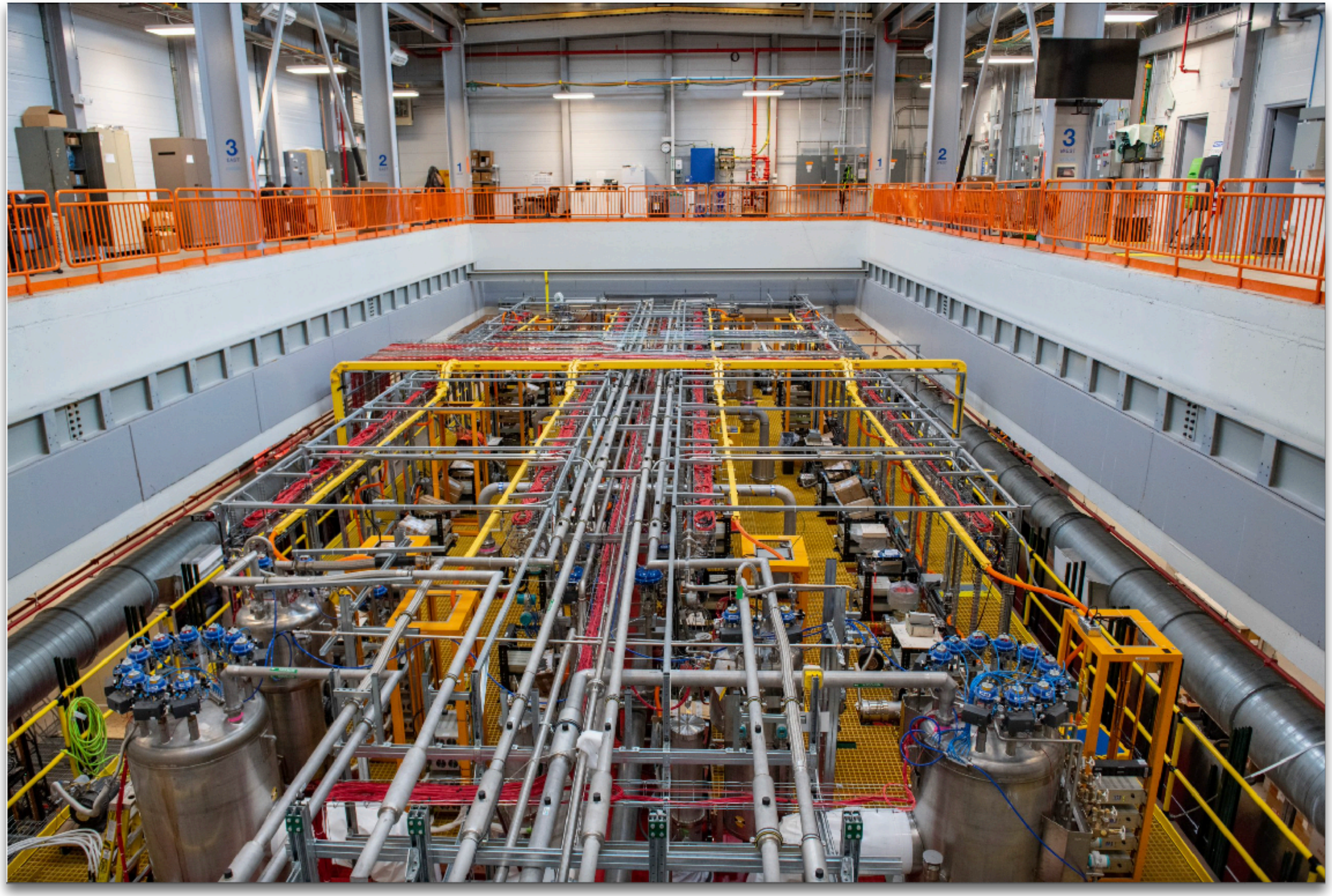


2nd Short-Baseline Experiment/Theory Workshop
Santa Fe, New Mexico
April 2nd to 5th 2024

Track reconstruction in liquid Argon TPC experiments

Alice Campani
on behalf of the ICARUS collaboration

Imaging Cosmic And Rare Underground Signals

Università di Genova

INFN Istituto Nazionale di Fisica Nucleare

4 April 2024

Overview of the content this talk

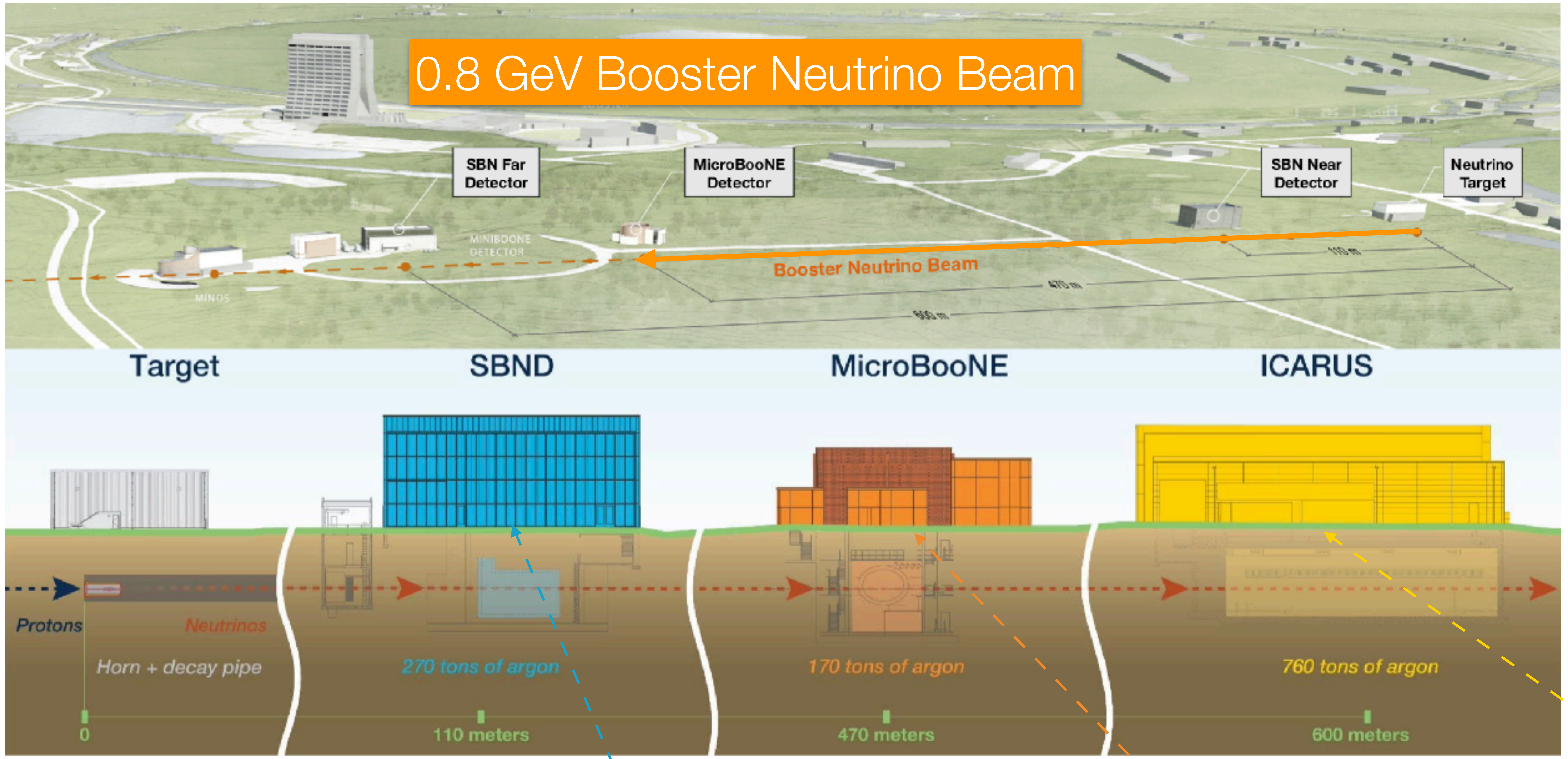
- Introduction to **LArTPC experiments** and SBN physics program
- General description of **TPC event reconstruction chain** and main steps
- Two *parallel* event reconstruction paths:
  - *Pandora-based* event reconstruction:
    overview of the hierarchy, insights on the main stages
  - *Machine Learning*- (ML) based event reconstruction:
    overview of the full reconstruction chain
- Conclusions and perspectives

The Short Baseline Neutrino (SBN) program

Precision search for **1 eV mass scale sterile ν** to confirm/rule out previous anomalies from past experiments

Sensitive searches for ν_μ **disappearance,** ν_e **appearance**

ICARUS exposed also to **NuMI beam** (6 degrees off axis)



