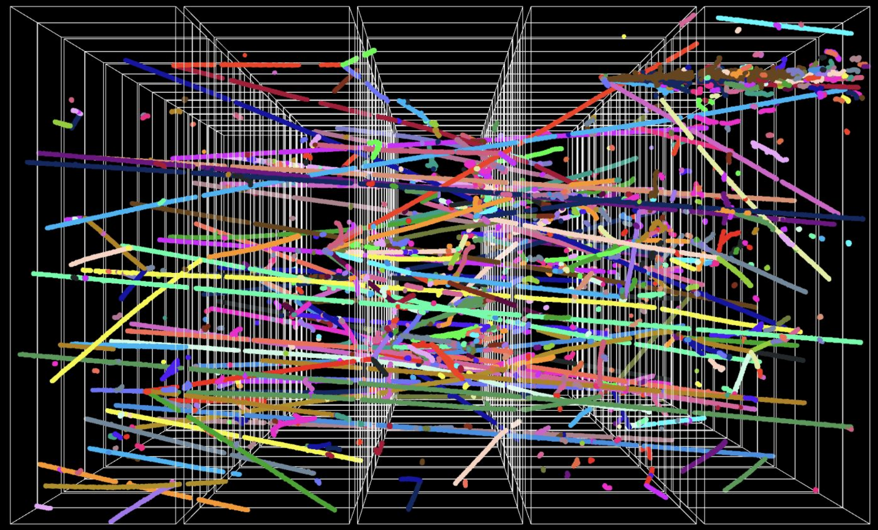
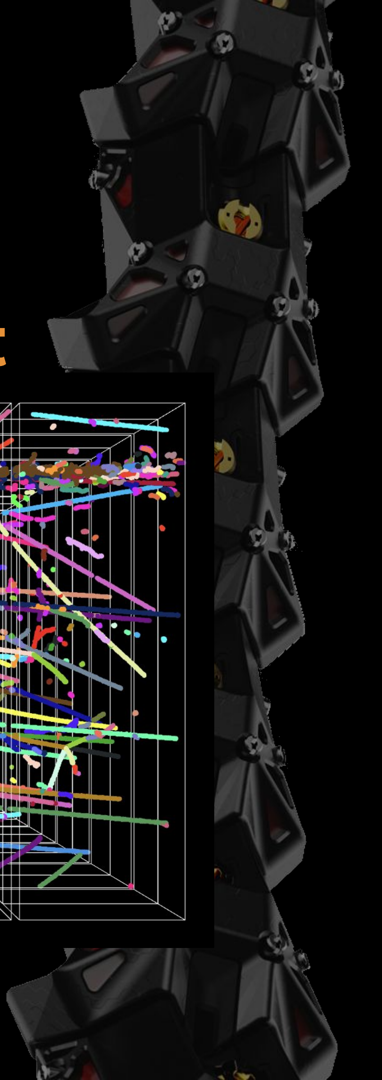
Deep Neural Network Cascade for the Deep Underground Neutrino Experiment

NPML 2025

François Drielsma (SLAC)
on behalf of the DUNE collaboration

October 29th, 2025





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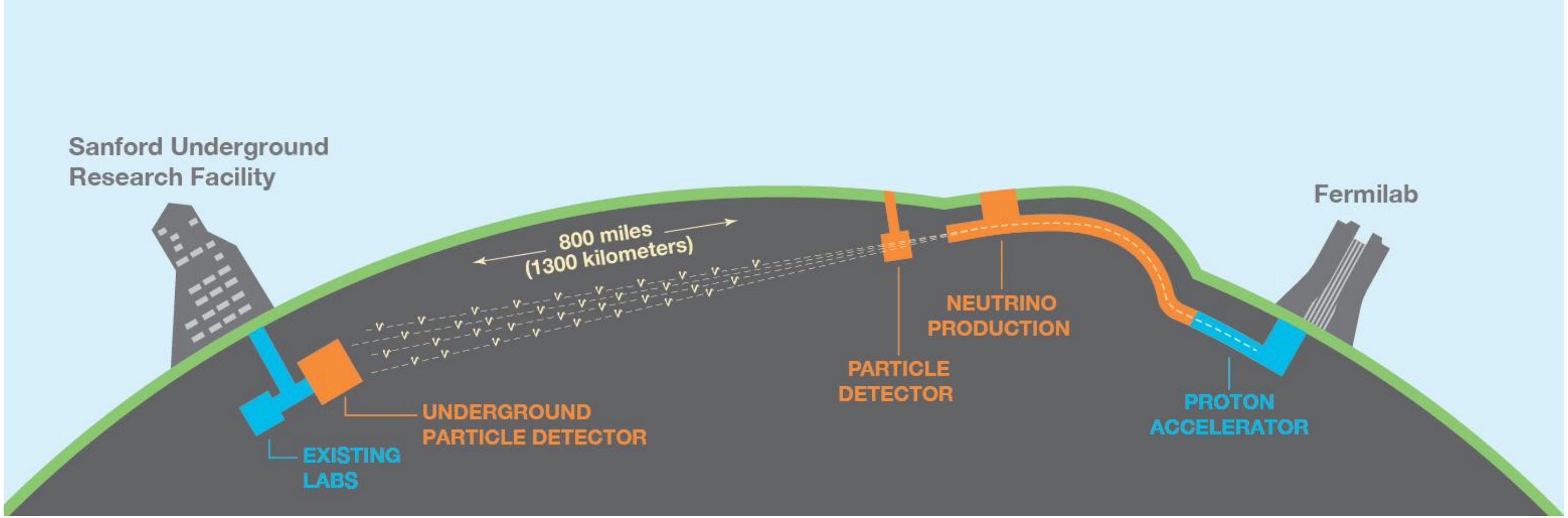
SPINE

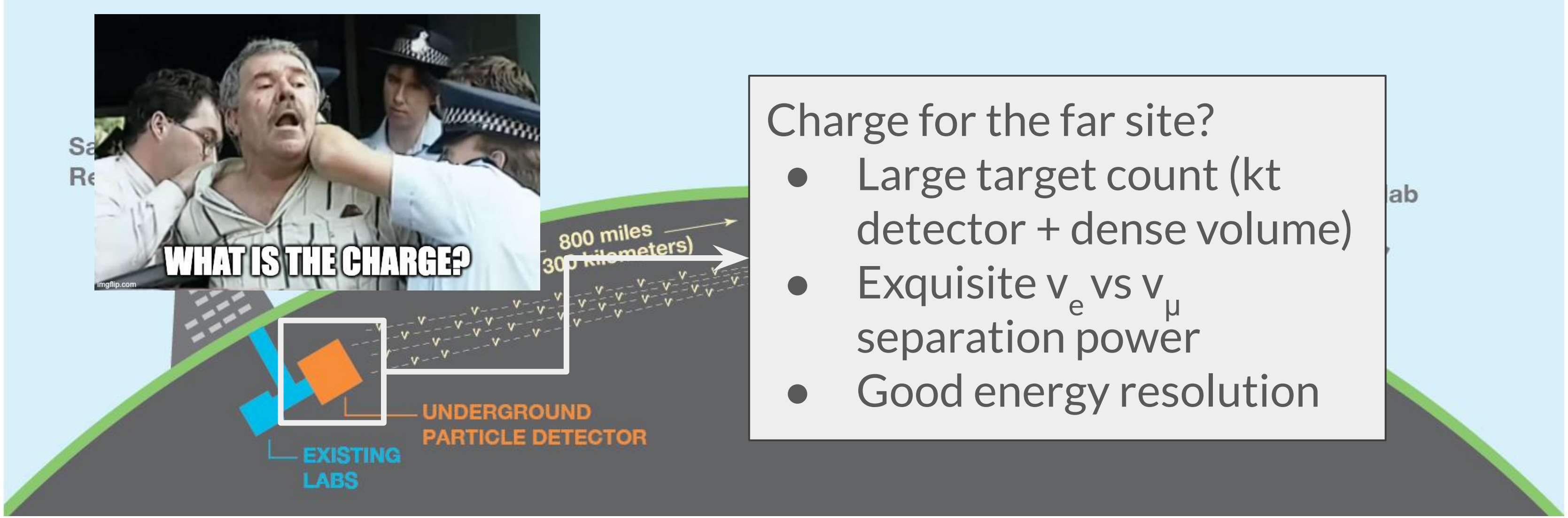
The Deep Underground Neutrino Experiment



DUNE is a long-baseline **neutrino oscillation experiment.** Ingredients:

- One **near detector** (flux constraint), one **far detector** (oscillated flux)
- Need to know: **neutrino species** (ν_e vs ν_μ) and **energy** (L/E)

The Deep Underground Neutrino Experiment



Charge for the far site?

- Large target count (kt detector + dense volume)
- Exquisite ν_e vs ν_μ separation power
- Good energy resolution

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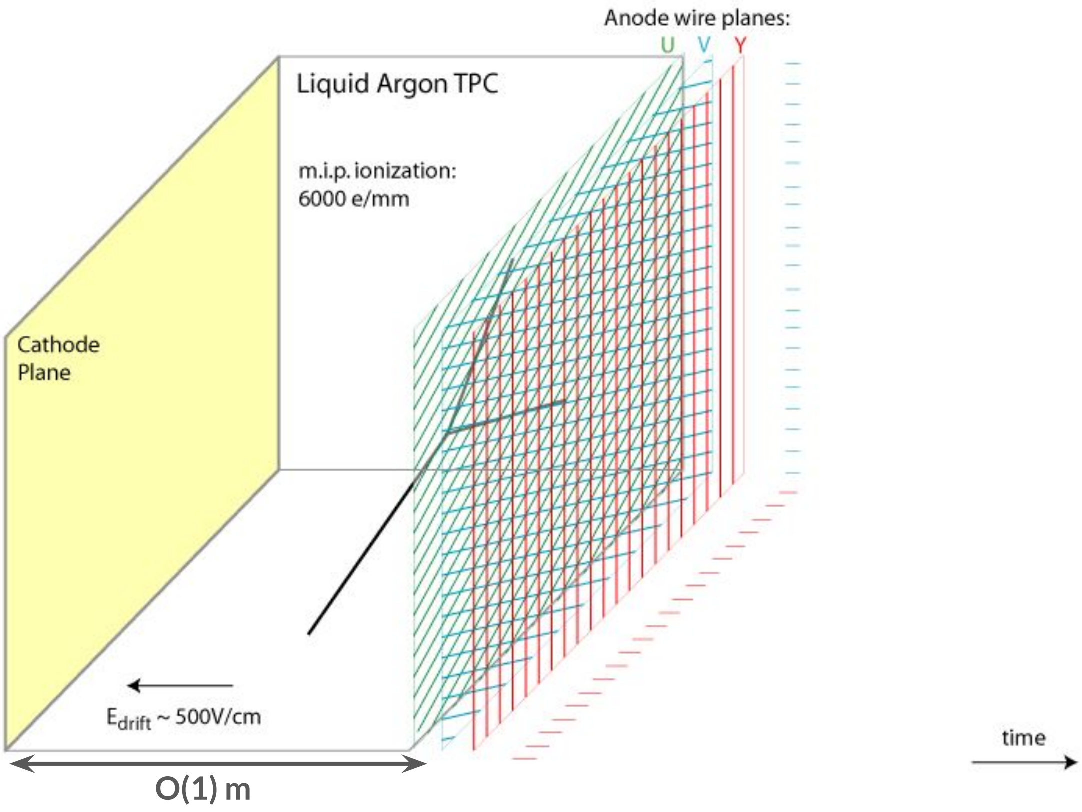
Liquid Argon Time Projection Chamber



Credit: B. Yu

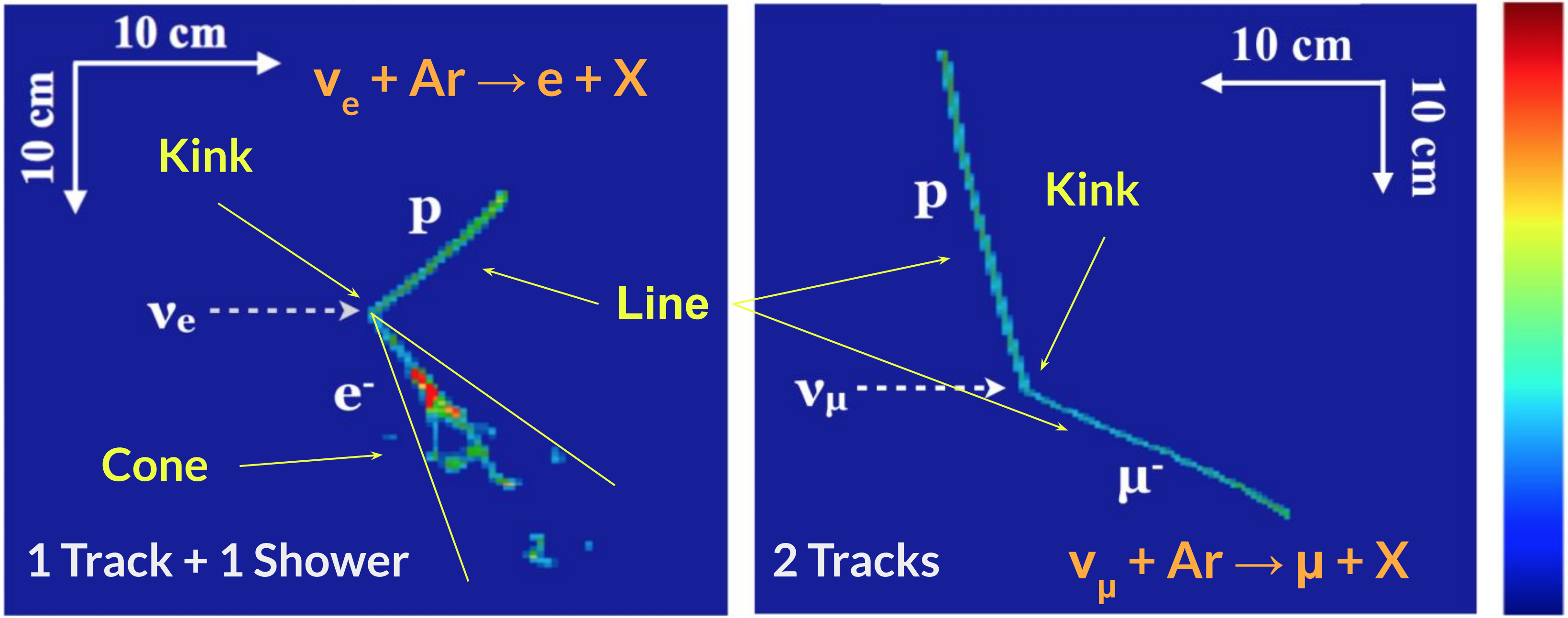
LArTPC: modern bubble chamber for neutrino physics (DUNE / SBN)

- Dense (1.4 g/cm^3) + Cheap (~ 1$/kg), **a.k.a. scalable to 40 kt (DUNE-FD)**
- **Precise particle tracking**
- **Detailed calorimetry**

Neutrino Identification

What does **precision tracking** give you?

- Visually, clear **distinction between neutrino species**

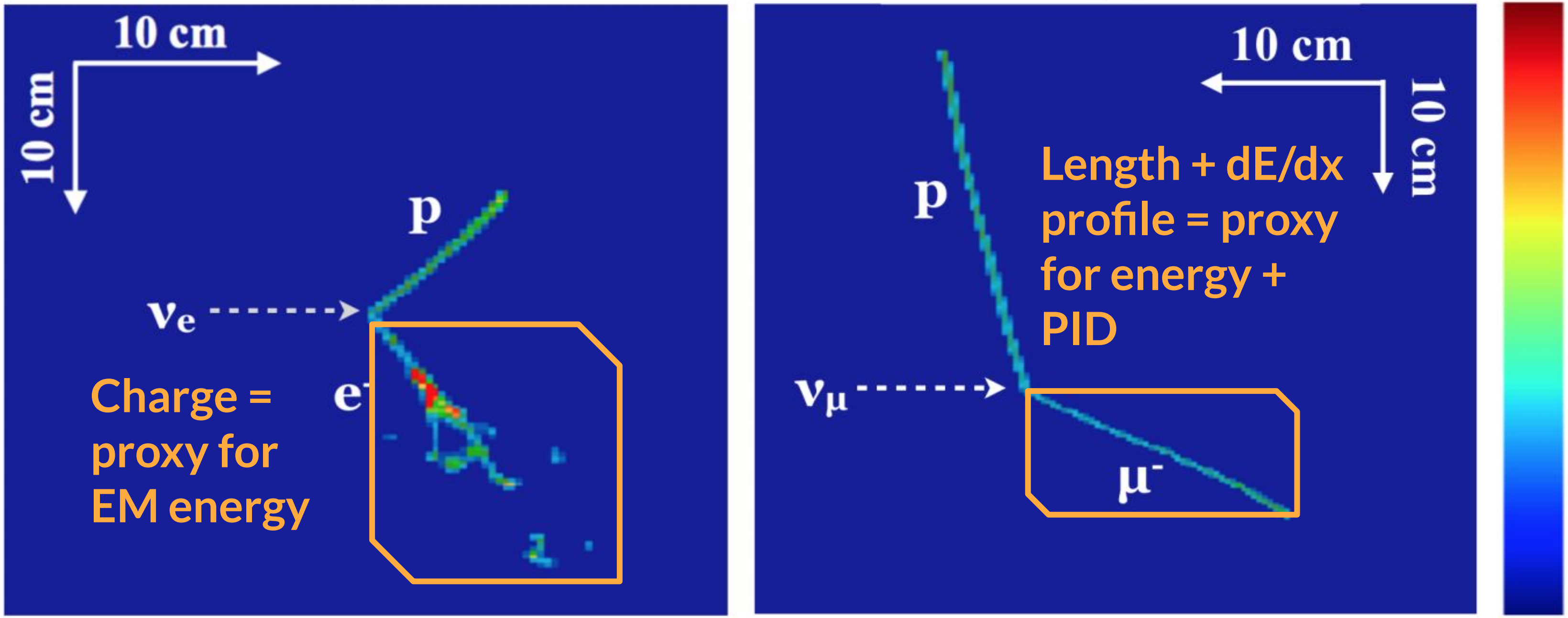


***Credit:** μBooNE simulation*

Neutrino Identification

What does **detailed calorimetry** give you?

- **Particle identification + energy reconstruction**

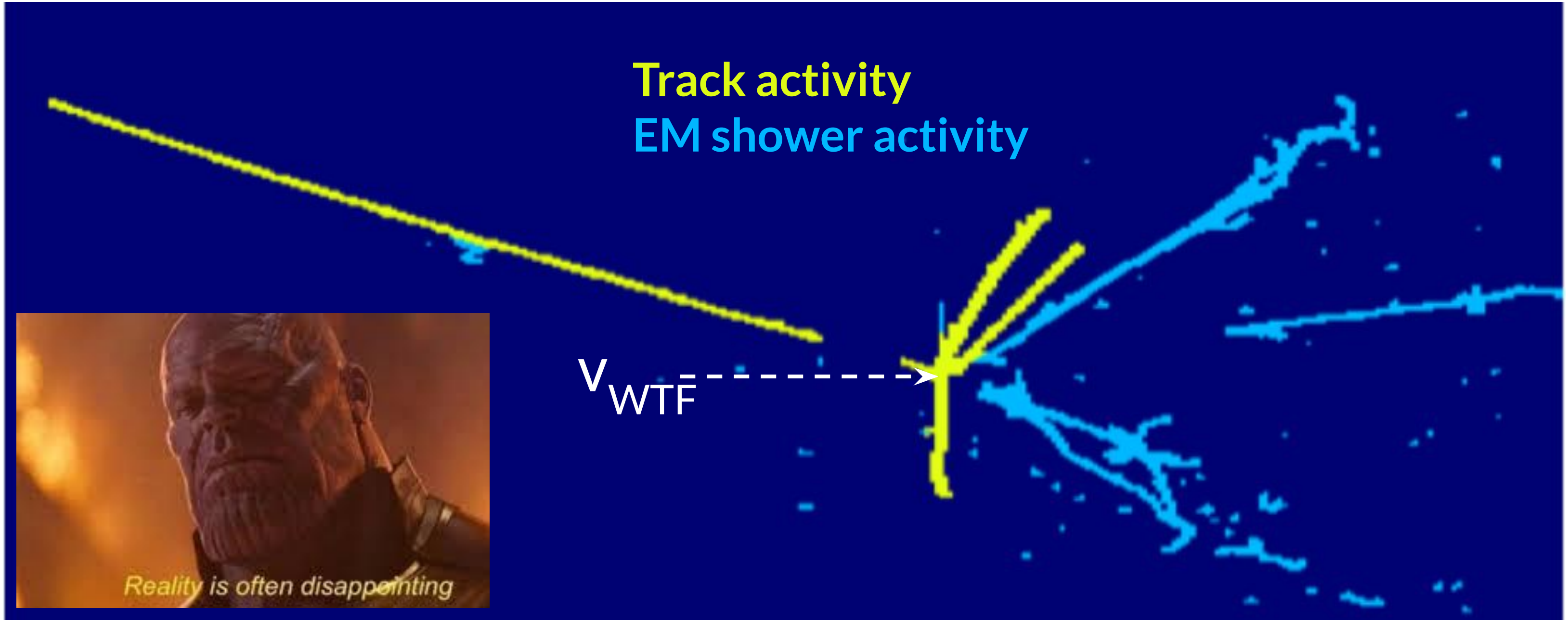


Credit: µBooNE simulation

Reality at the DUNE Beam Energies

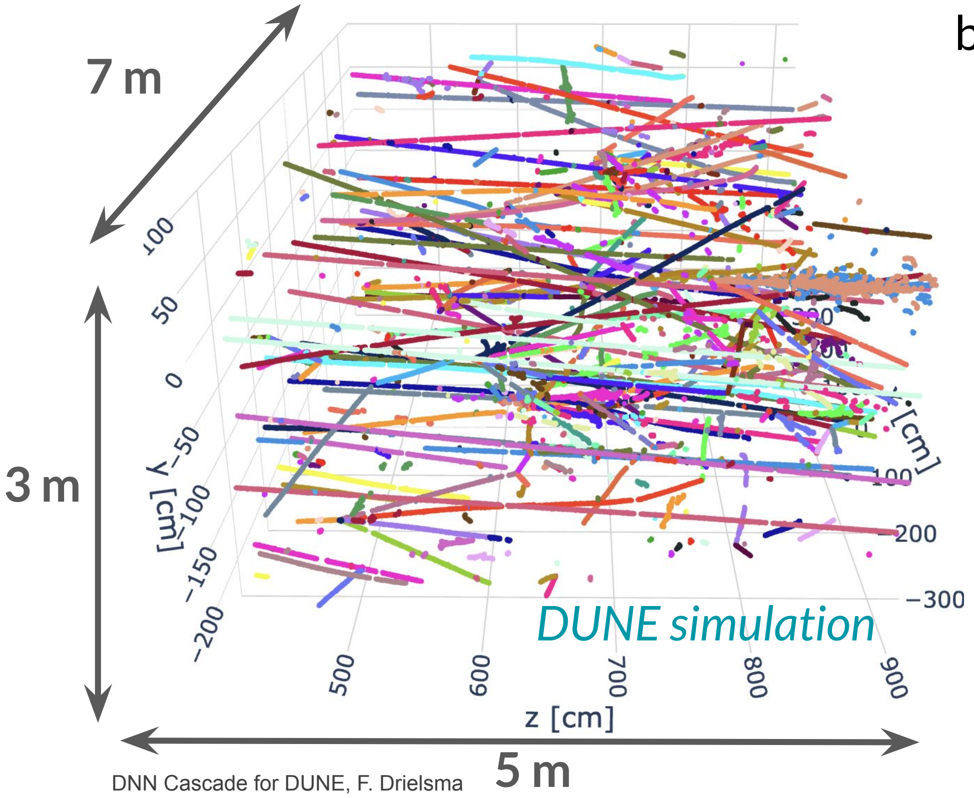
In practice, the **problem is much, much harder**

- At multi-GeV: **ν on Ar messy** + **hadron re-interaction likely**



Credit: μBooNE data

What about the Near Site?



Placing a LArTPC close to the neutrino beam source is a difficult proposition…

- **Brutal pile-up**: O(100) tons of LAr sees O(100) beam-related interactions per spill (10 us!!)

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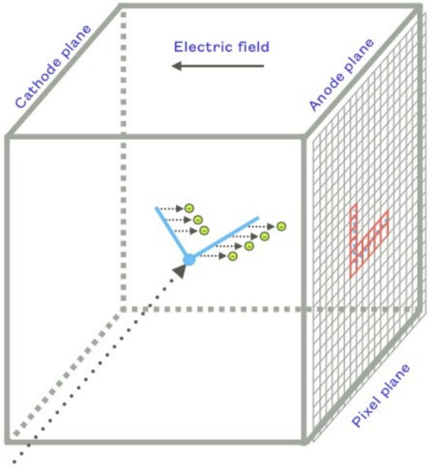
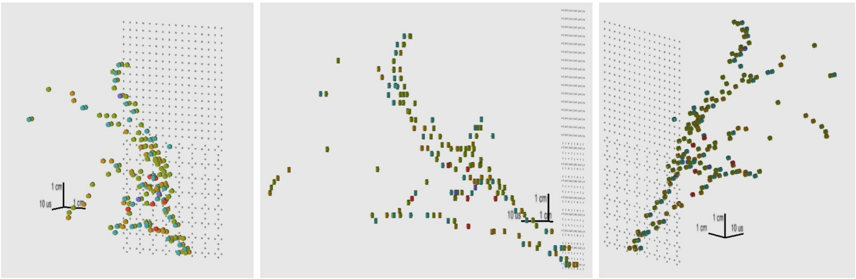


Credit: D. Dwyer



arXiv:1908.10956

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Subsequent design choices:

- **Drop wires, use pixels**: natively 3D images, help with pile-up

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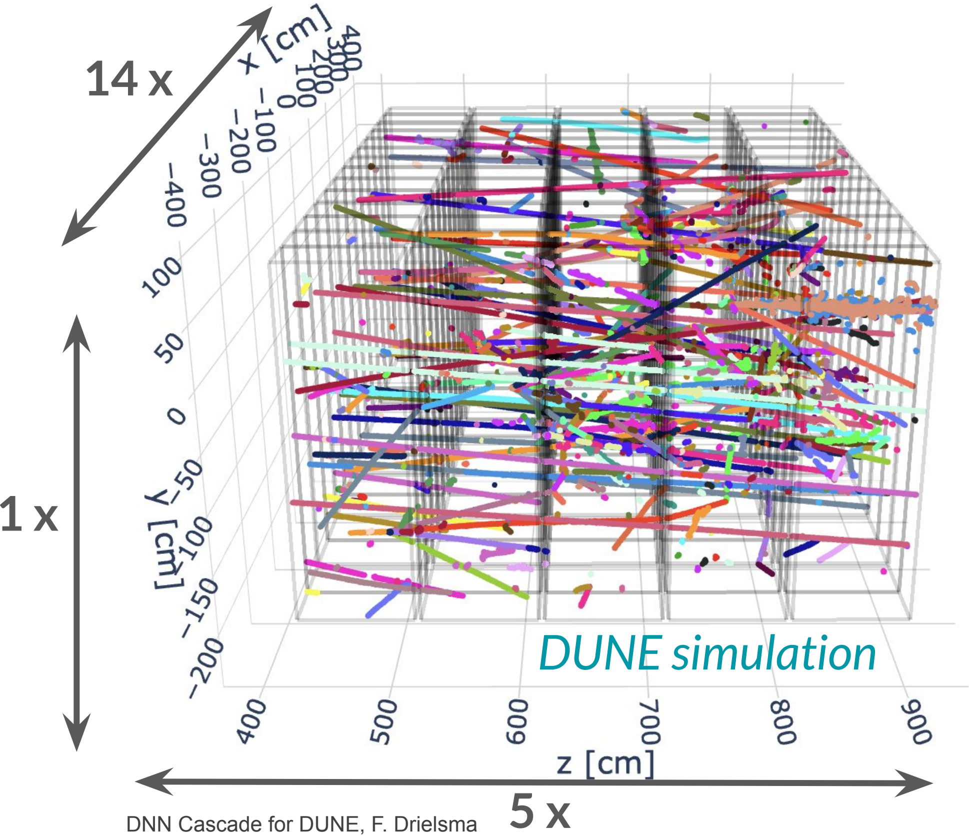

