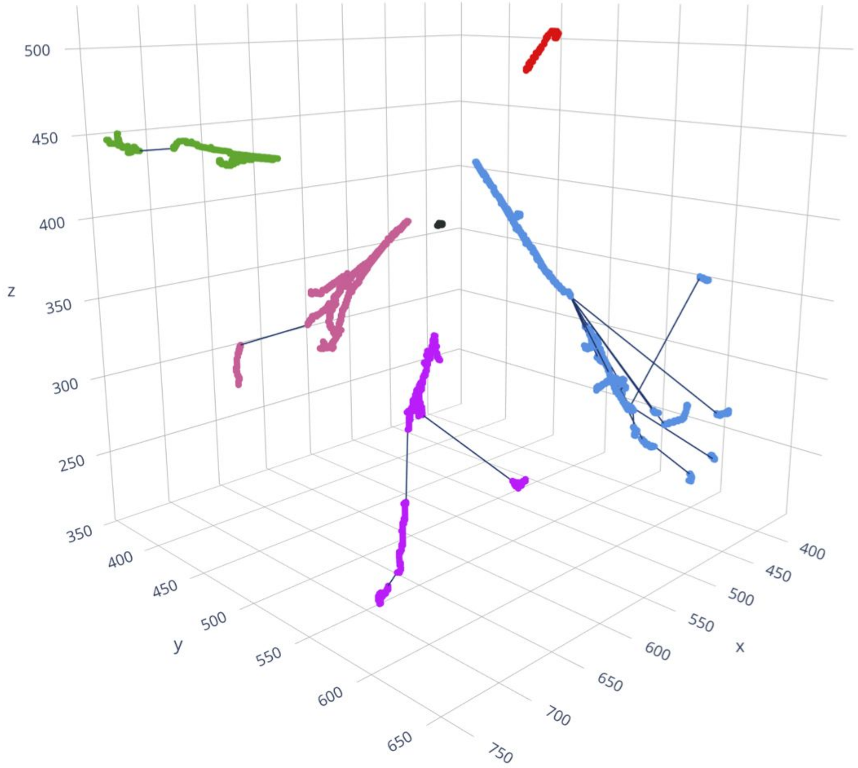
Stage 2-b: Sparse Fragment Clustering

Clustering using GrapPA

- Mean purity and efficiency > 99%
- Sufficient for moving to the next stage (particle analysis)



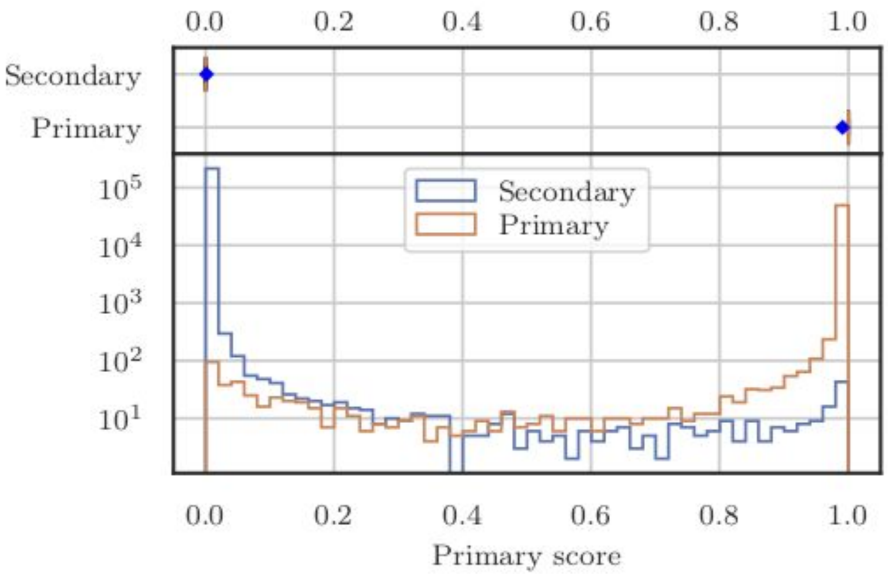
Edge Prediction



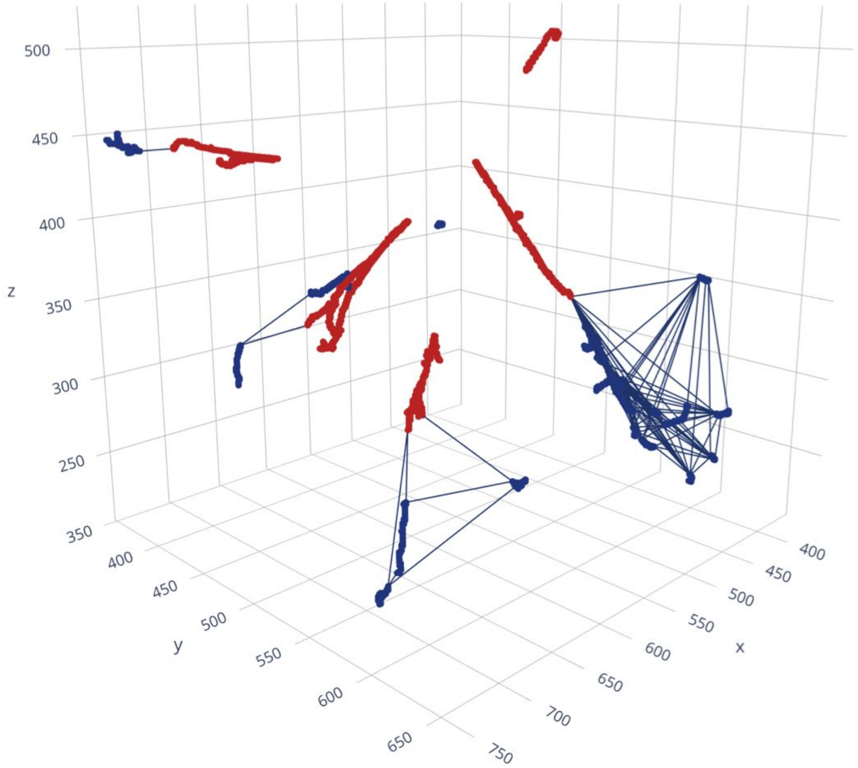
ML-based Neutrino Data Reconstruction Chain
Stage 2-b: Sparse Fragment Clustering

Start ID using GrapPA

- Important to identify the “primary fragment” (=shower start)
- >99% classification accuracy

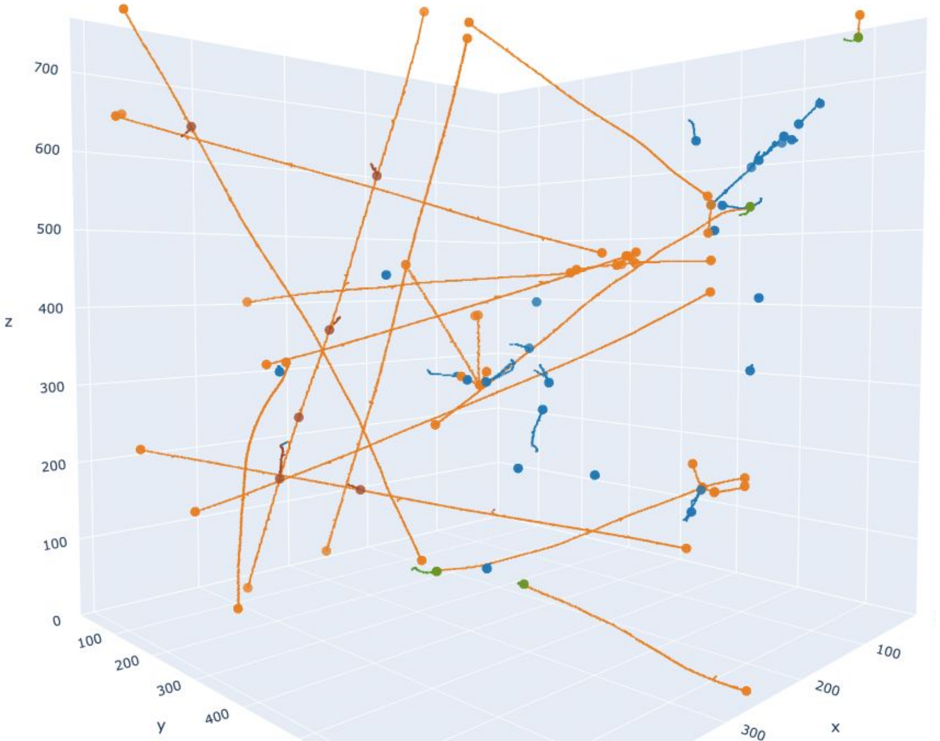


Node prediction

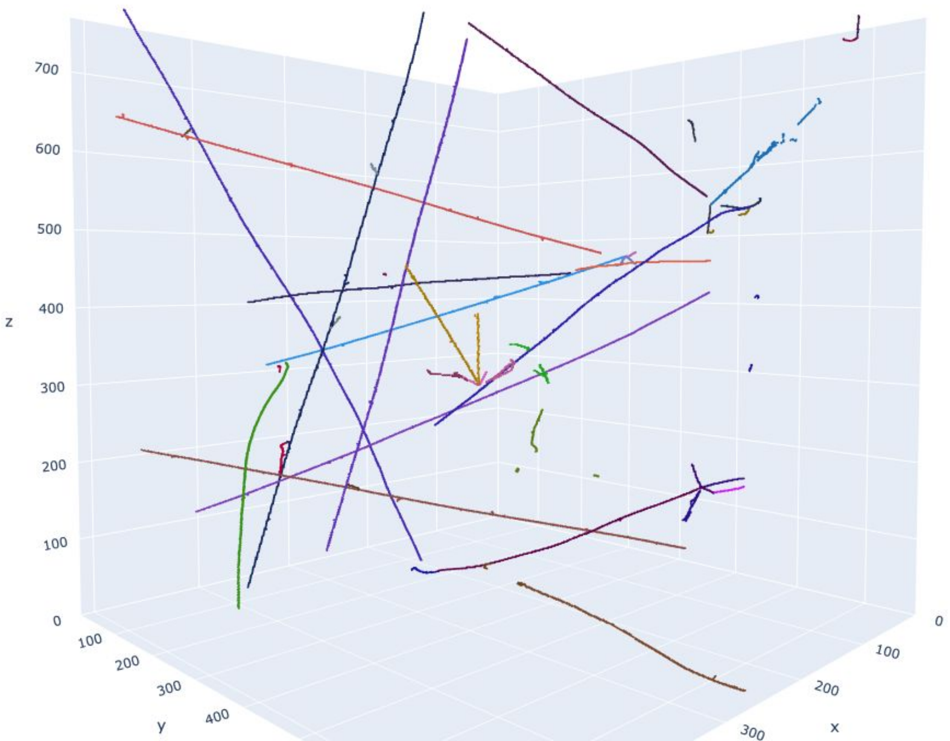


ML-based Neutrino Data Reconstruction Chain
Stage 2: input & output

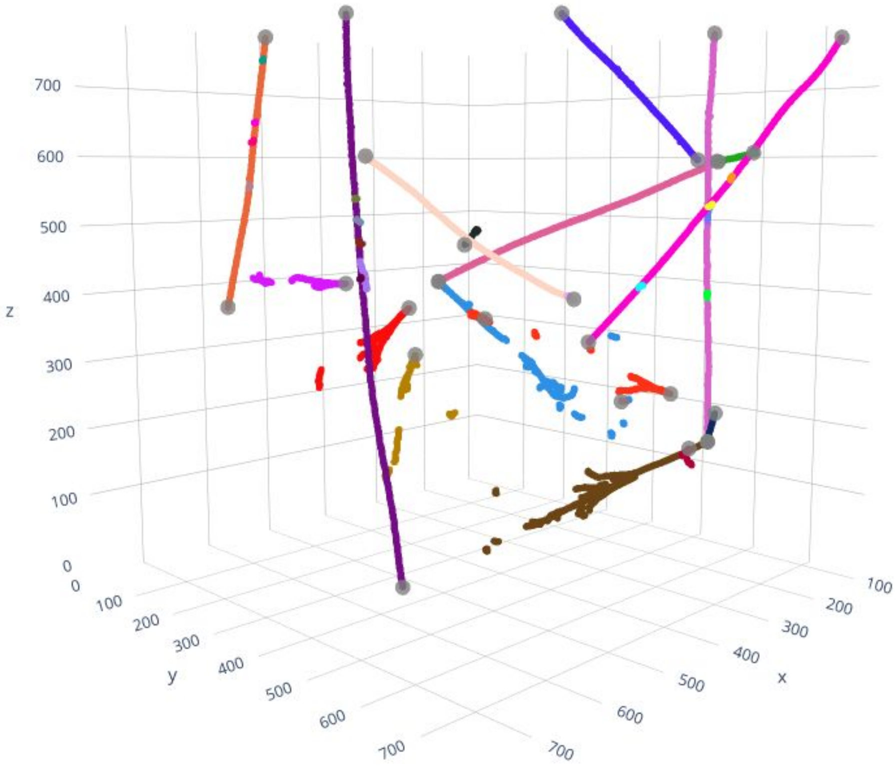
Stage 2 Input



Stage 2 Output



ML-based Neutrino Data Reconstruction Chain
Stage 3: Interaction Clustering



Identifying Each Interaction?