High statistics measurement of **ν-Argon** cross sections for **DUNE**

Search for Beyond Standard Model (**BSM**) physics

Same detector technology to reduce **systematics** and increase sensitivity

SBND
Near detector

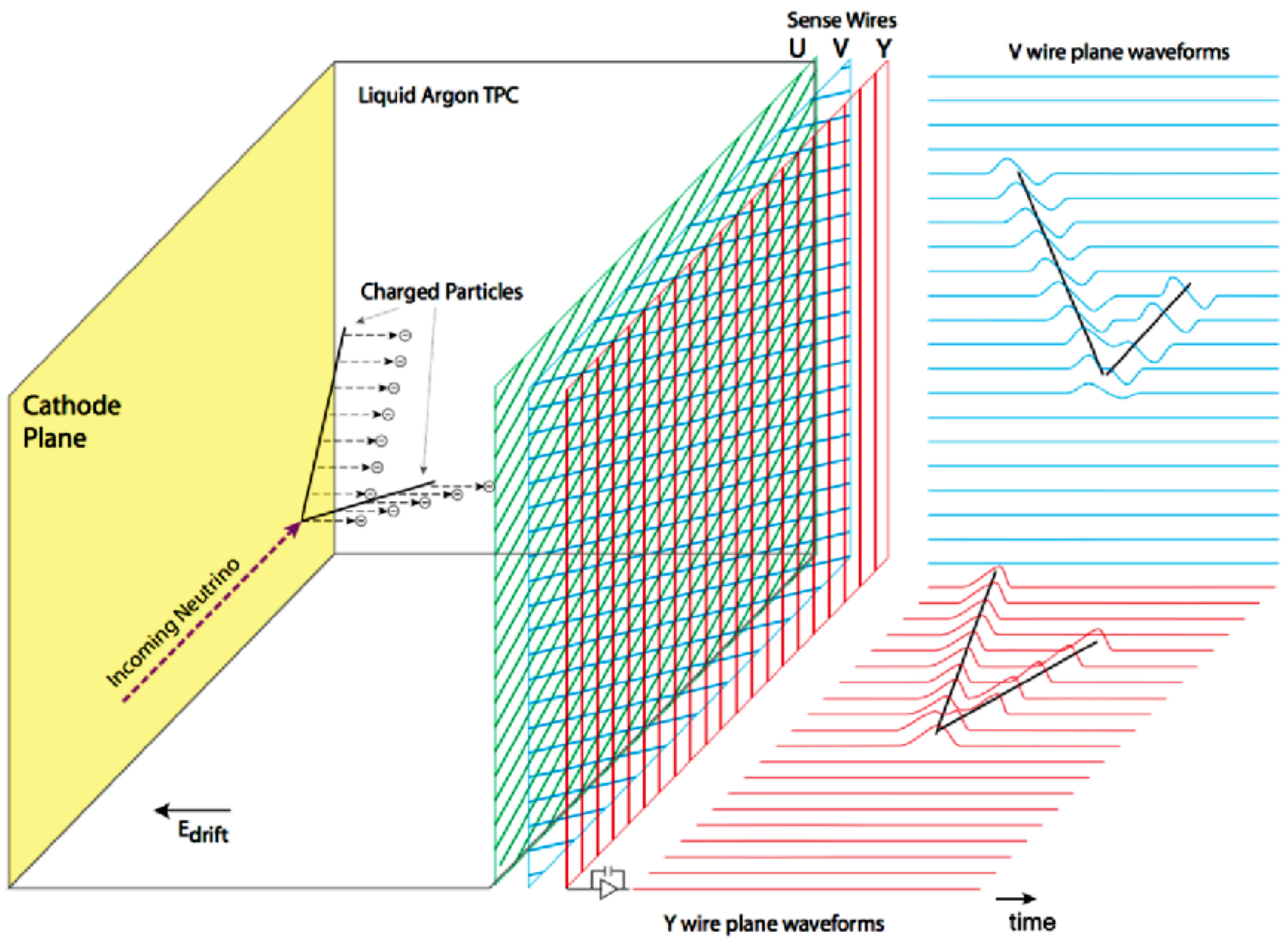
MicroBooNE

ICARUS
Far detector

Liquid Argon Time Projection Chambers (LArTPCs)

- Proposed by **C. Rubbia** in **1977**, LArTPCs are high granularity, continuously sensitive, self-triggering detectors

  - **Dense medium:** high rate of ν interactions
  - 2/3 **wire planes** (3-5 mm wire pitch) with different orientation to generate **2D views** of particle tracks
  - 3D **imaging** with **mm-scale resolution**
  - **Calorimetric** reconstruction capabilities
  - **Scalable** to large detector volumes $\mathrm{O(10)\ kton}$



Ideal for ν interaction studies in a wide energy range

Typical LArTPC detector components: ICARUS detector as example

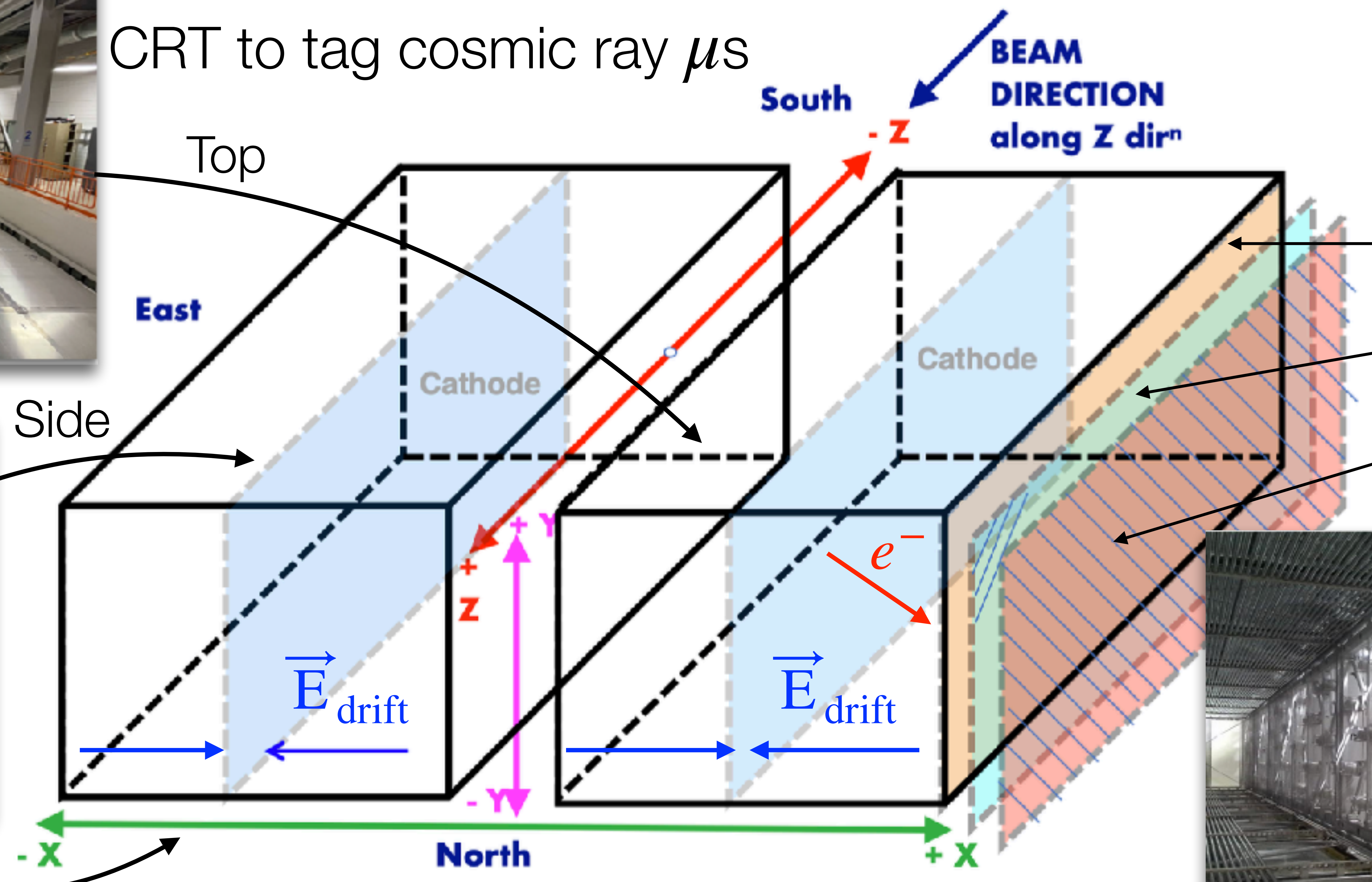
Two **identical cryostats** (3.6 x 3.9 x 19.6 m^3) housing two TPCs each, 760 tons of ultra pure liquid argon for a total **active mass** of **470 ton**

CRT to tag cosmic ray μs

Top

Side

Bottom



$E_{drift} = 500$ V/cm, $t_{drift} \sim 1$ ms

Ionization charge read by **3 wire planes** with different orientation:

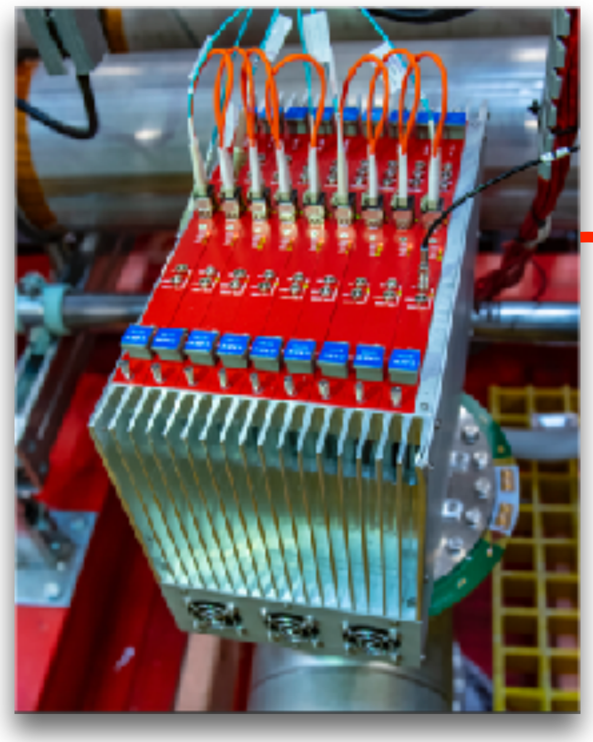
Induction1 (0°)

Induction 2 (+60°)

Collection (-60°)

360 **PMTs** behind the wires to collect scintillation light and trigger events

Event reconstruction in LAr TPCs: ICARUS reconstruction chain



Data

Unpack the data and turn it into a **raw waveform**

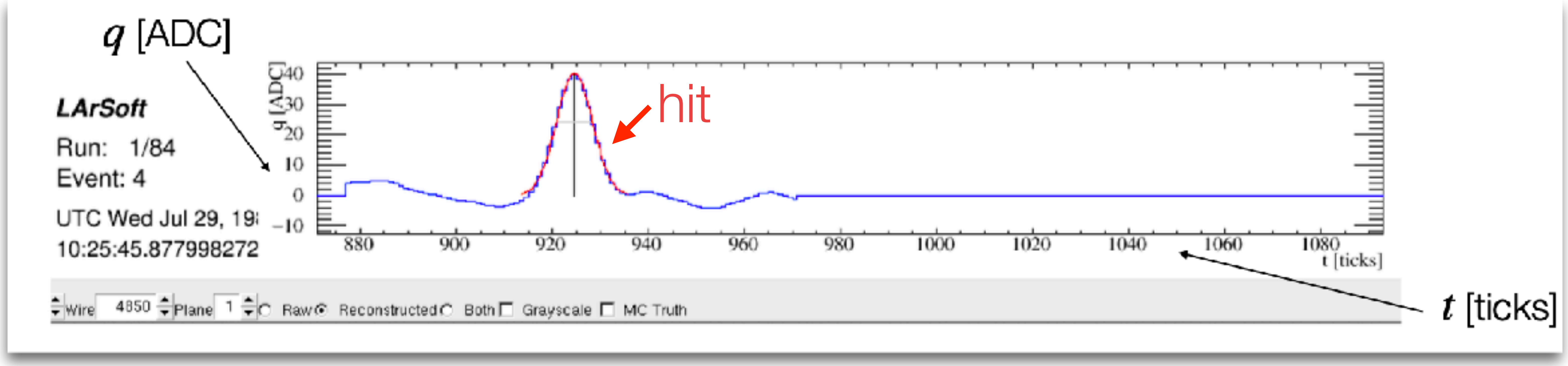
Threshold-based algorithm to identify regions containing *hits*, i.e. segments of waveforms corresponding to signal.