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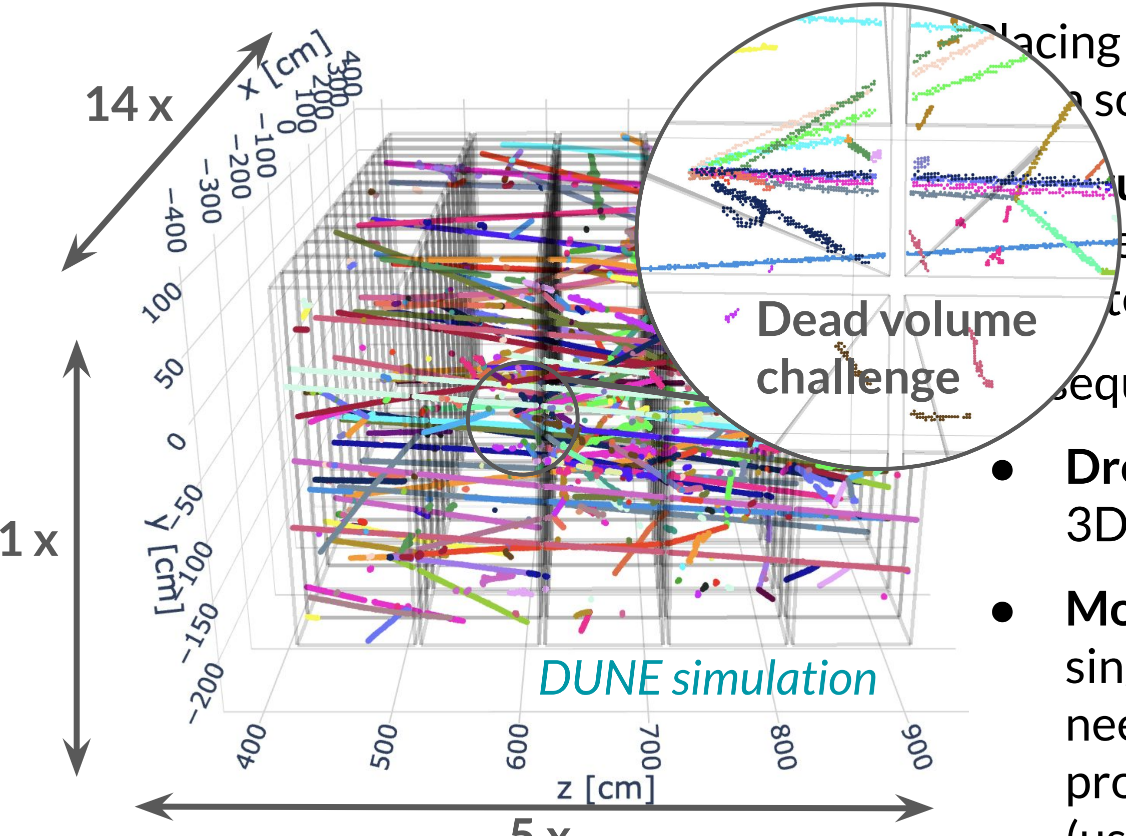

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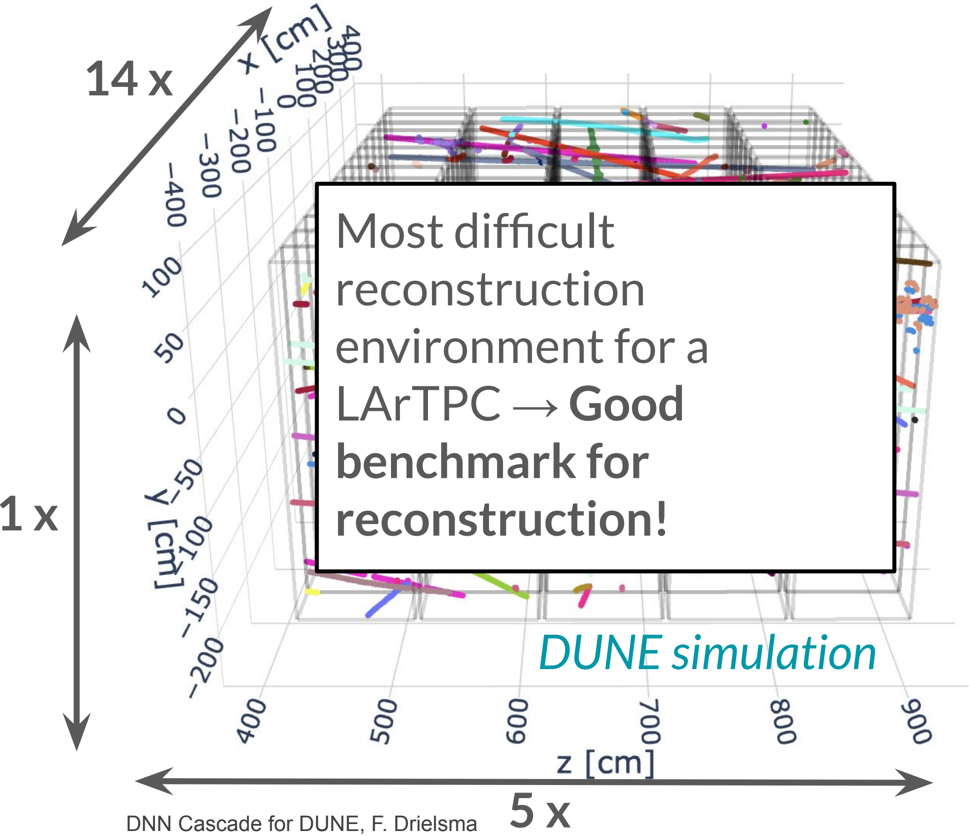

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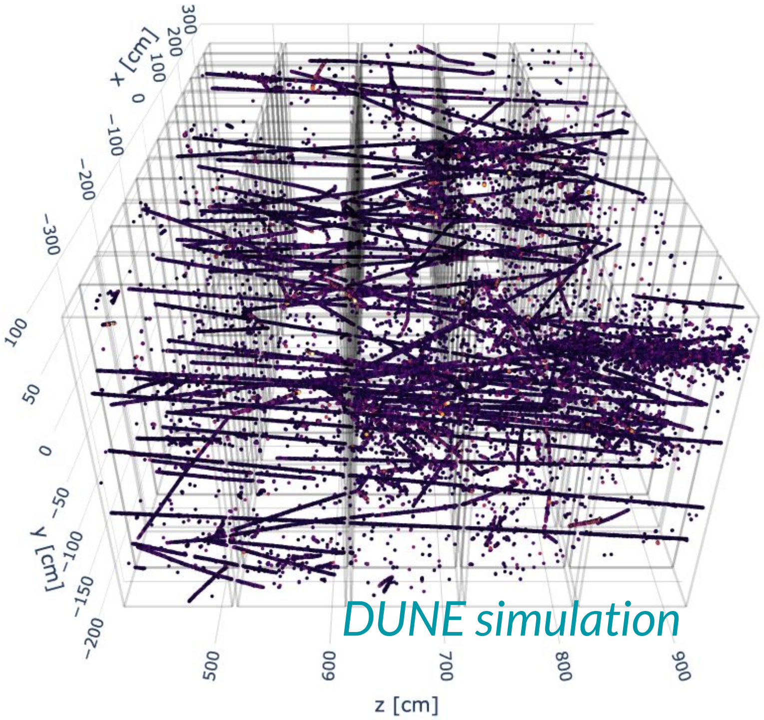
Reconstruction Goal

What we start with



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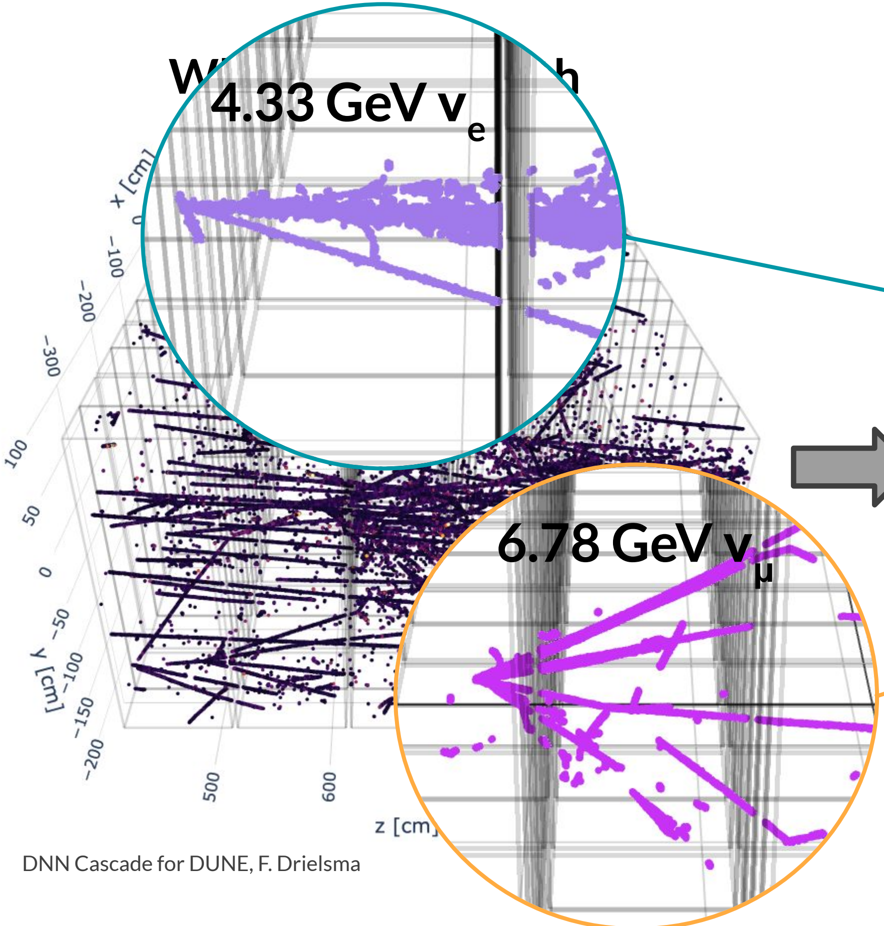
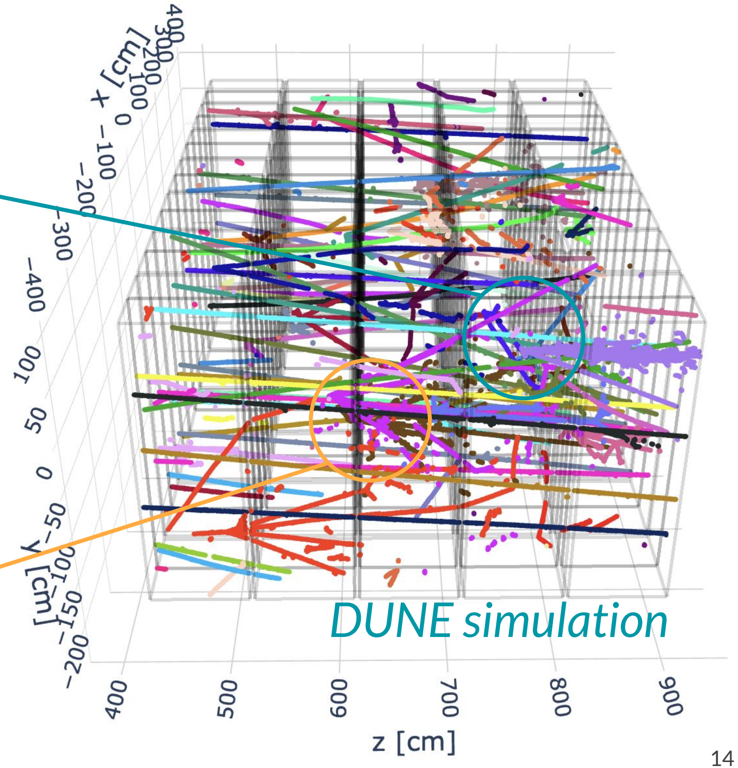
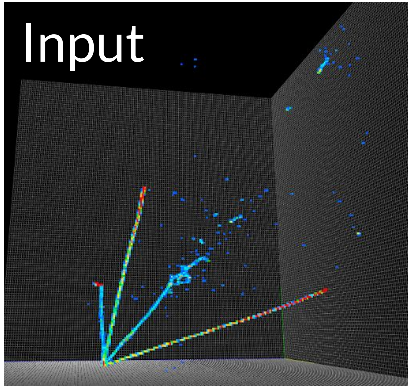


What we want



Physics-Informed ML Reconstruction

What is relevant to pattern recognition in a detailed interaction image?



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What is relevant to pattern recognition in a detailed interaction image?

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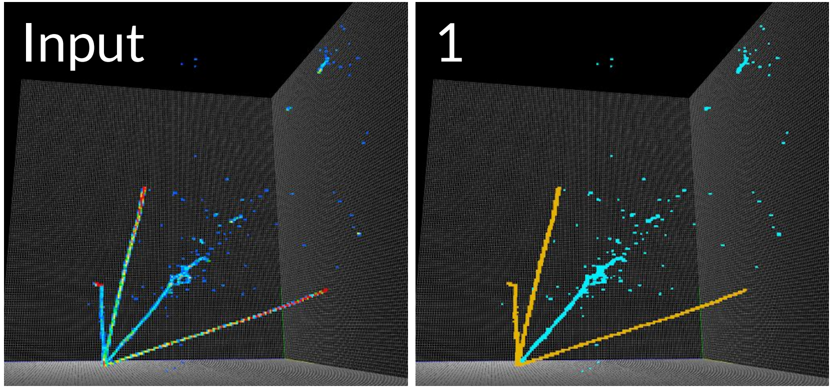
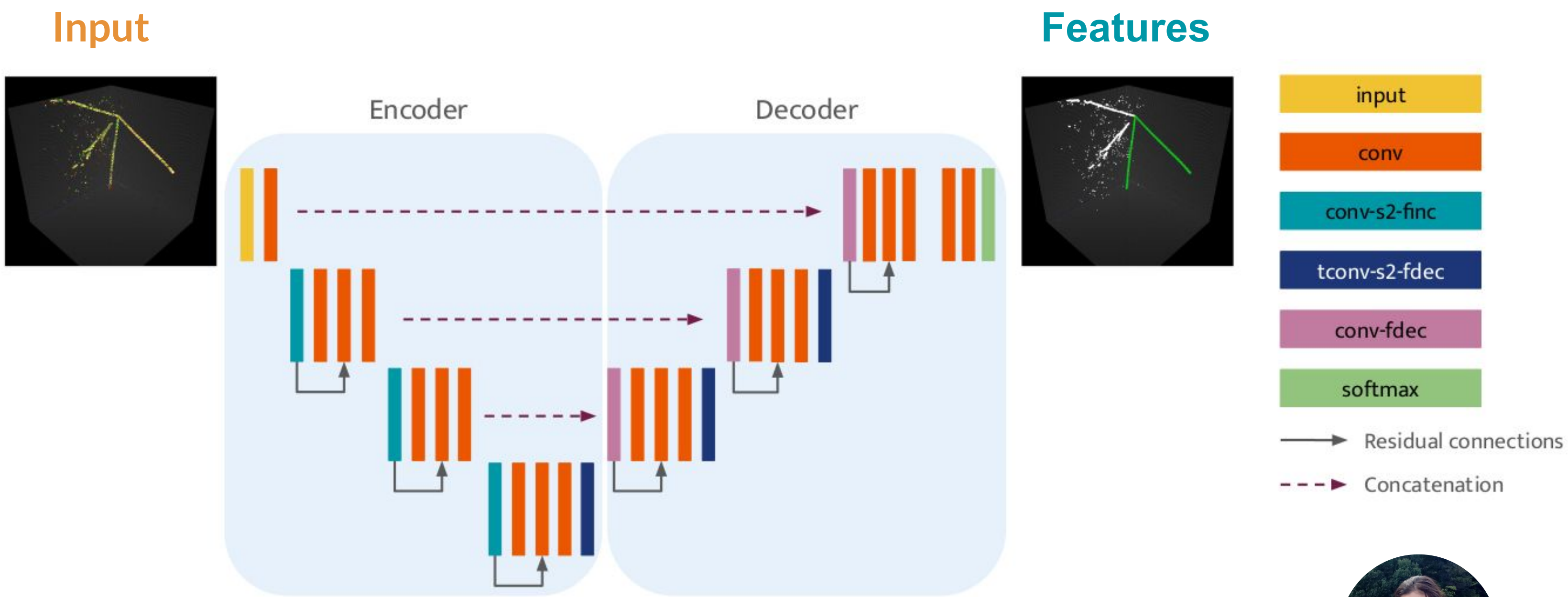


Pixel-Level Feature Extraction

UResNet (UNet + ResNet + Sparse Conv.) as the **backbone feature extractor**



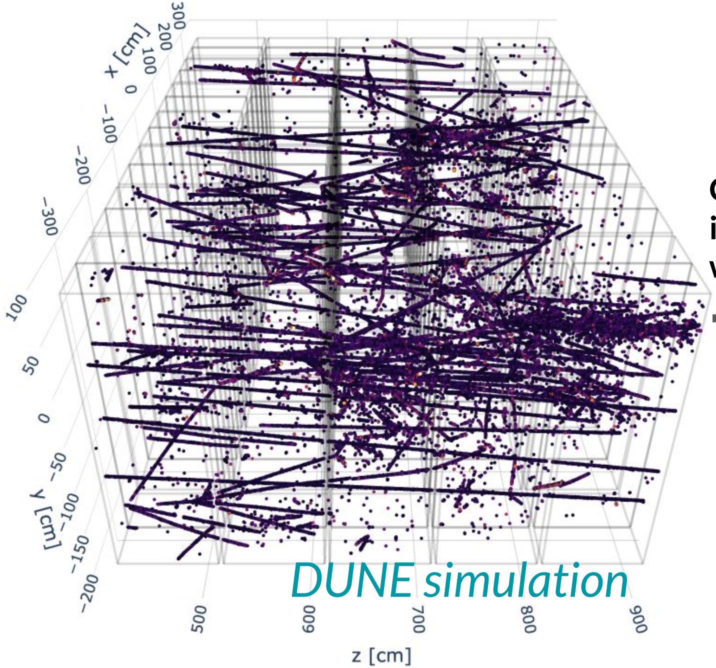
Paper: PhysRevD.102.012005

L. Dominé et al.

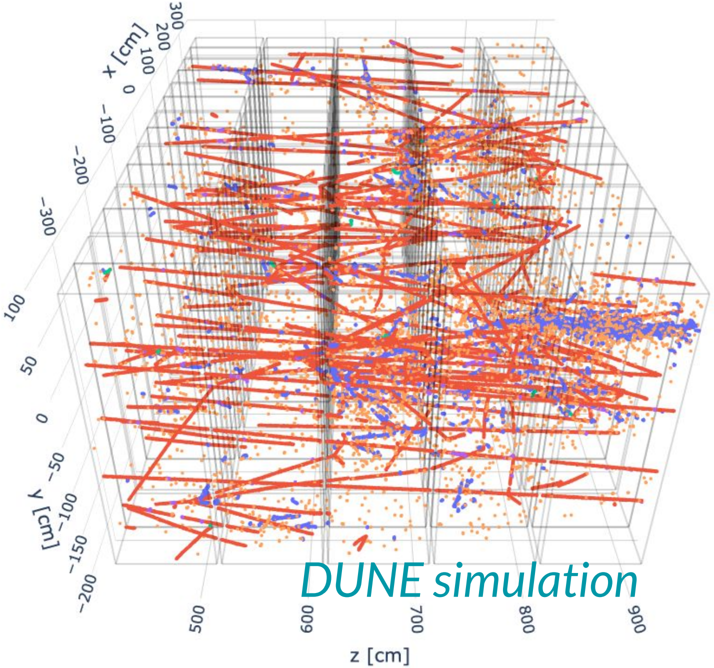
Semantic Segmentation

Separate **topologically different** types of activity

- **Tracks**, **Showers**, **delta rays**, **Michel electrons**, **low energy blips**



Classify pixels into categories with UResNet



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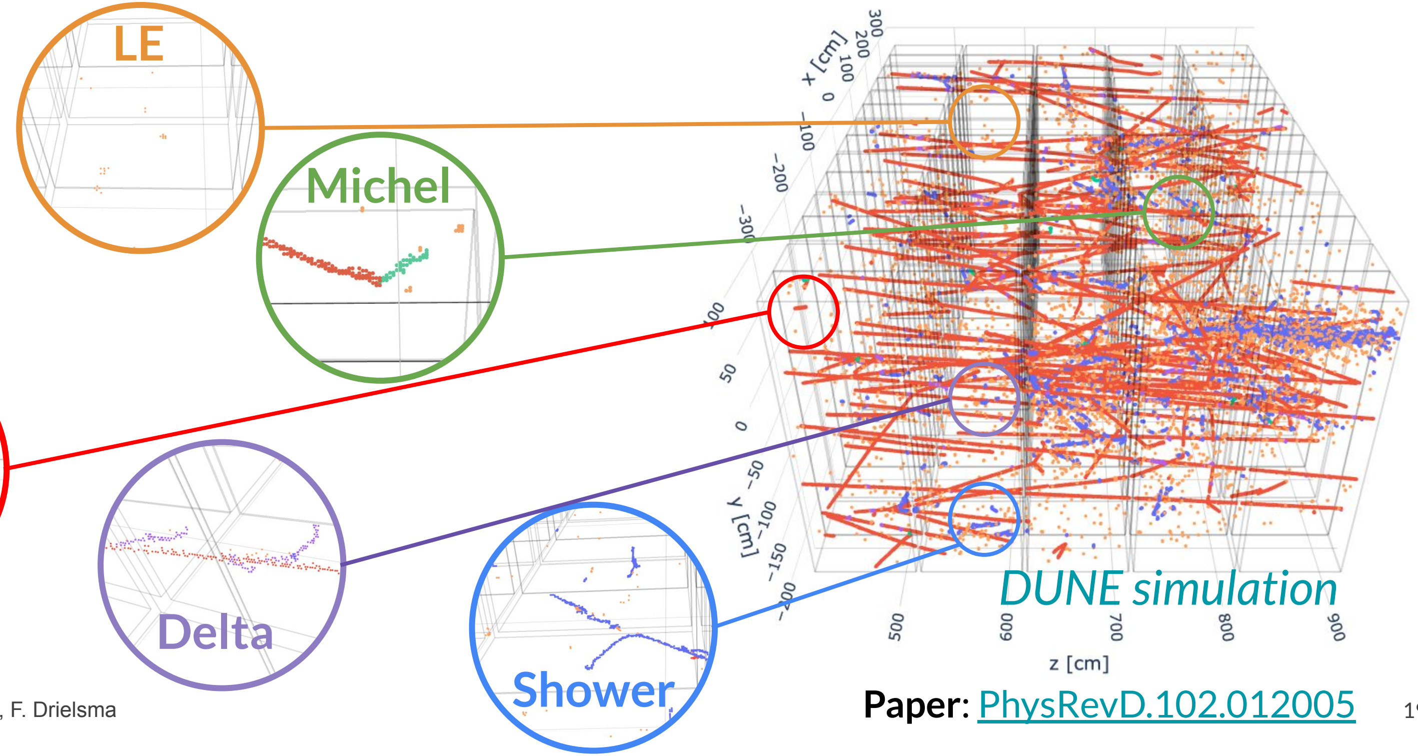

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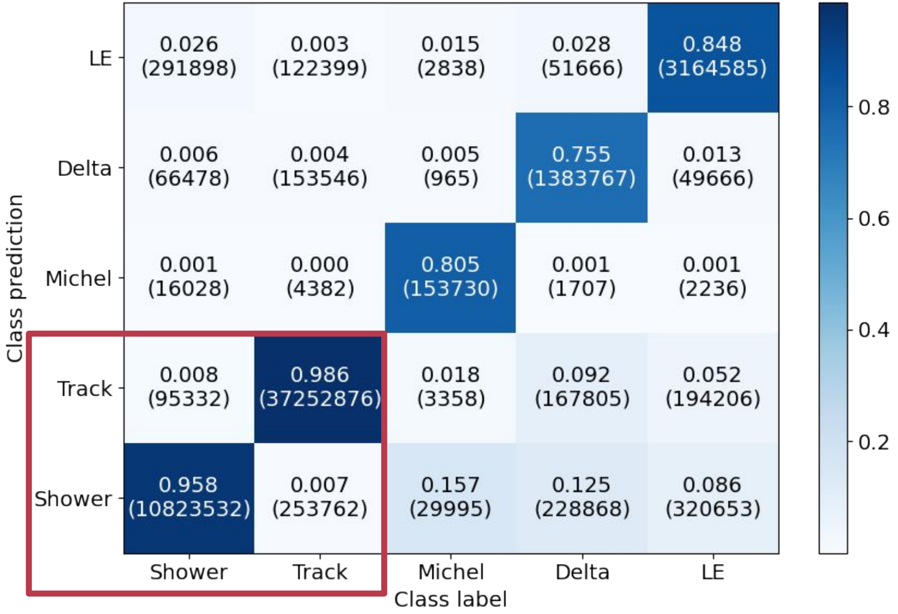
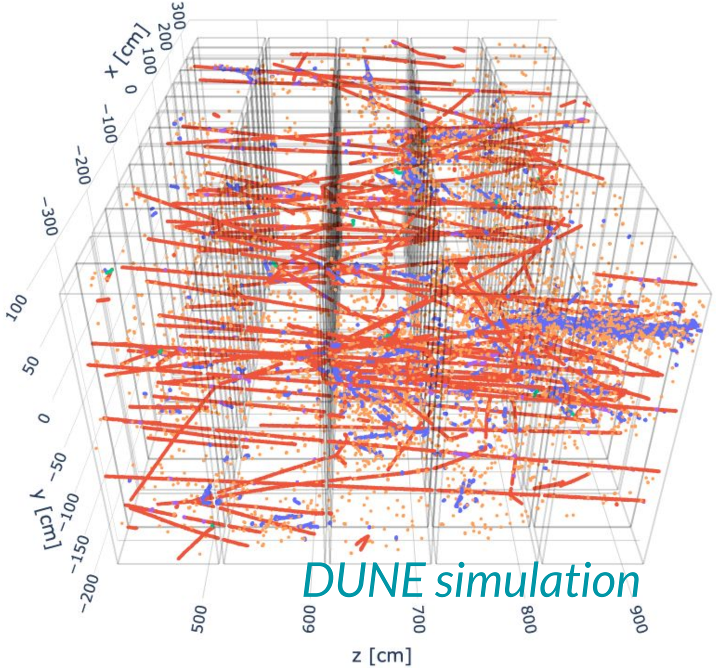
DUNE Simulation work-in-progress





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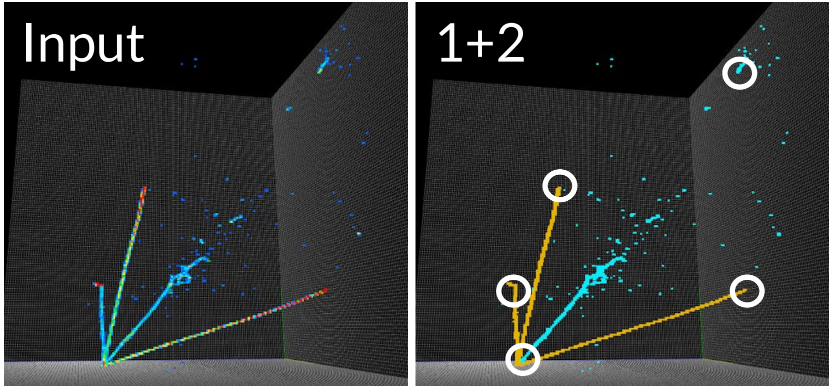
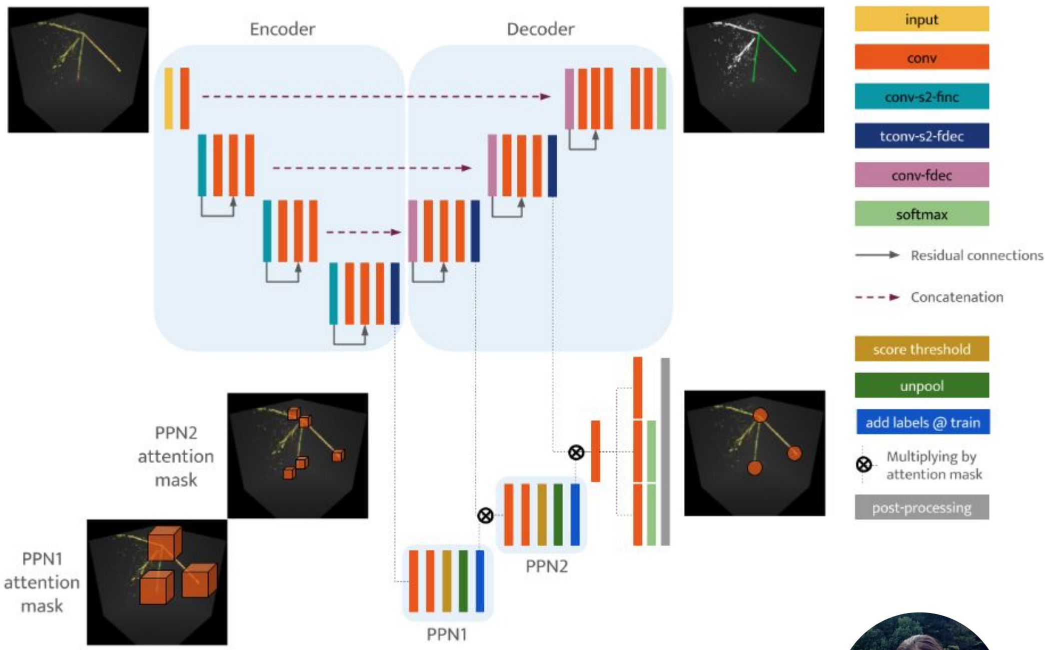


Points of Interest

The Point Proposal Network (PPN) uses decoder features

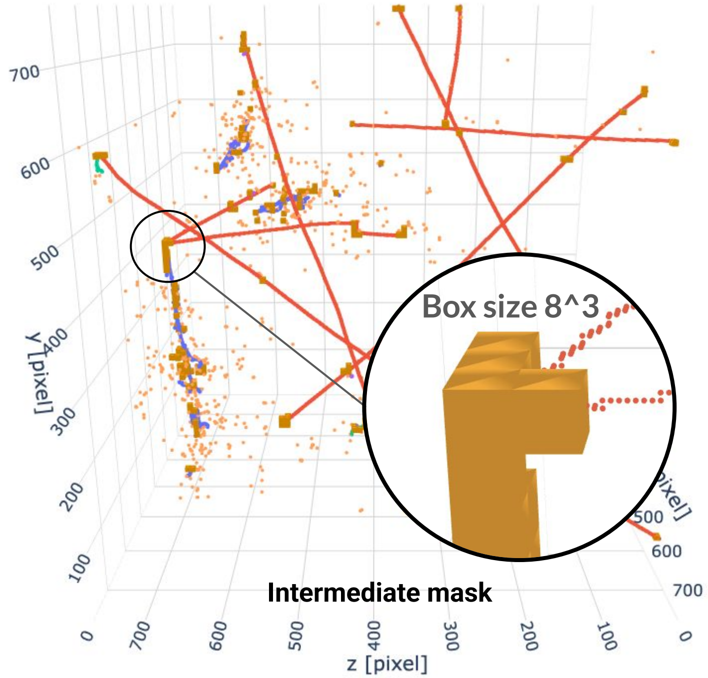
- CCN layers to narrow ROI at decoder layers
- Last layer reconstructs:
    - Relative position to pixel center of active pixel
    - Point type
- Post-processing aggregates nearby points

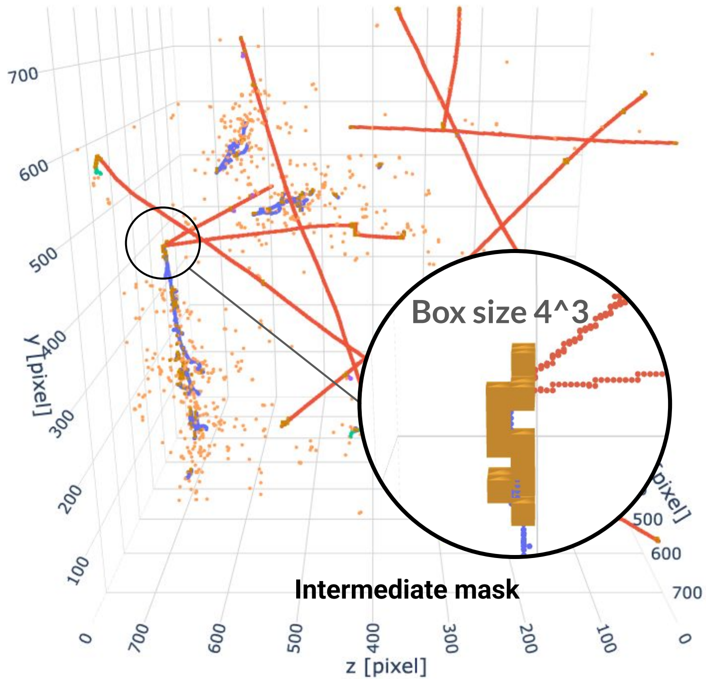


Paper: [PhysRevD.104.032004]   L. Dominé et al.