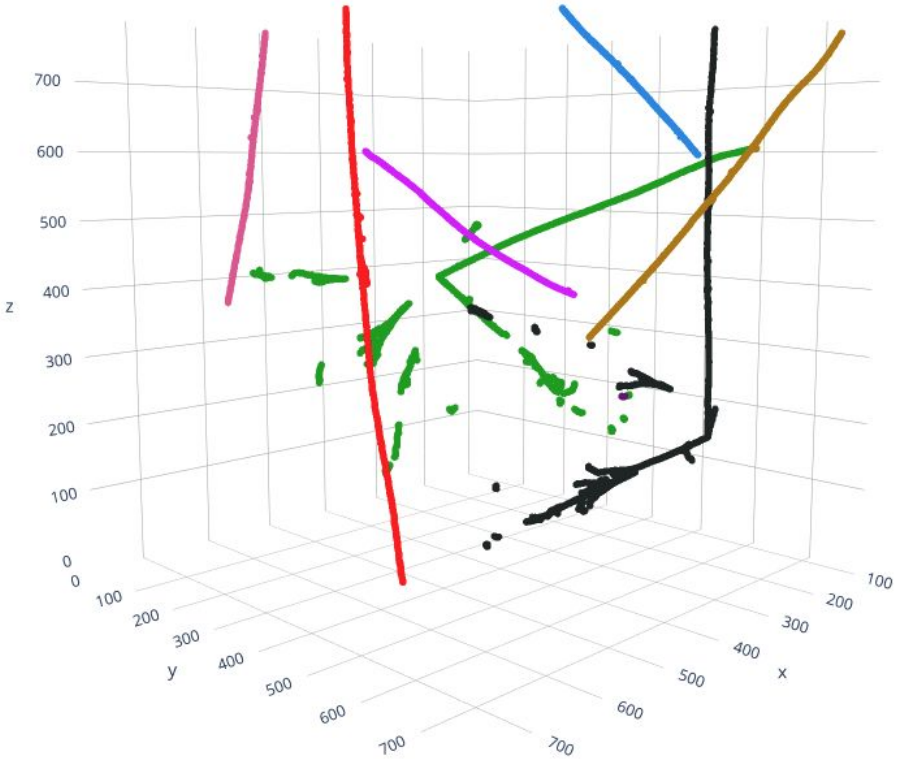
This task can be casted to the same task already solved using GrapPA!

- Interaction = a group of particles that shared the same origin (i.e. neutrino interaction)
- Edge classification to identify an interaction
- Node classification for particle type ID

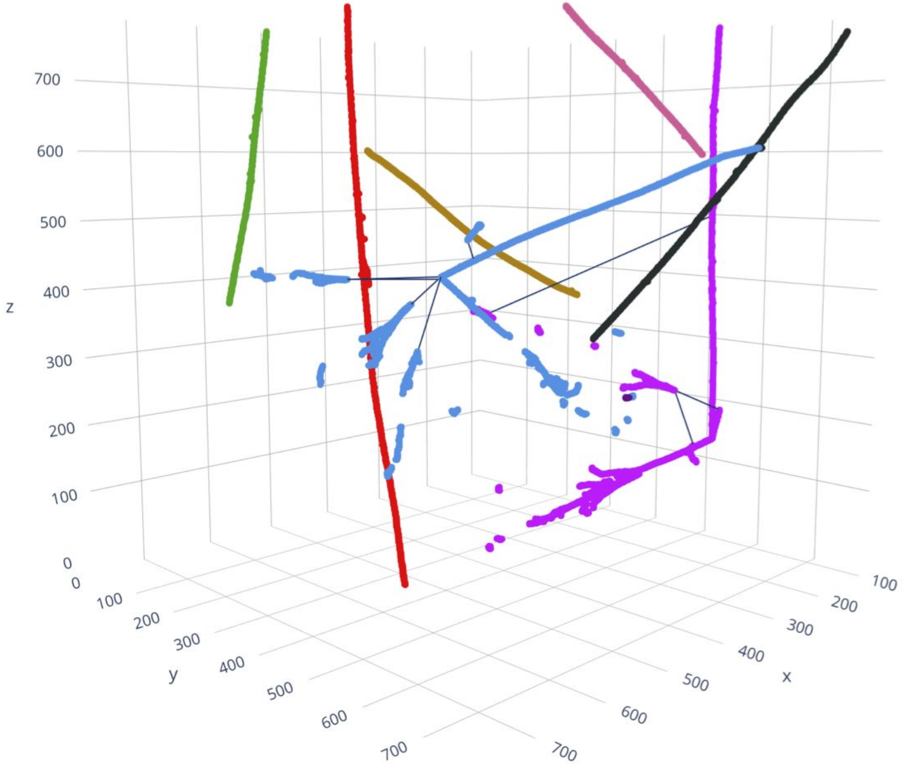
ML-based Neutrino Data Reconstruction Chain