Decoding → **Deconvolution** → **ROI Finder** → **Gauss hits**

- Removal of **coherent noise**
- **Deconvolution** to remove the $\vec{E}$ distortions and electronics shaping effects on wire signals

Fit each signal hit with **Gaussians**: the area is proportional to n_{e^-} drift electrons that generated that.

Example of deconvolved signal (charge vs time) on a single wire plane after ROI finding and Gaussian fit



Event reconstruction in LAr TPCs: ICARUS reconstruction chain

To reduce noise, keep only hits that are **consistent** with 3D points using 2 wire planes combinations.

Gauss hits

Cluster 3D

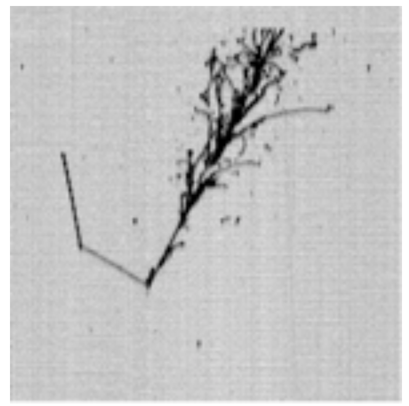
After **Cluster 3D** the reconstruction chain splits in **two parallel paths.**

Pandora-based reconstruction
Downstream reconstruction is based on cluster, *slice* (groups of tracks related to the same particle interaction) and pattern recognition.

Pandora reco

ML-reco

ML-based reconstruction
The full reconstruction chain is based on Machine Learning (ML) techniques



Analysis

Track and shower reconstruction, calorimetry

Signal processing: foreseen change from 1D to 2D deconvolution

- Wire signals are a convolution of **electric field** and **electronics responses**:

$$M(t) = \int_{-\infty}^{+\infty} R(t,t') \cdot S(t')dt$$

Measured signal

Response function

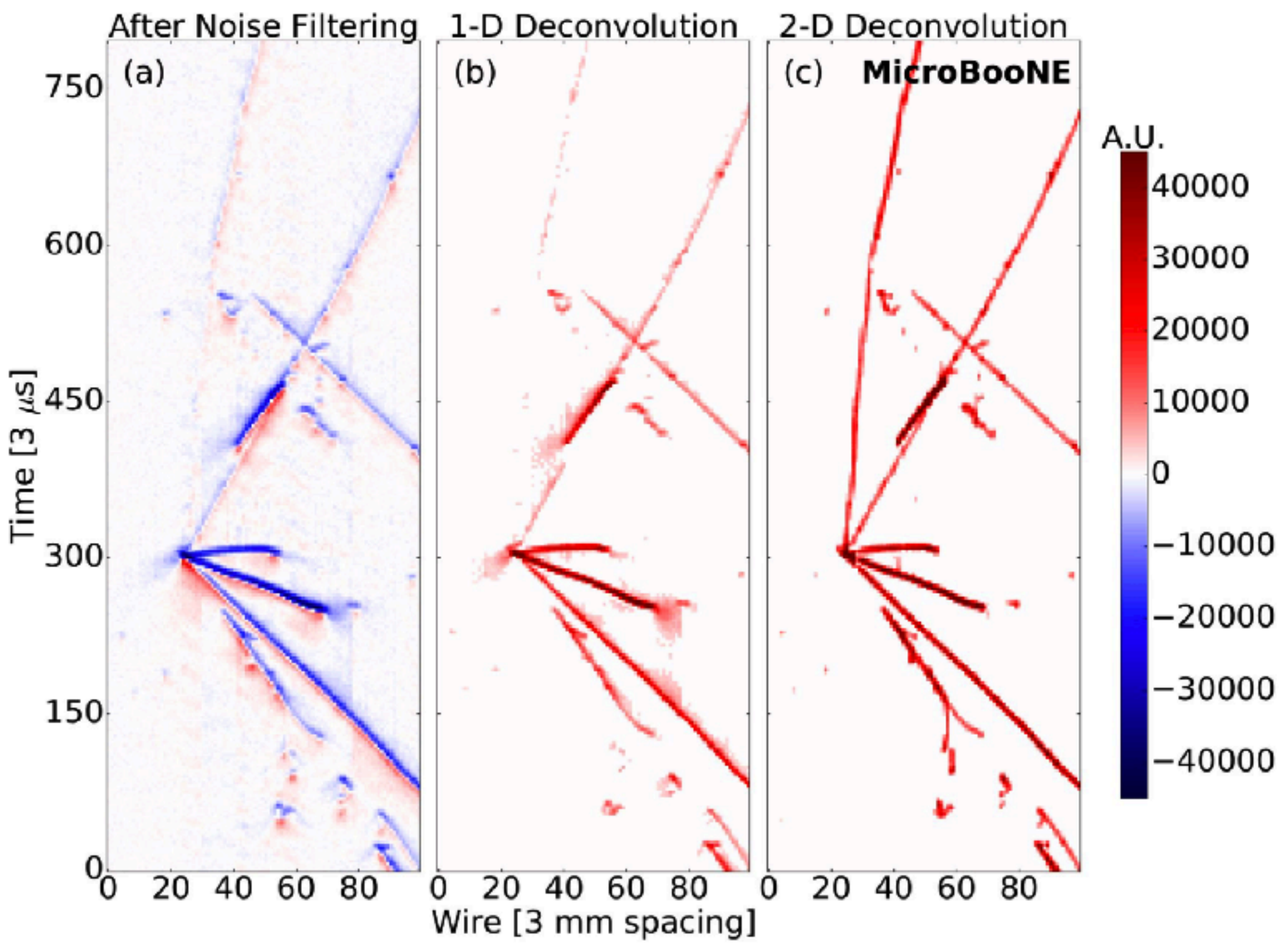
Original wire signal

- Original wire signal extracted with **1D deconvolution** after applying a filter for noise

- **2D deconvolution** to account for induced charge effects, i.e. charge drifting in nearby wire regions

- improvement of the charge resolution

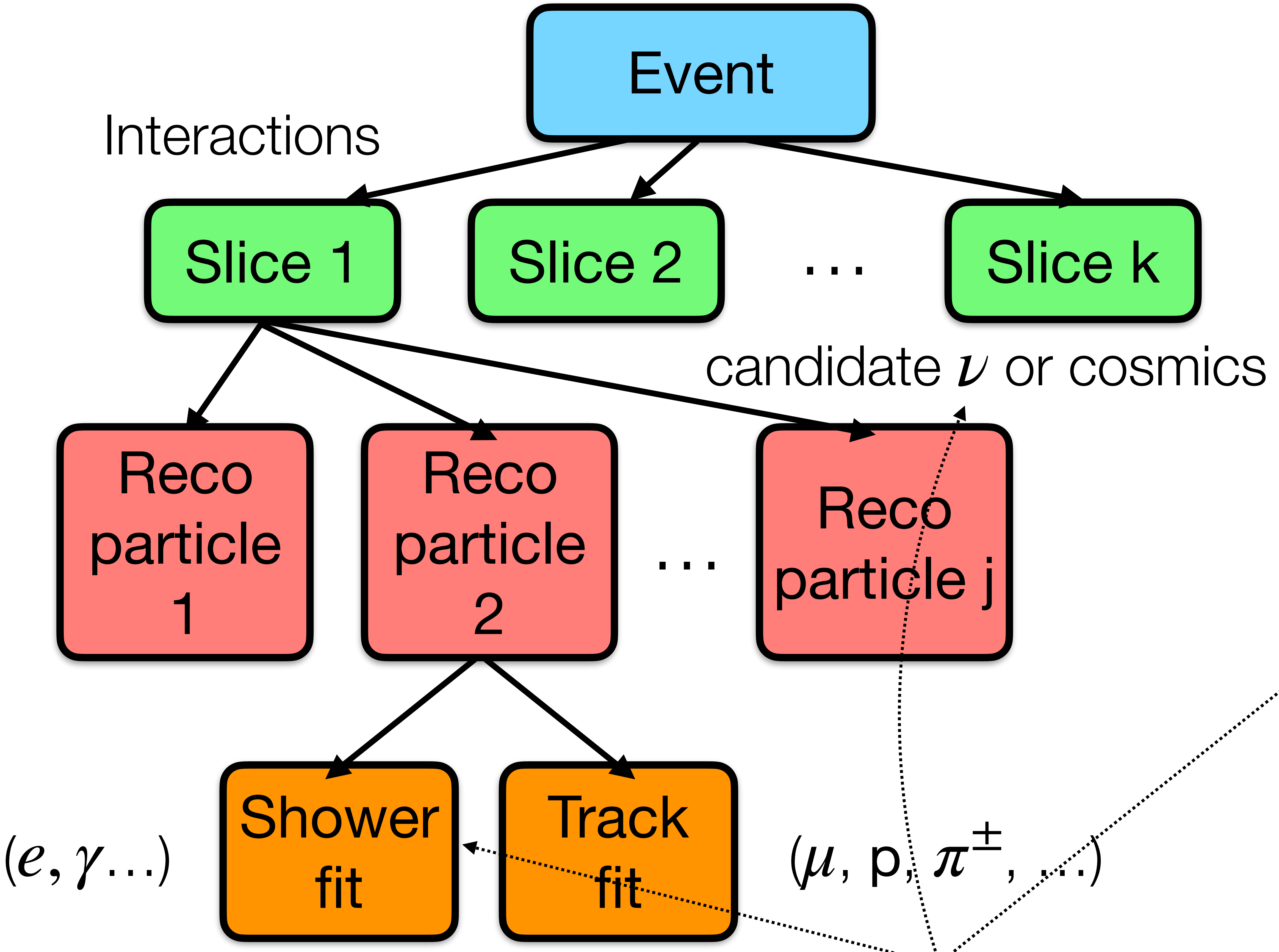
- higher ε on hits reconstruction for specific track classes