Intermediate masks

Mask out non-active voxels throughout the decoder





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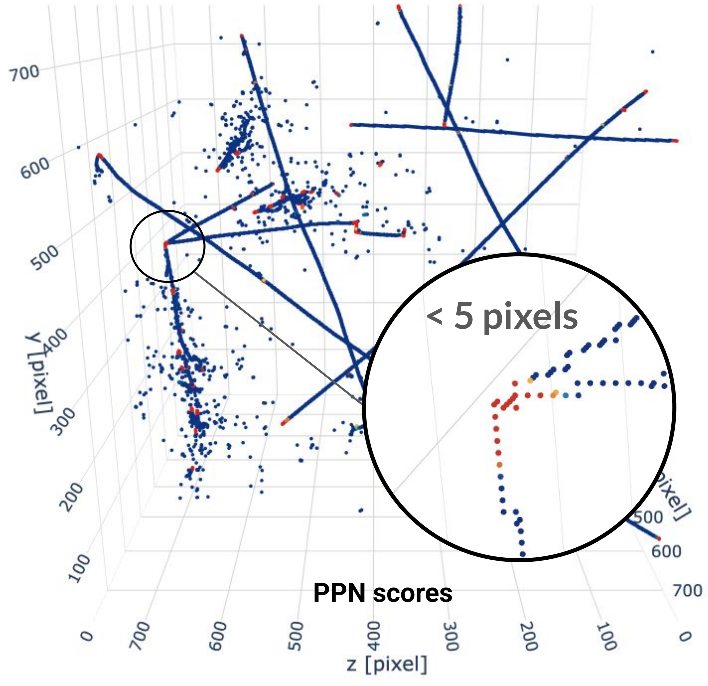
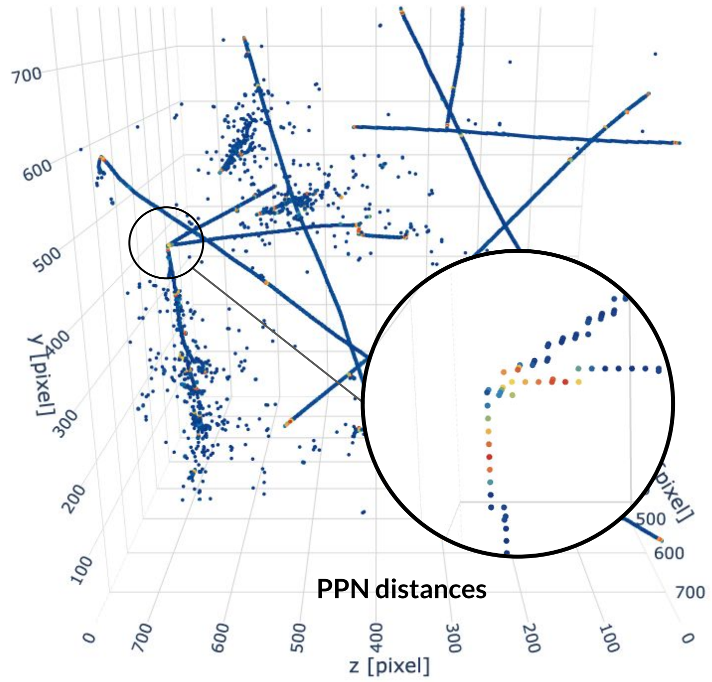
Last PPN layer

Predict positive **scores** and **proximity** to closest label





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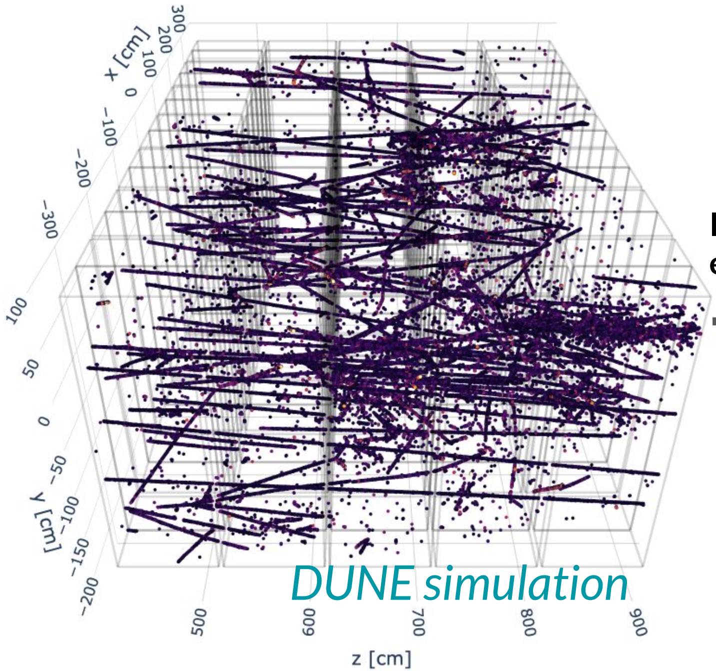
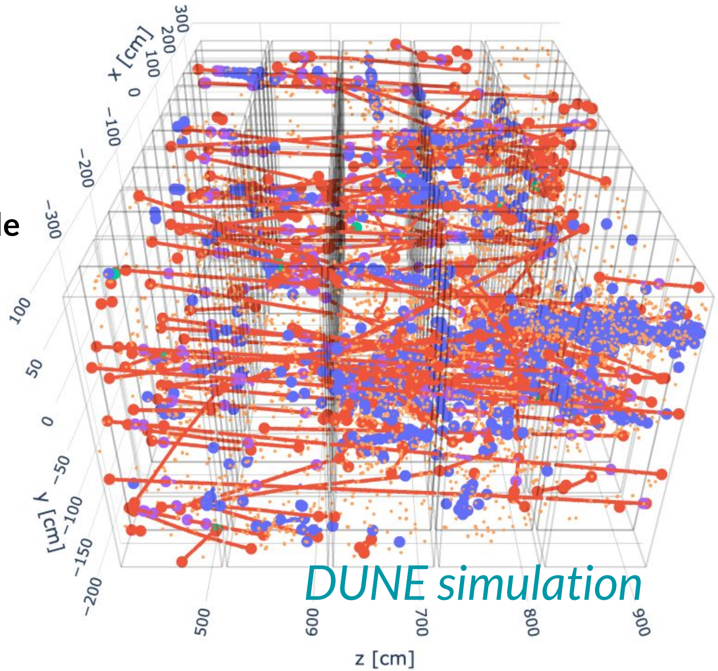
Points of Interest

Identify start points of showers and end points of tracks

- Tracks, Showers, delta rays, Michel electrons, low energy blips



Identify particle end points



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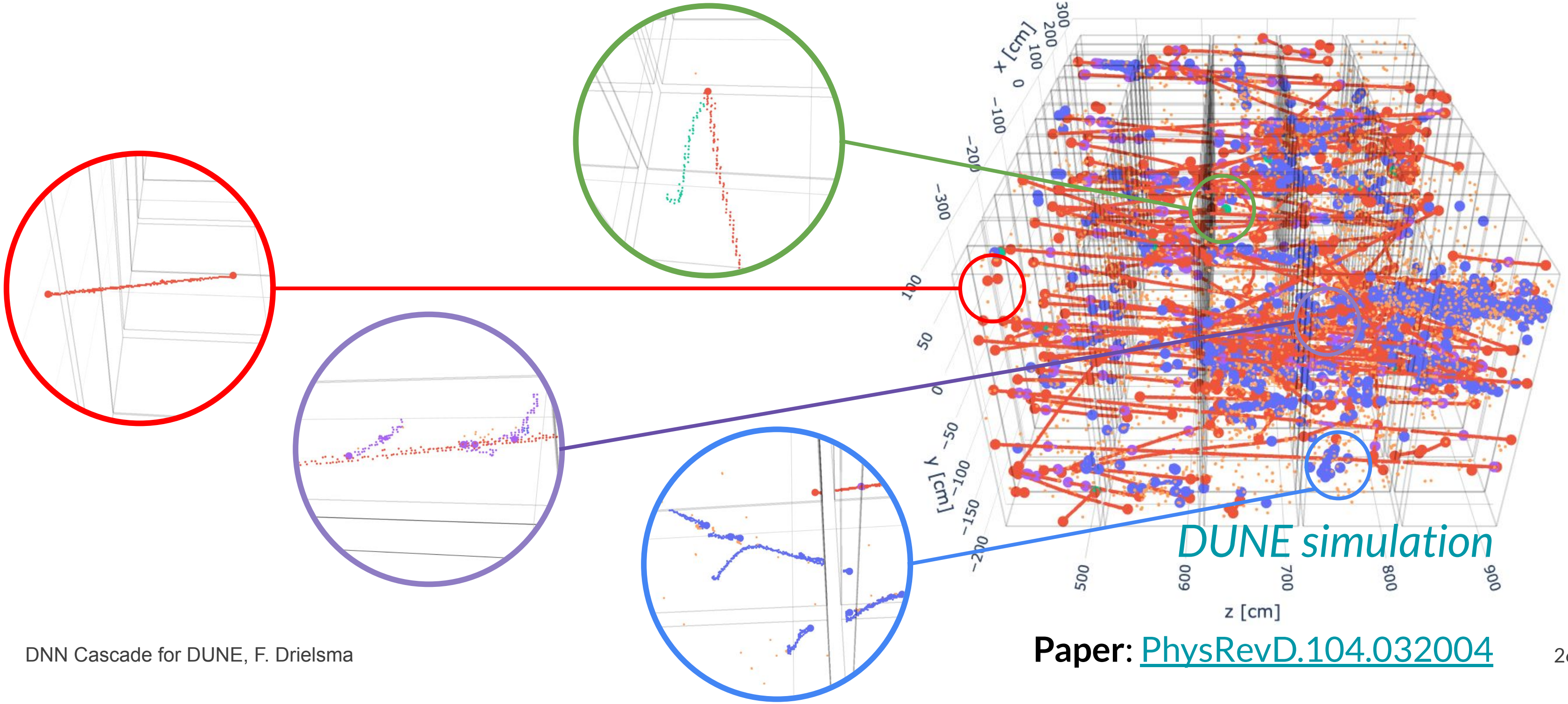

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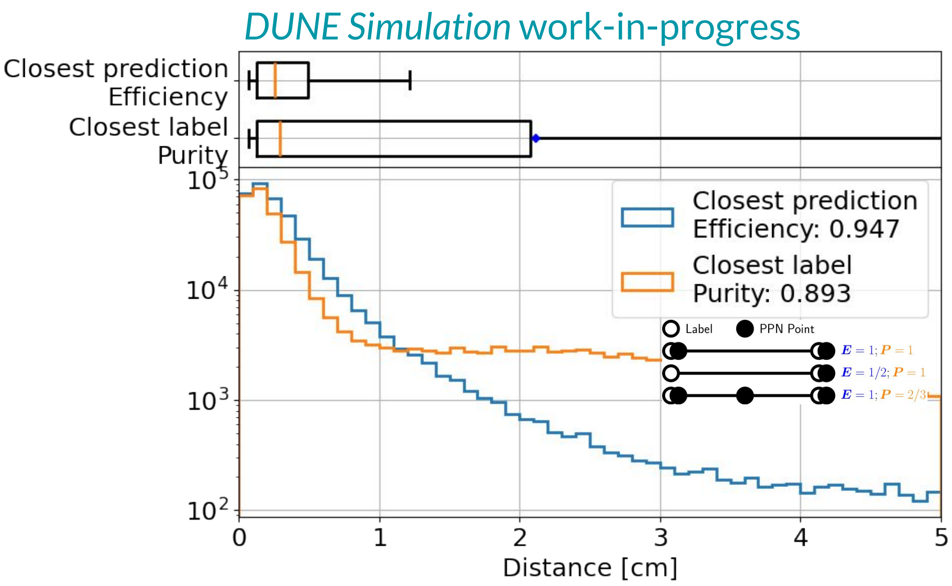
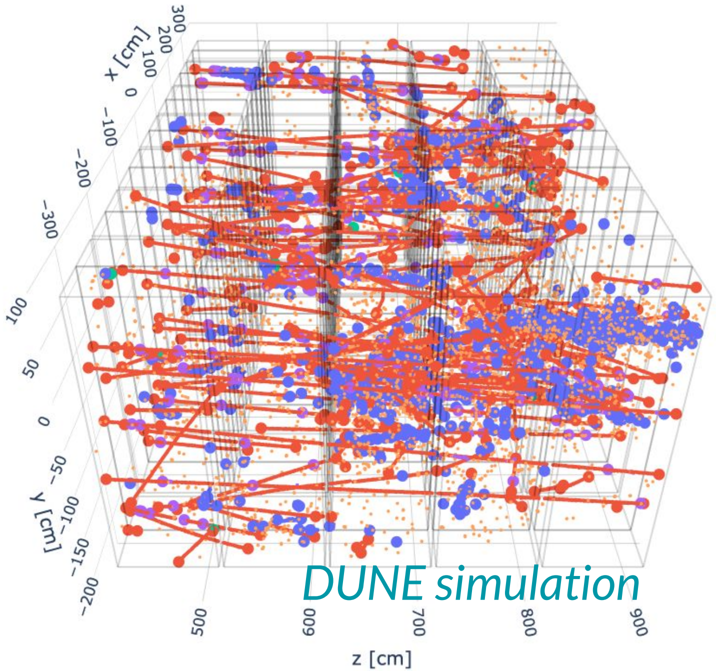
Points of Interest

Identify start points of showers and end points of tracks

- Point proposal very accurate, **median = 2.5 mm (pixel size = 3.7 mm)**





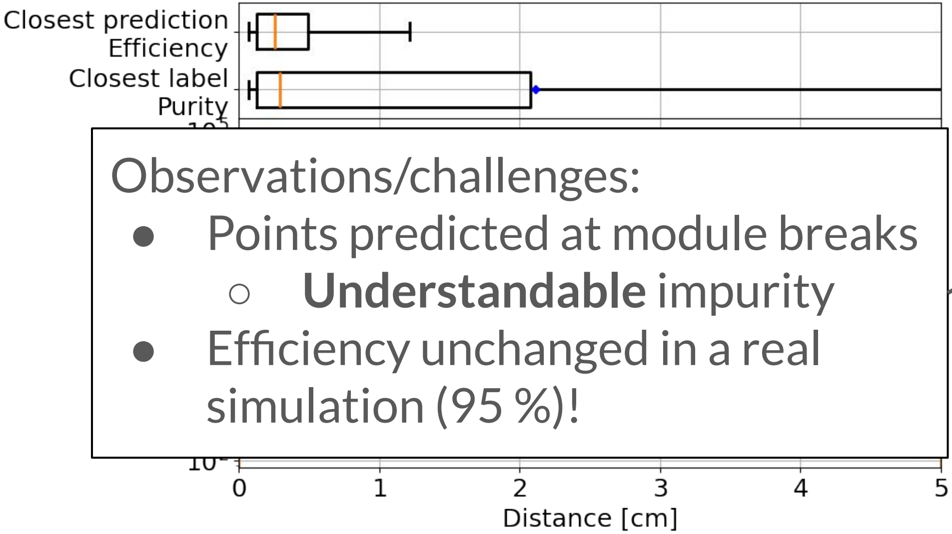
Paper: PhysRevD.104.032004

Points of Interest

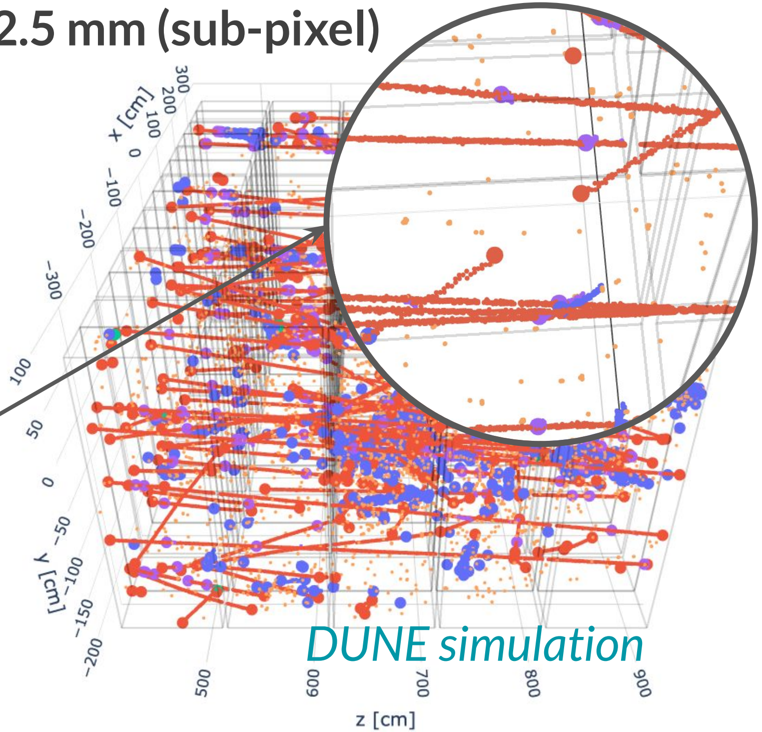
Identify start points of showers and end points of tracks

- Point proposal very accurate, **median = 2.5 mm (sub-pixel)**

DUNE Simulation work-in-progress



Observations/challenges:
- Points predicted at module breaks
  - **Understandable** impurity
- Efficiency unchanged in a real simulation (95 %)!



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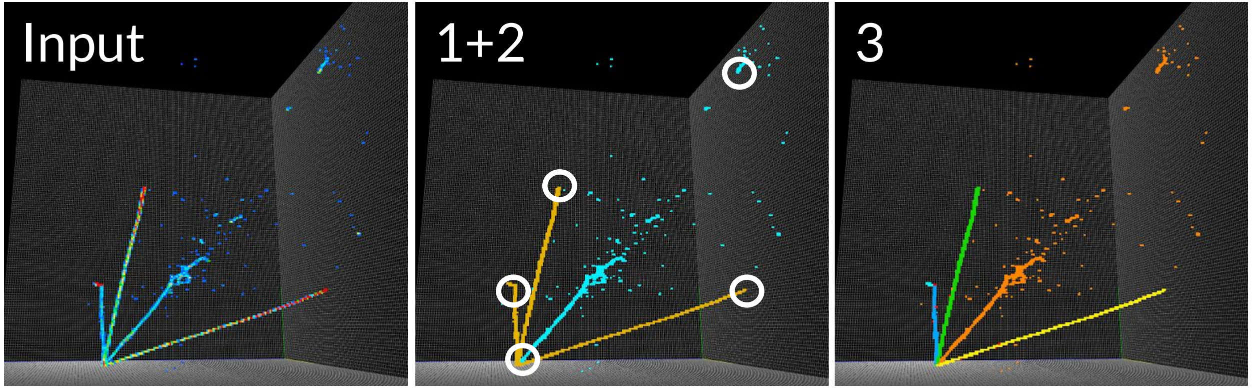
Physics-Informed ML Reconstruction

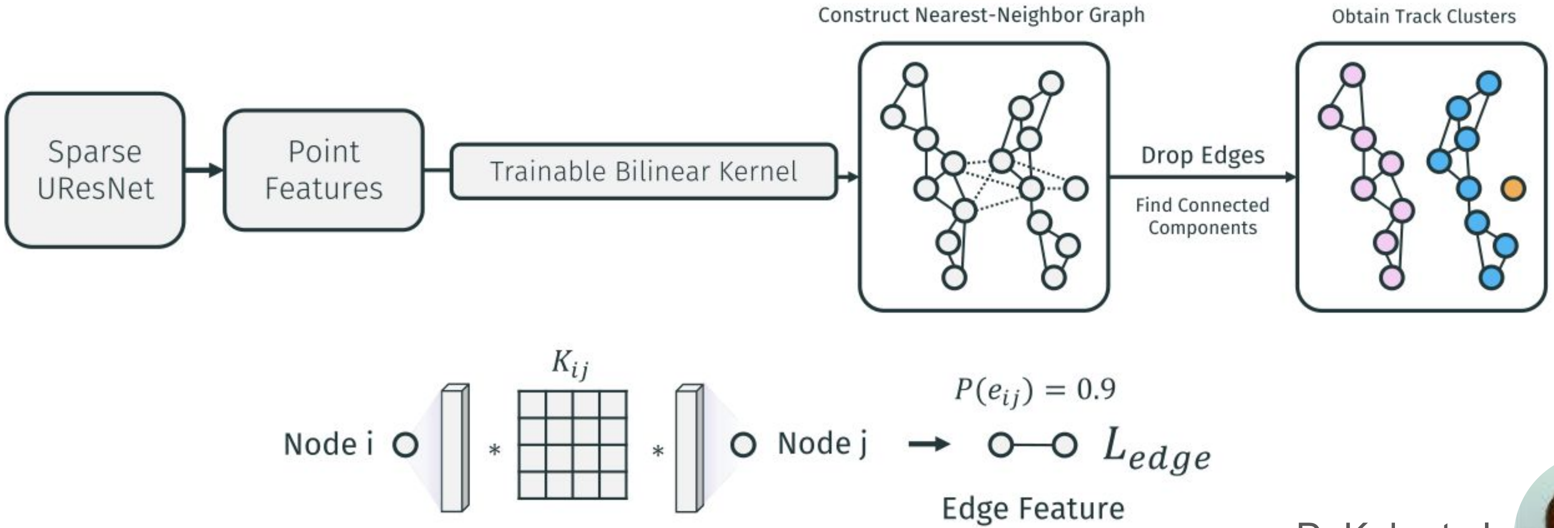
What is relevant to pattern recognition in a detailed interaction image?

1. Separate topologically distinguishable **types of activity**
2. Identify **important points** (vertex, start points, end points)
3. Cluster individual **particles** (tracks and full showers)



Supervised Connected Component Clustering

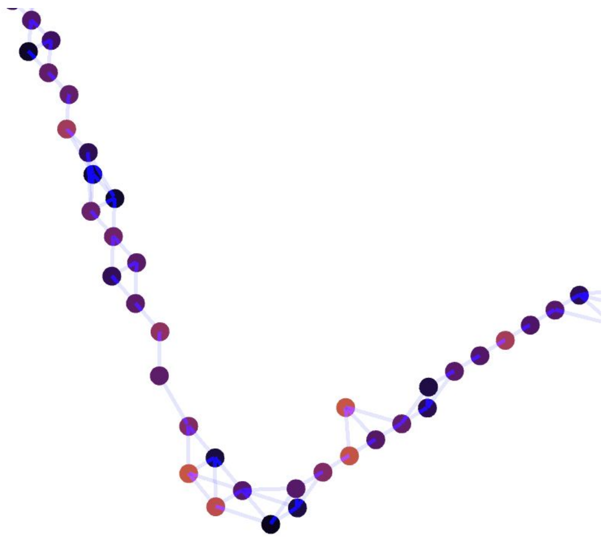
Learn a **smart** version of **DBSCAN** (connected components)



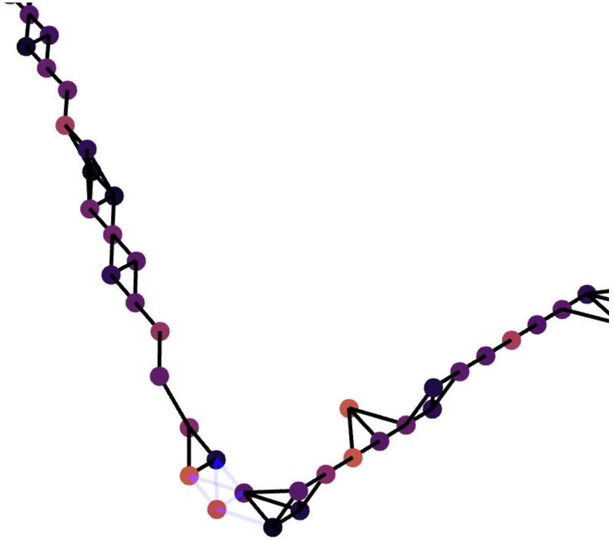
D. Koh et al.