Stage 3: Interaction Clustering

Target Group

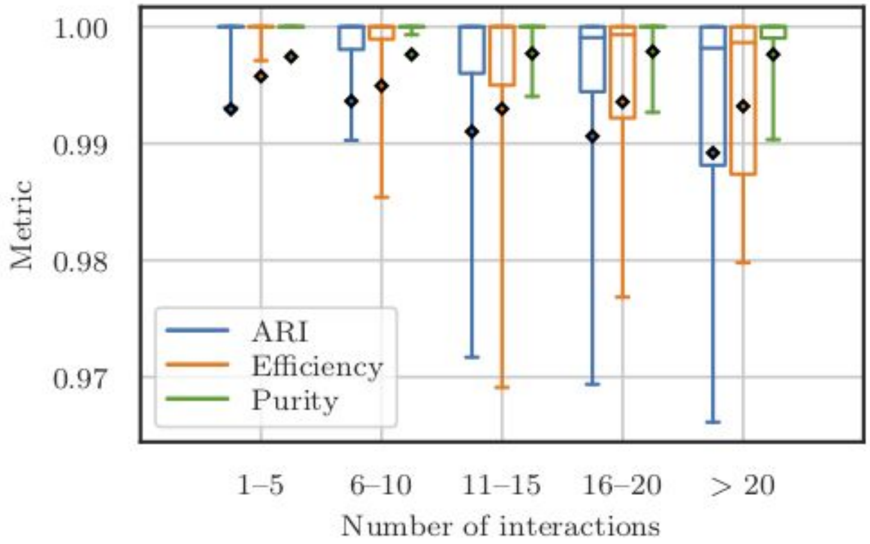


Predicted Interaction

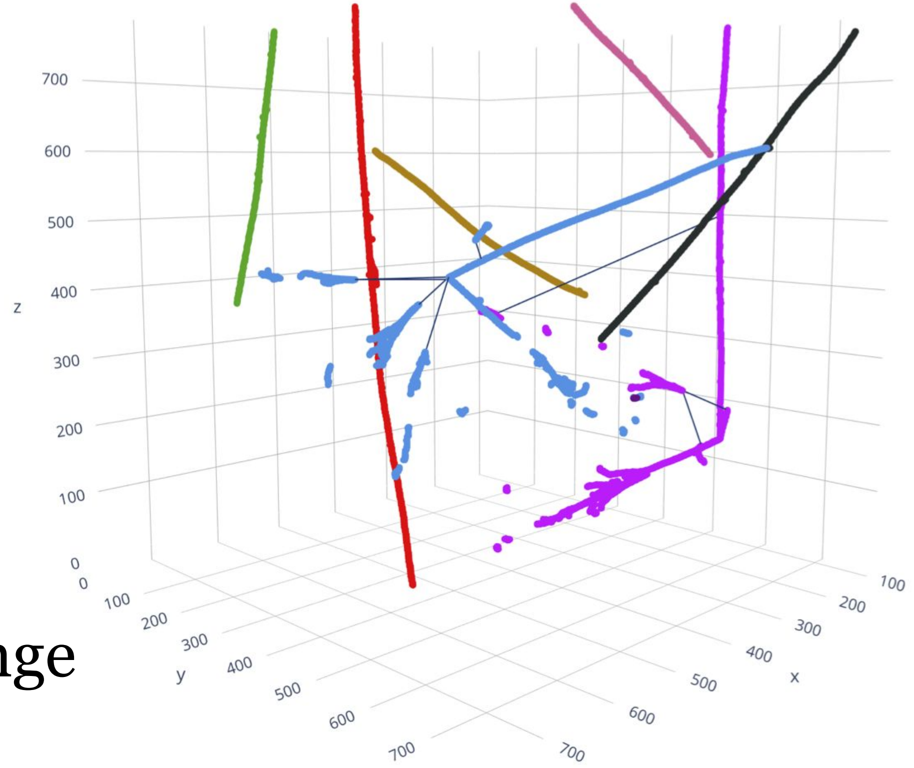


ML-based Neutrino Data Reconstruction Chain

Stage 3: Interaction Clustering



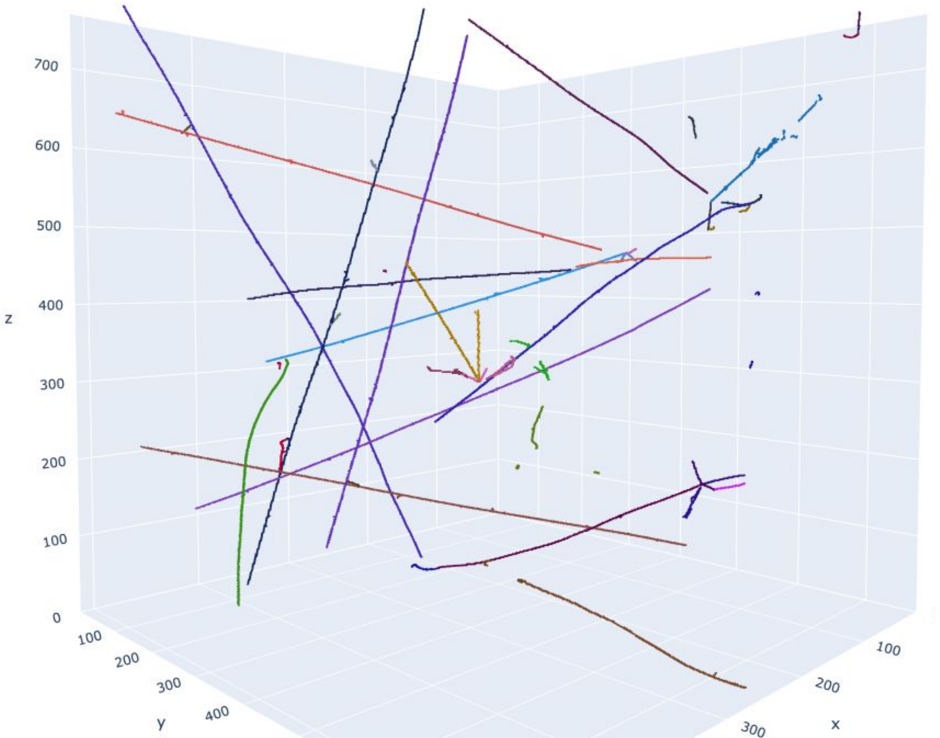
Predicted Interaction



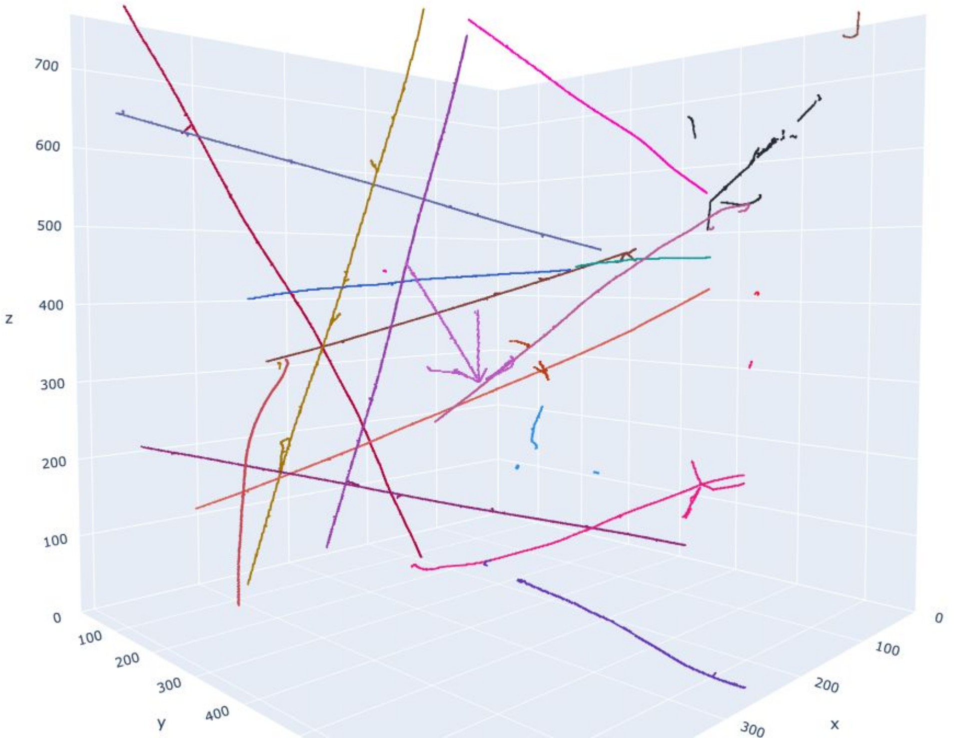
Promising result to address DUNE-ND reconstruction challenge (~20 neutrino pile-up)

ML-based Neutrino Data Reconstruction Chain
Stage 3: input & output

Stage 3 Input

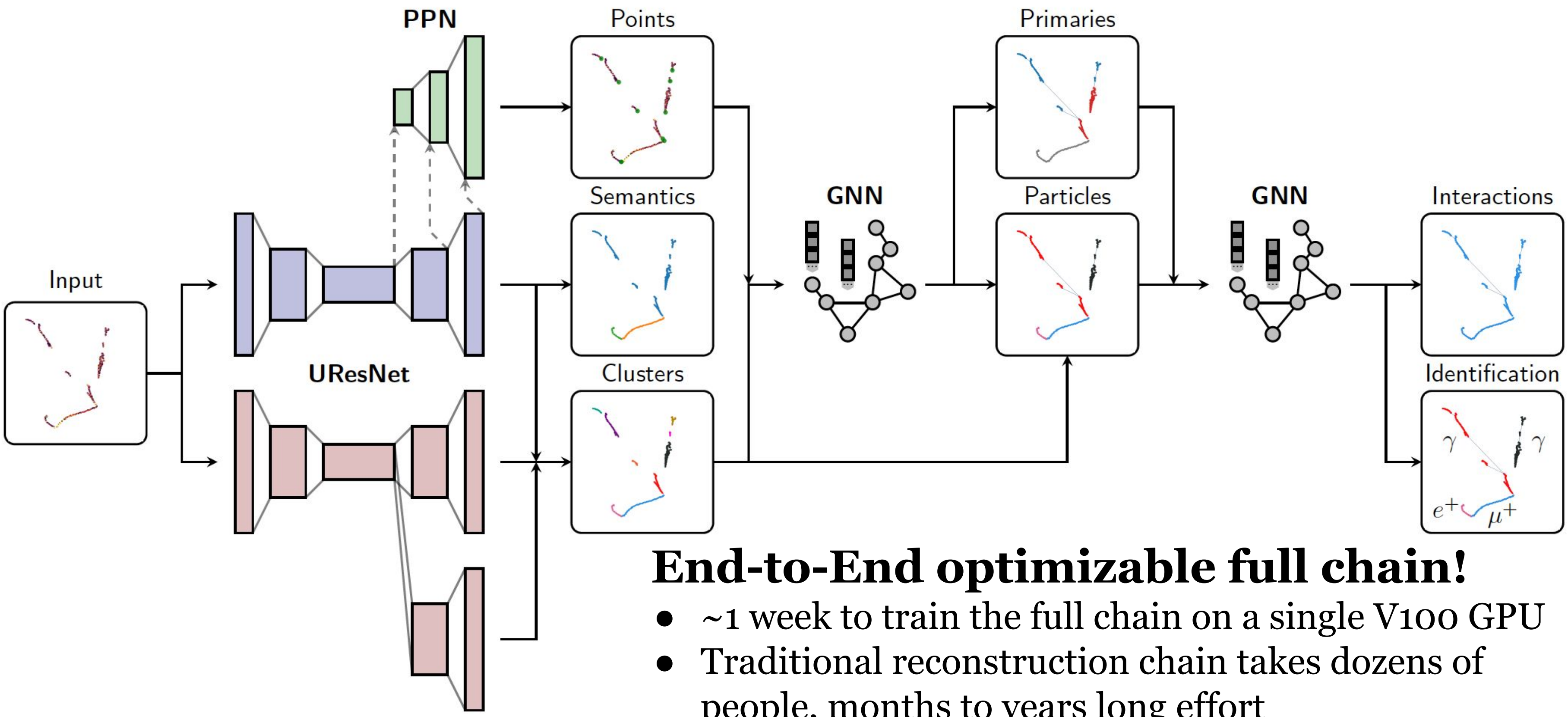


Stage 3 Output



… wrapping up …

ML-based Neutrino Data Reconstruction Chain
Wrapping up...



End-to-End optimizable full chain!

- ~1 week to train the full chain on a single V100 GPU
- Traditional reconstruction chain takes dozens of people, months to years long effort

Summary

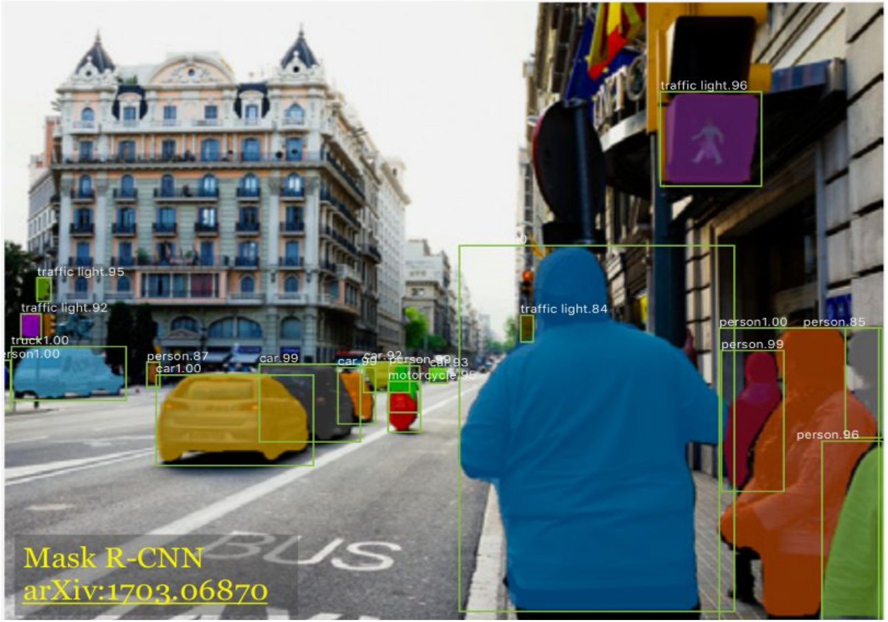
- **Neutrino detector trend: hi-res. particle imaging**
- **Analysis trend: computer vision algorithms**
  - Benefit the hi-resolution image = lots of heuristics (in non-ML)
  - ML-based approach has shown strong promise
- **ML-based data reconstruction approach**
  - especially for “busy” detectors … my research :)
  - Working on implementing inductive-bias/causality (“physics”)
- **Other active areas**: data/sim domain discrepancy adaptation
  - minimize the discrepancy, identify the source, quantify uncertainty

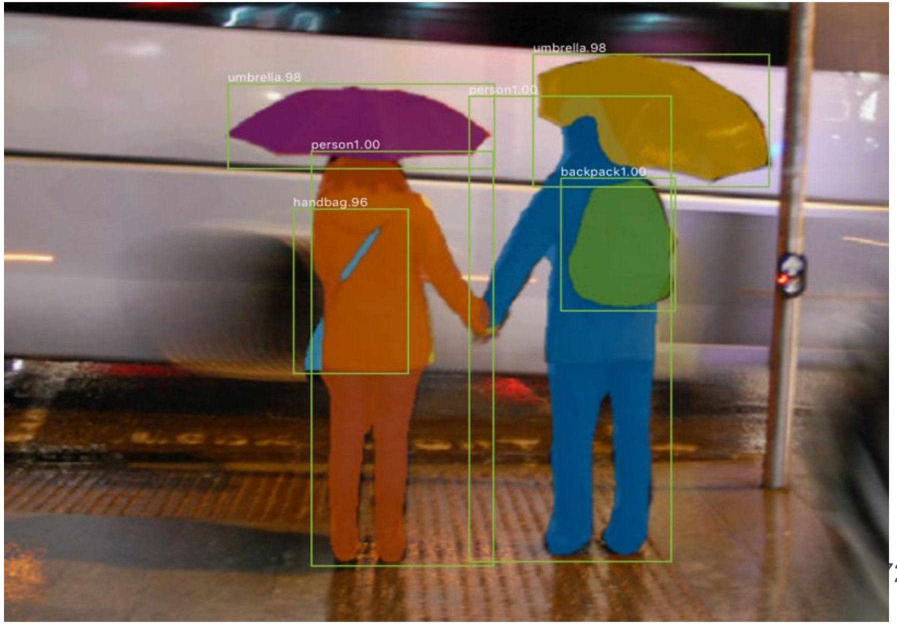
Questions?