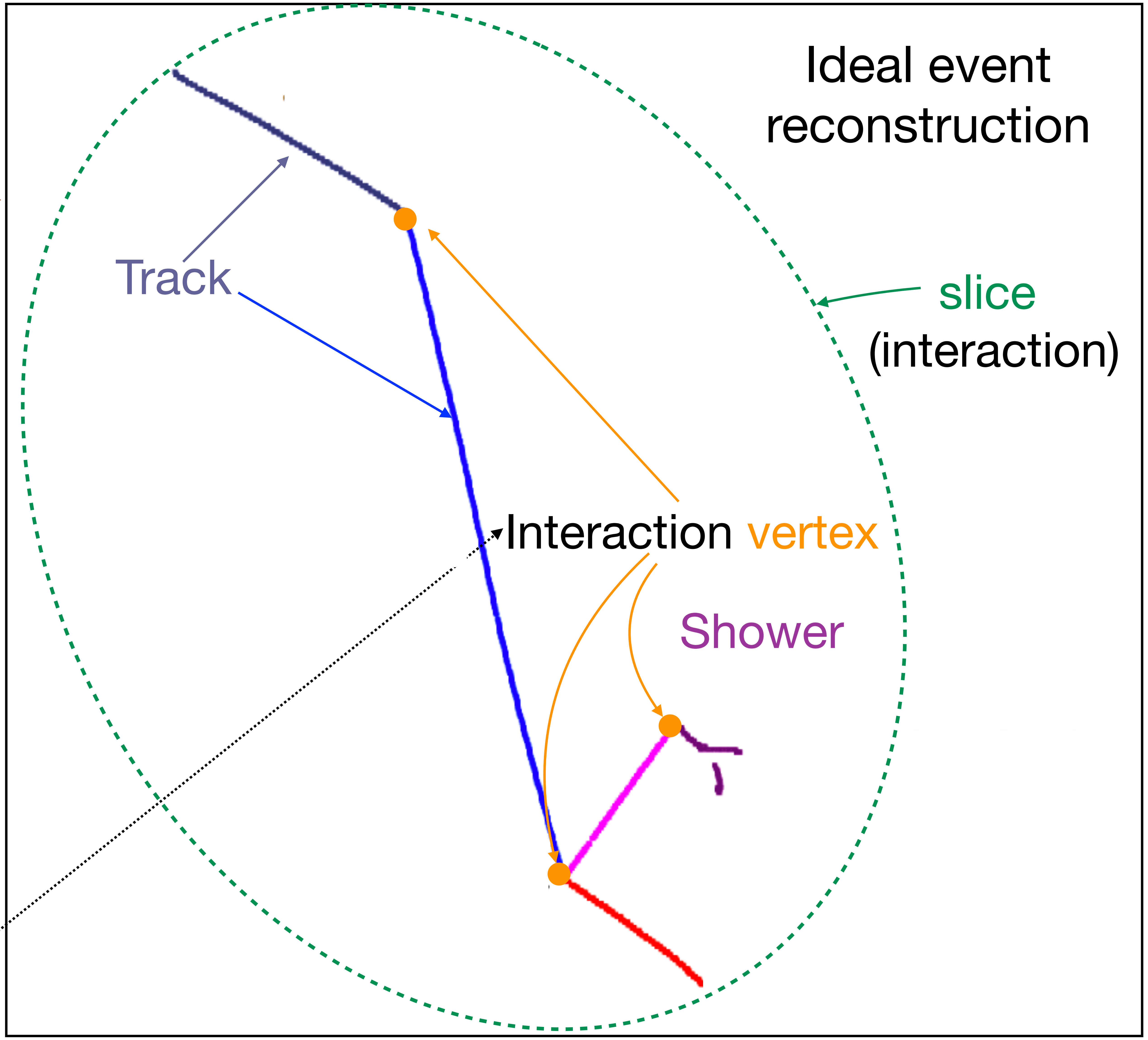


Example of charge recovery from MicroBooNE
Adams, C. et al. 2018 *JINST* 13 P07006 (ArXv link)

Pandora-based event reconstruction

- Multi-algorithm pattern-recognition software
- Goal: reconstruct **interaction hierarchies**





- https://github.com/PandoraPFA

Boosted Decision Trees (**BDTs**), i.e. ML algorithms, employed in three steps of the chain

Boosted Decision Tree (BDT)

We mentioned several places where Pandora uses this algorithm for the reconstruction.

- Idea: Identify a **signal** and a **background** class and a **set of input features** on which you expect there could be a good separation between them.

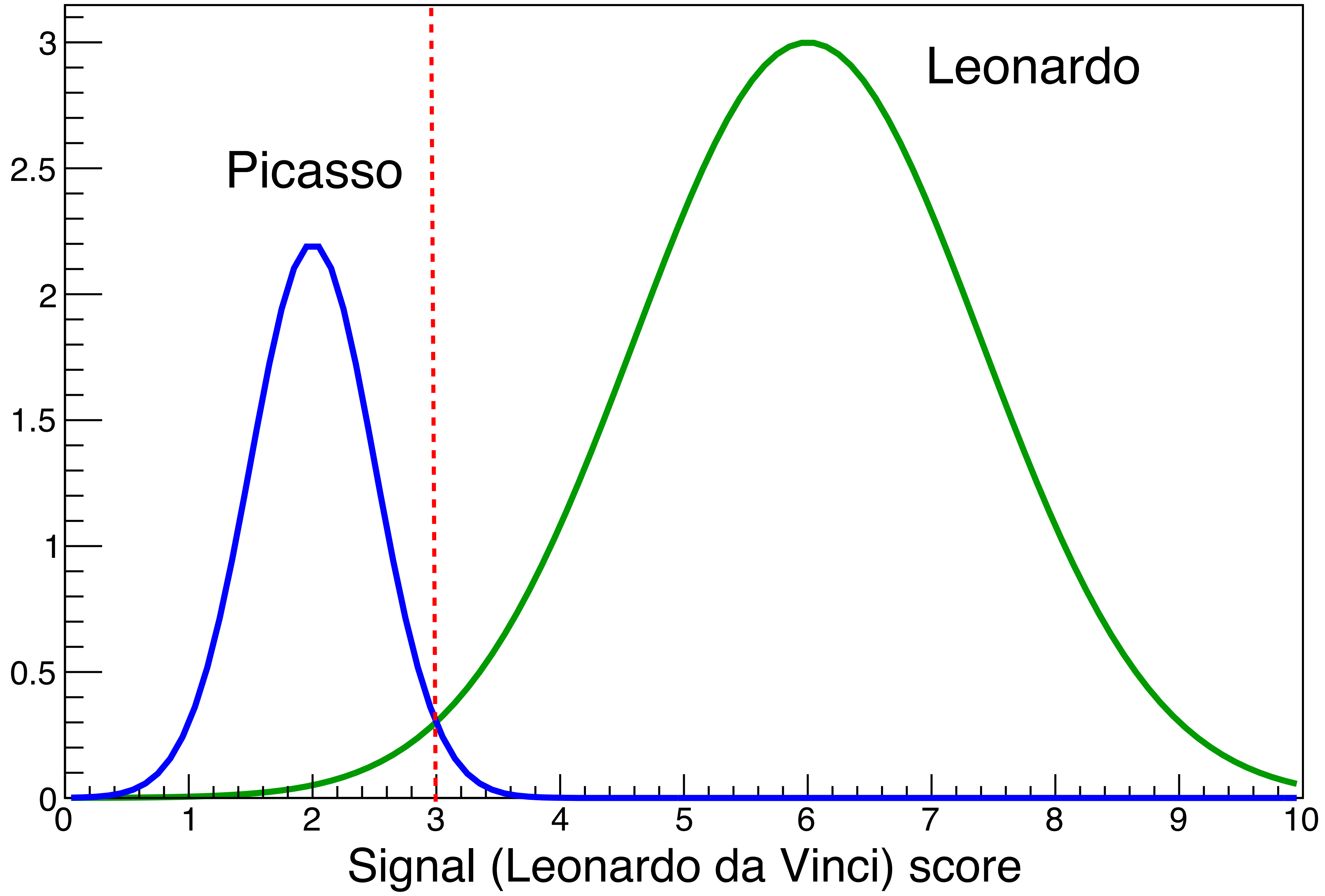
- Method: BDT is first **trained** on a sample where the true class is known and input features are used to have the power to distinguish between signal and background, then for a new sample with unknown class the same set of features is computed to define a **score** that quantifies how “signal-like" the sample is.