Graph-SPICE

Let's take a look at what the edge selection process look like



Input graph on tracks



Selected edge on tracks

Paper: arXiv:2007.03083

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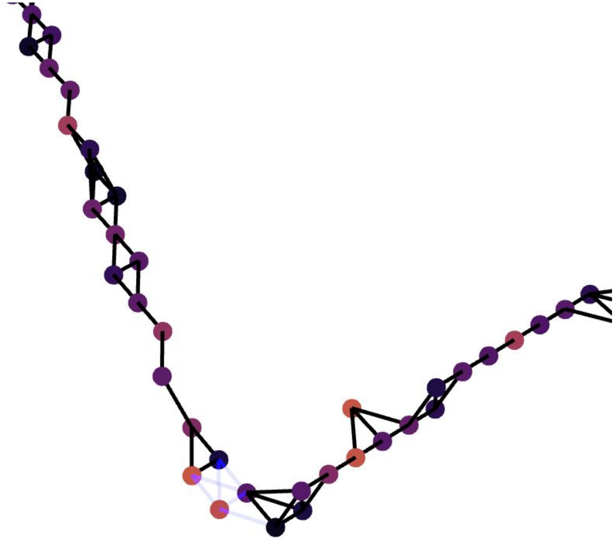

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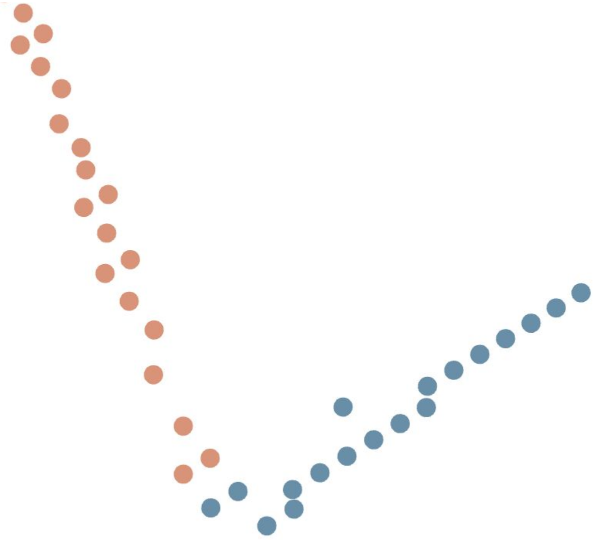


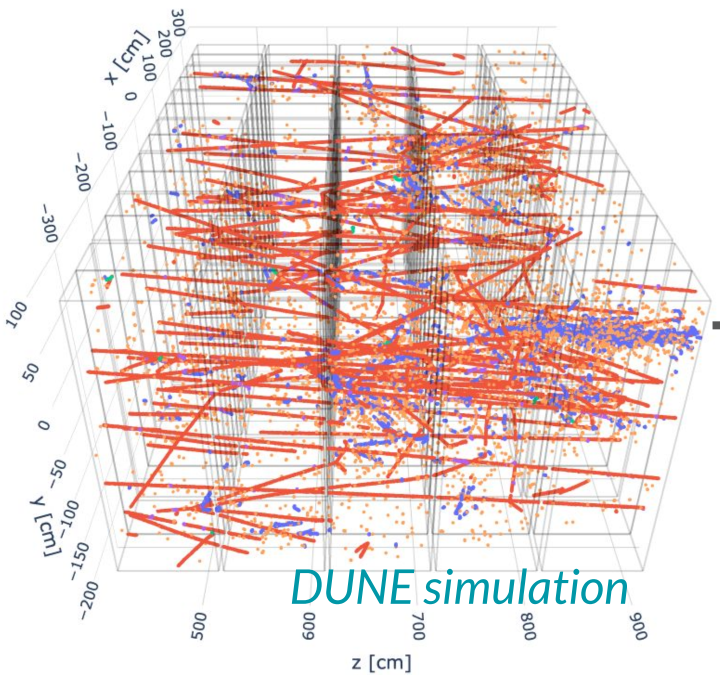
Connected components

Paper: arXiv:2007.03083

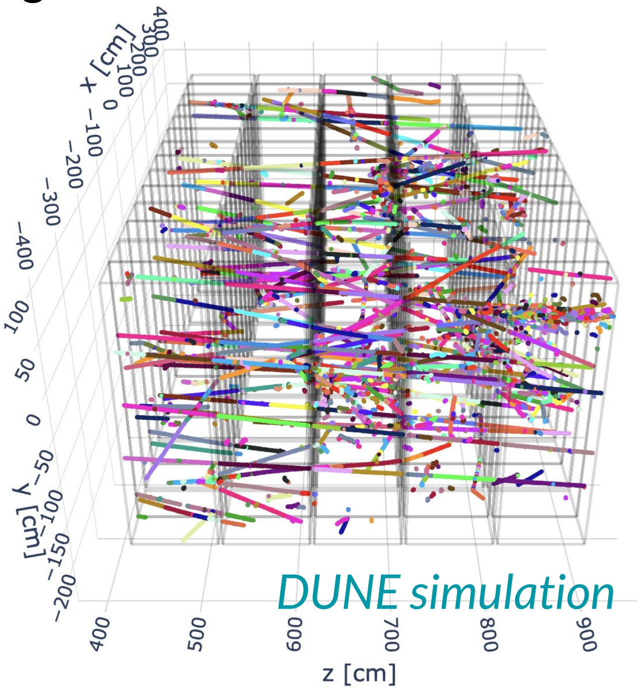
Dense Fragment Formation

Break track/shower fragment instances **where constituent pixels touch**

- Cluster track/shower **fragments** at this stage



Aggregate particles



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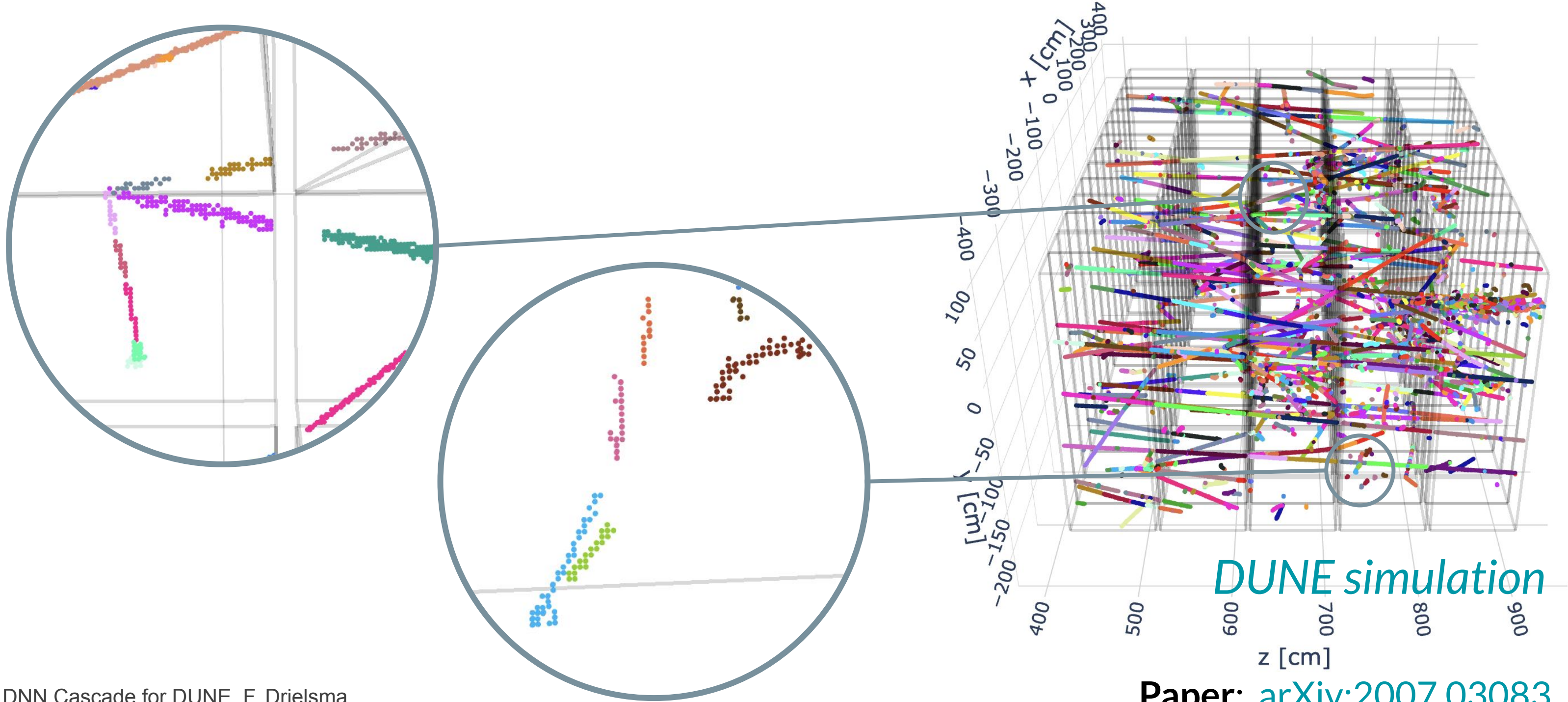
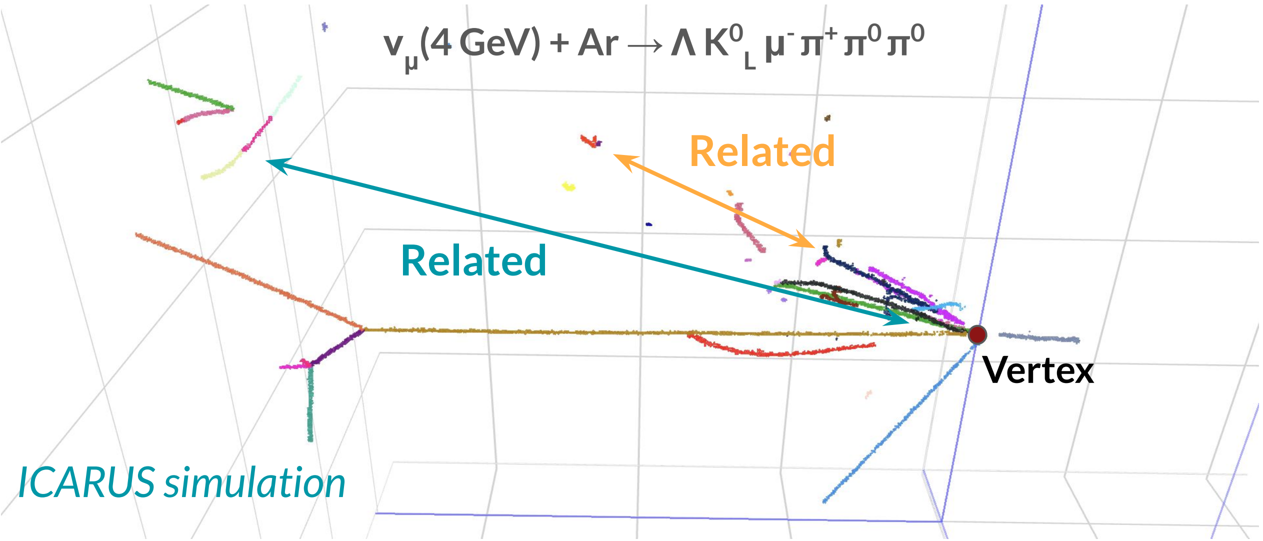


Paper: arXiv:2007.03083

Cluster-level feature extraction

CNN: mostly sensitive to **local neighborhood** of pixel, but…

- **EM showers**: photon mean free path in LAr = 18 cm (**50 pixels in DUNE-ND**)
- **Interactions**: π^0, K^0, Λ, neutrons



Cluster-level feature extraction

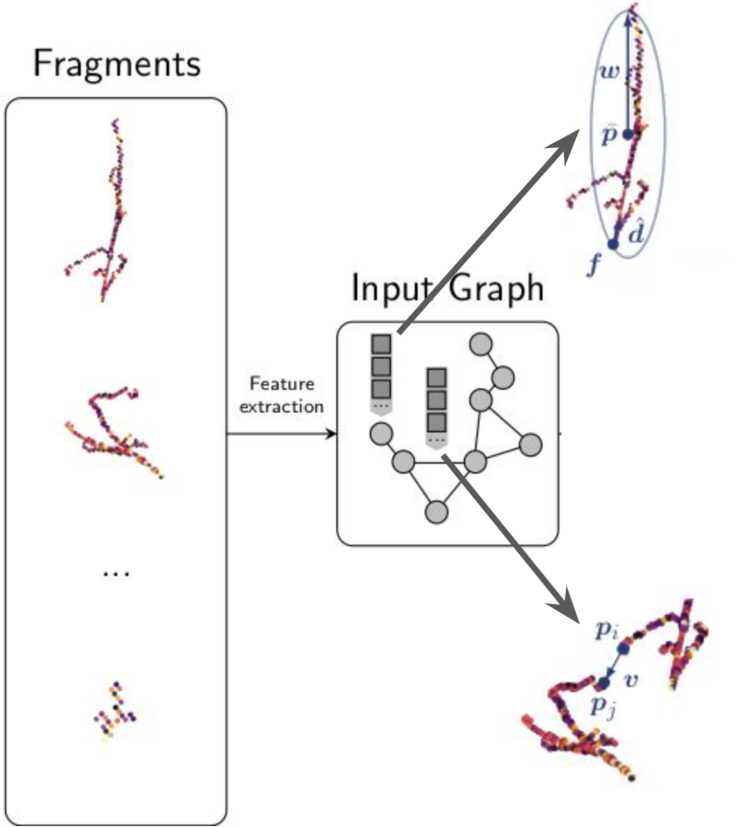
We now represent the set of fragments as a **set of nodes in a graph** where **edges represent correlations**

Node features:

- Centroid
- Covariance matrix
- Start point/direction
- . . .

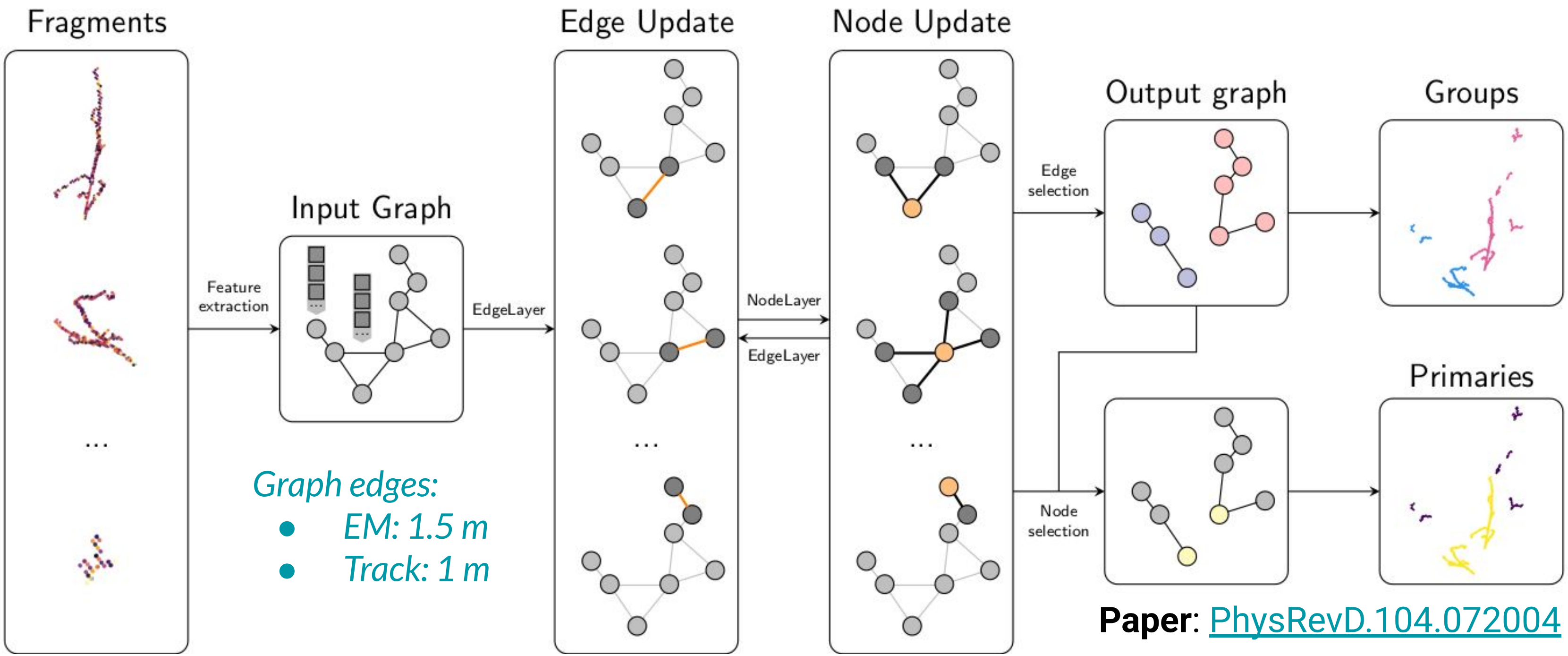
Edge features:

- Displacement vector
- . . .



Graph Particle Aggregator (GrapPA)

Graph Neural Network: develop features useful to node/edge classification



Graph edges:
- *EM: 1.5 m*
- *Track: 1 m*

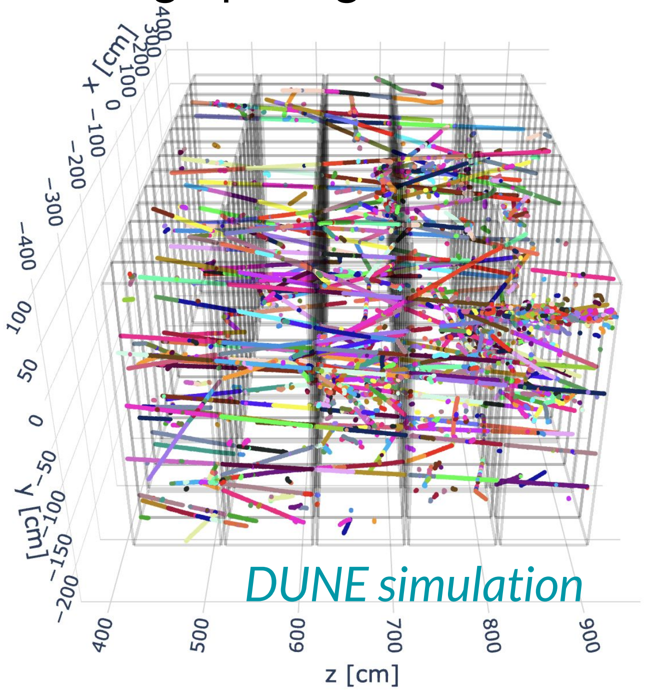
3 layers of message passing (MetaLayer with MLP)

Paper: PhysRevD.104.072004

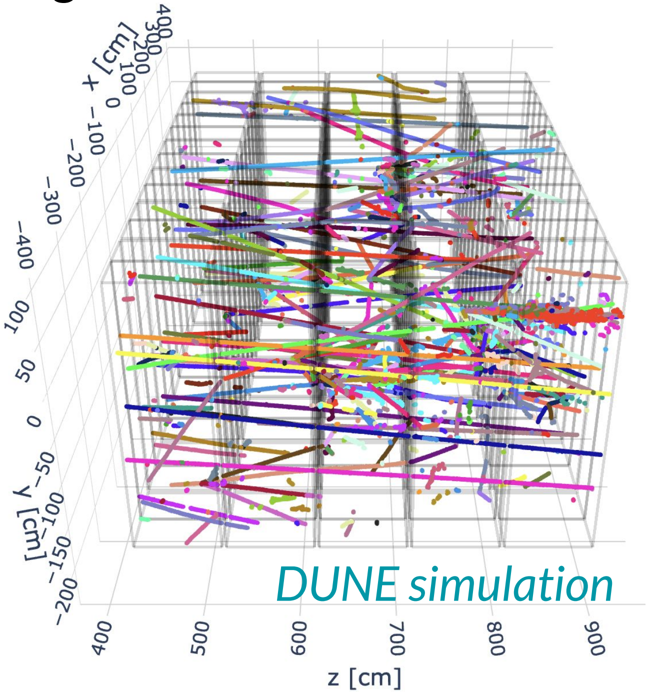
Particle Aggregation

Aggregate track/shower space points into **particles**

- Find graph edges that **connect fragments together**



Aggregate particles →



Paper: PhysRevD.104.072004

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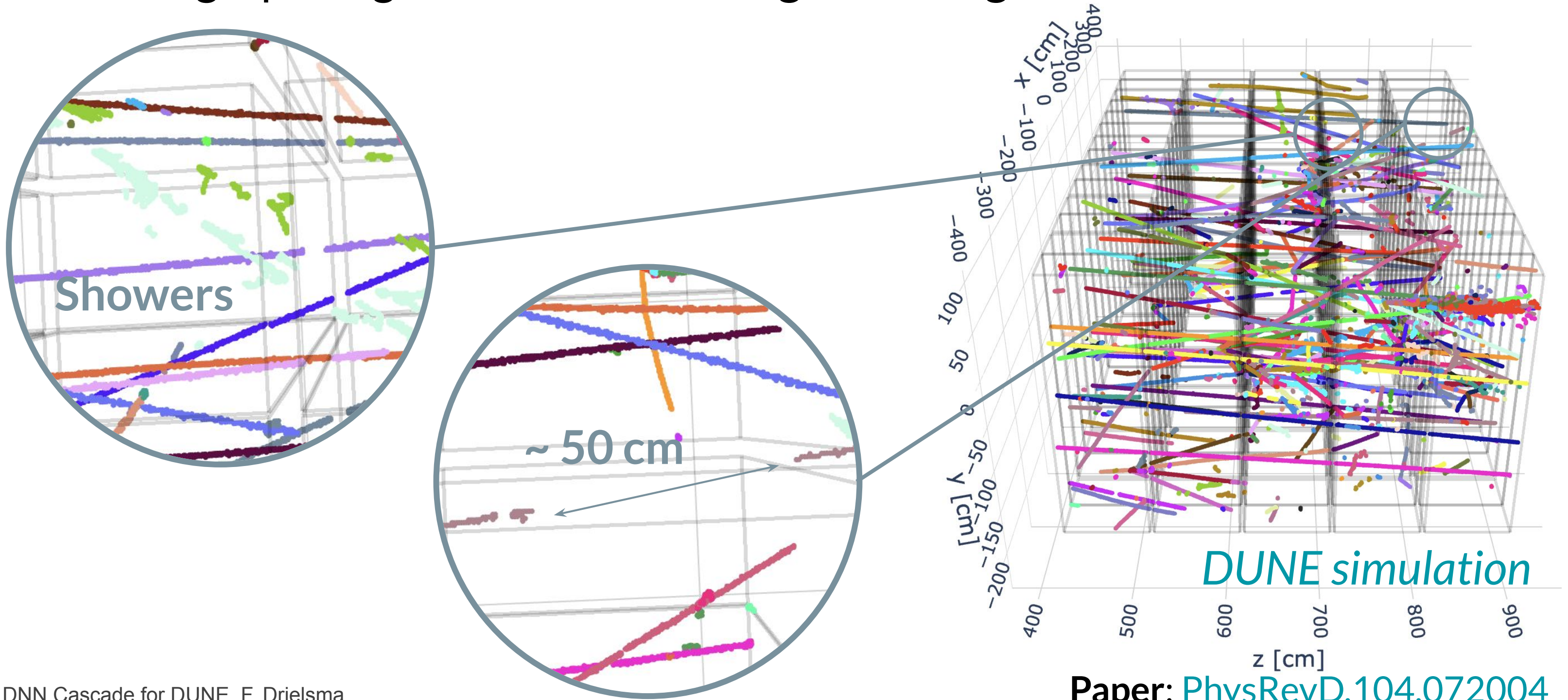

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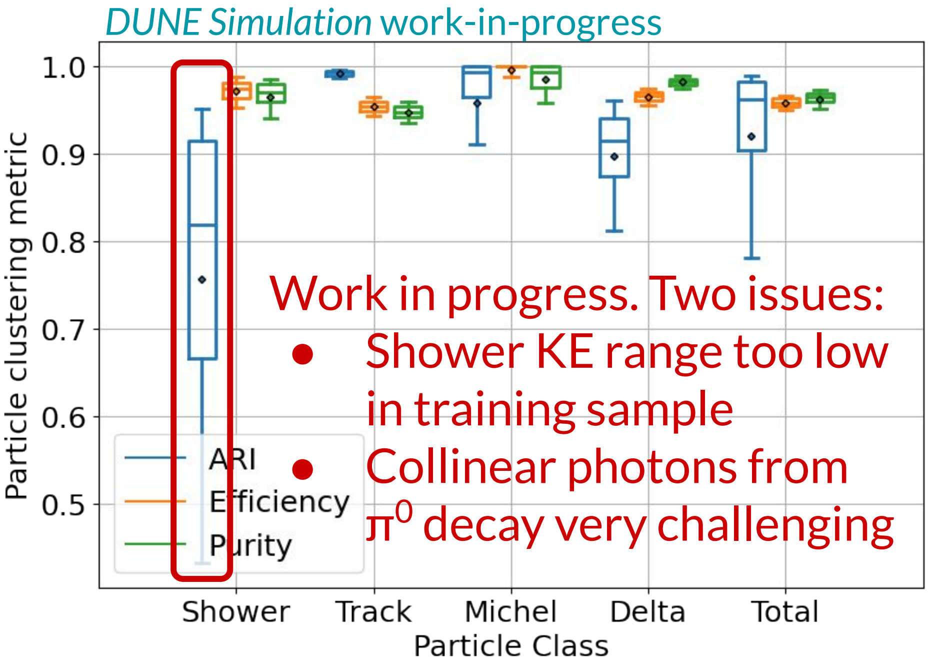
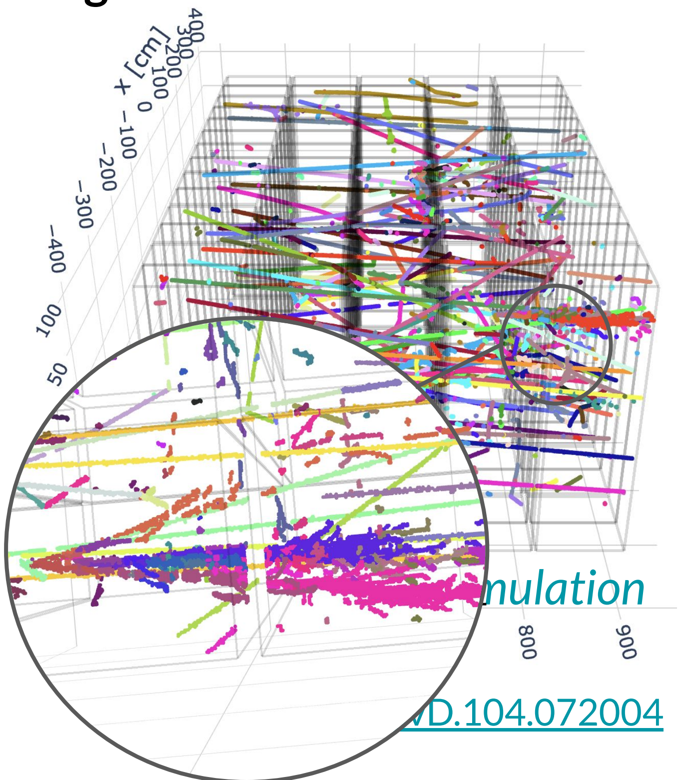


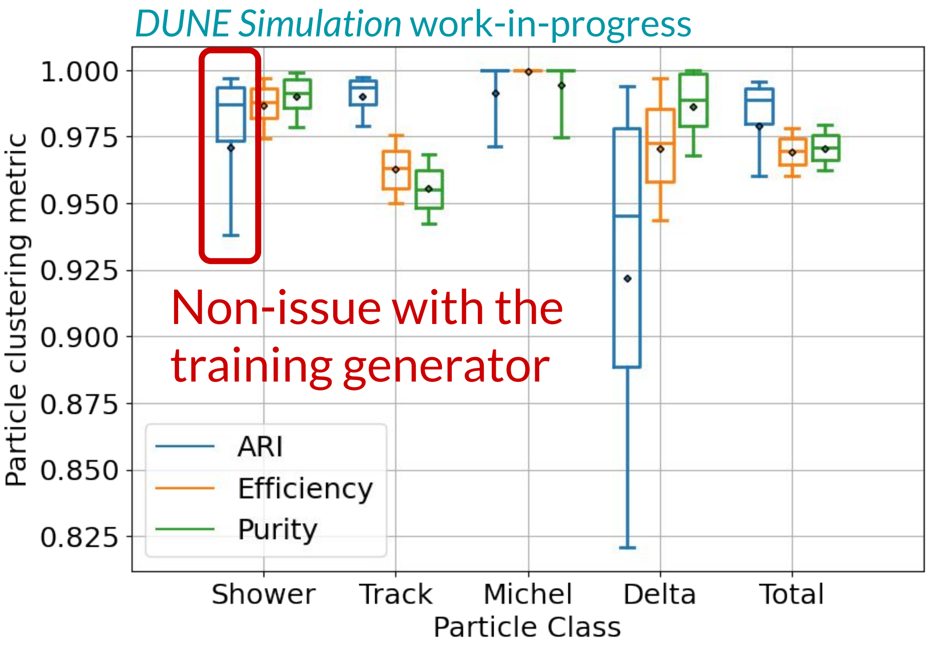


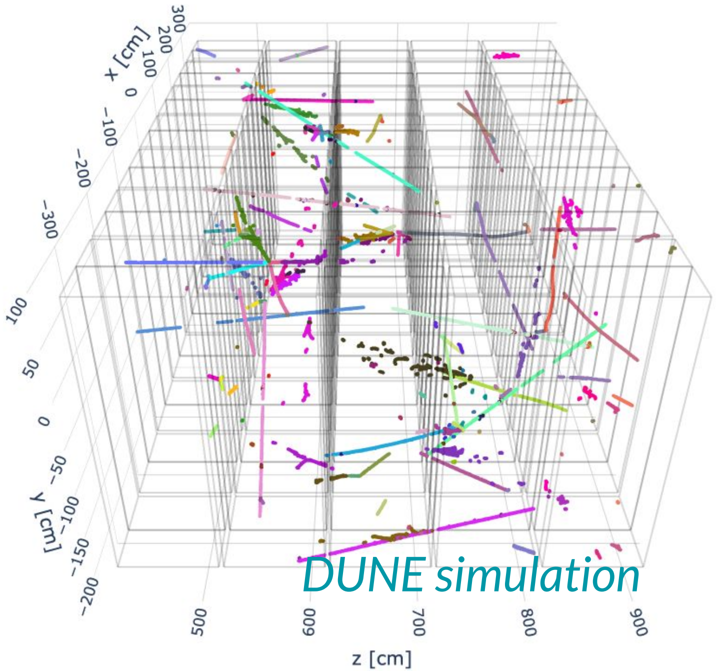
D.104.072004

Particle Aggregation

Aggregate track/shower space points into **particles**

- Find graph edges that **connect fragments together**



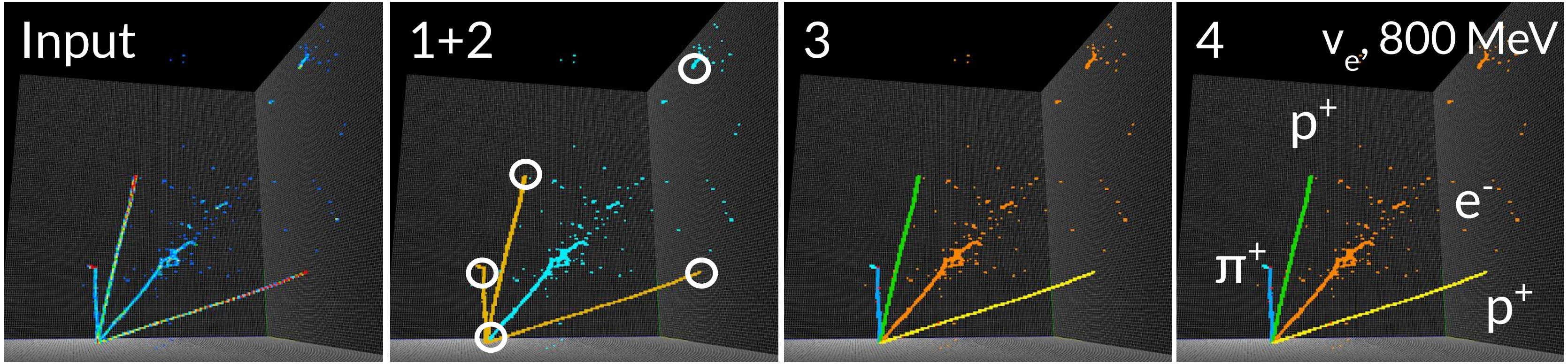


Paper: PhysRevD.104.072004

Physics-Informed ML Reconstruction

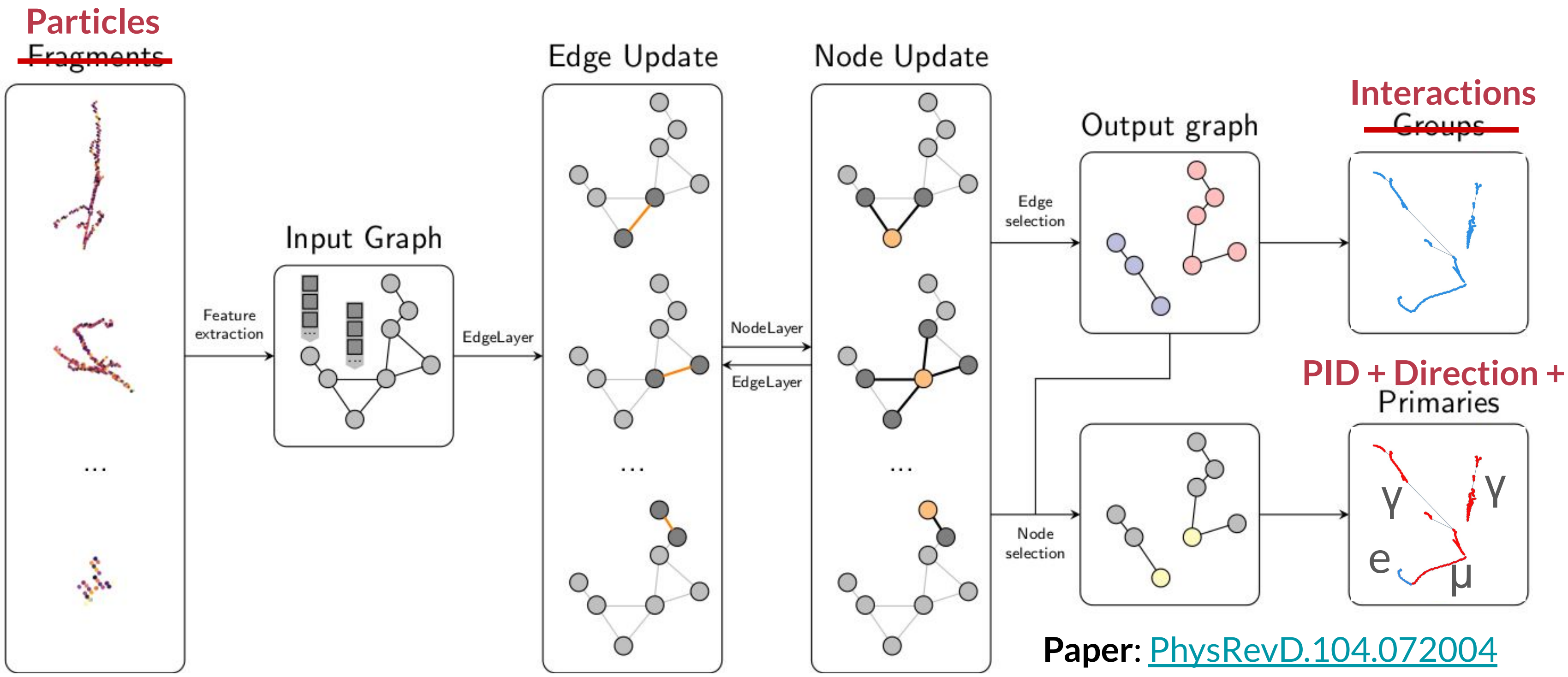
What is relevant to pattern recognition in a detailed interaction image?