SPICE

Instance+Semantic Segmentation

- **Mask R-CNN** … a popular solution, many applications in science/industries
  - Object (=instance) detection + instance pixel masking in a bounding box

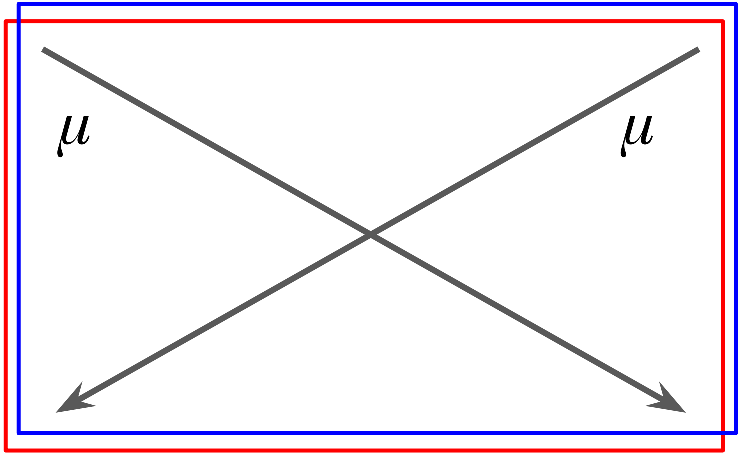


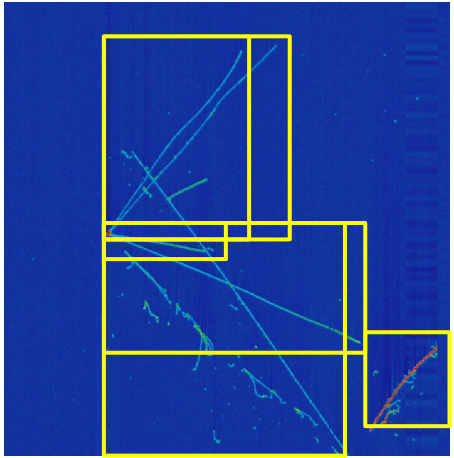


Stage 2: Particle & Interaction Clustering

Instance+Semantic Segmentation

- **Mask R-CNN** … a popular solution, many applications in science/industries
  - Object (=instance) detection + instance pixel masking in a bounding box
  - **Issue**: instance distinction is affected by BB position/size
  - Another family: Single-Shot-Detection (SSD) based (not covered here)





Occlusion issue

The overlap rate of particles is very high especially for our signal (neutrinos) with an event vertex.

ML-based Neutrino Data Reconstruction Chain
Stage 2: Particle & Interaction Clustering

Instance+Semantic Segmentation

- **Mask R-CNN** … a popular solution, many applications in science/industries
  - Object (=instance) detection + instance pixel masking in a bounding box
  - **Issue**: instance distinction is affected by BB position/size
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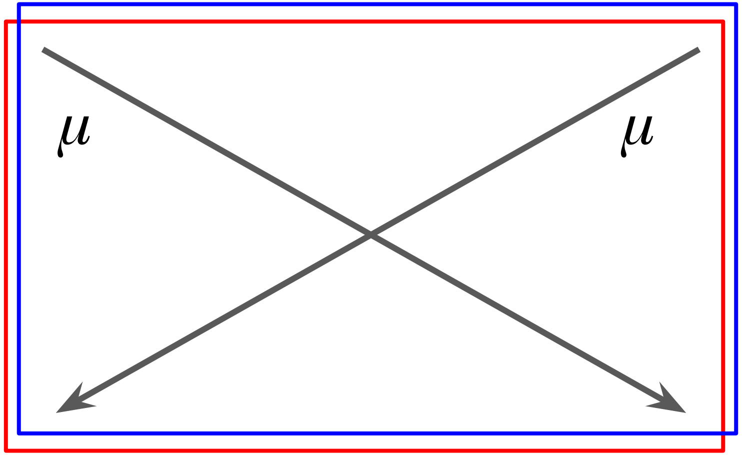
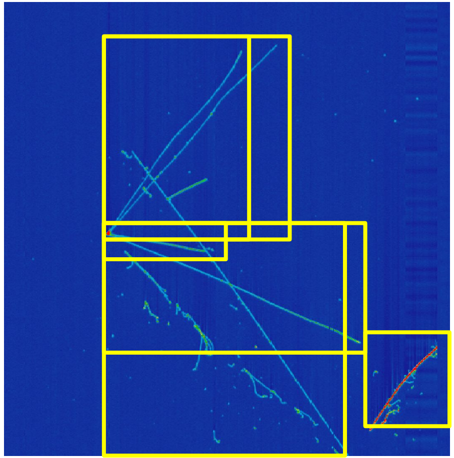
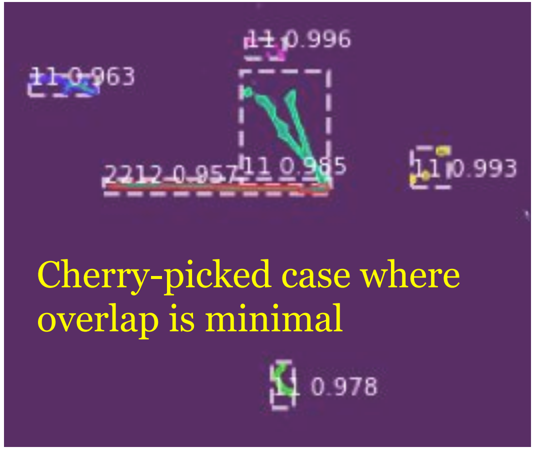






Instance+Semantic Segmentation

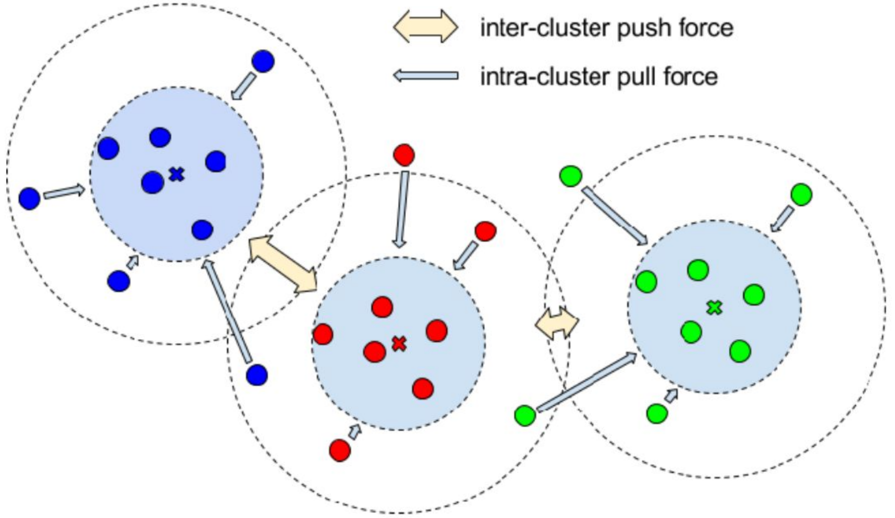
- Three component loss: pull together points that belong to the same cluster, keep distance between clusters, and regularization

$$L = \alpha L_{var} + \beta L_{dist} + \gamma L_{reg},$$

$$L_{var} = \frac{1}{C}\sum_{c=1}^{C}\frac{1}{N_c}\sum_{i=1}^{N_c}\left[\max\left(0, \|\mu_c - x_i\| - \delta_v\right)\right]^2$$

$$L_{dist} = \frac{1}{C(C-1)}\sum_{\substack{c_A,c_B=1\\ c_A\neq c_B}}^{C}\left[\max\left(0, 2\delta_d - \|\mu_{c_A} - \mu_{c_B}\|\right)\right]^2$$

$$L_{reg} = \frac{1}{C}\sum_{c=1}^{C}\|\mu_c\|$$

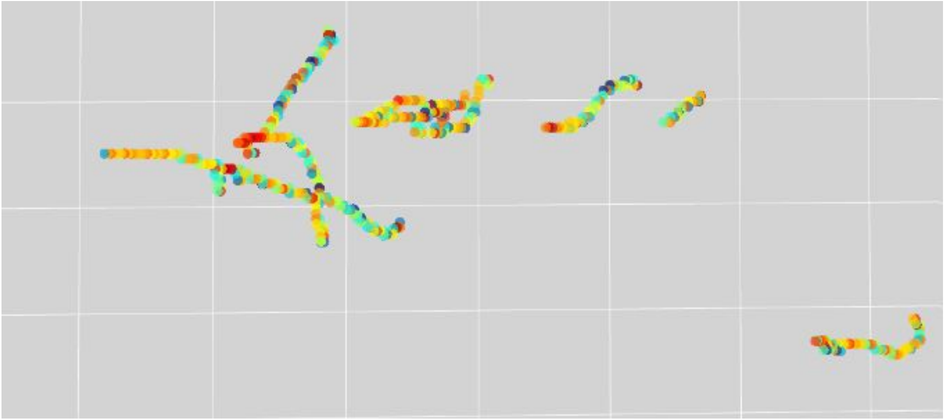


Equation credit: Dae Hyun K. @ Stanford

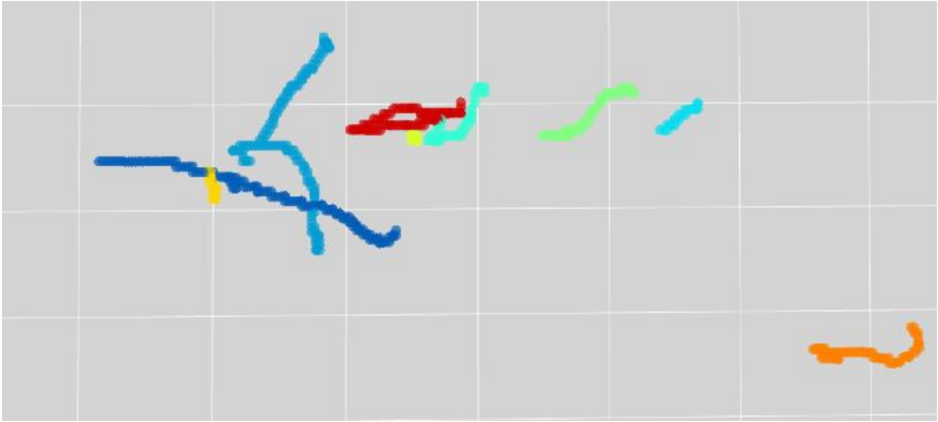
Image credit: arXiv 1708.02551

Instance+Semantic Segmentation

- Three component loss: pull together points that belong to the same cluster, keep distance between clusters, and regularization



Input: 3D pixel energy depositions



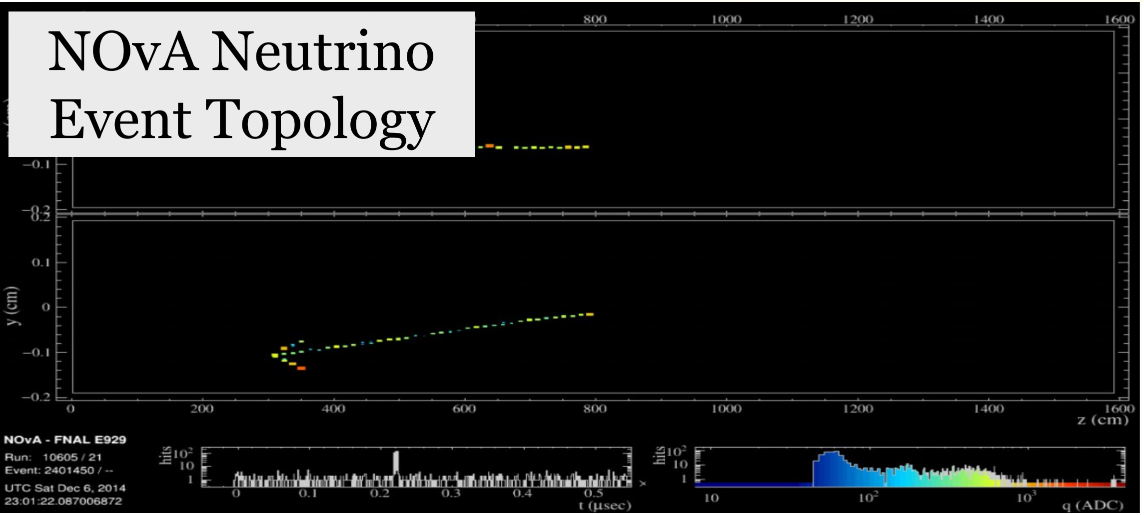
Output: 3D pixel clusters (DBScan in hyperspace)

Image Classification?