- Example:
  Signal: Leonardo da Vinci art work
  Background: Pablo Picasso art work (from the cubism period)
  Sample: a generic painting
  Input parameters: use of colors, light and shadow, presence of geometric shapes

Boosted Decision Tree (BDT)

- <u>Example</u>: Signal: Leonardo da Vinci art work
  Background: Pablo Picasso art work (from the cubism period)
  Sample: a generic painting
  Input parameters: use of colors, light and shadow, geometric shapes, …

Signal



Background

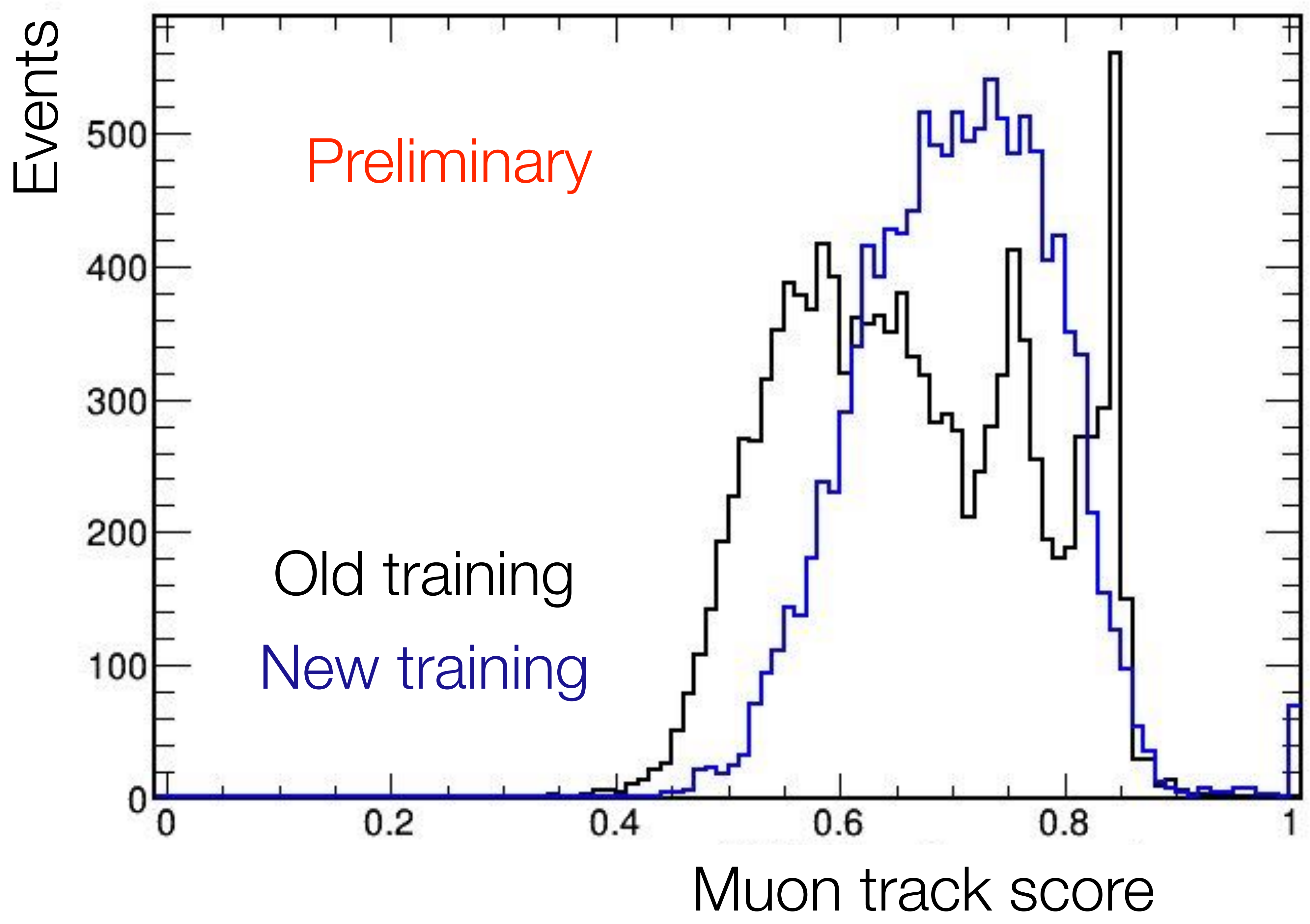
Pandora-based event reconstruction: new BDT training to discriminate tracks and showers

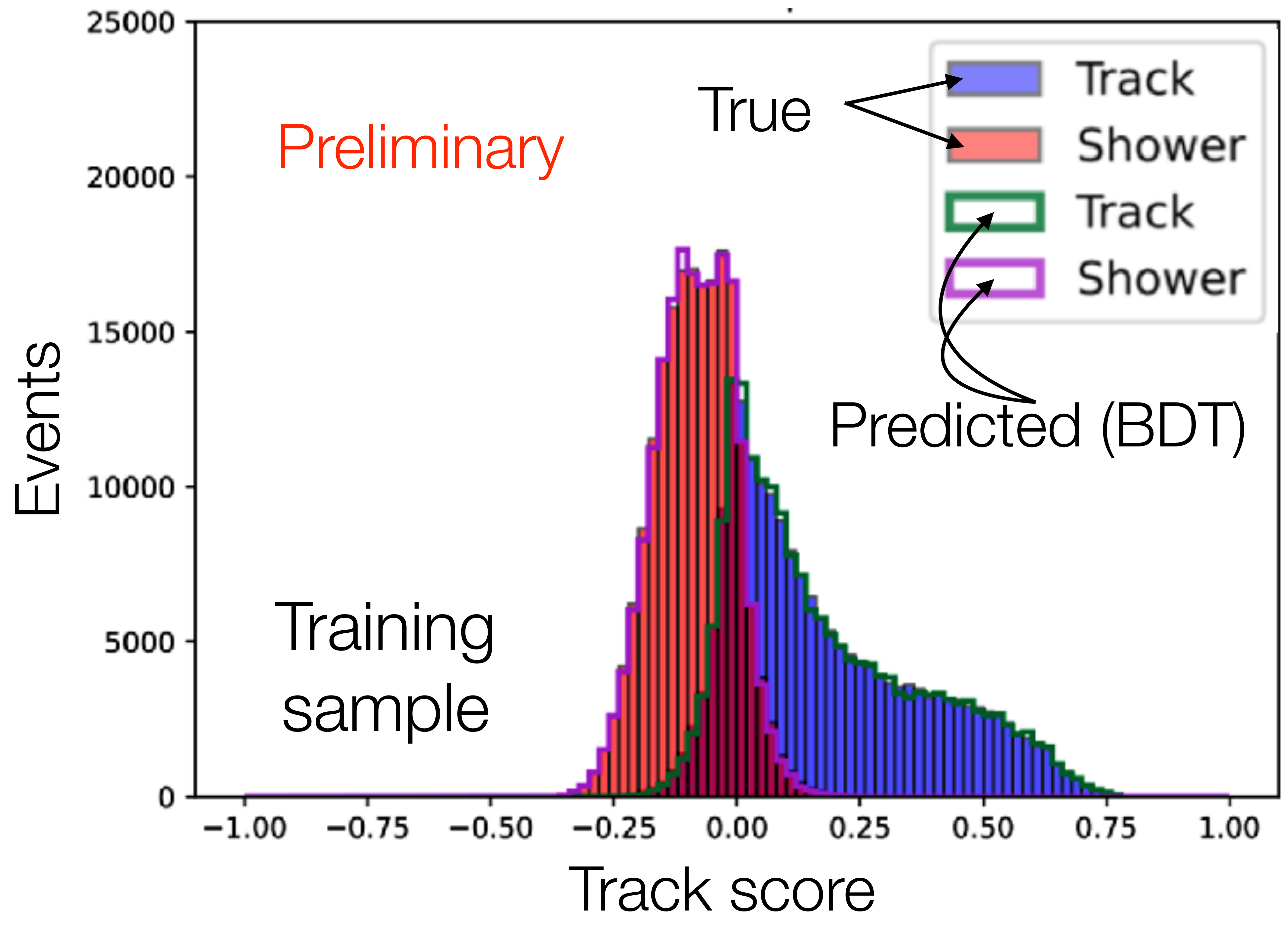
- Training based on 8 **geometrical** variables (5 **calorimetrical**) from the 3D coordinates (charge) of the hits

New training based on BNB ν-only MC

Preliminary

$\varepsilon_{classification}$	Old training	New training	Δ
BNB ν only	72.3%	80.3%	8.0%
NuMI ν only pre-tuning [*]	67.8%	79.9%	12.1%
NuMI ν only tuned [*]	66.7%	79.2%	12.5%