1. Separate topologically distinguishable **types of activity**
2. Identify **important points** (vertex, start points, end points)
3. Cluster individual **particles** (tracks and full showers)
4. Cluster **interactions**, identify **particle properties** in context



Cluster-level feature extraction

Graph Neural Network: develop features useful to node/edge classification

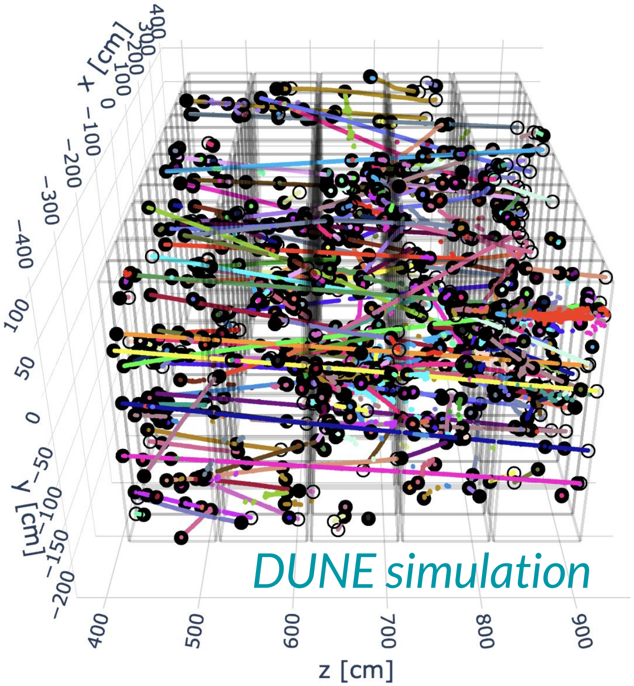


Paper: PhysRevD.104.072004

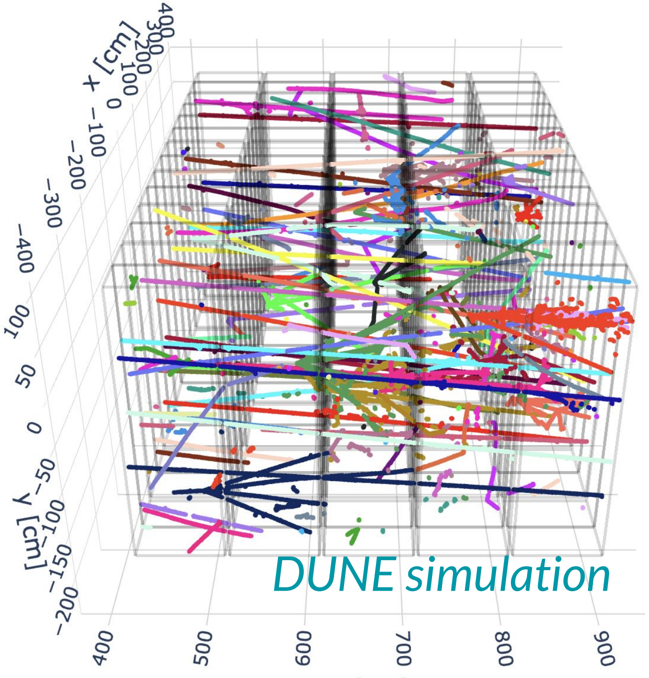
Interaction Aggregation

Aggregate track/shower instances into **interactions**

- Find graph edges that connect **particles that belong together**



Aggregate particles



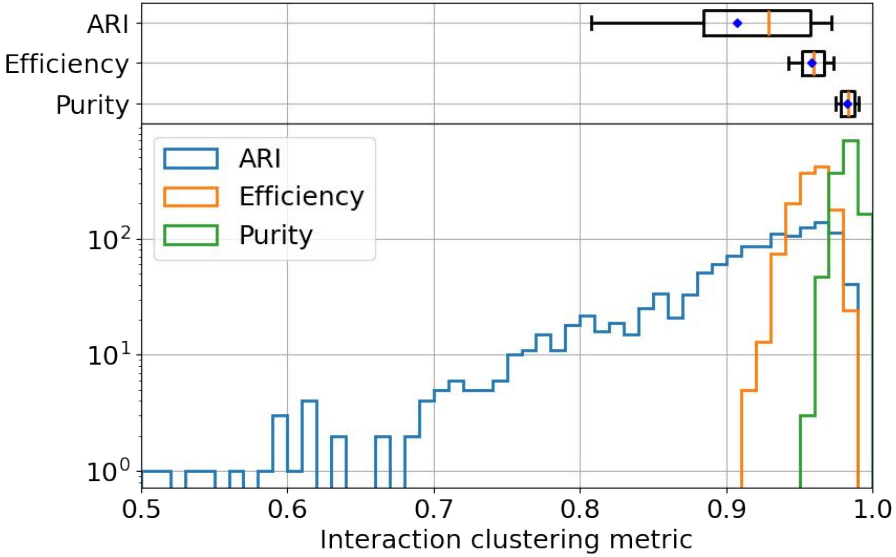
Paper: [PhysRevD.104.072004]

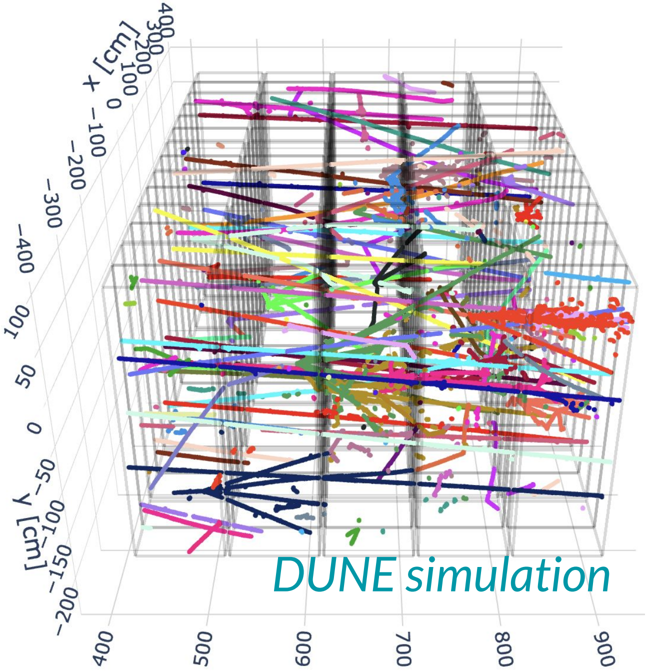
Interaction Aggregation

Aggregate track/shower instances into **interactions**

- Find graph edges that connect **particles that belong together**

DUNE Simulation work-in-progress



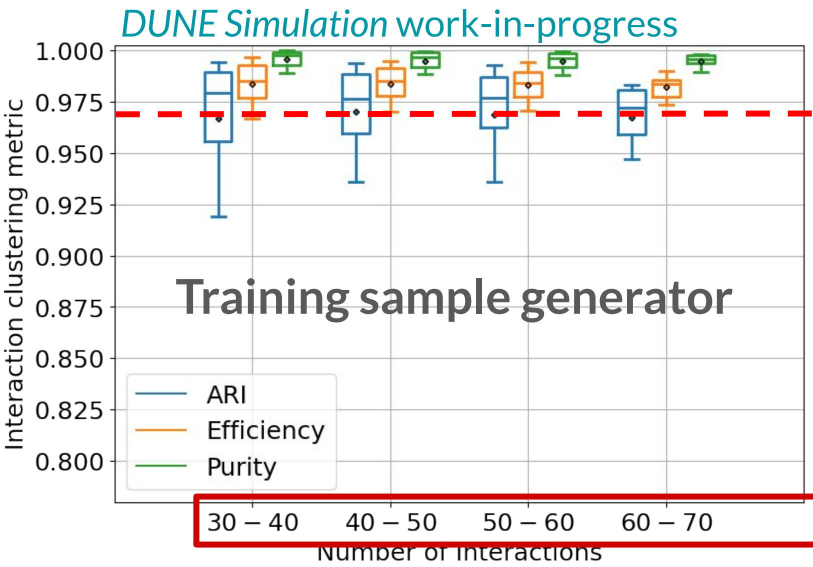


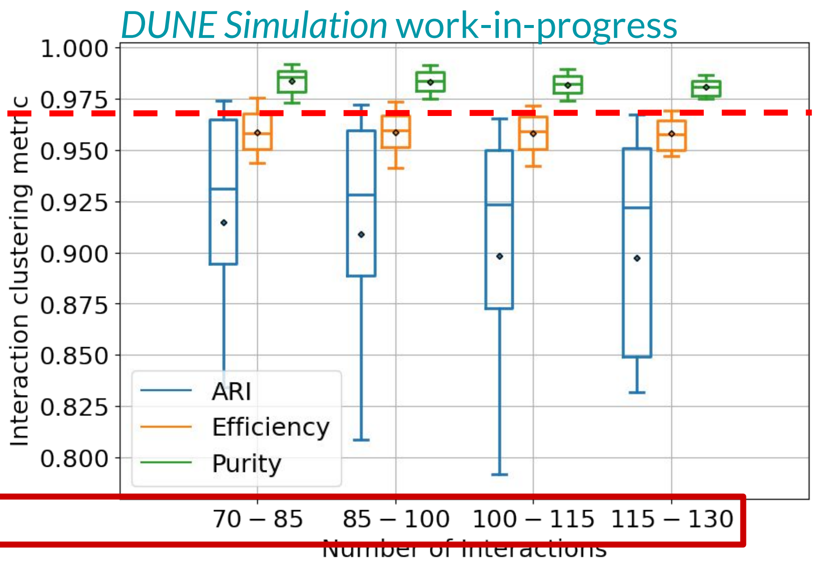
Paper: PhysRevD.104.072004

Interaction Aggregation

Aggregate track/shower instances into **interactions**

- Find graph edges that connect **particles that belong together**
- **Close to meeting 97 % DUNE efficiency requirements out of the box!**

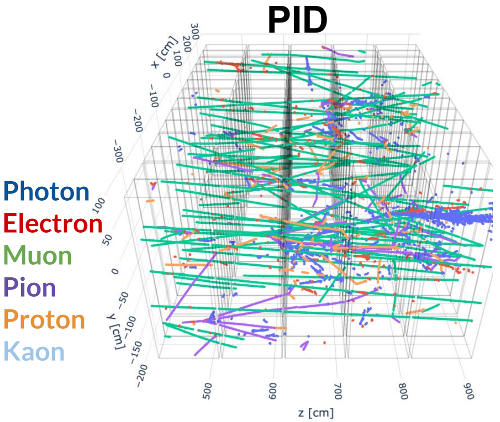


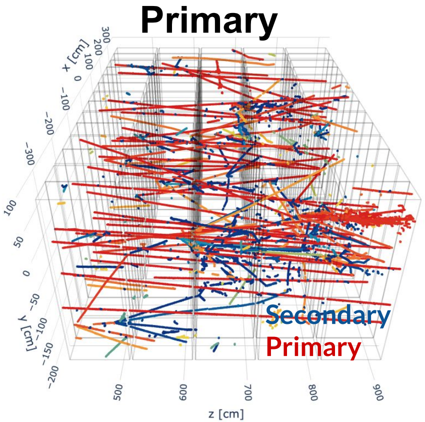


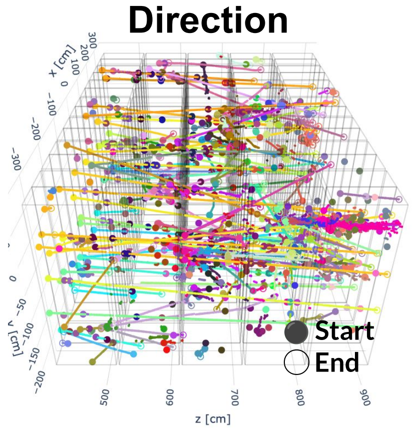
Paper: PhysRevD.104.072004

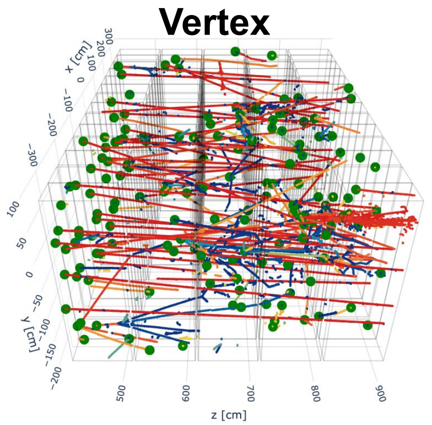
Interaction Node Tasks Overview

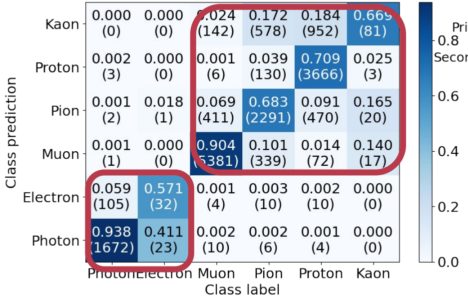
No time for detail, but GrapPA provides a **slew of node-level predictions**

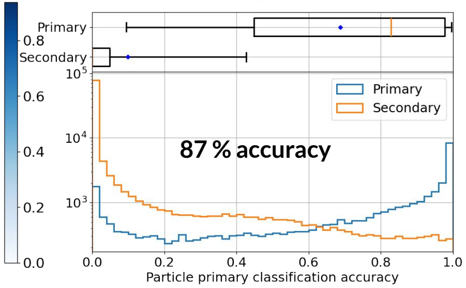


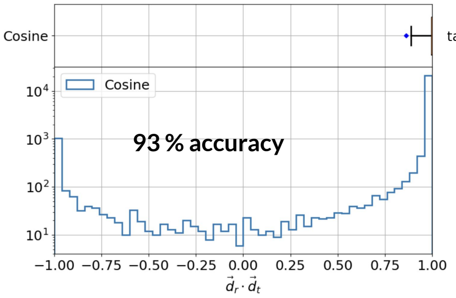


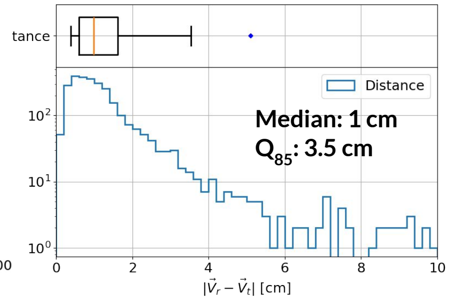










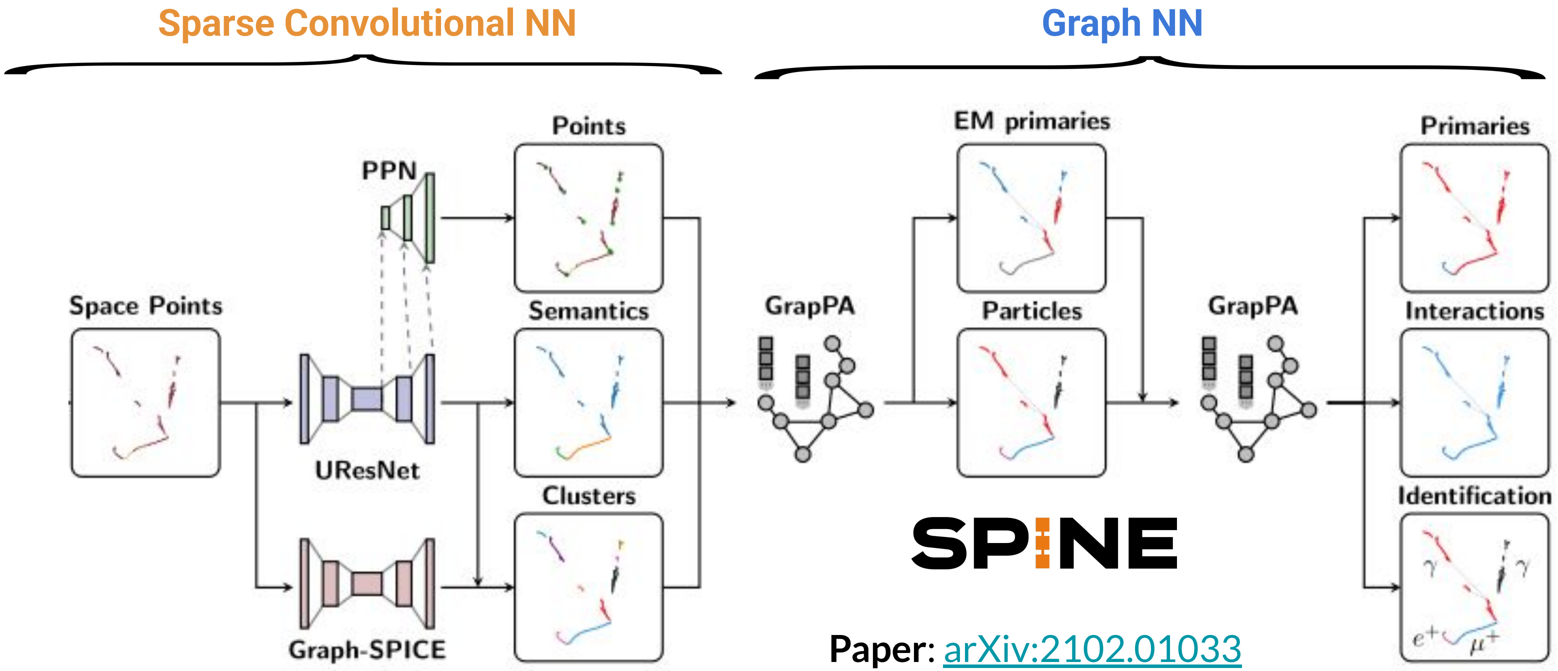


Metrics evaluated for fiducial interactions

Reconstruction in LArTPCs

Scalable Particle Imaging with Neural Embeddings (SPINE)

- **Sparse CNN** for pixel-level features, **GrapPA** for superstructure formation

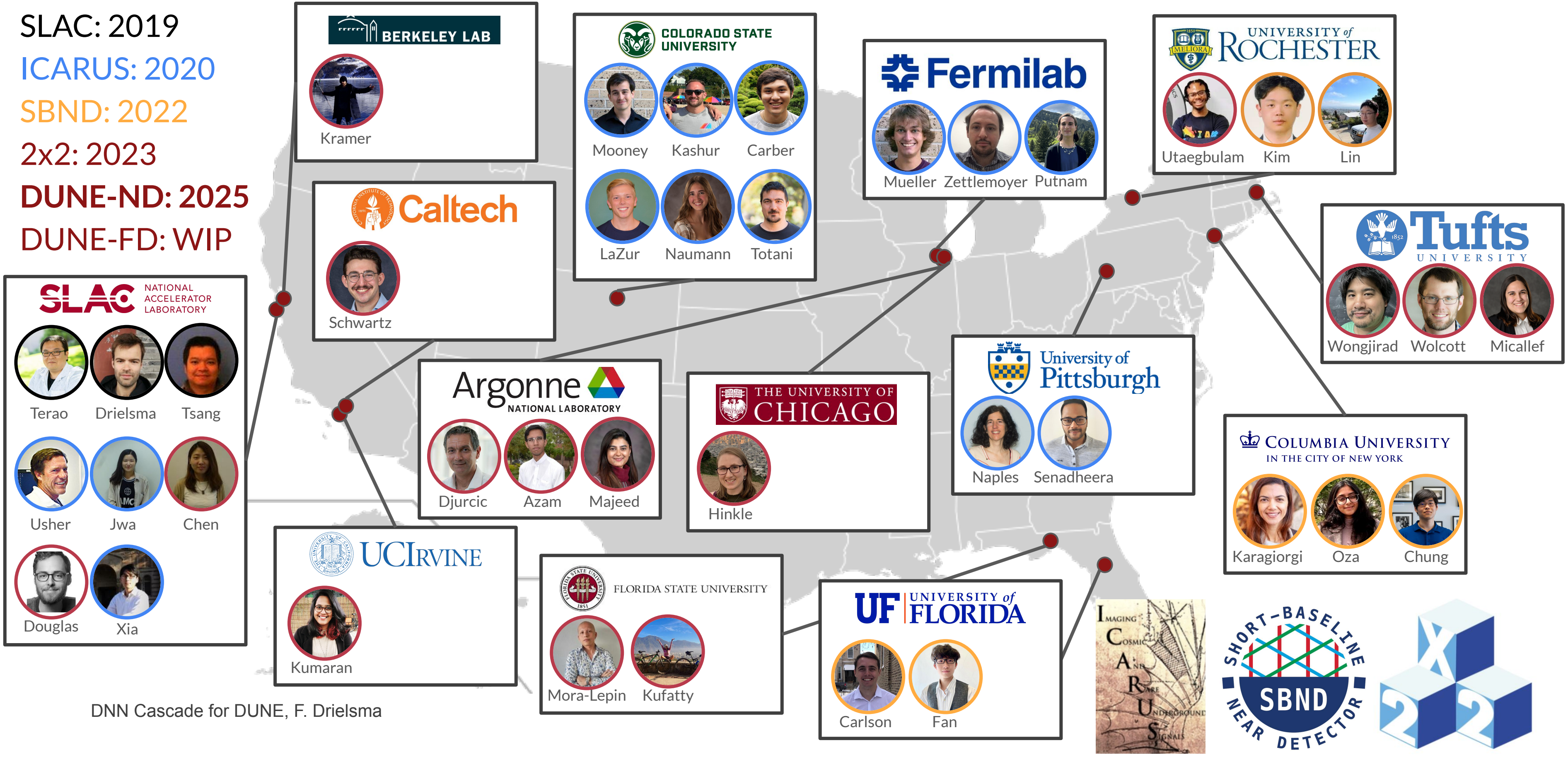


Paper: [arXiv:2102.01033]

SPINE “Network”

SLAC NATIONAL ACCELERATOR LABORATORY

SLAC: 2019
ICARUS: 2020
SBND: 2022
2x2: 2023
DUNE-ND: 2025
DUNE-FD: WIP



SPINE Talks at This Conference!