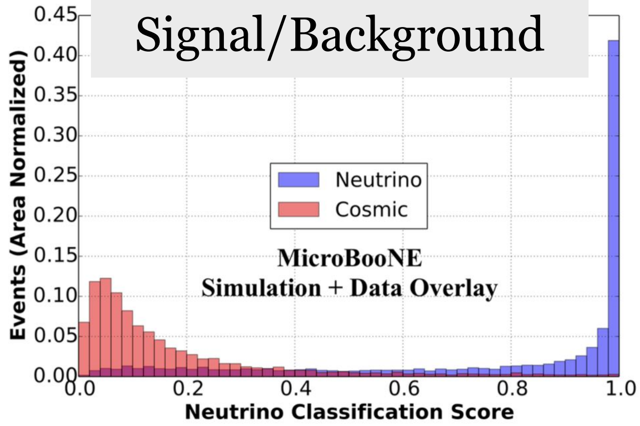
Machine Learning & Computer Vision in Neutrino Physics

Image Classifications: a lot of applications

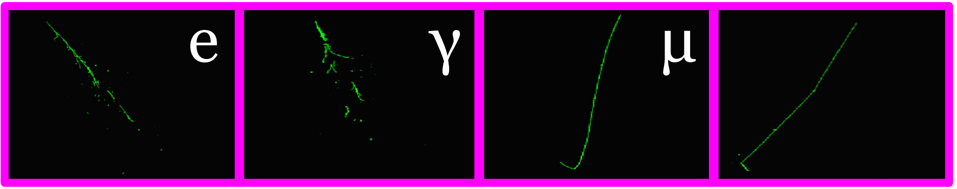
NOvA Neutrino Event Topology



MicroBooNE Signal/Background



LArLIAT Particle Type Identification



NEXT Signal vs. Background

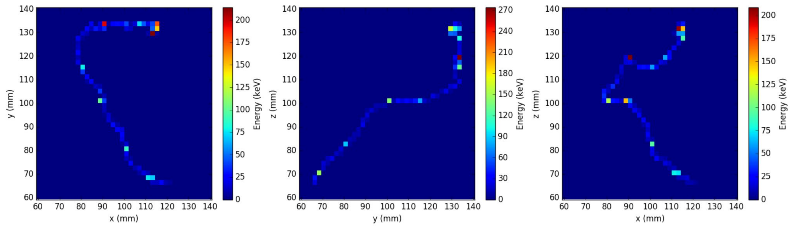


Image Classifications: a lot of applications

SLAC

Especially great for: **"a rare event in a quiet detector"**

- **Quiet** = can assume "almost always neutrino"
  - e.g.) no cosmic-ray background
- **Rare** = "only 1 neutrino"

Image Classifications: a lot of application

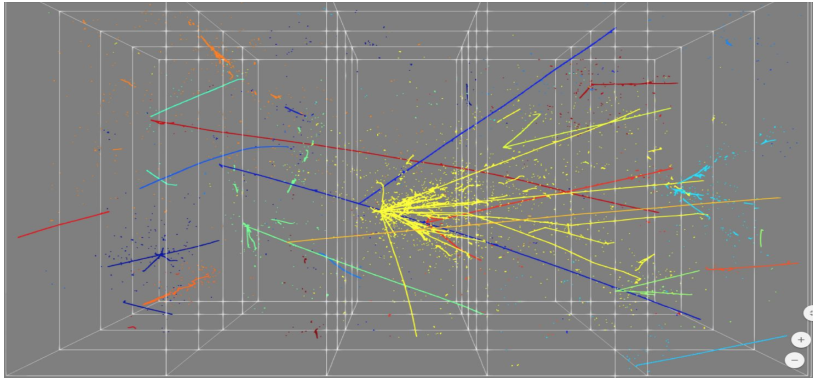
Especially great for: **"a rare event in a quiet detector"**

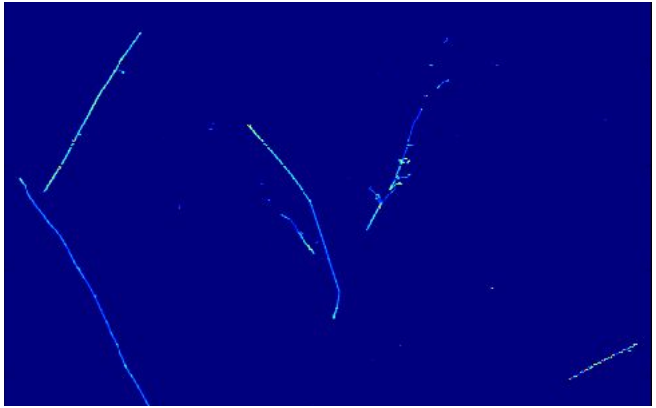
- **Quiet** = can assume "almost always neutrino"
  - e.g.) no cosmic-ray background
- **Rare** = "only 1 neutrino"
  - the same "image classification architecture" can be applied for…
    - neutrino flavor (topology) classification
    - energy regression (image to one FP32 value)
    - vertex regression (image to three FP32 value)
    - etc. …

Image Classifications: a lot of applications

SLAC

Especially great for: **“a rare event in a quiet detector”**



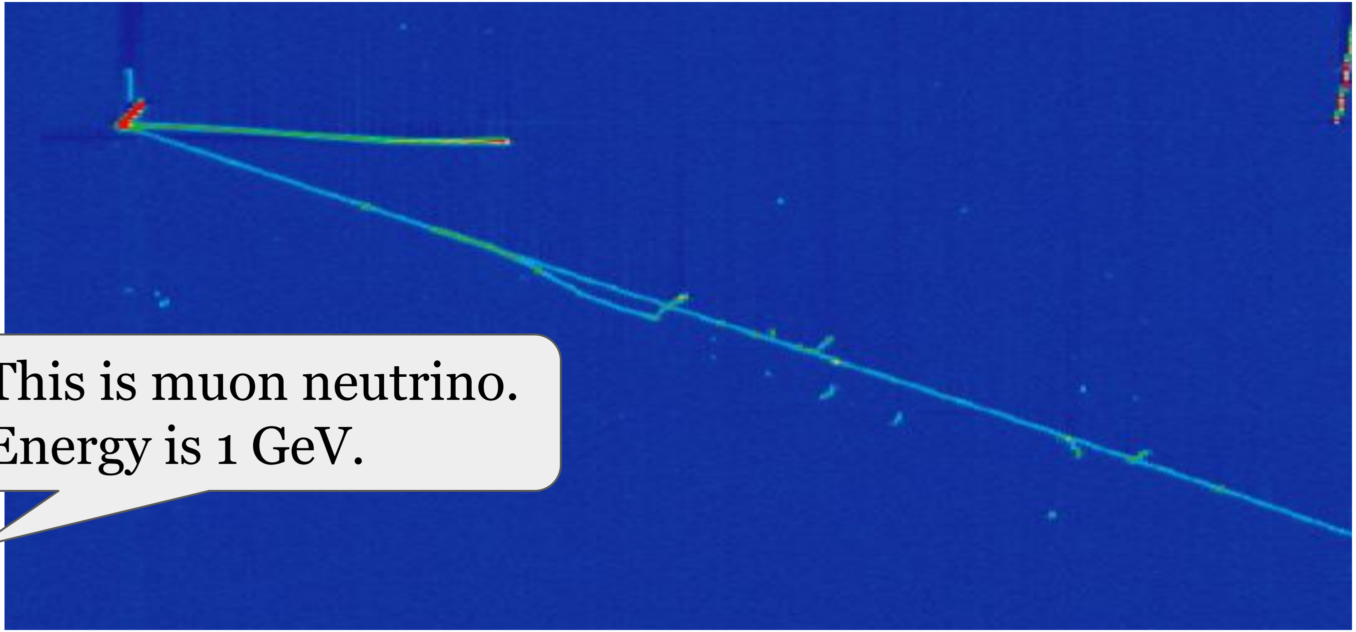


… **but most of LArTPC detectors are not** …

- MicroBooNE, ICARUS, SBND, ProtoDUNE … physics in next 5 years
  - Busy: typically dozens of cosmic rays in each event
- DUNE-ND
  - Not rare (busy): a dozen of neutrino interaction pile-up in each event

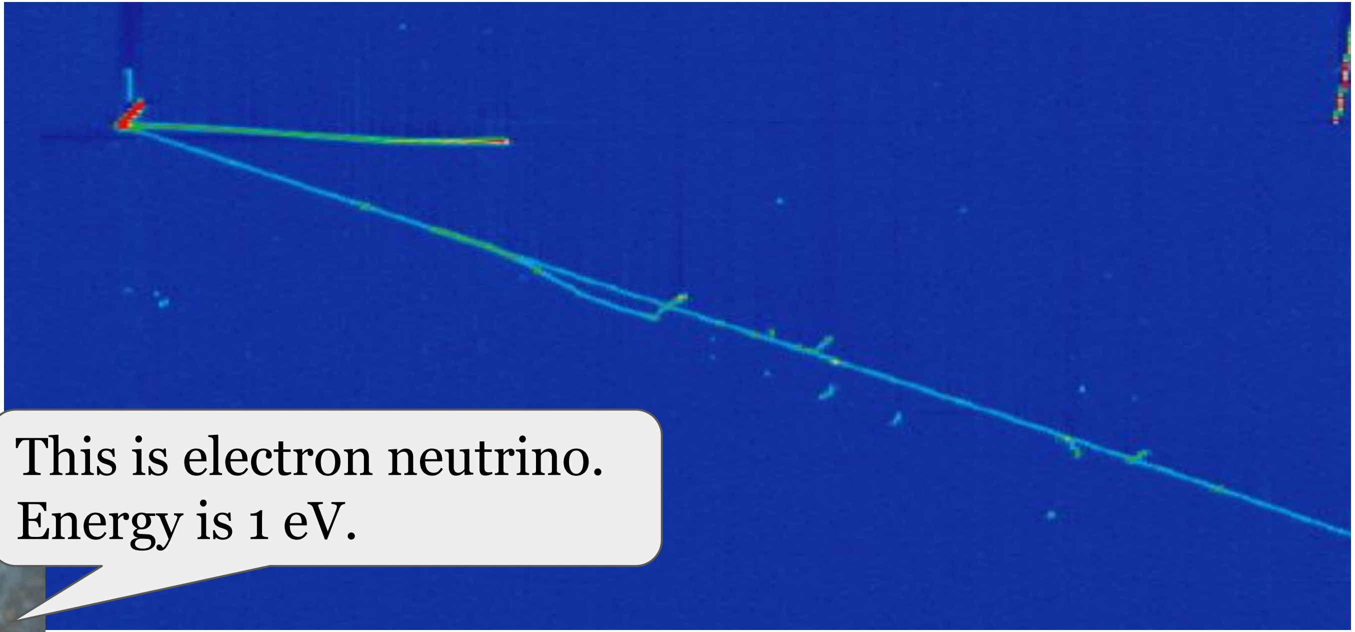
Why Data Reconstruction

Image classification/regression: straight to “**flavour & energy**”



Why Data Reconstruction

... but also challenging: a huge single-step of information reduction



This is electron neutrino.
Energy is 1 eV.

... **would be nice to know why you thought so ...**

Machine Learning & Computer Vision in Neutrino Physics

Why Data Reconstruction

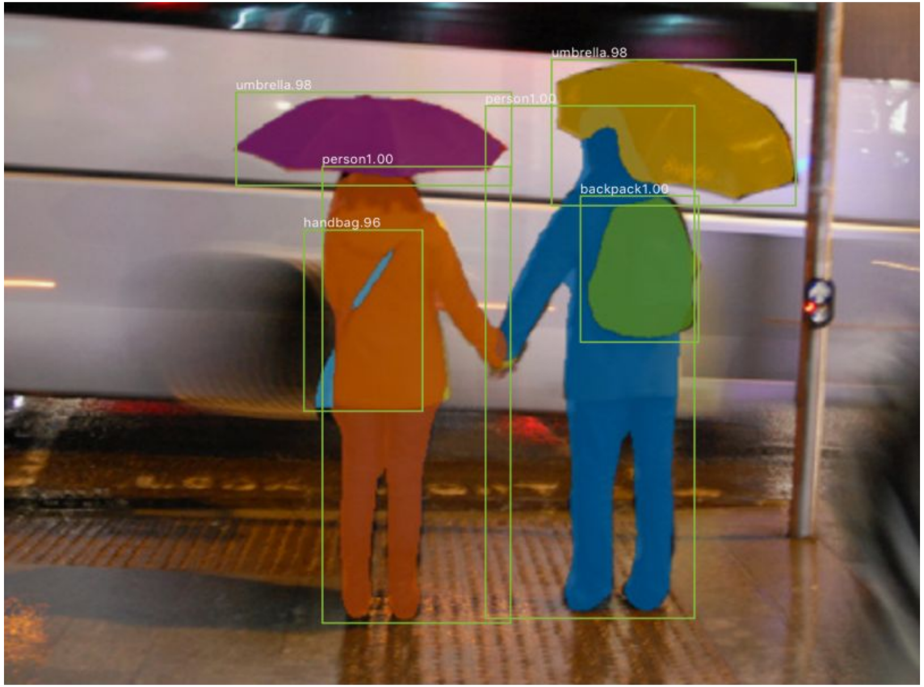


Image Context Identification

Why Data Reconstruction

"girl in pink dress is jumping in air."