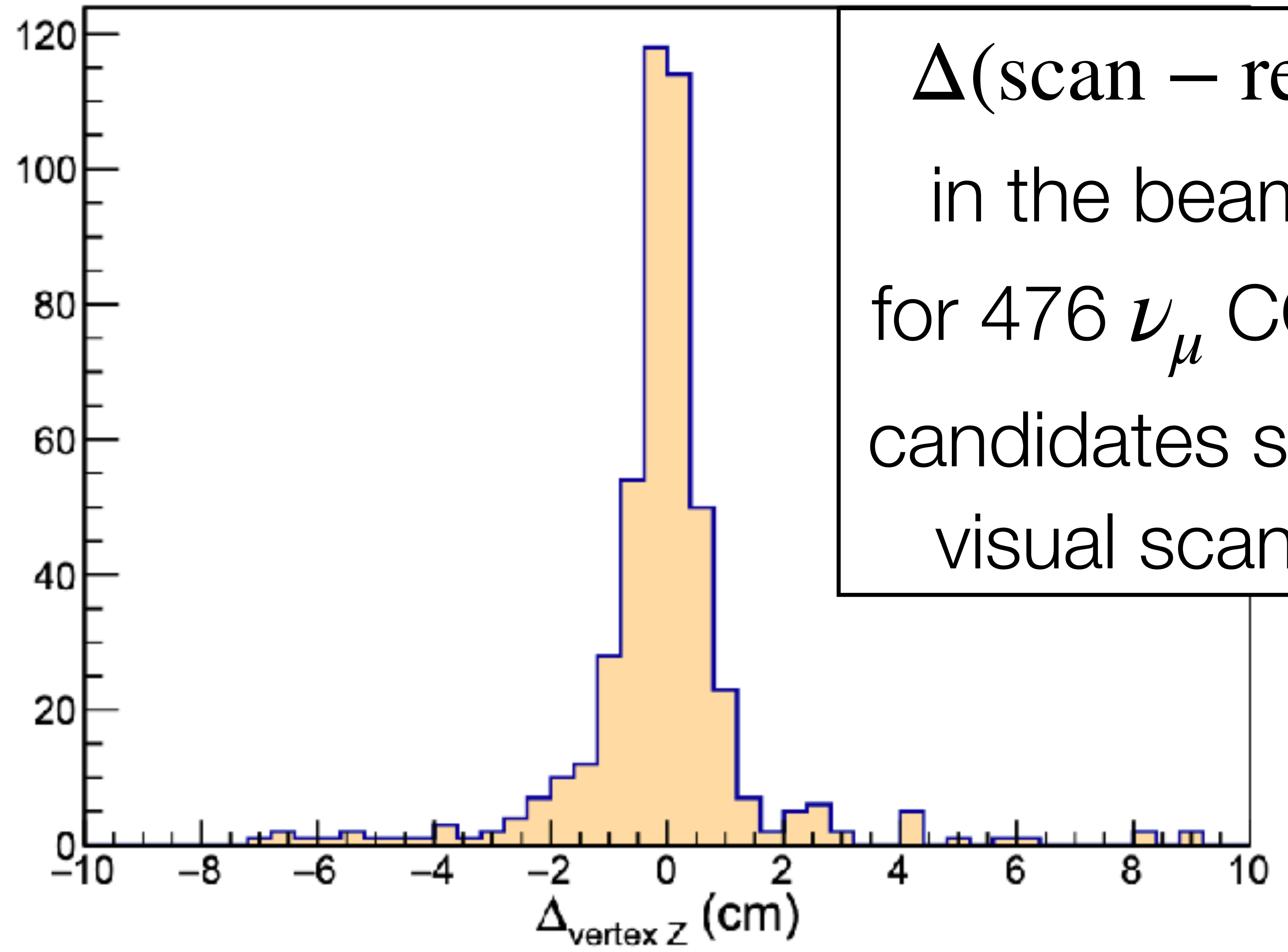




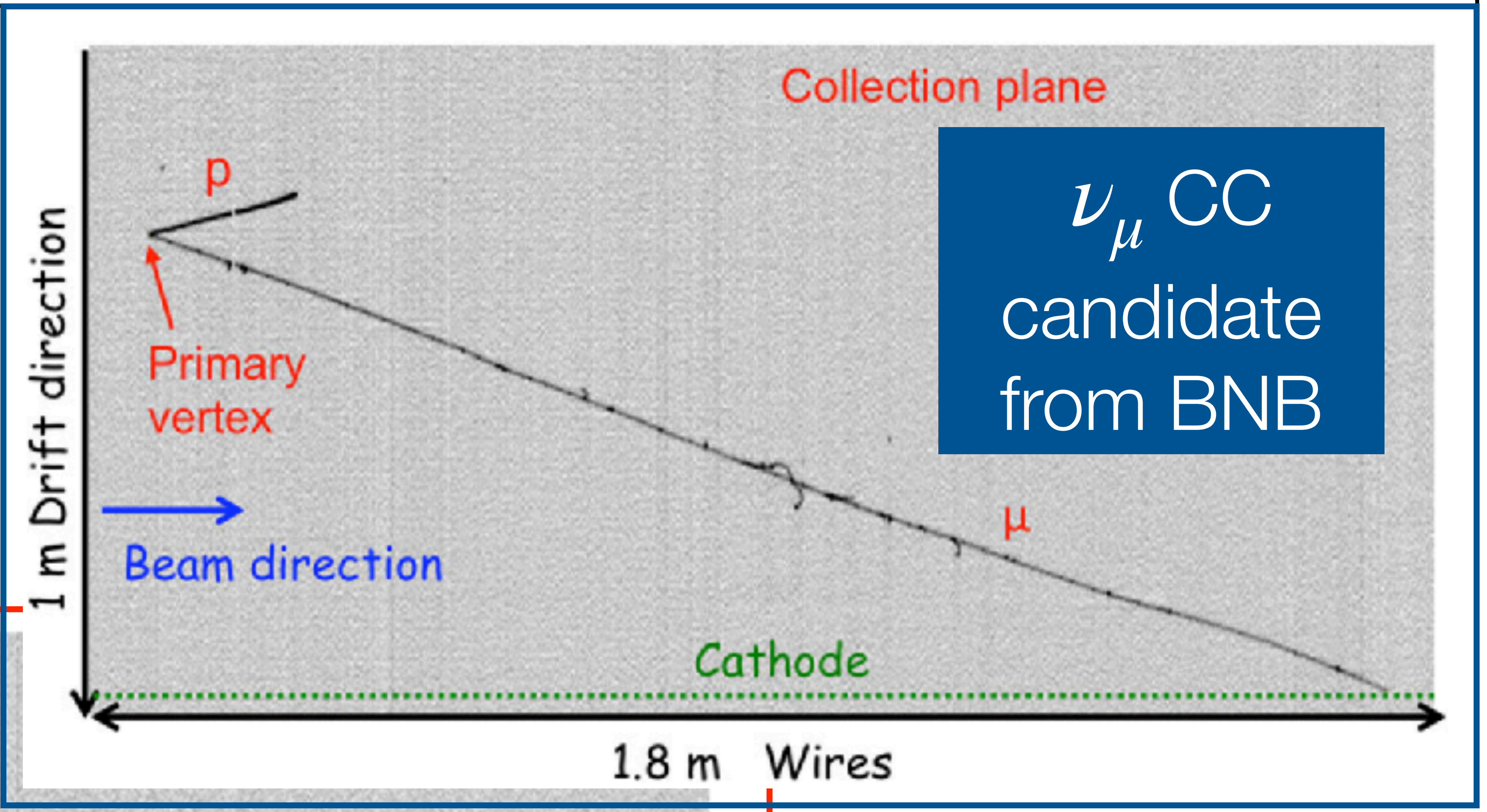
Pandora event reconstruction: visual scanning and data/MonteCarlo comparison to evaluate performance/improvements

- We employ **visual scan ν events selection** and **Monte Carlo** simulations to identify reconstruction pathologies, explore reconstruction improvements and tune our selection algorithms for analyses

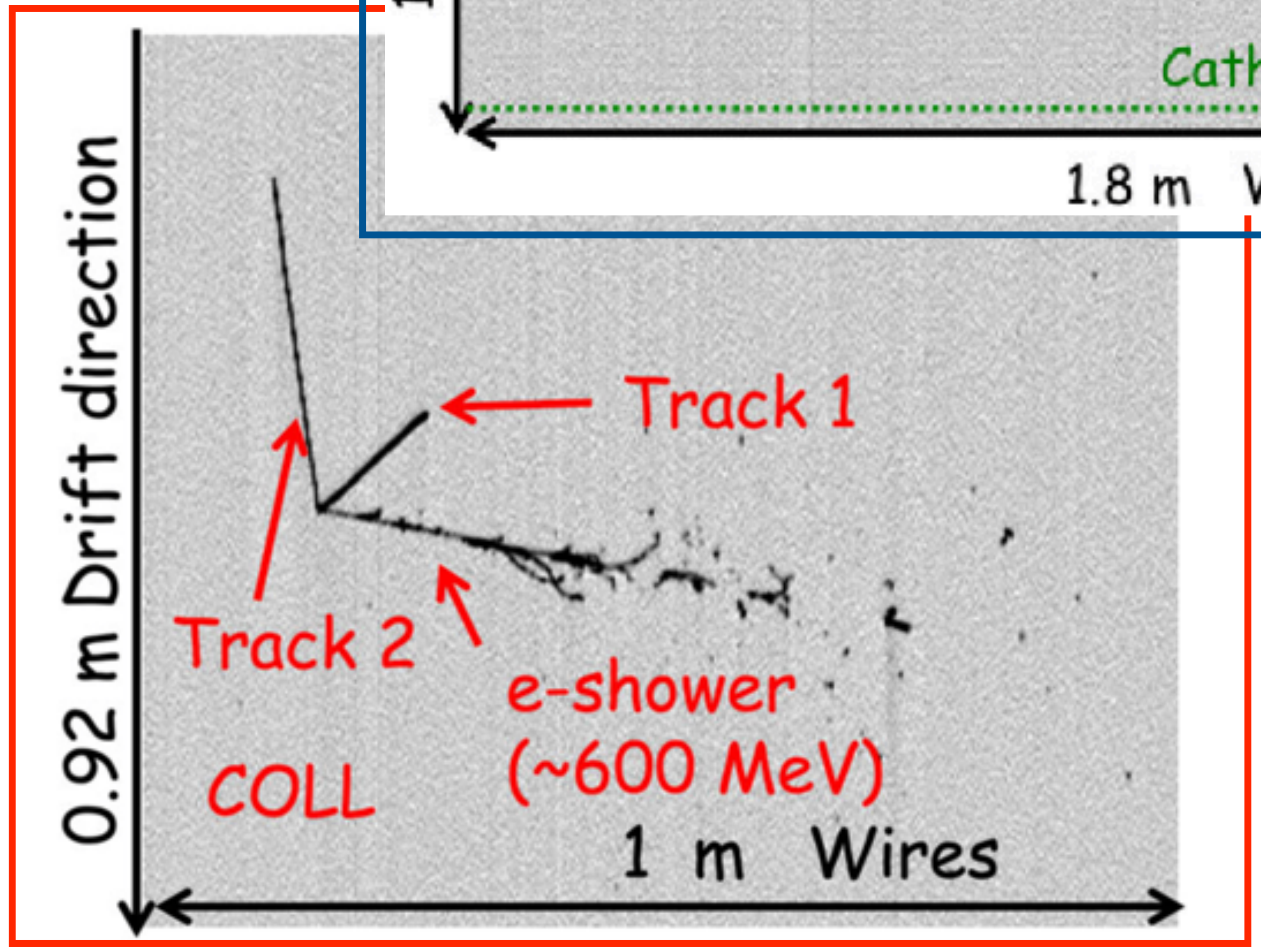
- Most frequent pathology is **track splitting** $\mathcal{O}$(6-7%), followed by **wrong vertex ID** $\mathcal{O}$(4%) and **track/shower ID**
- Validation w/ visual scan based on the 3D position of the vertex V, end point and length of μ track



Δ(scan − reco)vertex$_z$ in the beam direction for 476 ν_μ CC contained candidates selected with visual scan of events