SLAC: 2019
ICARUS: 2020
SBND: 2022
2x2: 2023
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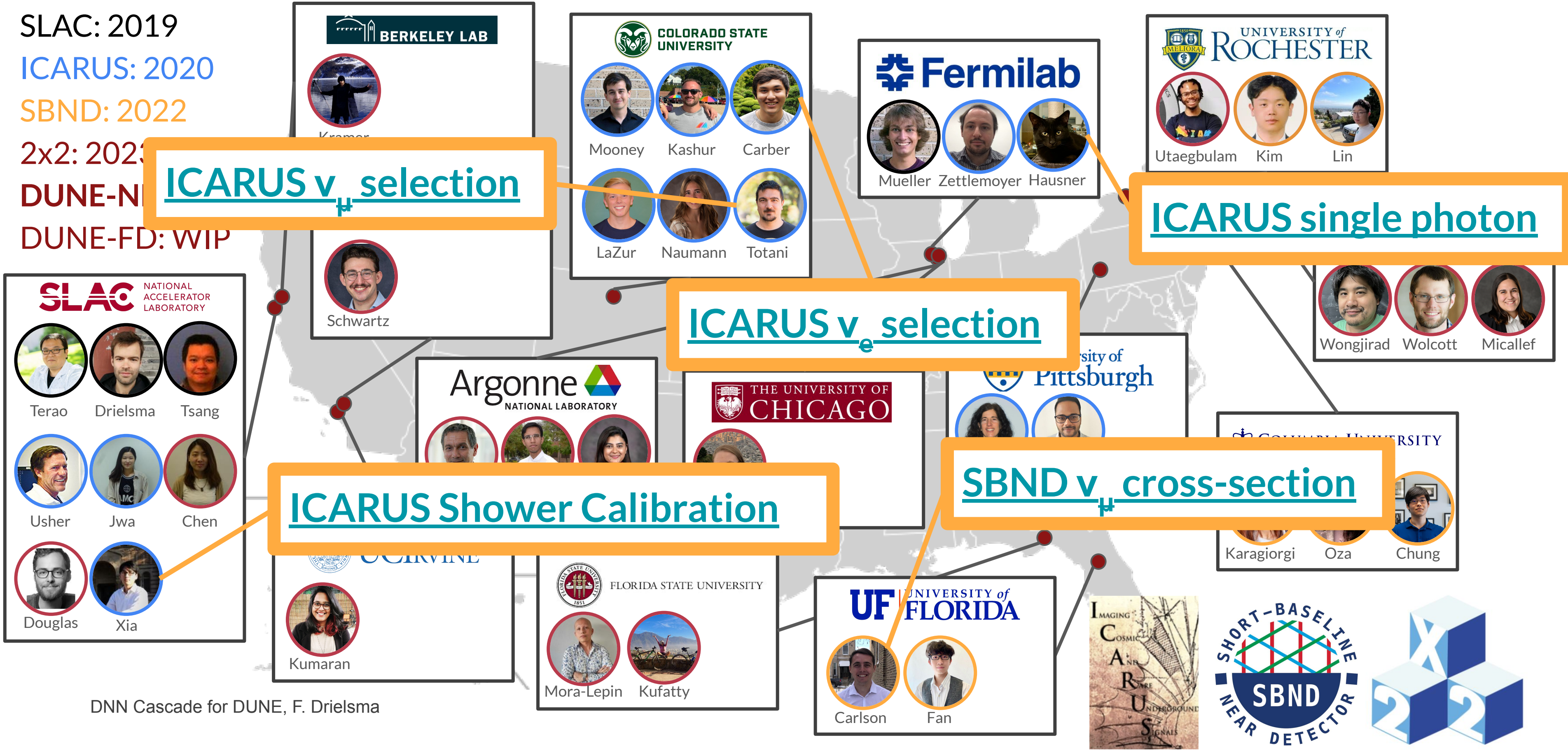
DUNE-FD: WIP



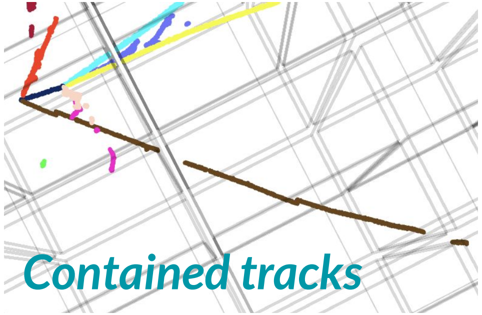
ND-LAr Energy Reconstruction

Three **particle-level** reconstruction strategies on offer

Range-based (CSDA)

Continuously slowing down approximation:

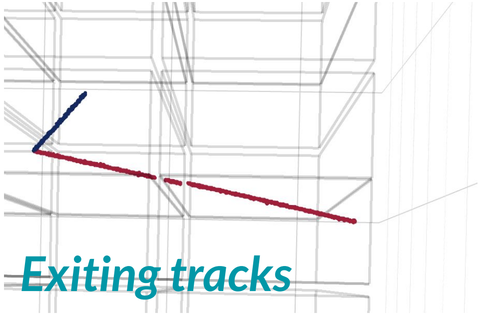
- Measure range
- Assume <dE/dx>, given PID hypothesis



Scattering-based (MCS)

Multiple Coulomb Scattering approach:

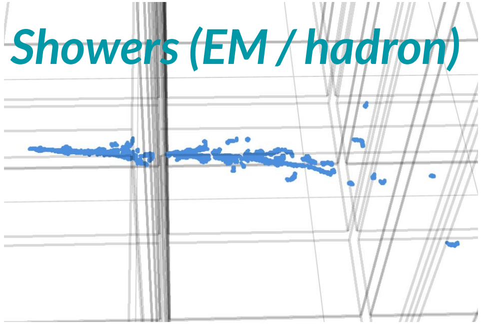
- Measure angles
- Optimize KE based on observed angles



Calorimetry

Calorimetry:

- Apply corrections (recomb, lifetime, ...)
- Estimate KE by summing all visible Q

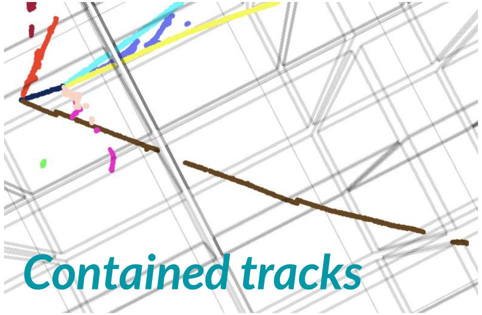


ND-LAr Specific Challenges

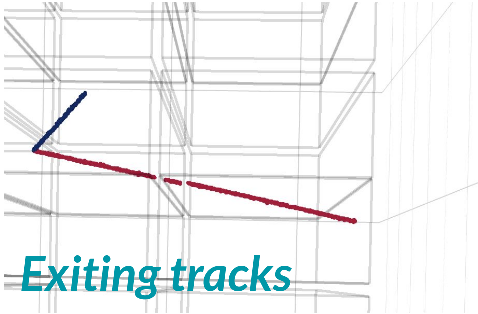
At DUNE energies in a 5 m deep detector, multiple difficulties:

- Muons are very rarely contained and MCS breaks down at high energies
    - Downstream spectrometer used to estimate it, see Jessie's talk right after!
- EM showers are not always fully contained + go through dead volume

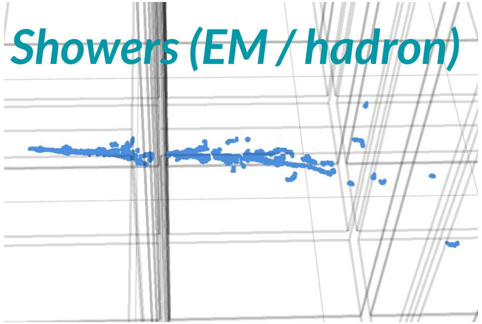
Range-based (CSDA)



Scattering-based (MCS)



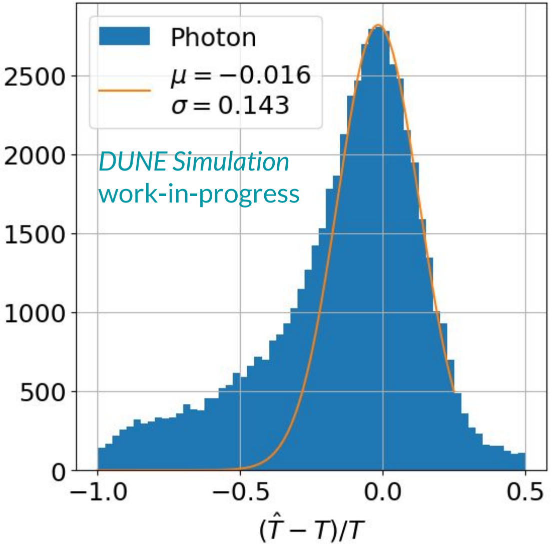
Calorimetry

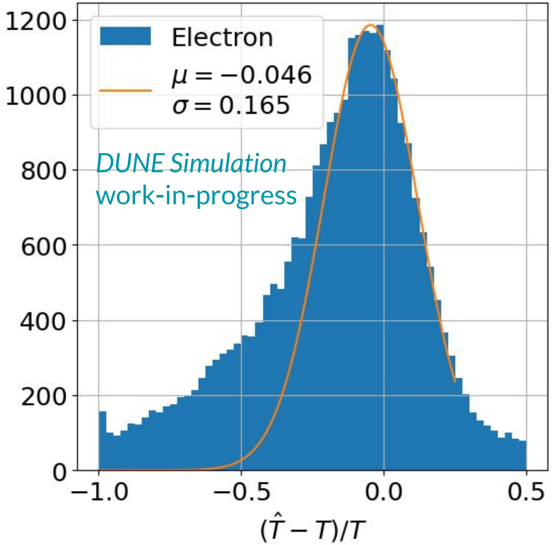


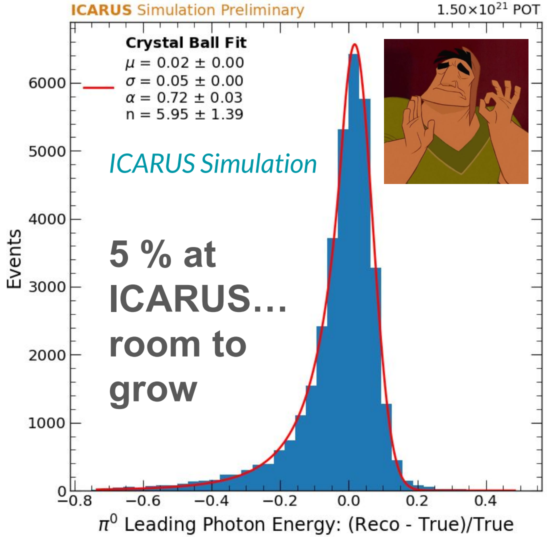
EM Shower Energy Reconstruction

EM Shower reconstructions strategy:

- **Calorimetry** (pixel charge sum)
  - In roughly the right place, modulo **issues with containment/overclustering**
  - **Broad peak** (~15 %) **+ bias due to dead material** (~5 % electron showers)







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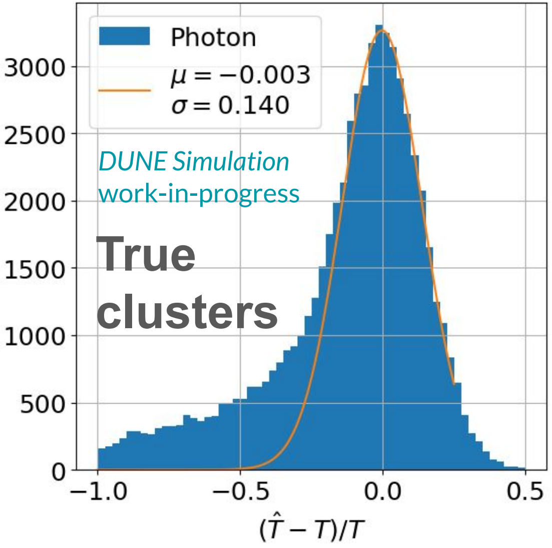
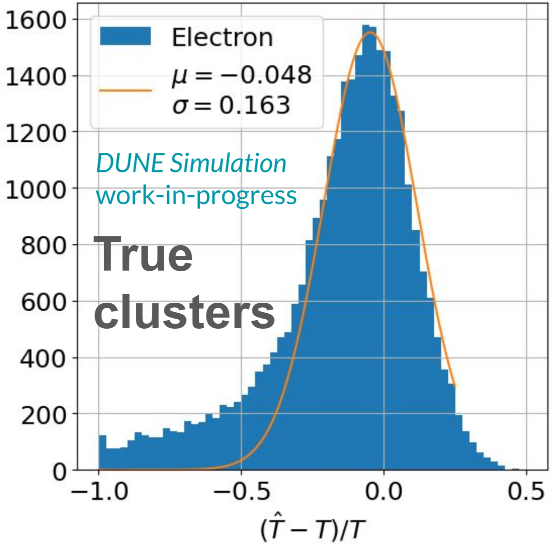
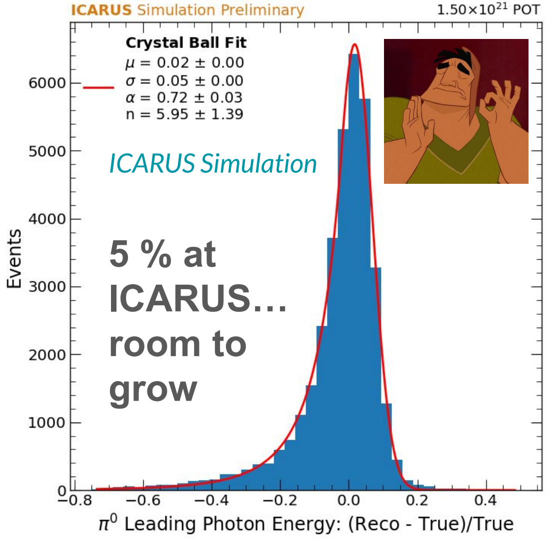


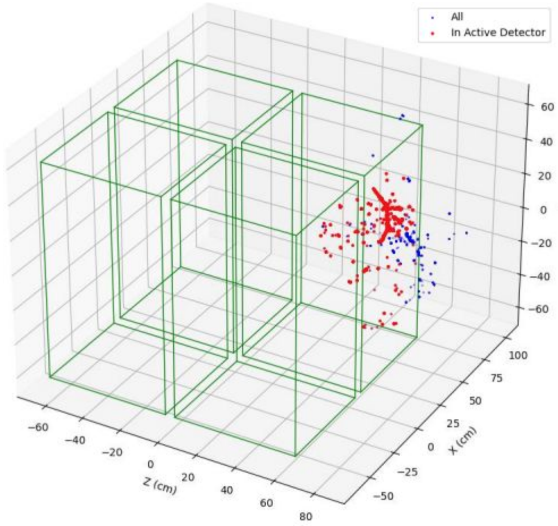


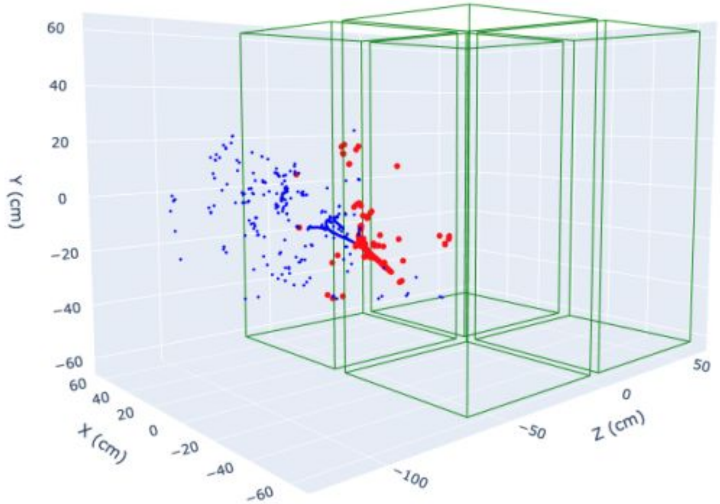


ML-based shower energy regression (E. Hinkle)

Simplified **test case at 2x2 (harder)** described here:

- Generate single e$^{+/-}$ in an "infinite" volume of LAr with **edep-sim**
- Loop over e$^{+/-}$, **randomize start point/direction in 2x2 geometry**





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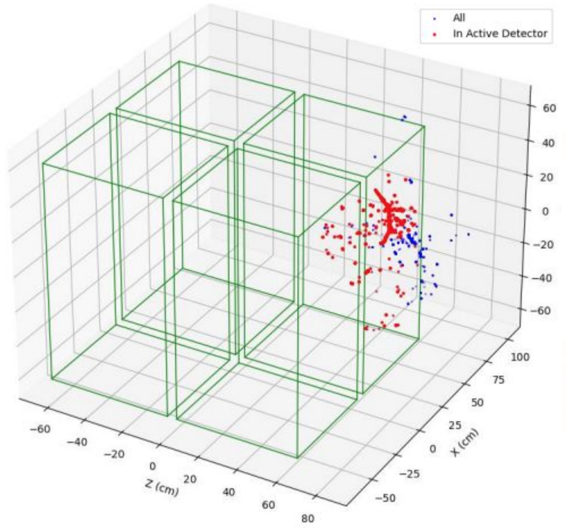
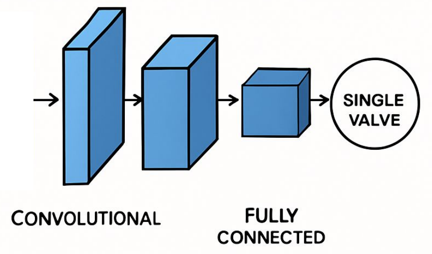
- Generate single $e^{+/-}$ in an "infinite" volume of LAr with **edep-sim**
- Loop over $e^{+/-}$, **randomize start point/direction in 2x2 geometry**
- Input the **visible points** into a **CNN**, try to guess the true shower energy





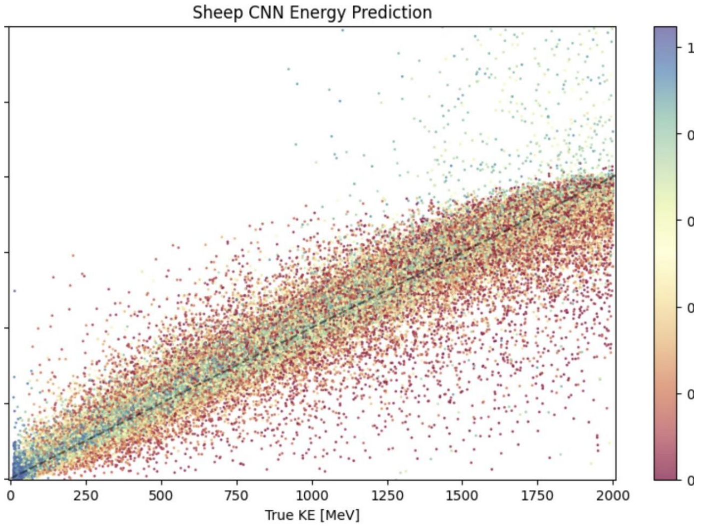
True underlying energy

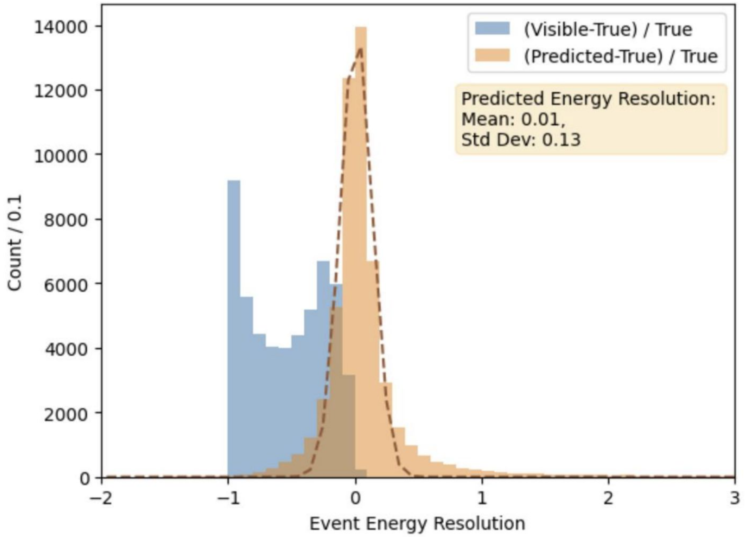
ML-based shower energy regression (E. Hinkle)

NATIONAL ACCELERATOR LABORATORY

Very promising:

- Making steady progress since the summer
- Does show **ability to recover/guess energy of partial showers**
- Shortish training, idealistic simulation for now… **more soon!**





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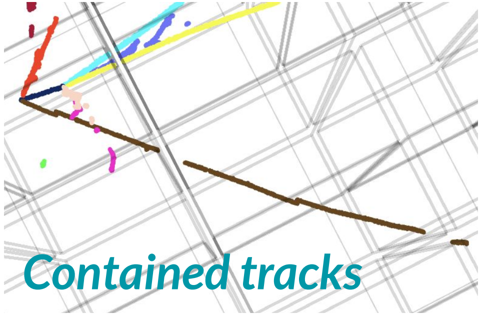
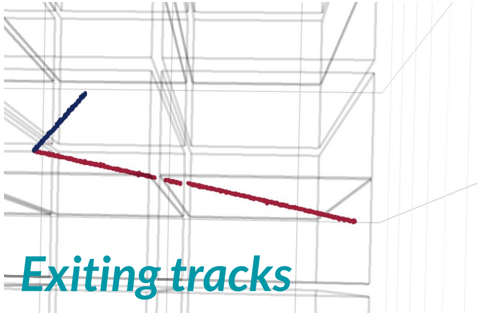
- Muons are very rarely contained and MCS breaks down at high energies
  - Downstream spectrometer used to estimate it, see Jessie's talk right after!
- EM showers are not always fully contained + go through dead volume
- Range is very poor energy proxy for hard-scattering hadrons

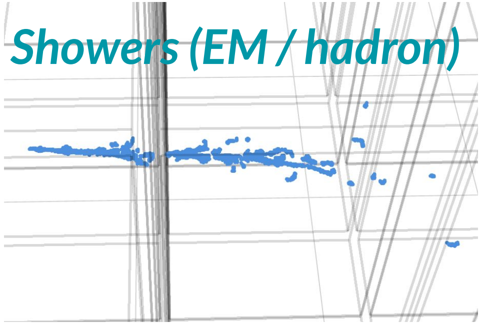
Range-based (CSDA)



Scattering-based (MCS)



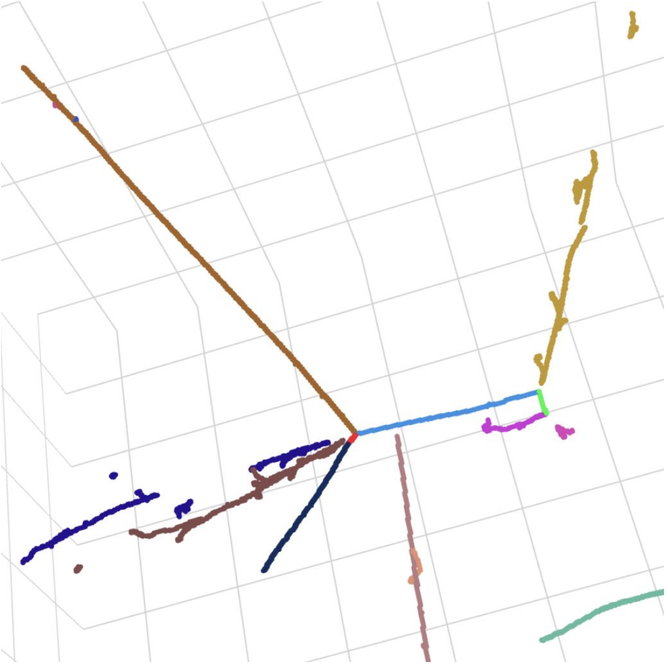
Calorimetry



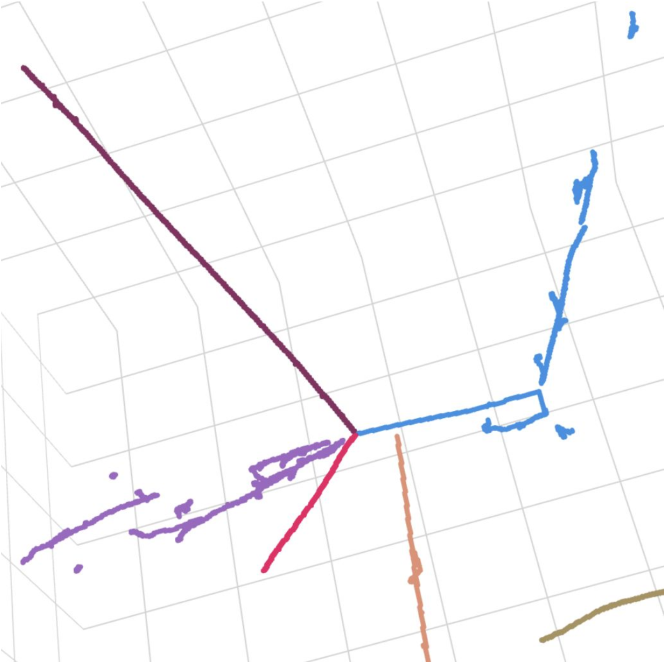
Hadron Shower Reconstruction

We **need to treat hadron showers as a whole**

- Introduced a new clustering head which builds hadron showers



Reco. ancestor groups!



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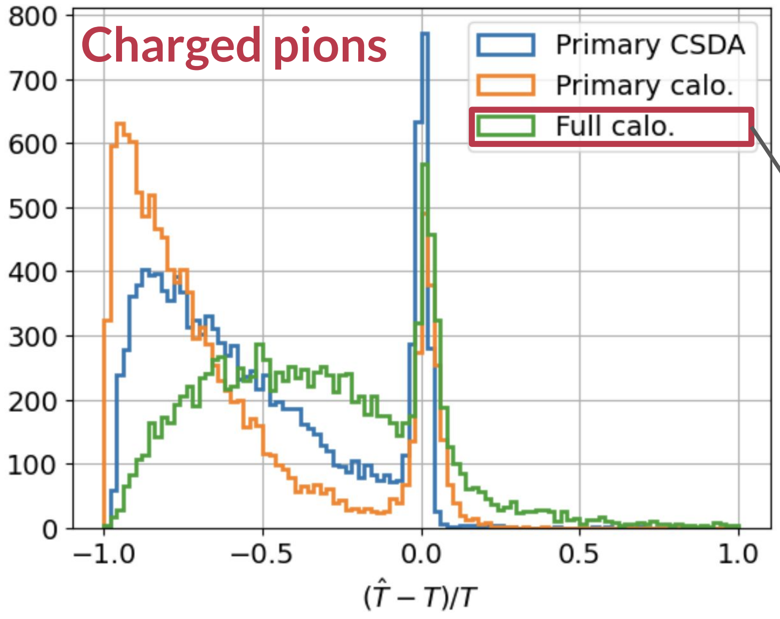


*Calorimetry of the **hadronic shower gets you closer**, but:*

- *Issue with decays injecting more energy (e.g. $\pi \to \mu \to e$)*
- *Invisible energy (mostly sub-threshold protons, neutrons)*

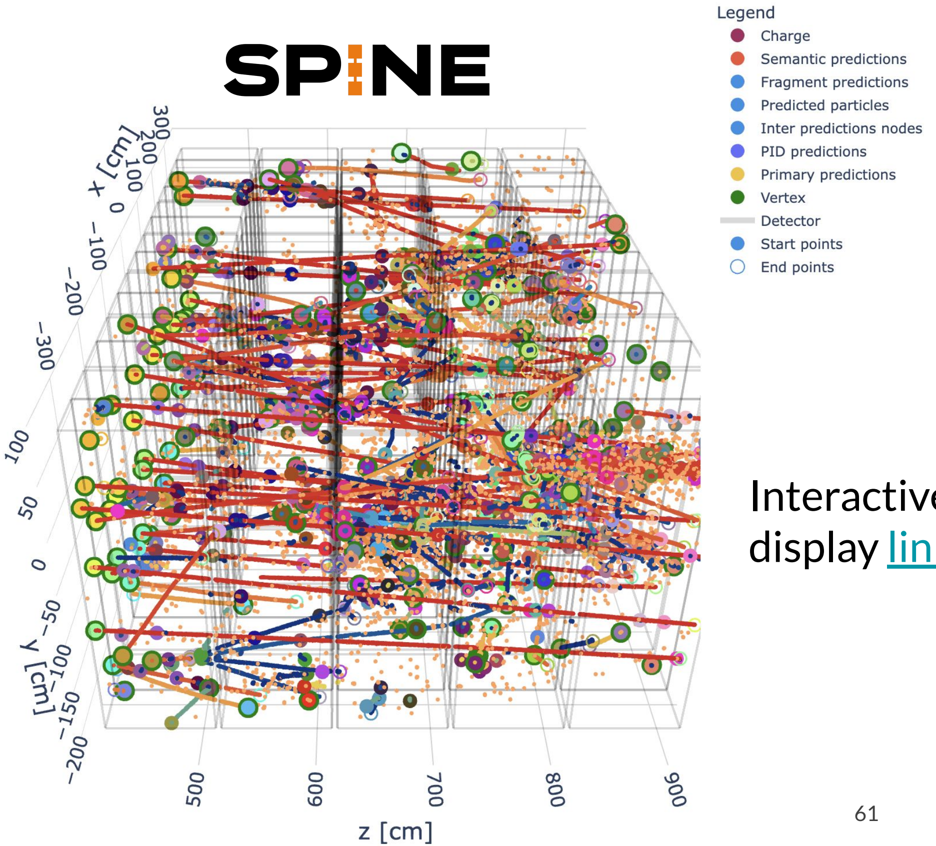
To be done:

- *Particle tree, energy regression, PID*

Conclusions

First full ND-LAr simulation:

- SPINE is the **only working reconstruction** on a LArTPC with ND-LAr's pile-up!
- It is resilient at pile-ups beyond the current design
- Unique energy reco. challenge being addressed with extensions to SPINE



Interactive display link

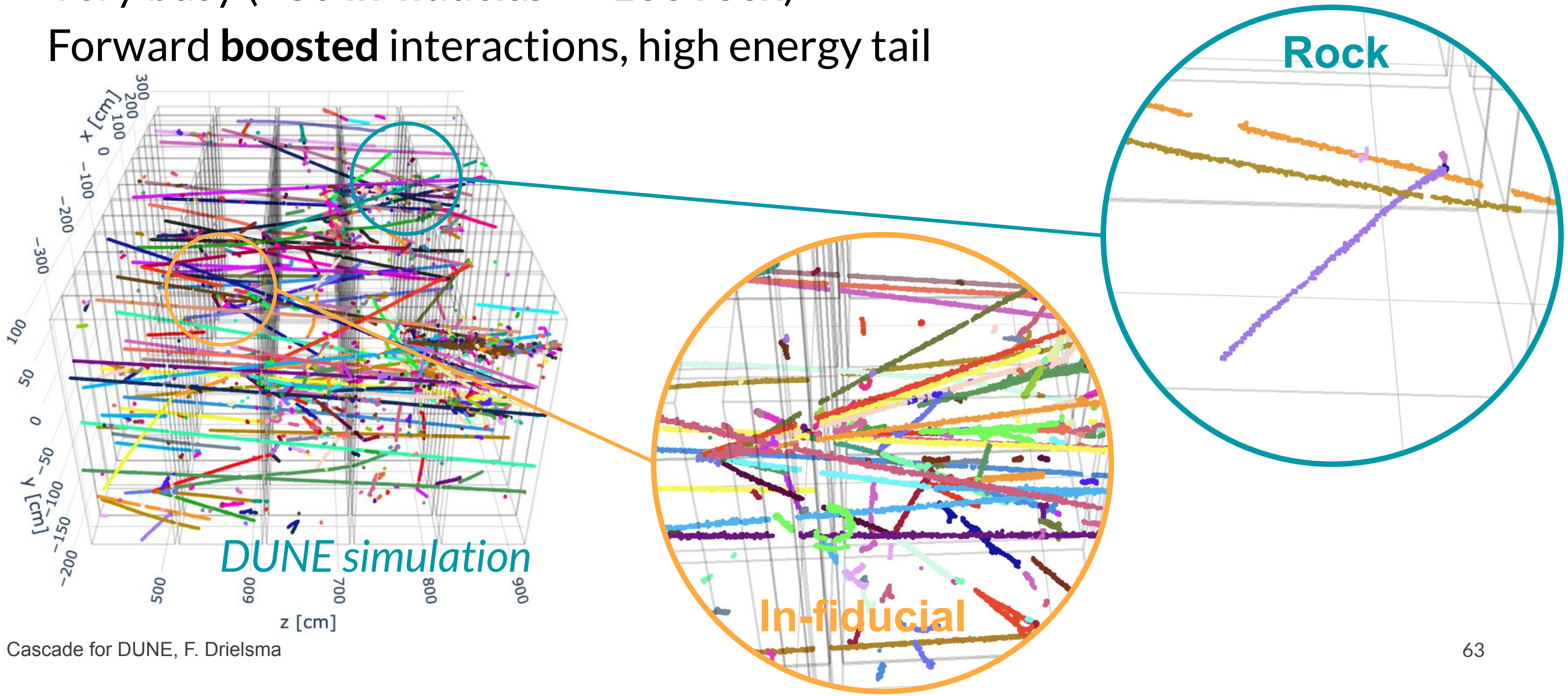
→ FD + osc. physics next!