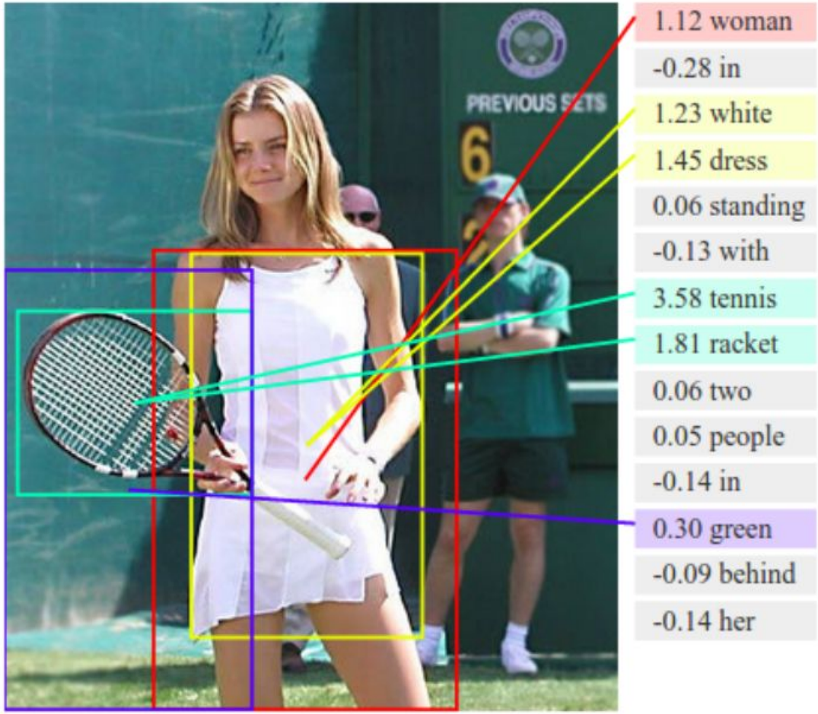
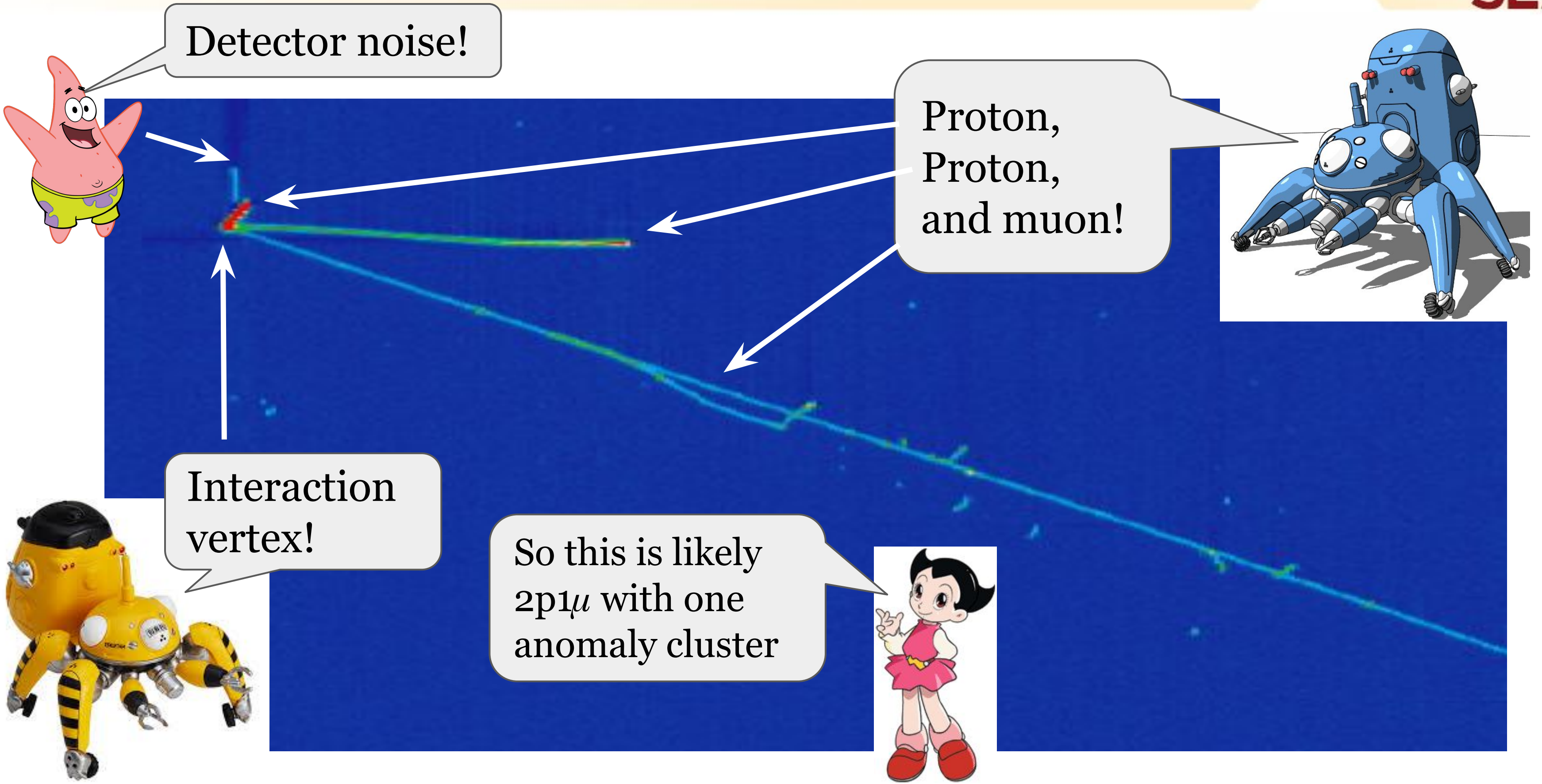


Image Context Correlation/Hierarchy Analysis

Machine Learning & Computer Vision in Neutrino Physics

Why Data Reconstruction



Segmentation Data

Machine Learning & Computer Vision in Neutrino Physics
Object Detection & Semantic Segmentation

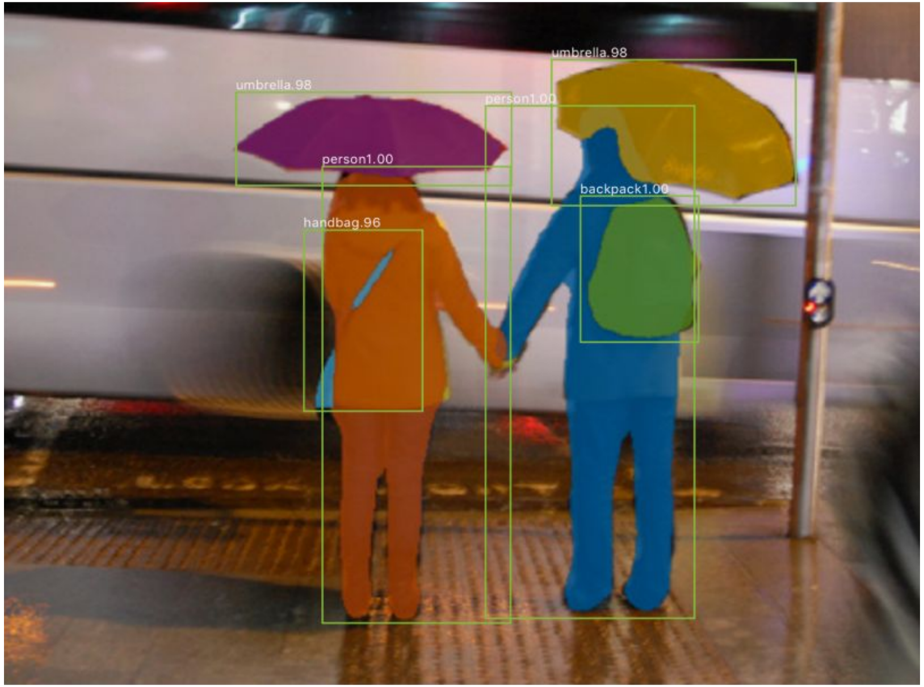


Image Context Identification

Hierarchy and Correlation of Context

"girl in pink dress is jumping in air."