Backup Slides

Full ND-LAr FHC Spills

Thanks to **Alex Booth** (++), we now have **full FHC spills** (μP4.1)! **1.2 k events**

- Very busy (**~30 in-fiducial** + **~100 rock**)
- Forward **boosted** interactions, high energy tail

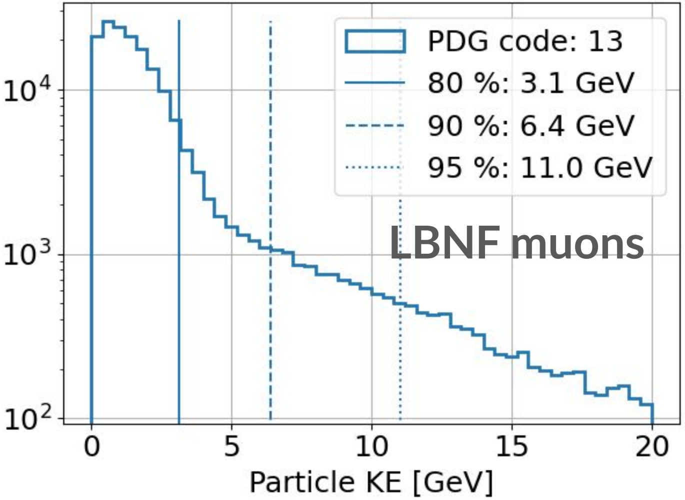


Training/Validation/Test Samples

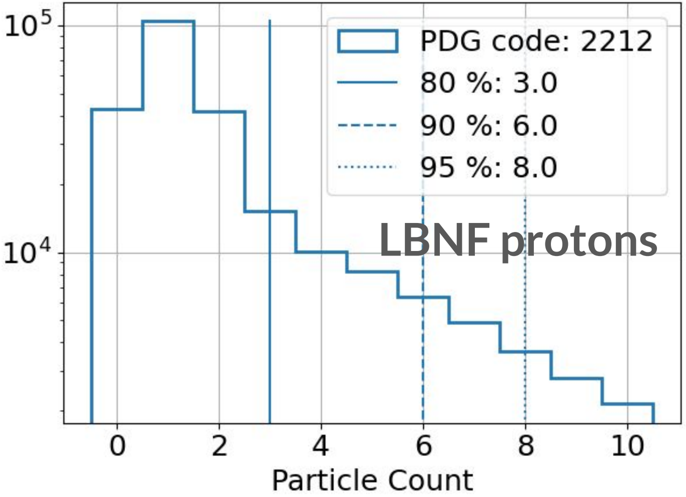
We use an **generic dataset** designed for **unbiased phase space coverage**

- To study both **KE and multiplicity coverage**, we use LBNF flux files
- **Uniformly** sample KE, multiplicity and angle to cover up to 90th percentile

DUNE Simulation work-in-progress



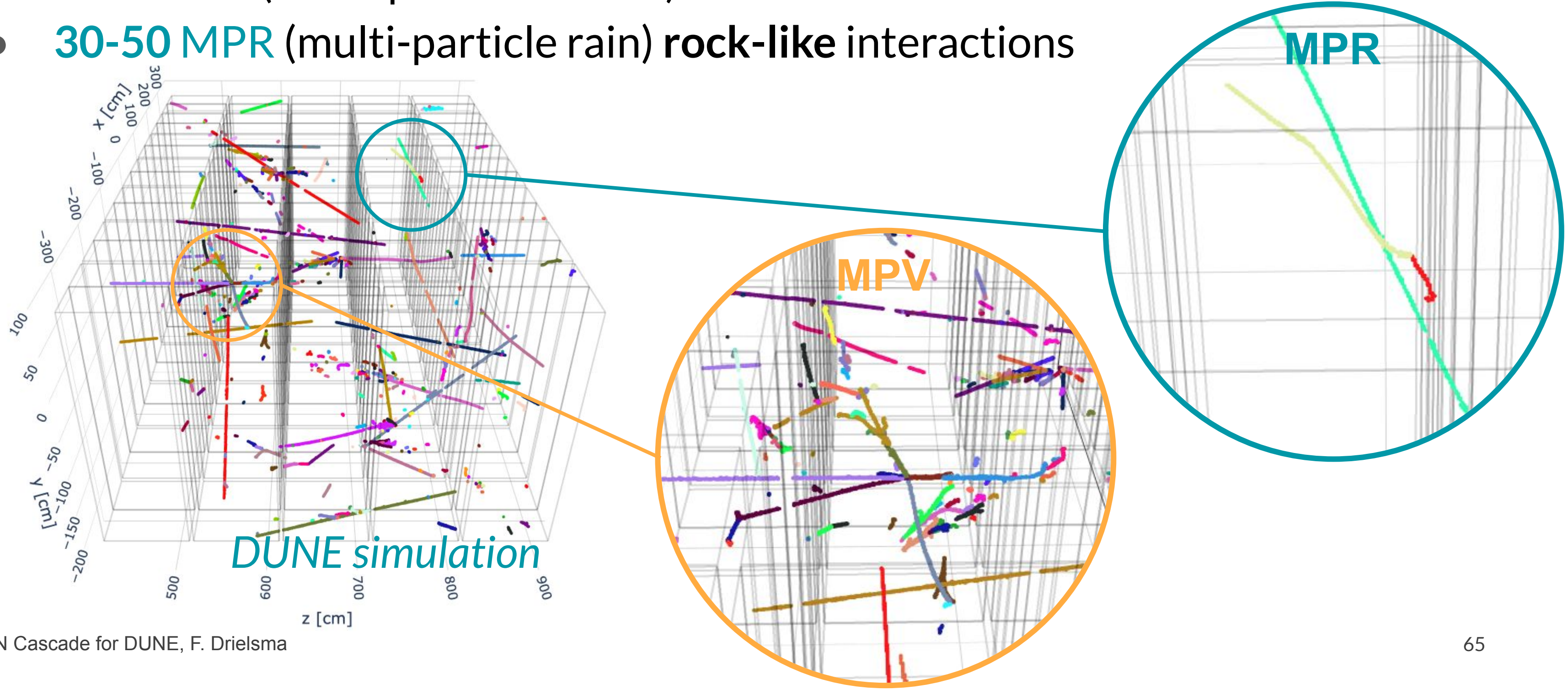
DUNE Simulation work-in-progress



Training/Validation/Test Samples

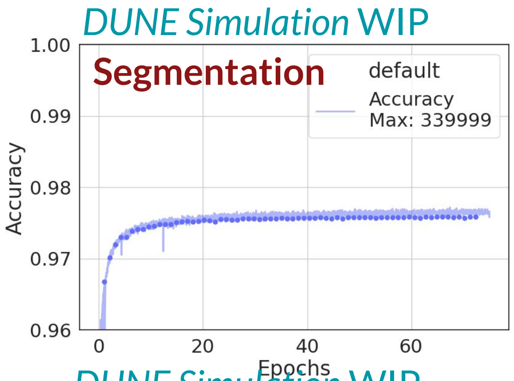
The **MPV/MPR dataset** includes 300k to **train**, 12.5k to **validate**, 25k to **test**

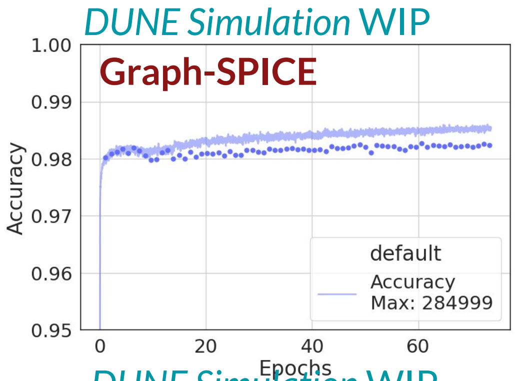
- 8-22 MPV (multi-particle vertex) **in-fiducial nu-like** interactions
- 30-50 MPR (multi-particle rain) **rock-like** interactions

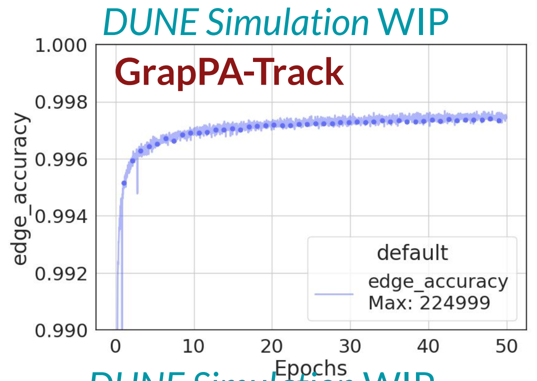


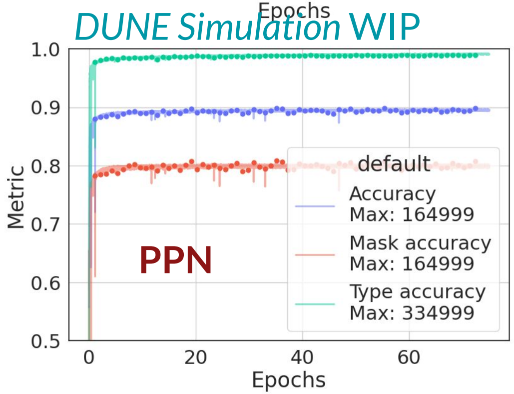
Training/Validation

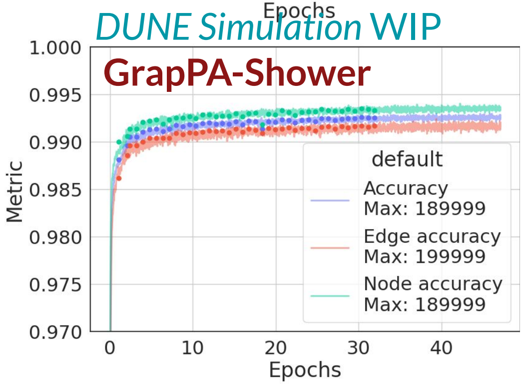
Trained the **full chain** from scratch (**04/23 – 05/02**), no issue!

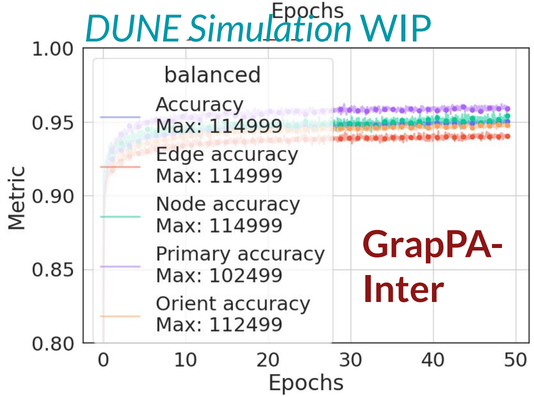








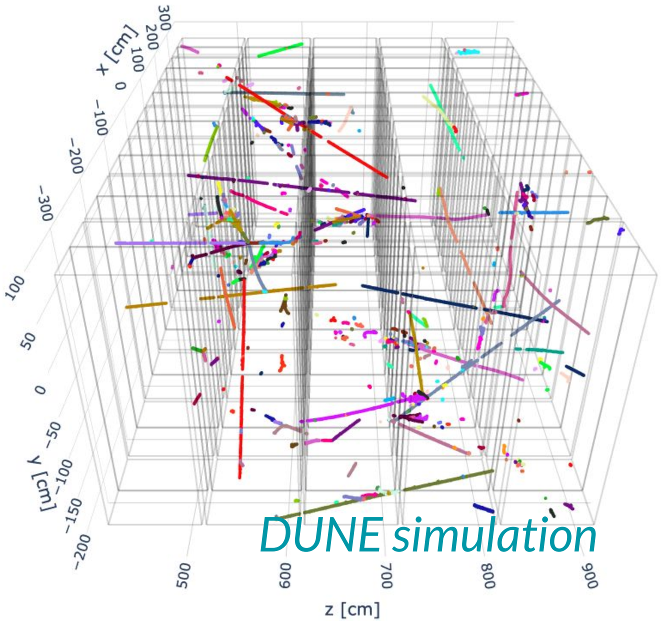


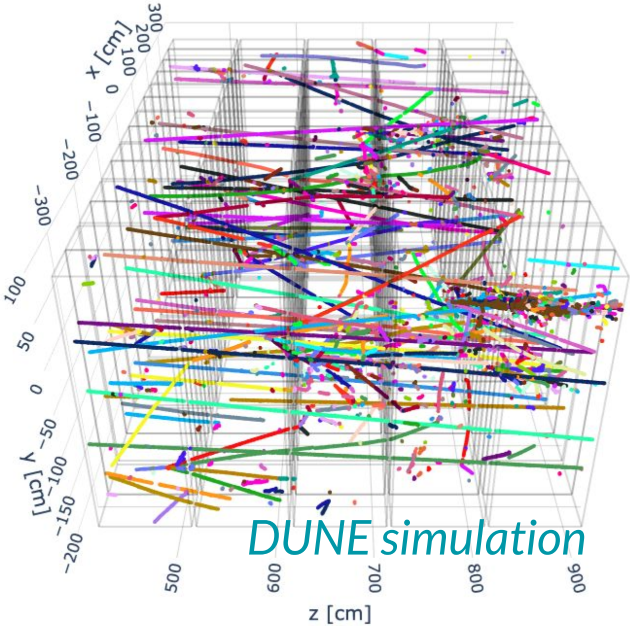


ND-LAr Pile-up

SPINE handles the ND-LAr pile-up well out of the box but…

- The training sample underestimates the number of interactions

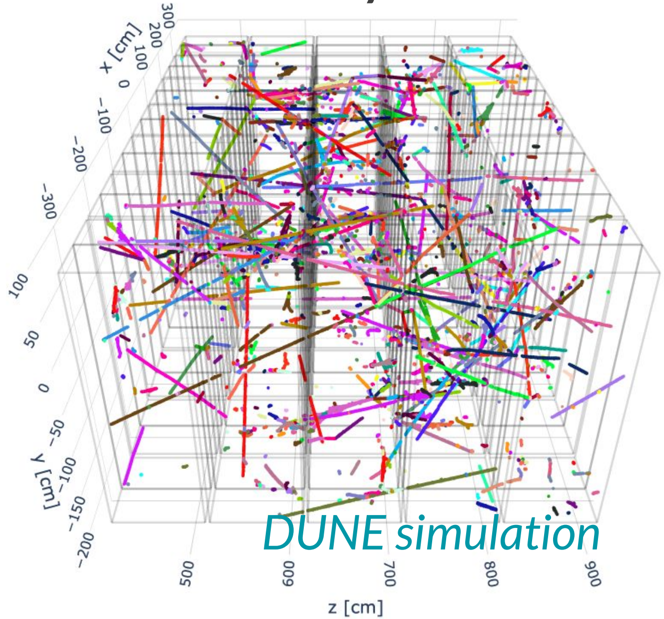


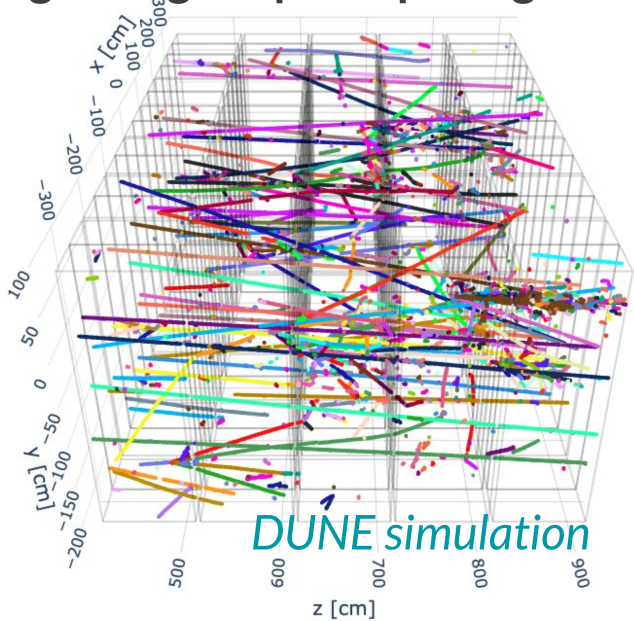


ND-LAr Overlays

SPINE handles the ND-LAr pile-up out of the box but…

- The training sample underestimates the number of interactions
- Wrote **overlay code** to enable **training on higher pile-up images**





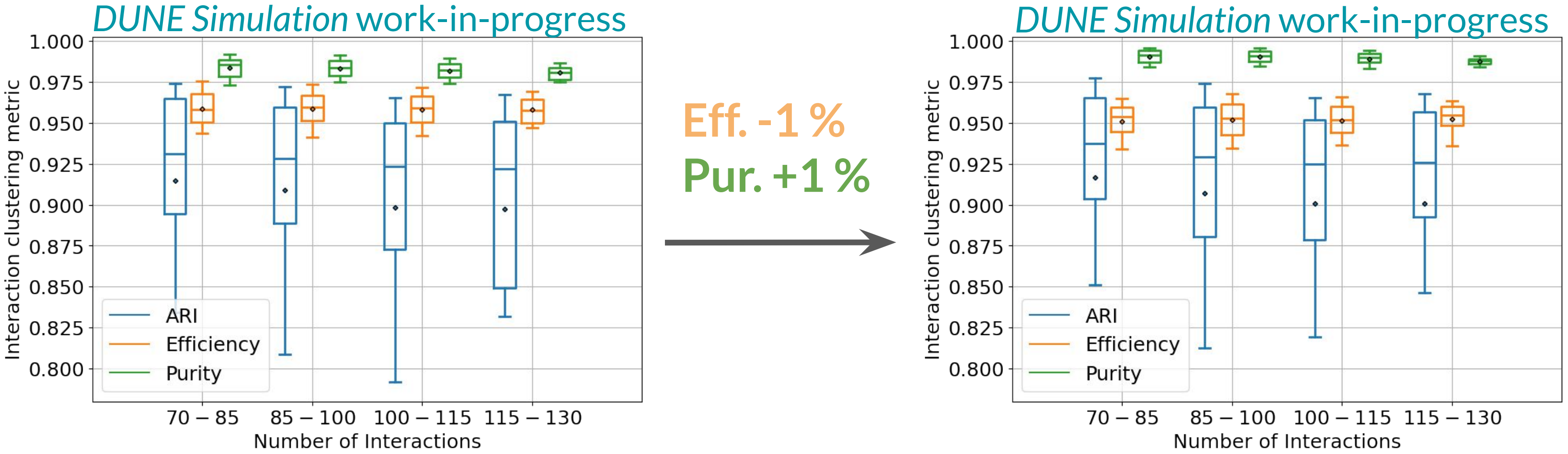
ND-LAr Overlay Training

SLAC NATIONAL ACCELERATOR LABORATORY

Lessons learned in the training process

- Segmentation, point proposal, fragmentation do not need to be retrained
- Shower/Track clustering does seem to benefit from transfer training
  - Shower clustering cannot be trained with overlay > 2 (memory issue)

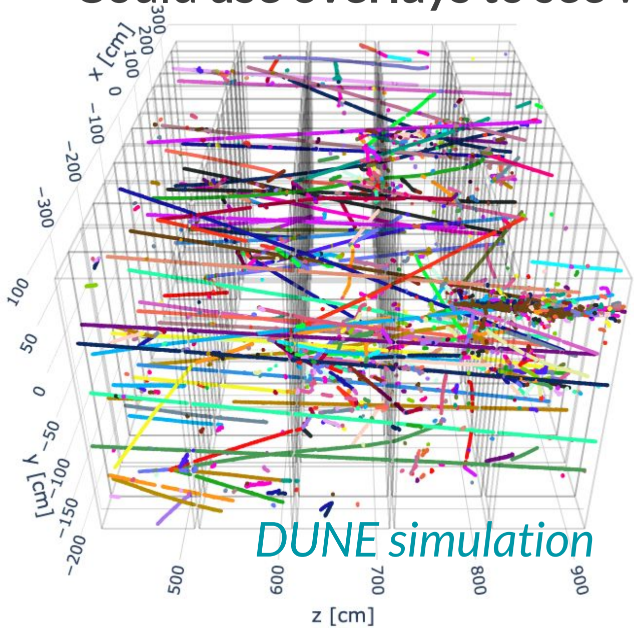
→ **Minor impact at the interaction level** (network slightly more conservative)



Even higher Pile-up?

What if we crank the pile-up even further?

- 4x in the interaction count w.r.t. nominal translates **400+ interactions**
- Could **use overlays** to see what that does to clustering



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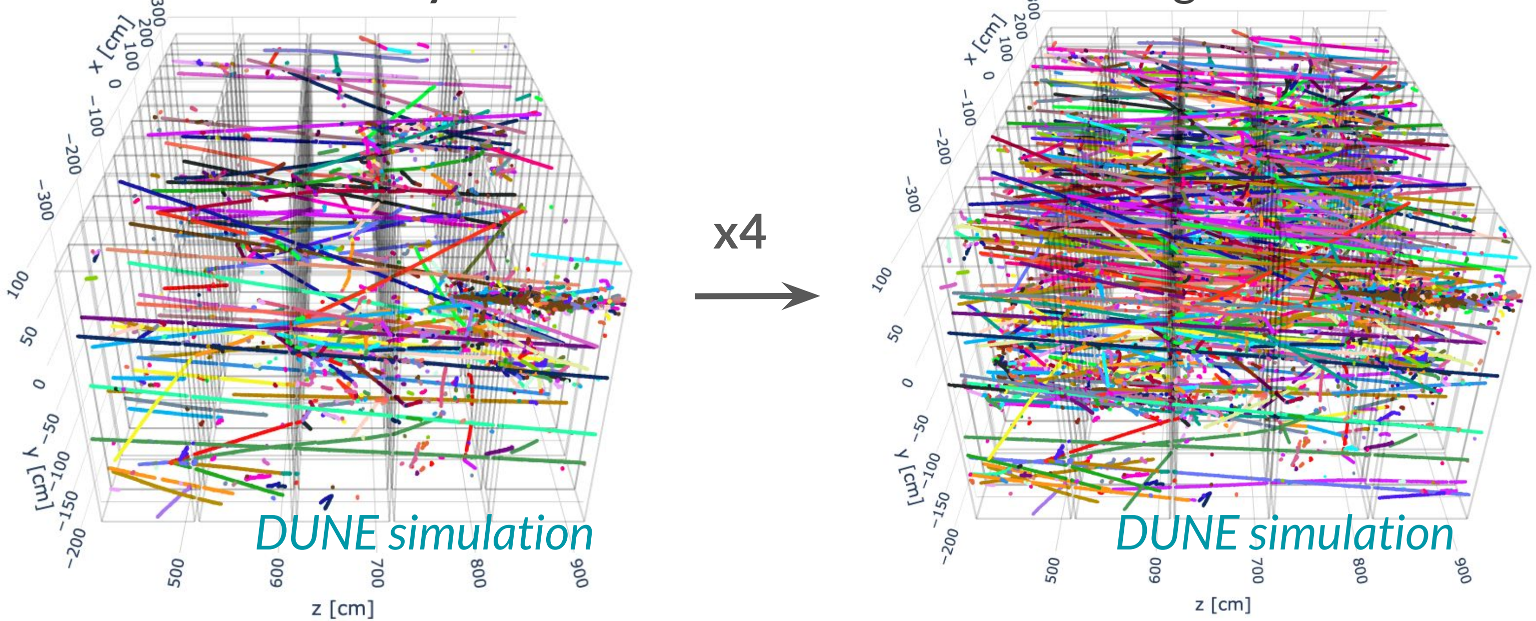
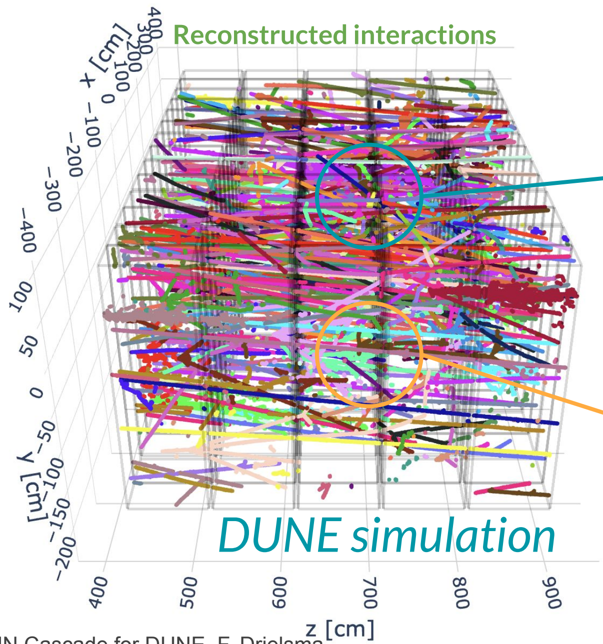
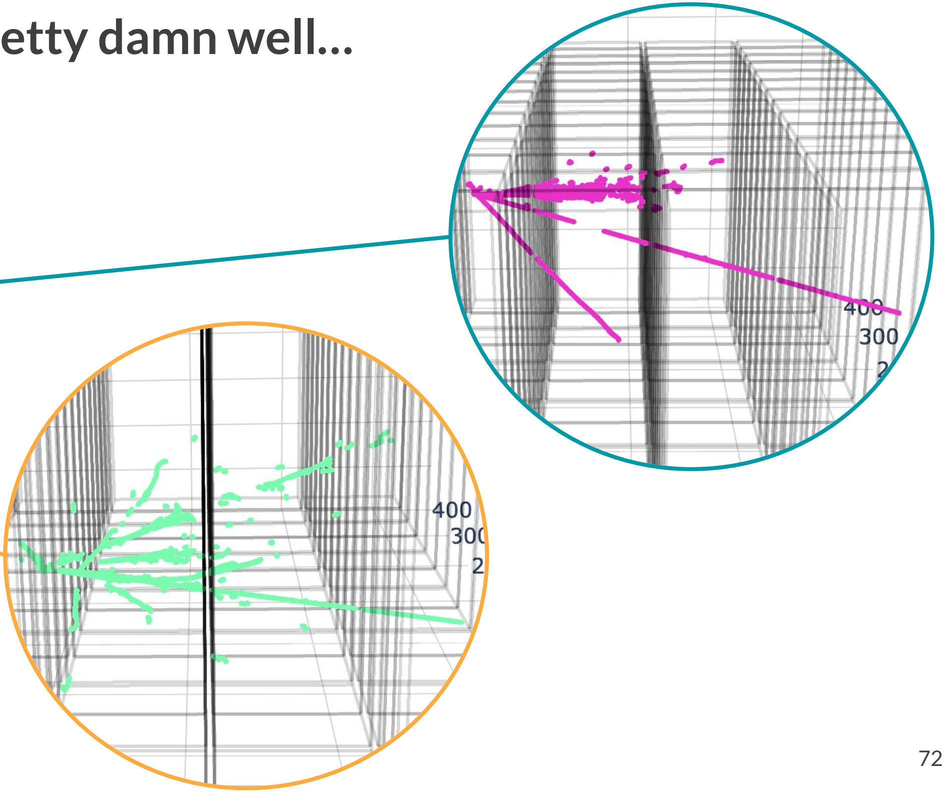


Even higher Pile-up?

What does it do to the reconstruction quality out-of-the-box?

- Against all odds, **it holds up pretty damn well...**



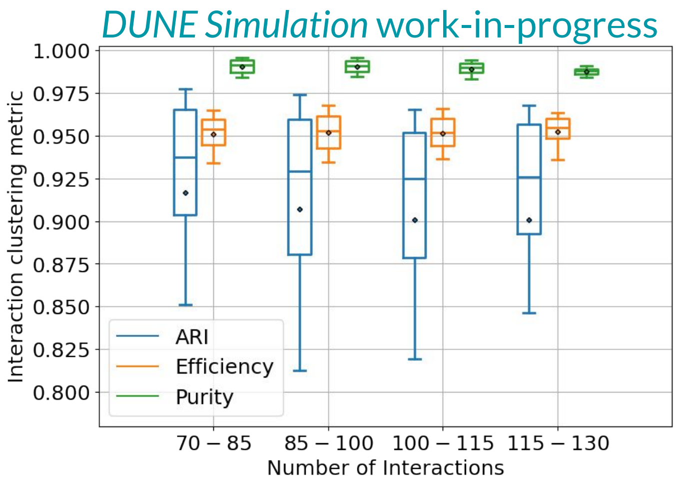


Even higher Pile-up?

What does it do to the reconstruction quality out-of-the-box?

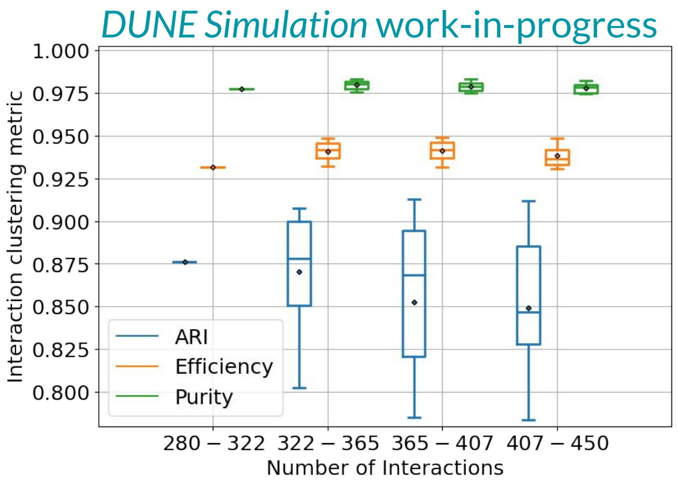
- Against all odds, **it holds up pretty damn well…**
- Percent-level loss for both purity in completeness, 4 % loss in ARI

→ This is all **without a dedicated training at all!**



Eff. -1 %

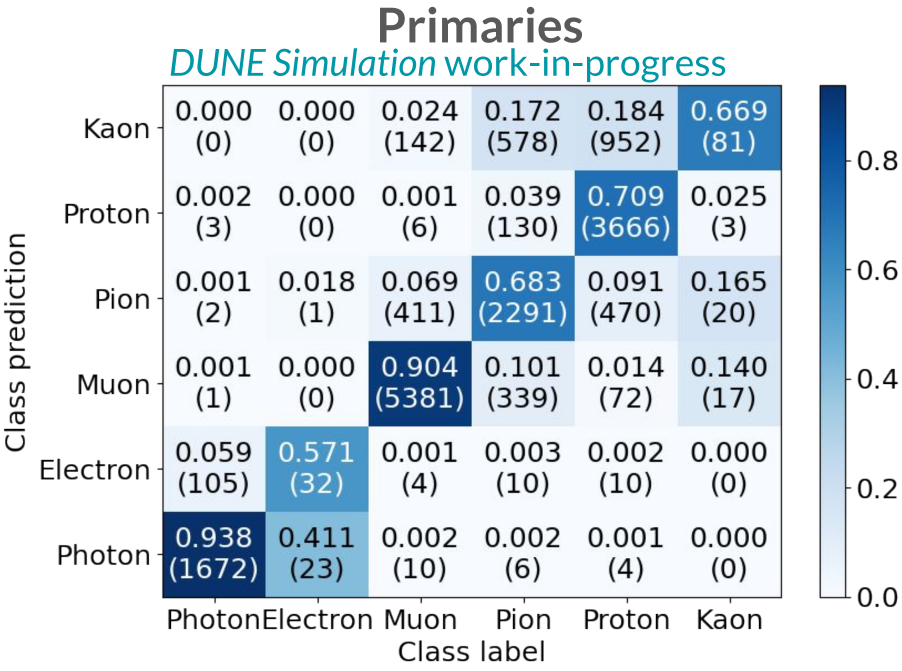
Pur. -1 %

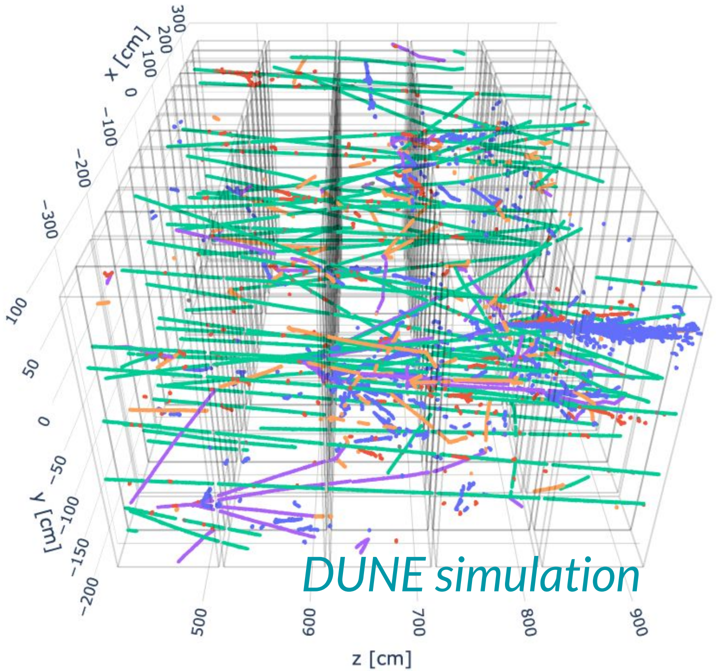


Particle Identification

Classify **particles** within interactions into different species

- Photons (0), Electron (1), Muons (2), Pions (3), Protons (4), Kaons (5)





Paper: PhysRevD.104.072004

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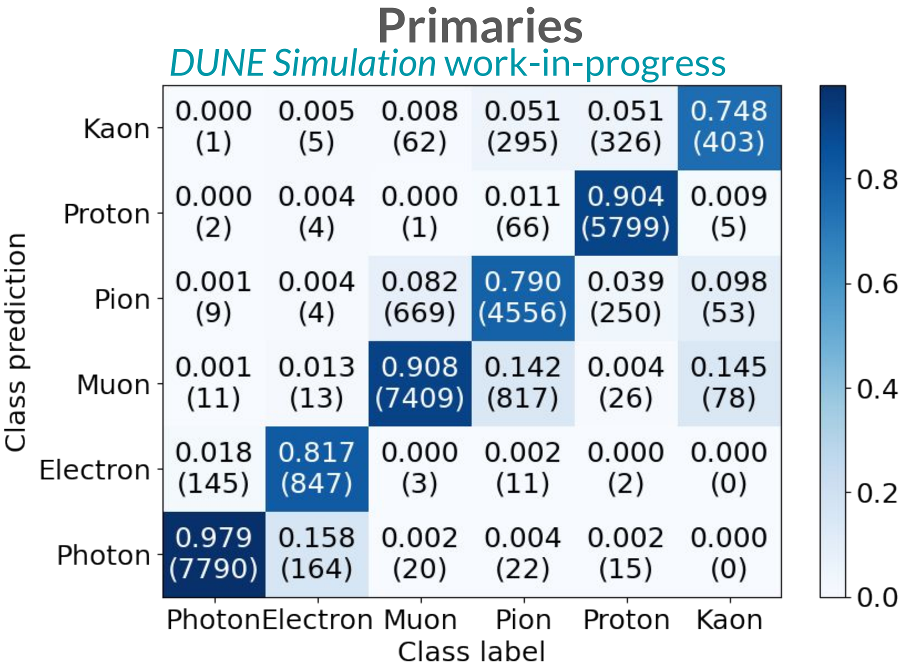
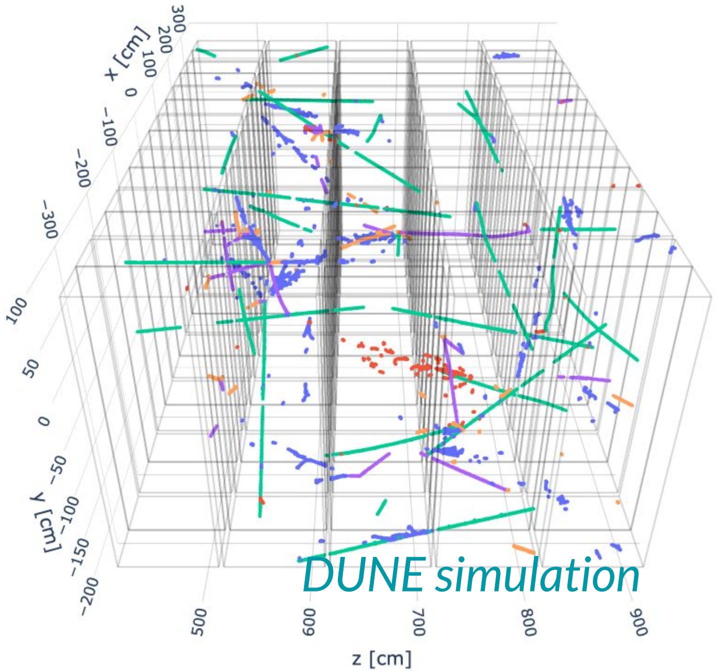


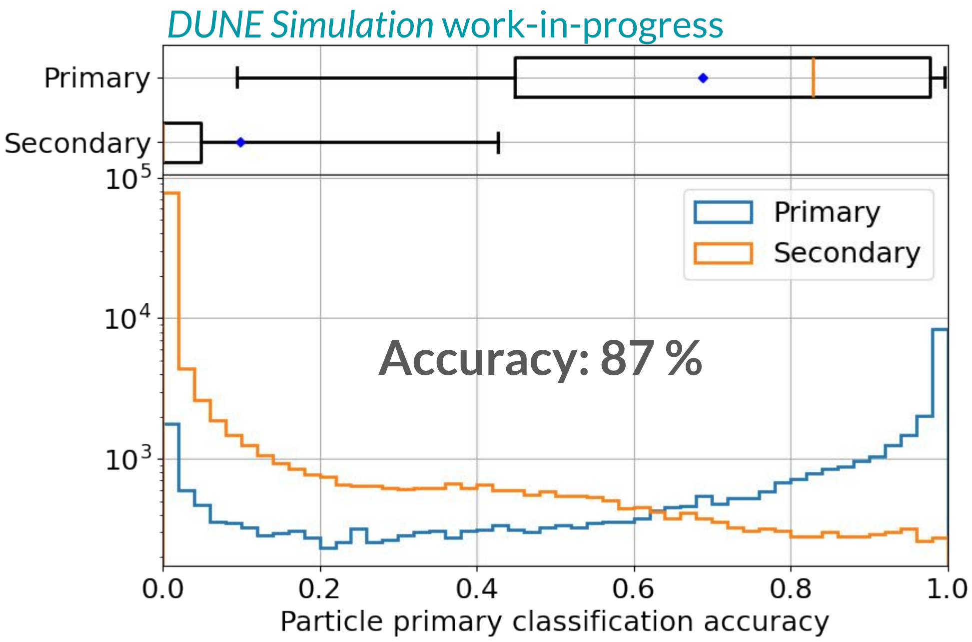


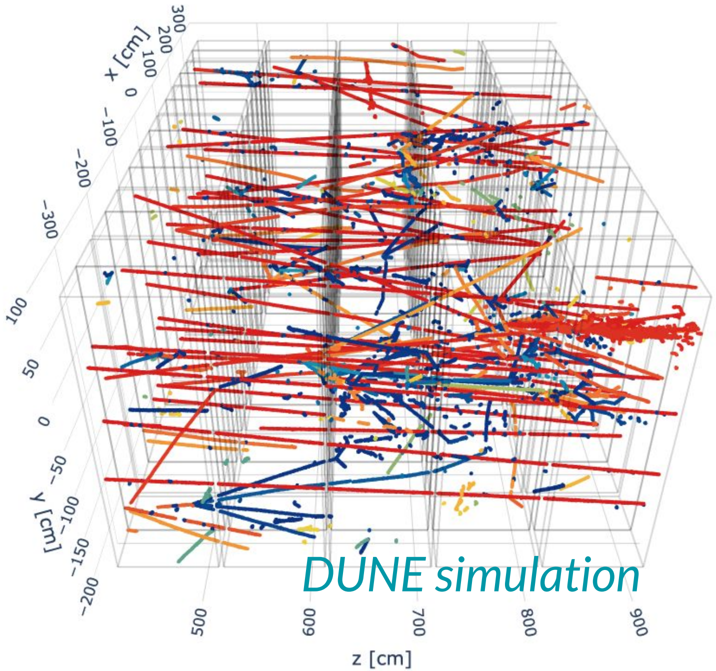
Paper: PhysRevD.104.072004

Primary Identification

Identify particle originating from the primary vertex

- Secondaries – Primaries





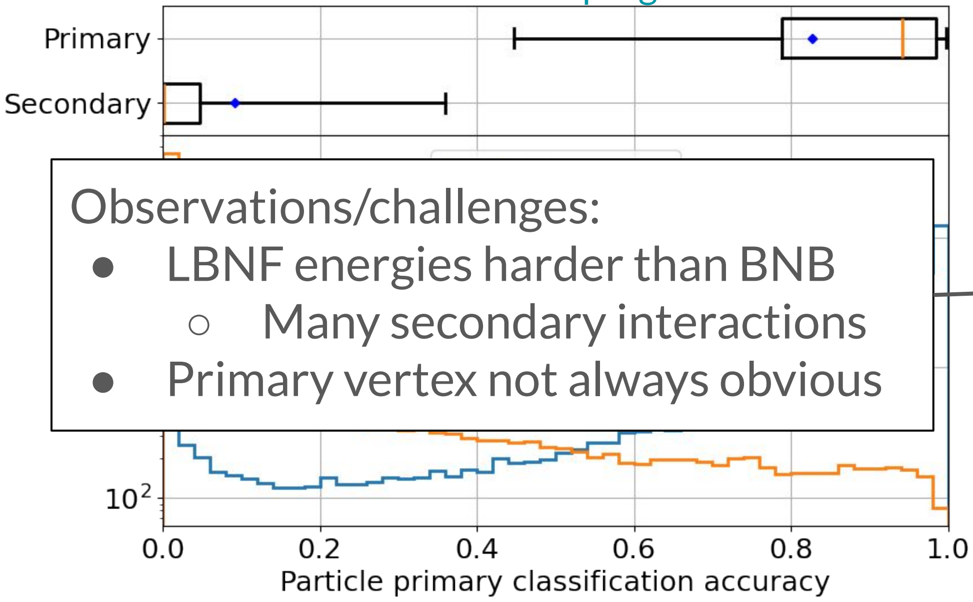
Paper: PhysRevD.104.072004

Primary Identification

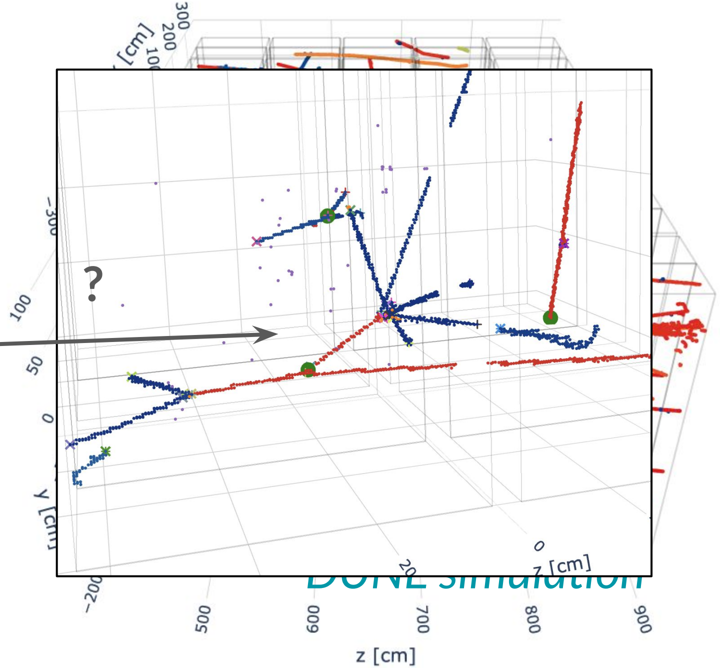
Identify particle originating from the **primary vertex**

- Secondaries — Primaries

DUNE Simulation work-in-progress



Observations/challenges:
- LBNF energies harder than BNB
  - Many secondary interactions
- Primary vertex not always obvious

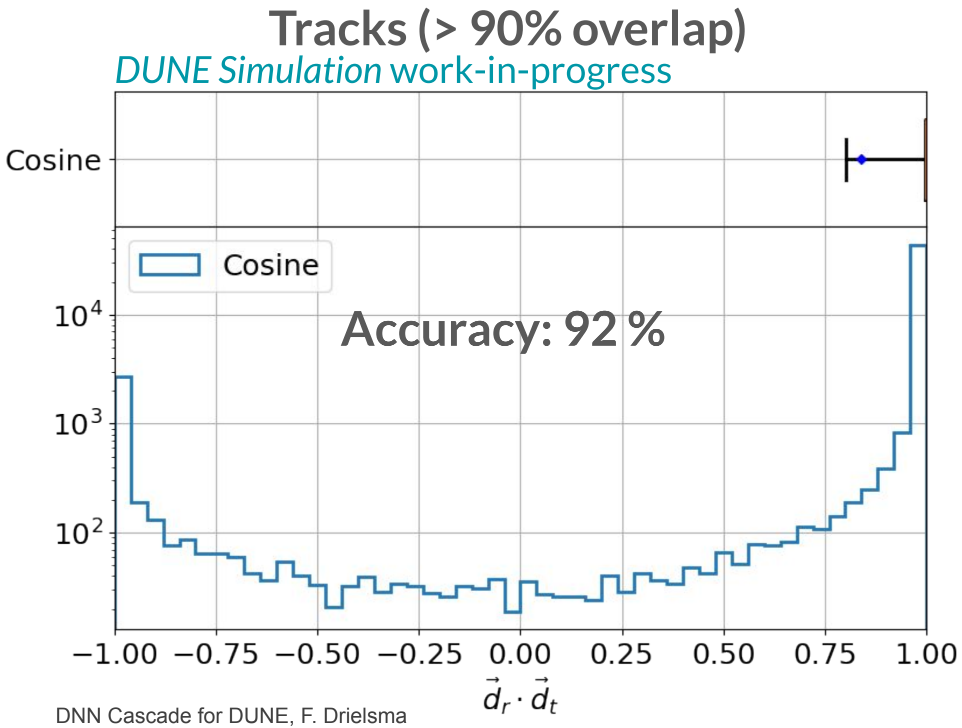


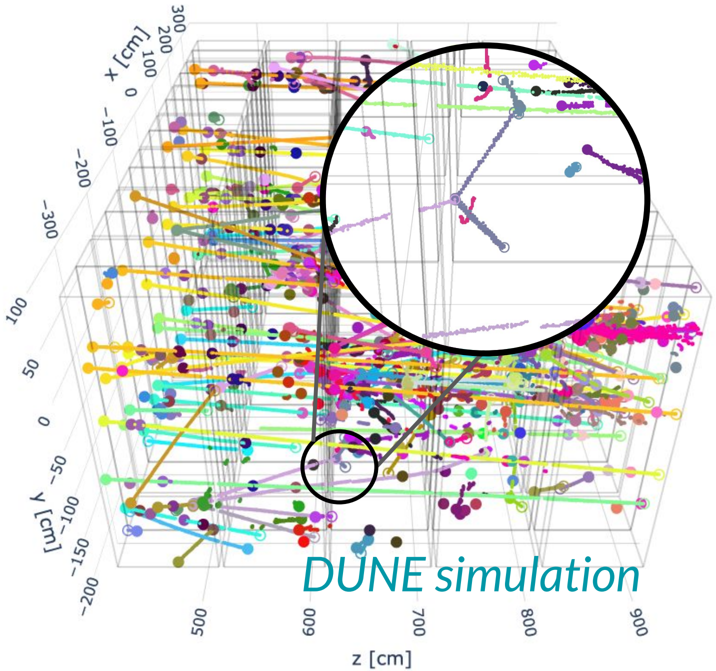
Paper: PhysRevD.104.072004

Particle orientation

Orient **tracks** within interactions

- Start points (⚫) and end points (◯)





Paper: PhysRevD.104.072004

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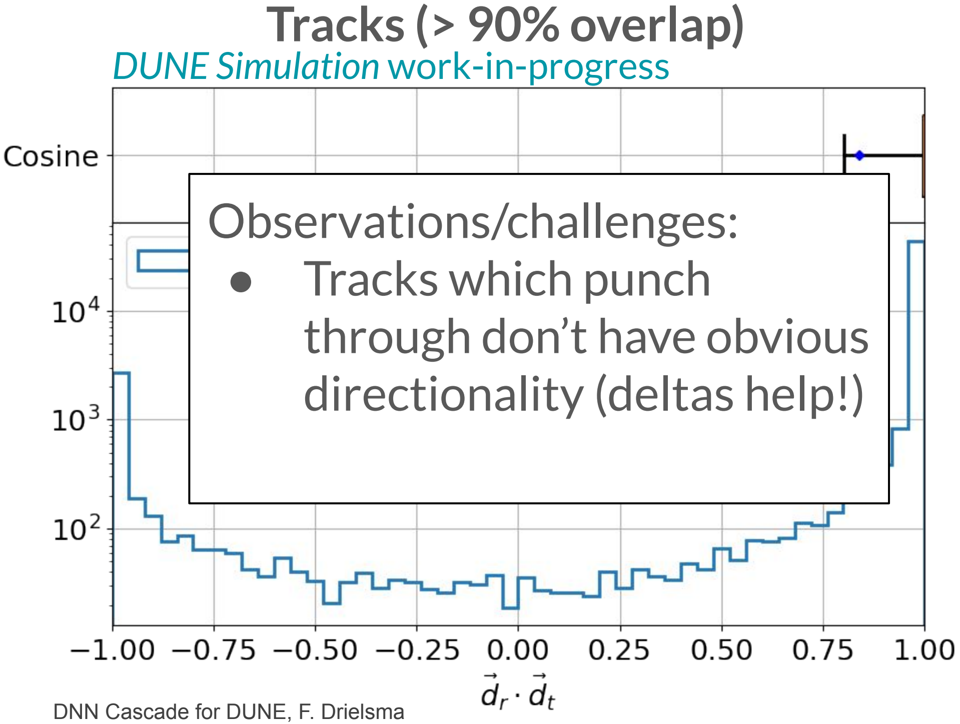
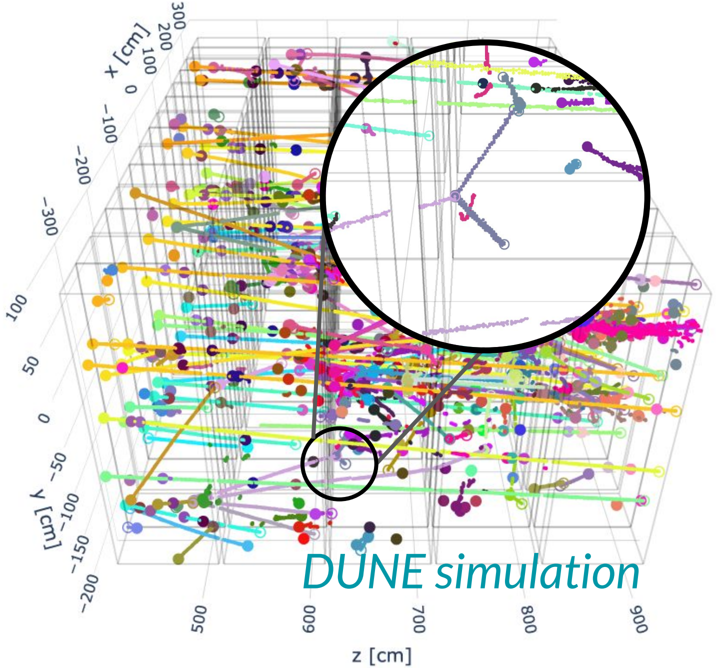


Observations/challenges:

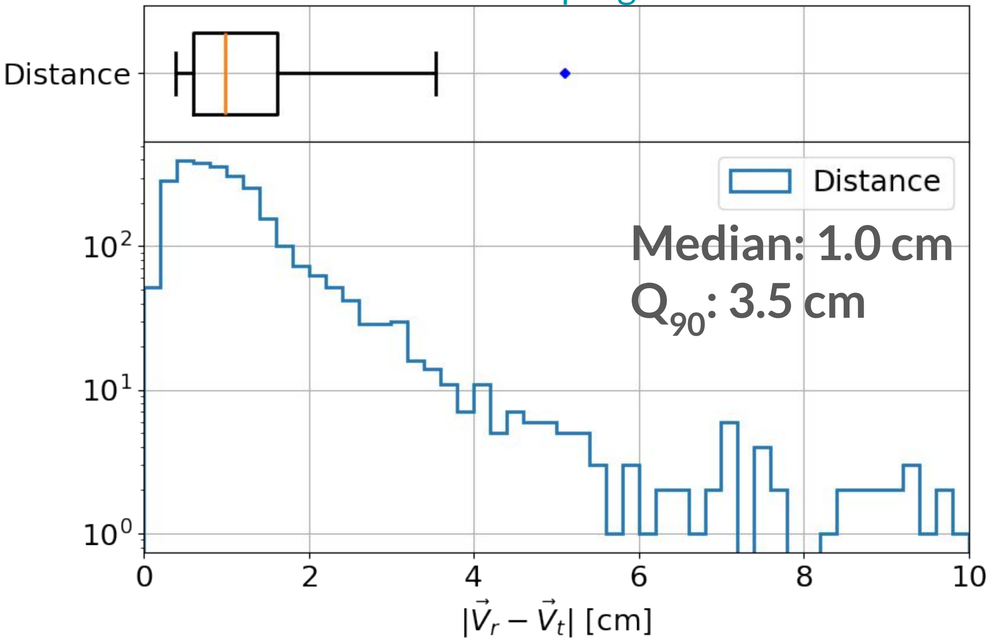
- Tracks which punch through don't have obvious directionality (deltas help!)

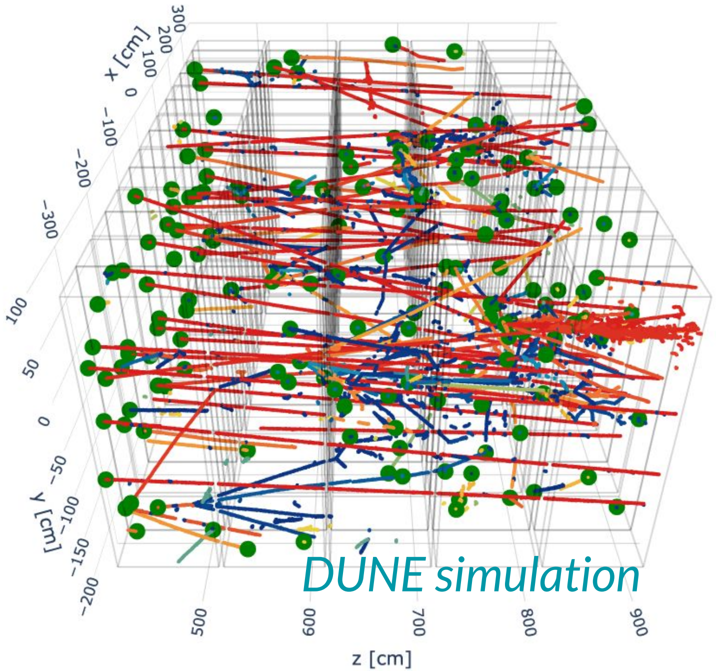


Paper: PhysRevD.104.072004

Vertex reconstruction

Using the primary and orientation prediction, one can infer vertex positions



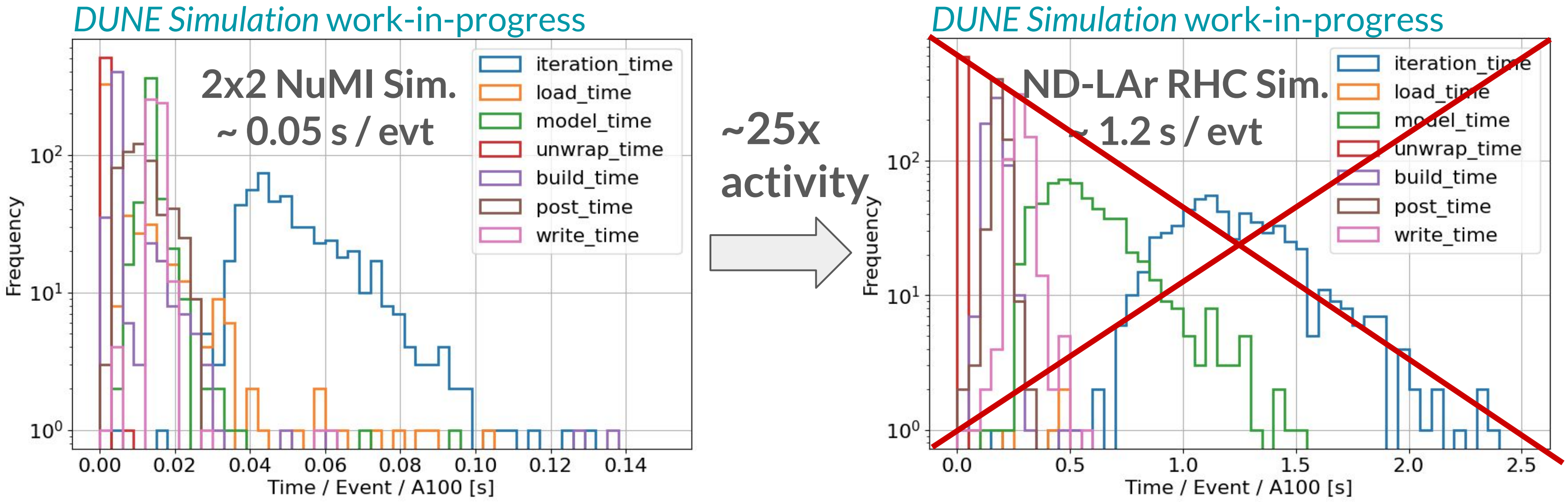


Paper: [PhysRevD.104.072004]

ND-LAr: Scalability

"SPINE" would be "PINE" without scalability…

- SPINE leverages **GPU acceleration** extensively
- **Scales with activity**, i.e. number of active voxels (**DUNE-FD << DUNE-ND**)
- Can reco a **full run** (active year) of ICARUS in **< 1 day with 20 GPUs**



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