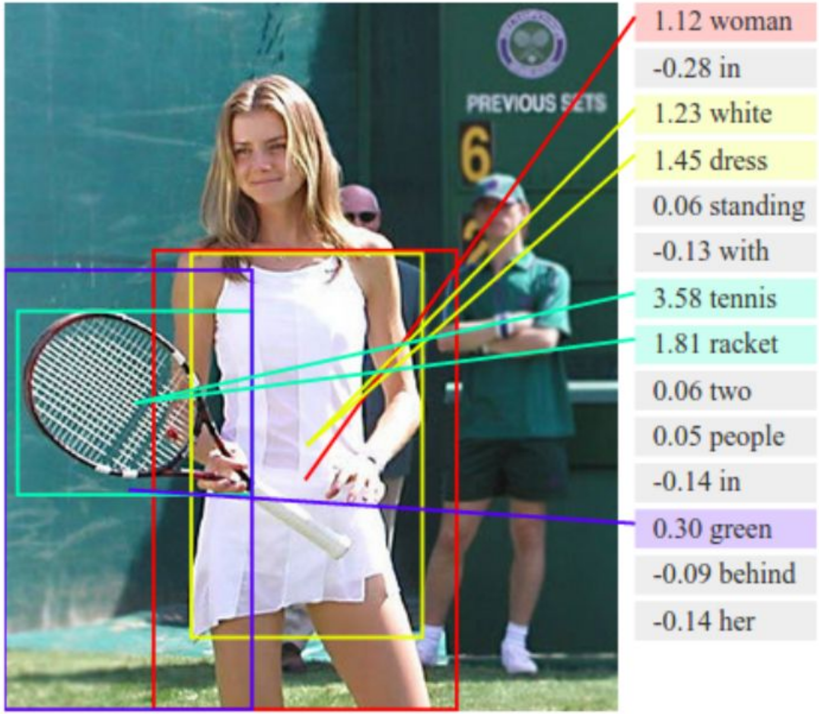
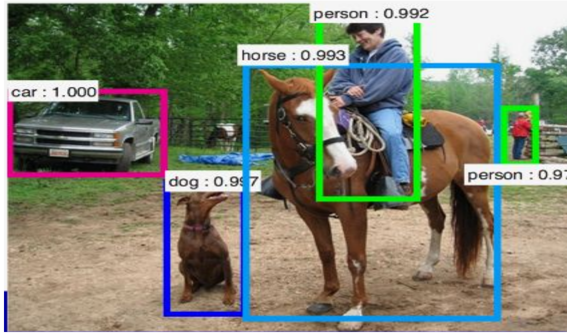
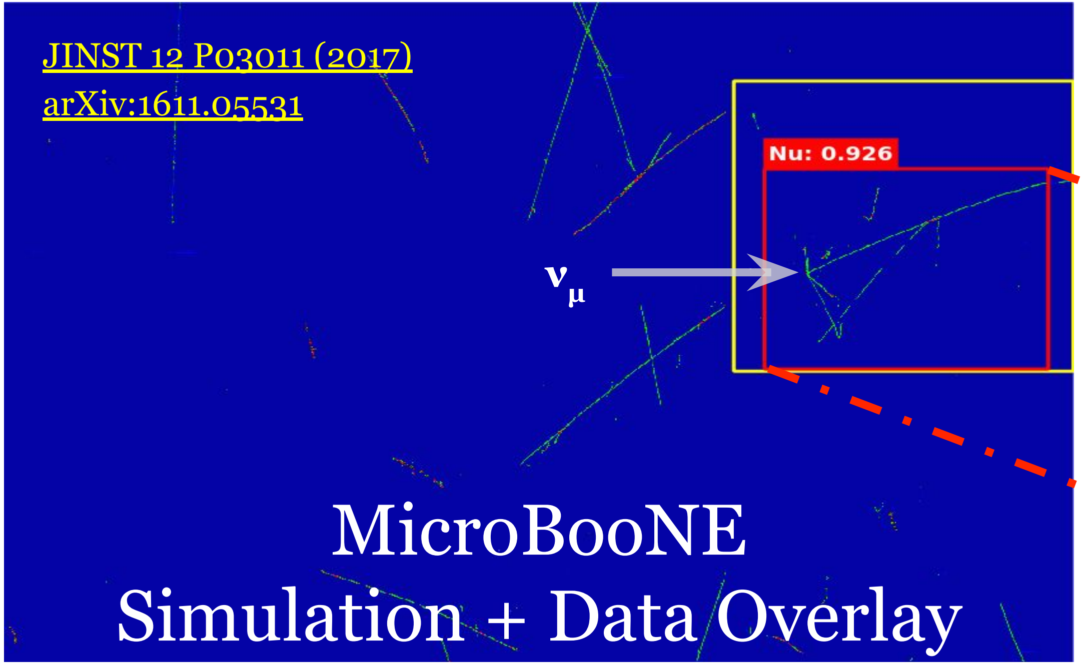
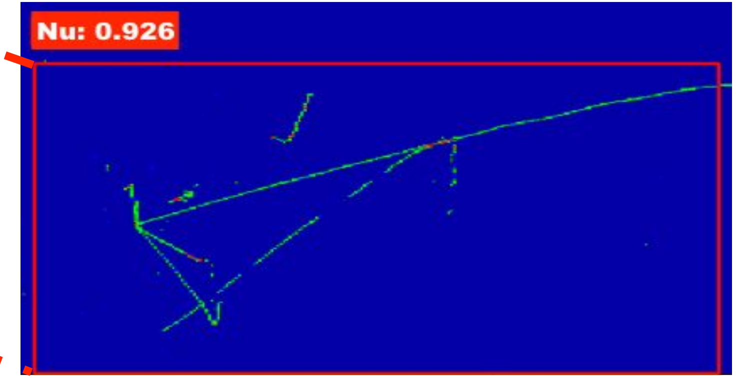


Image Context Correlation/Hierarchy Analysis

Neutrino Detection w/ R-CNN (MicroBooNE LArTPC)



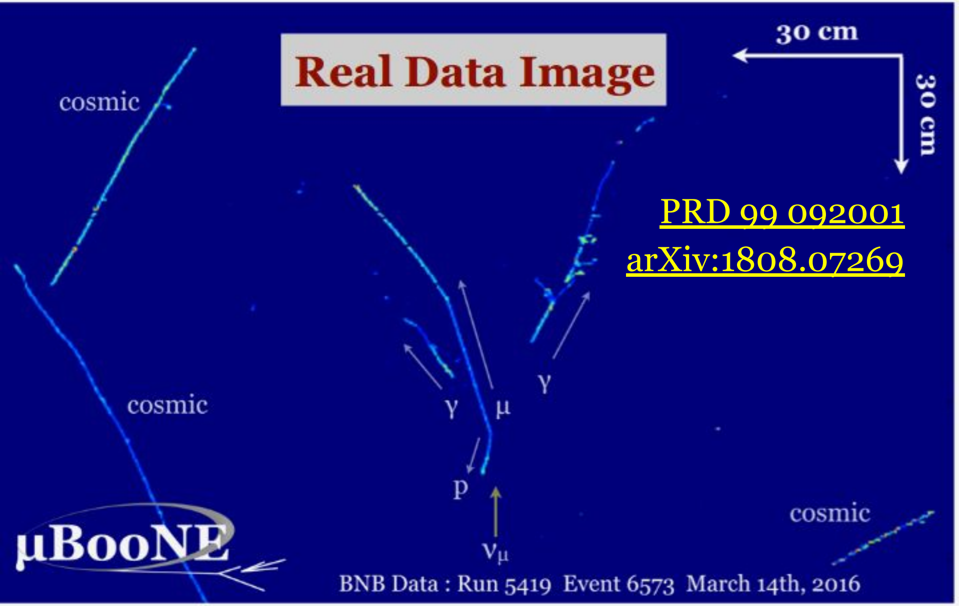


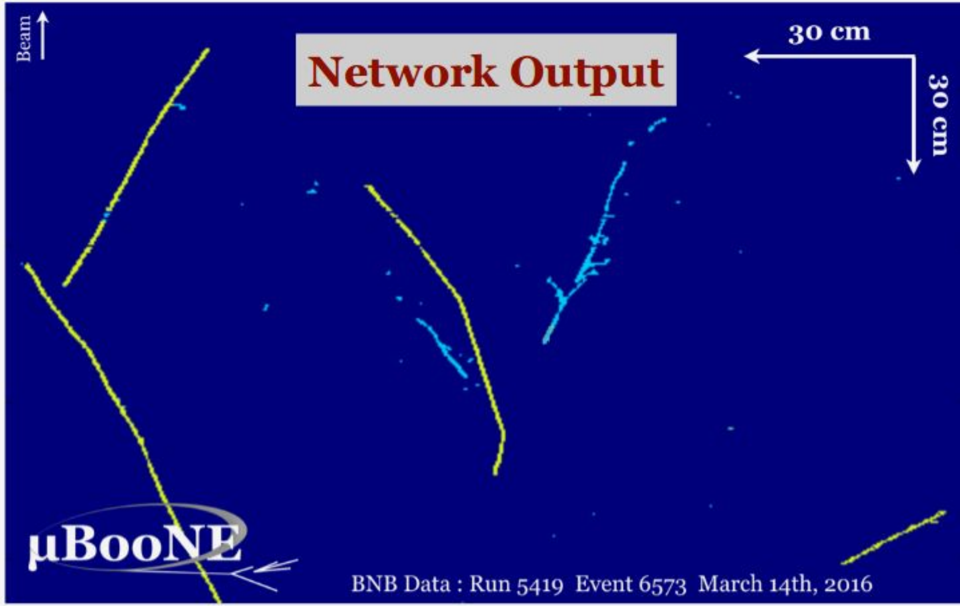


Task: propose a rectangular box that contains neutrino interaction (location & size)

Machine Learning & Computer Vision in Neutrino Physics
Semantic Segmentation for Pixel-level Particle ID

Separate electron/positron energy depositions from other types at raw waveform level.
Helps the downstream clustering algorithms (**data/sim comp. @ arxiv:1808.07269**)

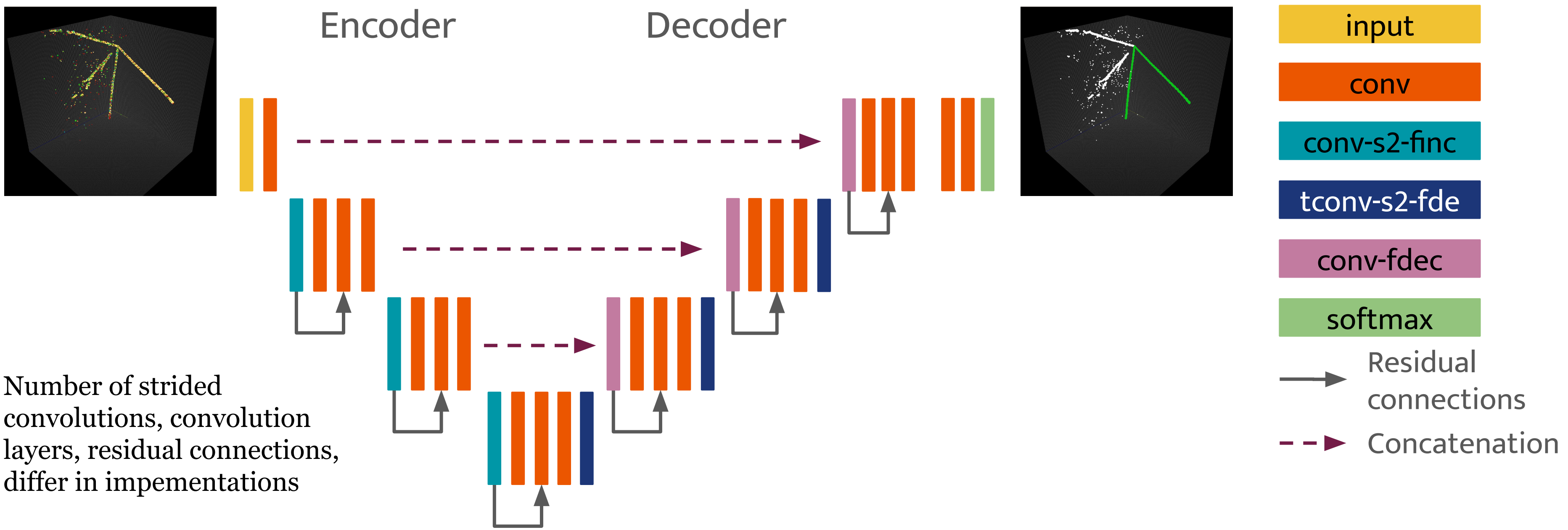




Network Input **Network Output**

Semantic Segmentation for Pixel-level Particle ID

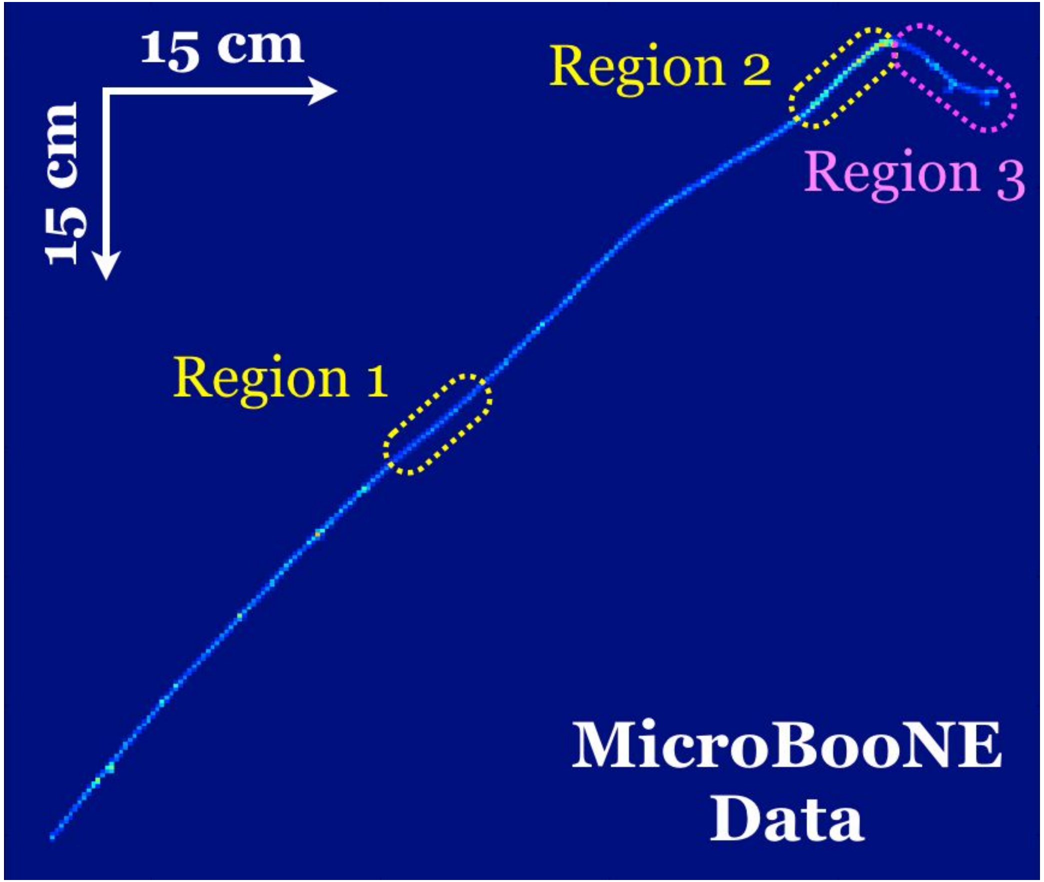
Architecture: **U-Net + Residual Connections**



Number of strided convolutions, convolution layers, residual connections, differ in impementations

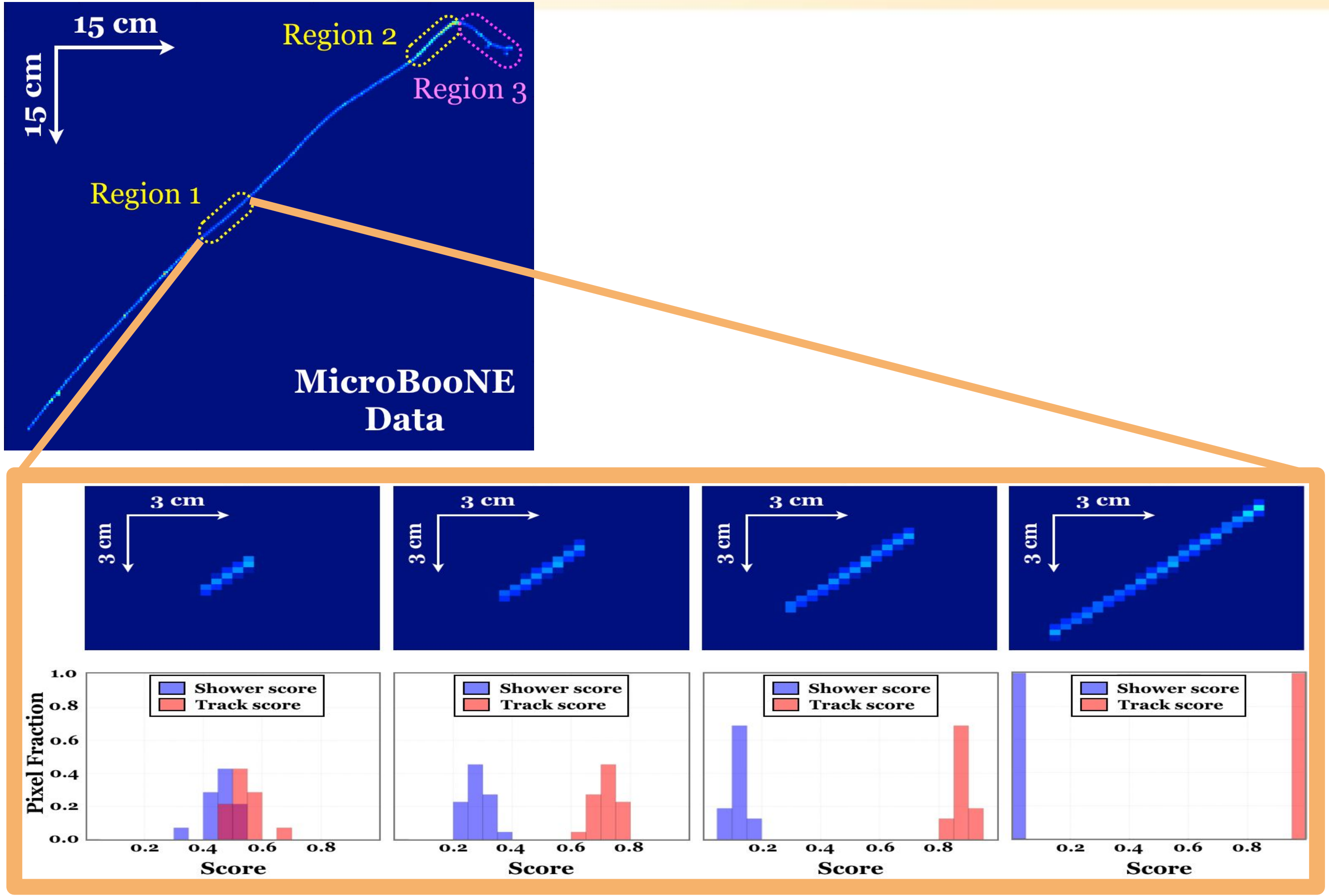
Image credit: Laura Domine @ Stanford

Fun Playing with Semantic Segmentation



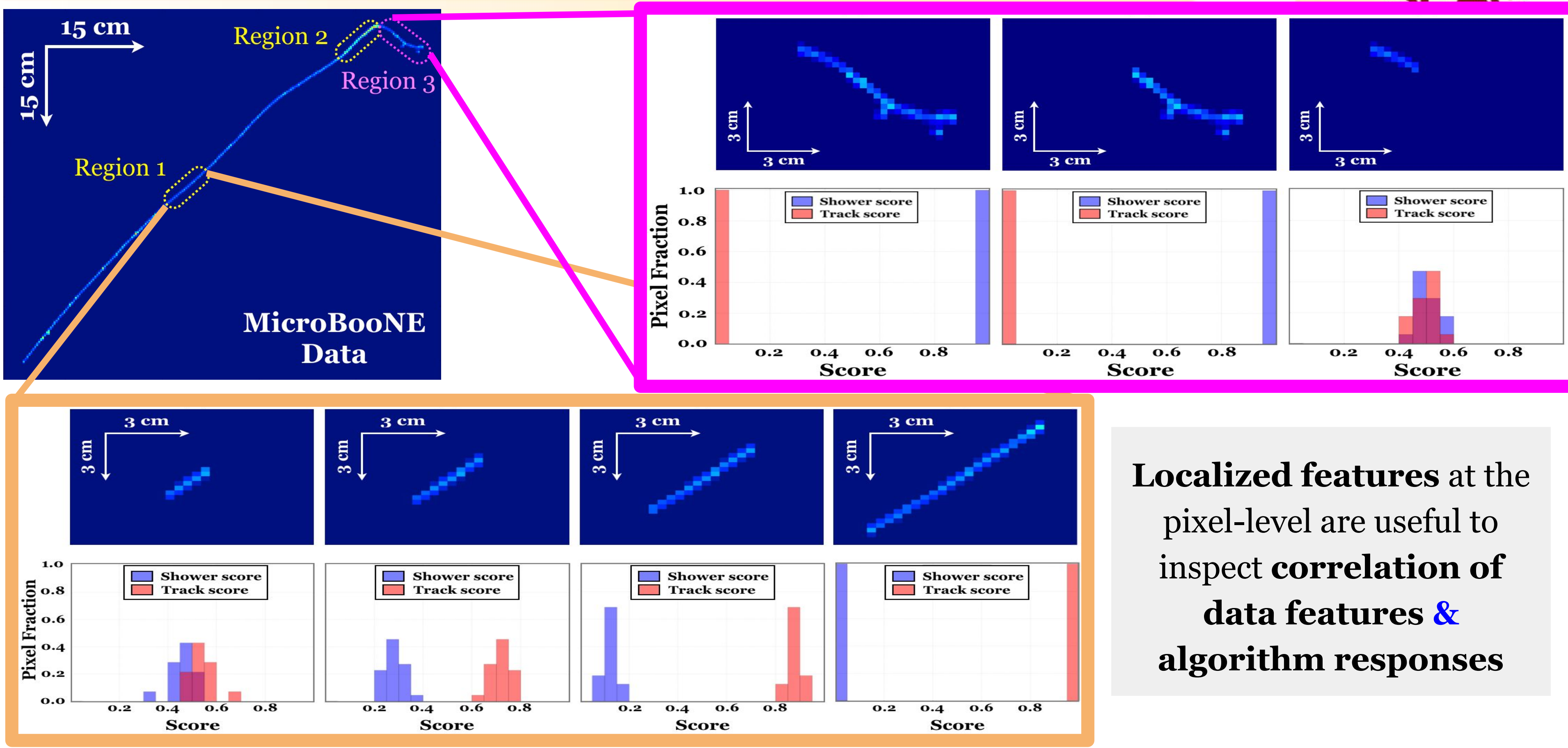
Machine Learning & Computer Vision in Neutrino Physics

Fun Playing with Semantic Segmentation



Localized features at the pixel-level are useful to inspect **correlation of data features & algorithm responses**

Machine Learning & Computer Vision in Neutrino Physics
Fun Playing with Semantic Segmentation



Localized features at the pixel-level are useful to inspect **correlation of data features & algorithm responses**

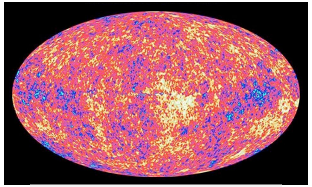
Why Neutrino

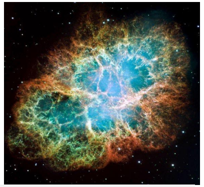
Machine Learning & Computer Vision in Neutrino Physics

Why neutrinos?

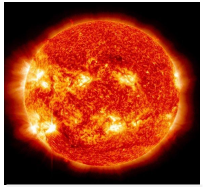
Neutrinos are everywhere!

... which makes them the **natural probe to the universe and its history**


Early Universe


Supernova

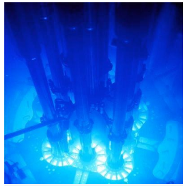

AGN

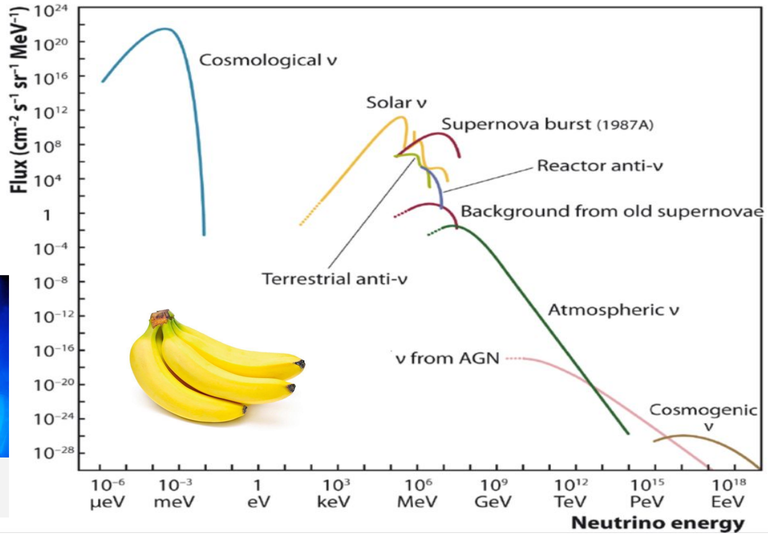

Stars


Atmosphere


Earth (planets)


Accelerators


Reactors



Want to detect & understand more of them

First, understand how neutrinos travel over spacetime (neutrino oscillations)

Neutrino Detectors: What's Important

SLAC

Neutrino Oscillation Measurement

Use a neutrino source (flavour X), measure flavour Y at the detector

What's important?

Three important detector features for oscillation measurement

$$P(\nu_\mu \to \nu_e) = \sin^2 2\theta \sin^2\left(\frac{1.27\,\Delta m^2\,L}{E_\nu}\right)$$

Good Energy Resolution

Precise E_ν reduce oscillation uncertainty

Large Mass (scalable)

"More" statistics to measure rare physics process

Particle ID Capability

Better ν identification background rejection