ν_μ CC candidate from BNB

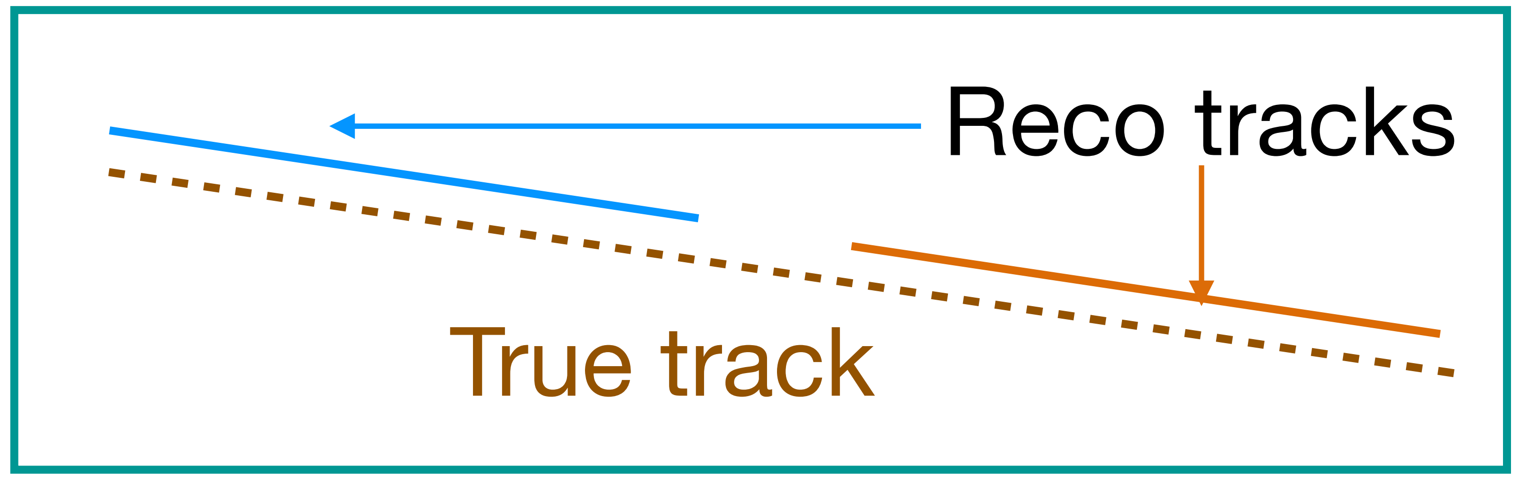


ν_e CC candidate from NuMI

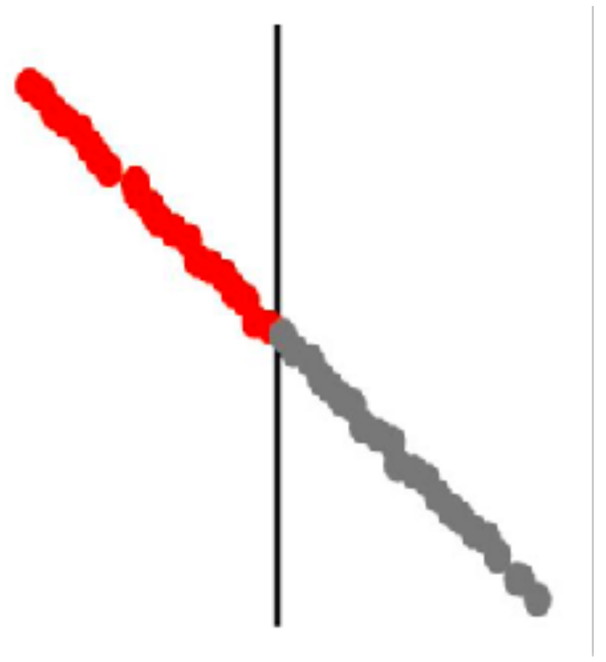
Eur. Phys. J. C 83:467 (2023)

Pandora-based event reconstruction: track splitting

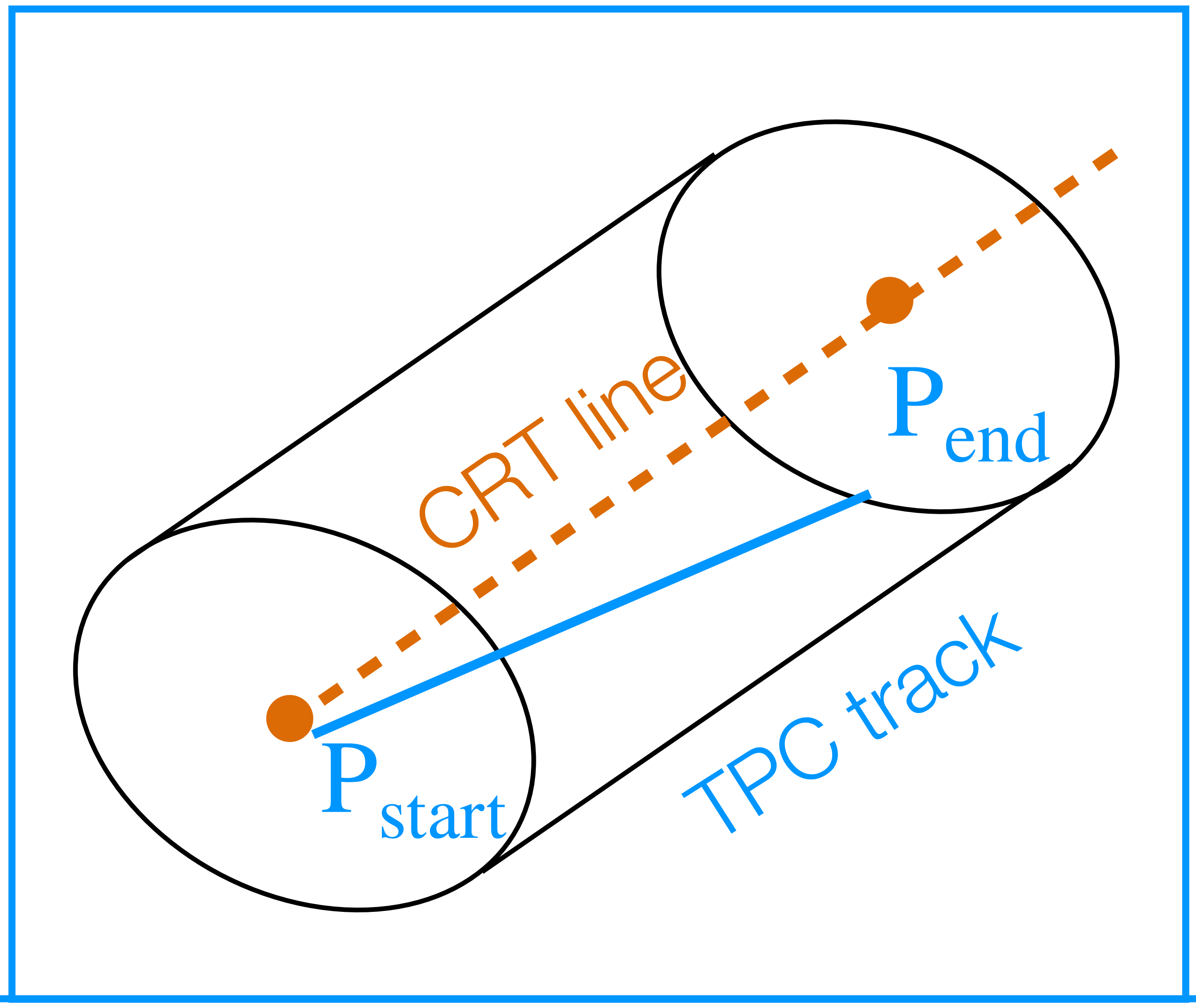
- Several studies to mitigate the problem of **track splitting:** e.g. the single track of a μ is reconstructed as $n \geq 1$ segments



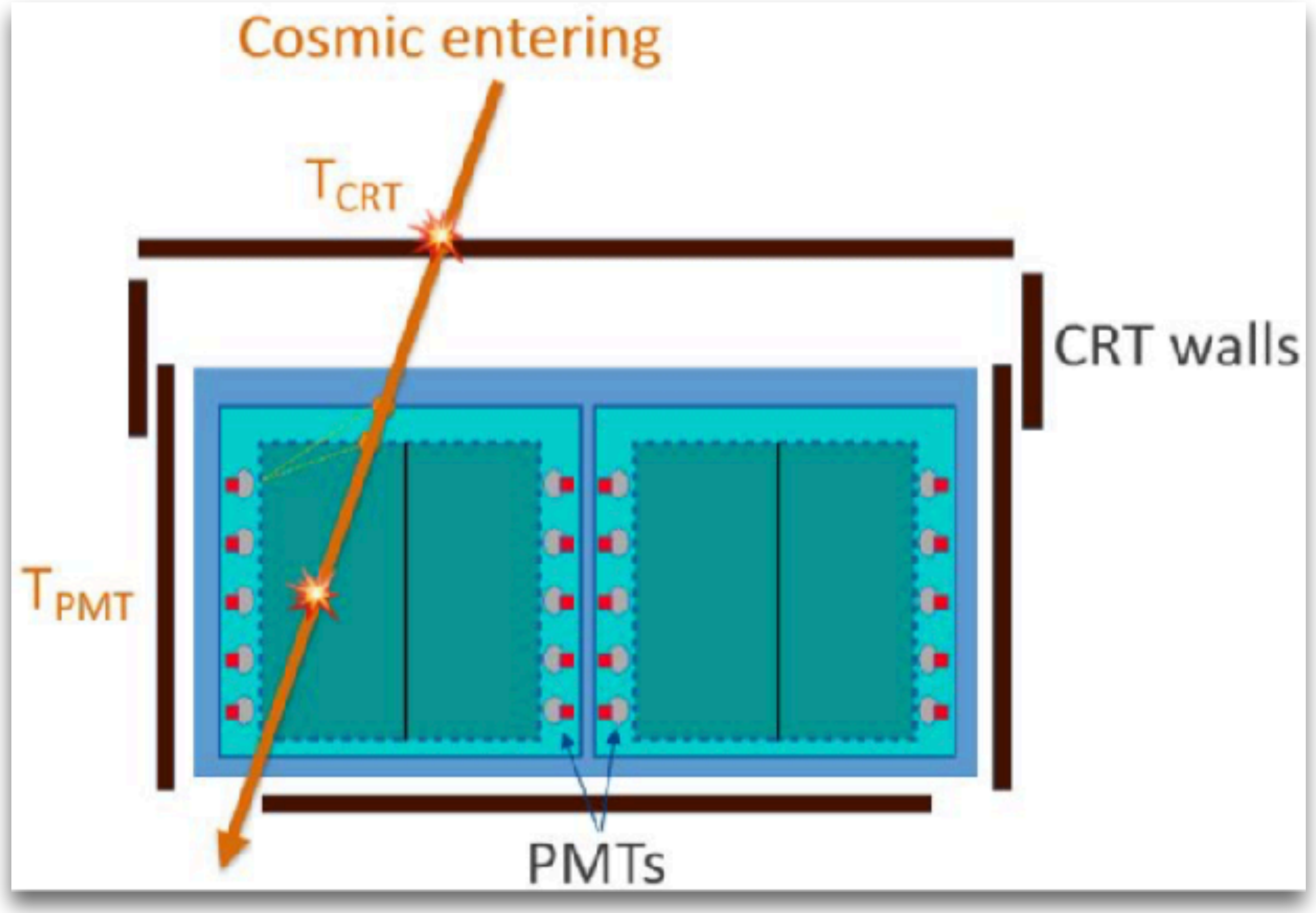
  - Track splitting happening at detector boundaries: $z = 0$, at the **cathode**
  - Ongoing study of a **stitching algorithm** to join track pieces post-reconstruction based on **MC**
  - Study of a stitching algorithm on **cosmic μ in data:** TPC tracks are identified after CRT-PMT info
  - Study of the **systematic** induced by track-splitting:



  - Basic idea: break tracks study how reco is affected

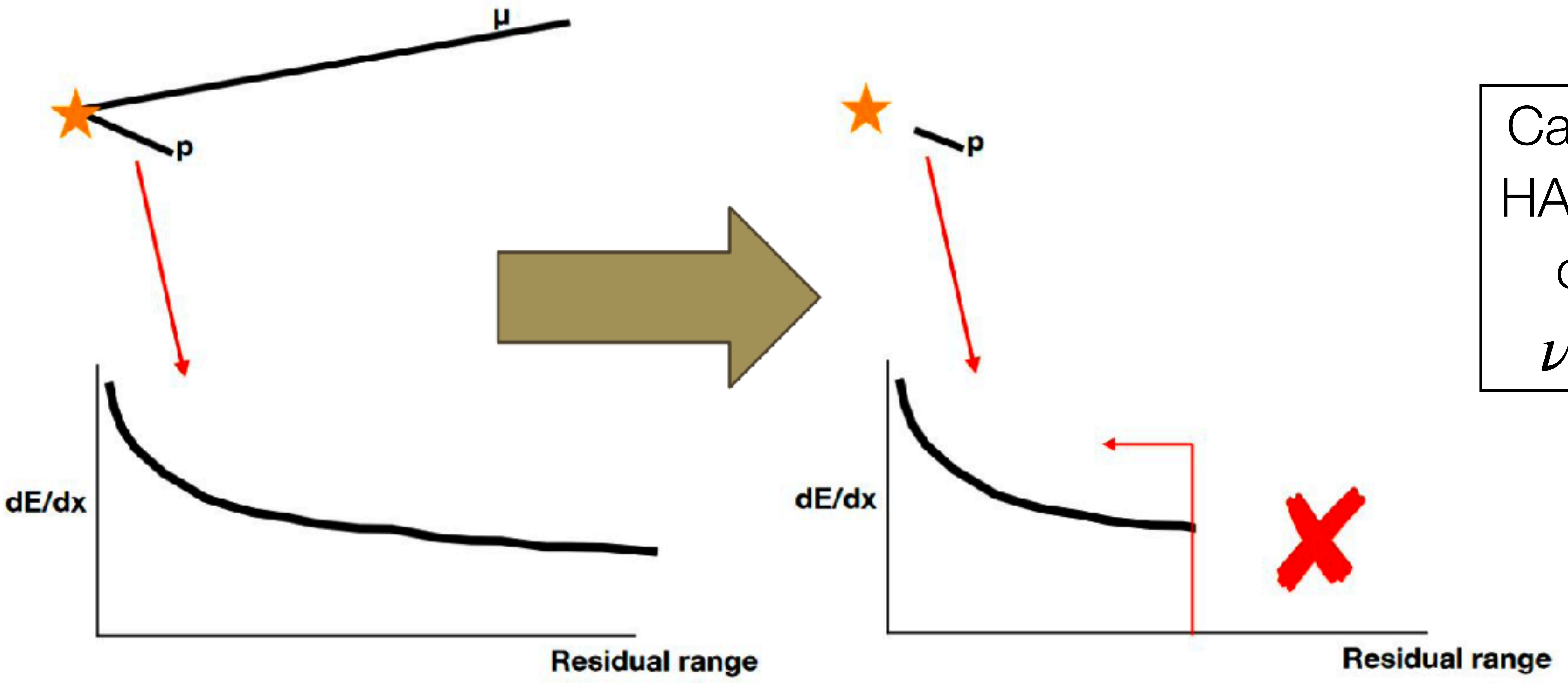


Cartoon of the stitching algorithm



Pandora-based event reconstruction: data-driven systematics study

- Goal: understand and account for differences in reconstruction between data and MC
- Foreseen goal: data driven validation of ML algorithms
- *Hit Activity Removal from Particles for Systematics* (**HARPS**): operate on specific particles and reduce their size ↔ similar to starting with a lower energy particle and analyse the impact on reconstructed quantities



Cartoon of the idea: HARPS on a sample of **protons** from ν + **cosmics MC**

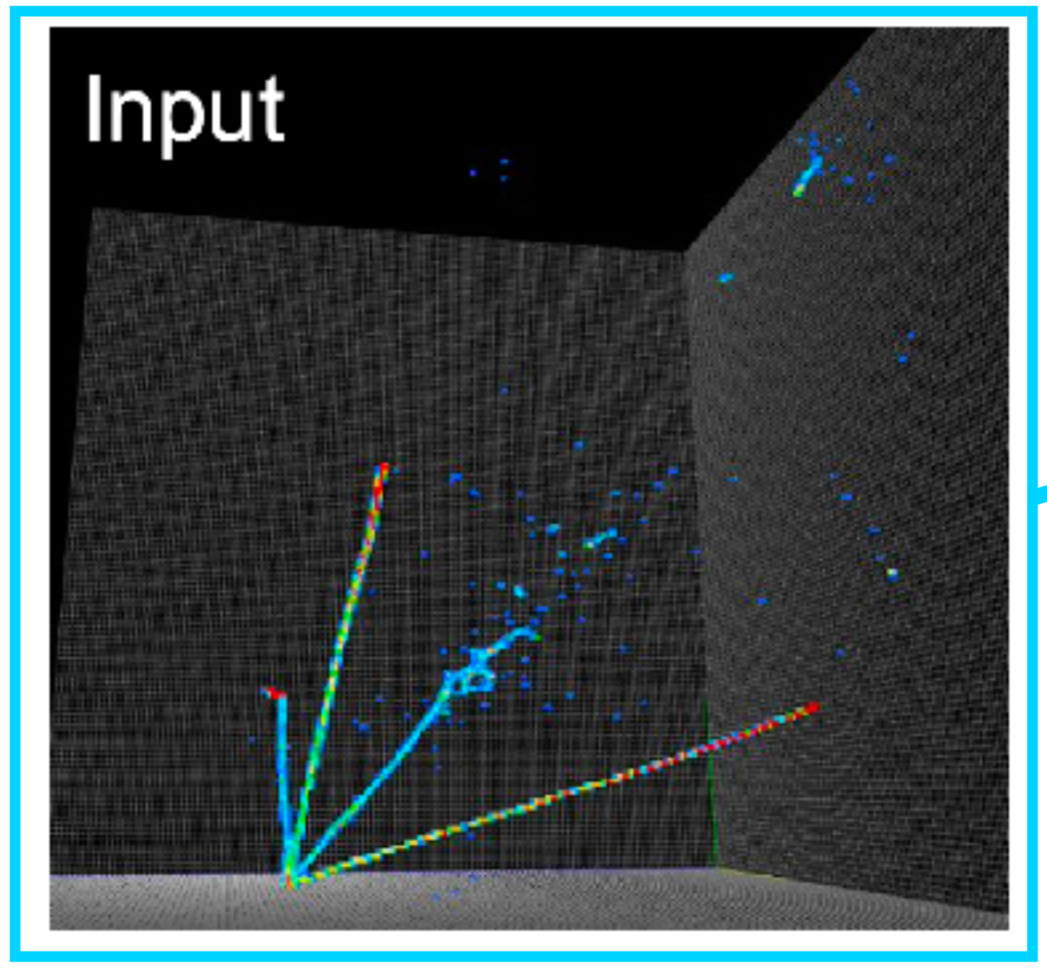
Pandora-based event reconstruction: summary and next steps

- Strong **interplay** with the needs/results of the ongoing analysis efforts in defining our goals: we are increasing our effort towards evaluating **reconstruction (detector) systematics**

- Several efforts to mitigate the effects of the most relevant reconstruction pathologies at different levels including track splitting, track vs shower misidentification, vertex reconstruction

- Next steps foreseen: continuous **validation** of the reconstruction chain and (re)training of the **ML algorithms** employed in several points of the reconstruction any time relevant changes to signal processing at previous stage are included in the data processing chain

Machine Learning (ML) based LArTPC event reconstruction



Hierarchical feature extraction

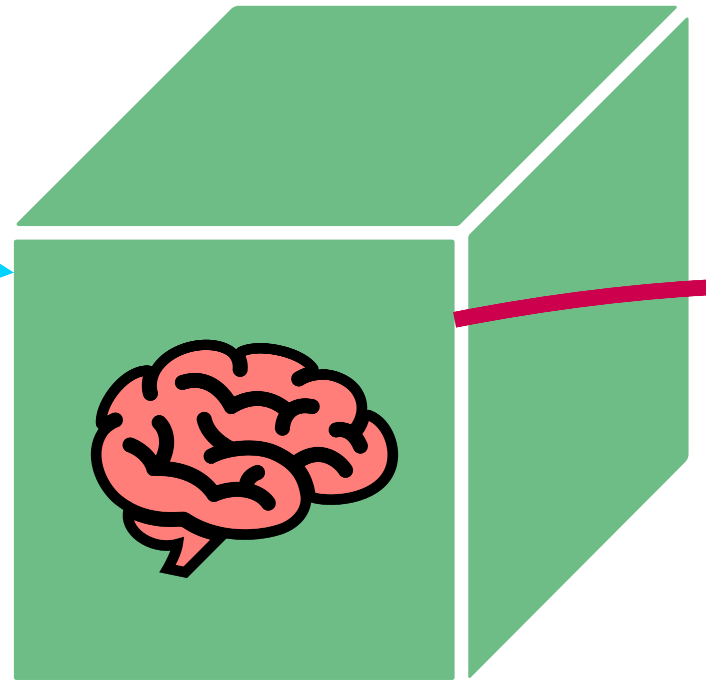
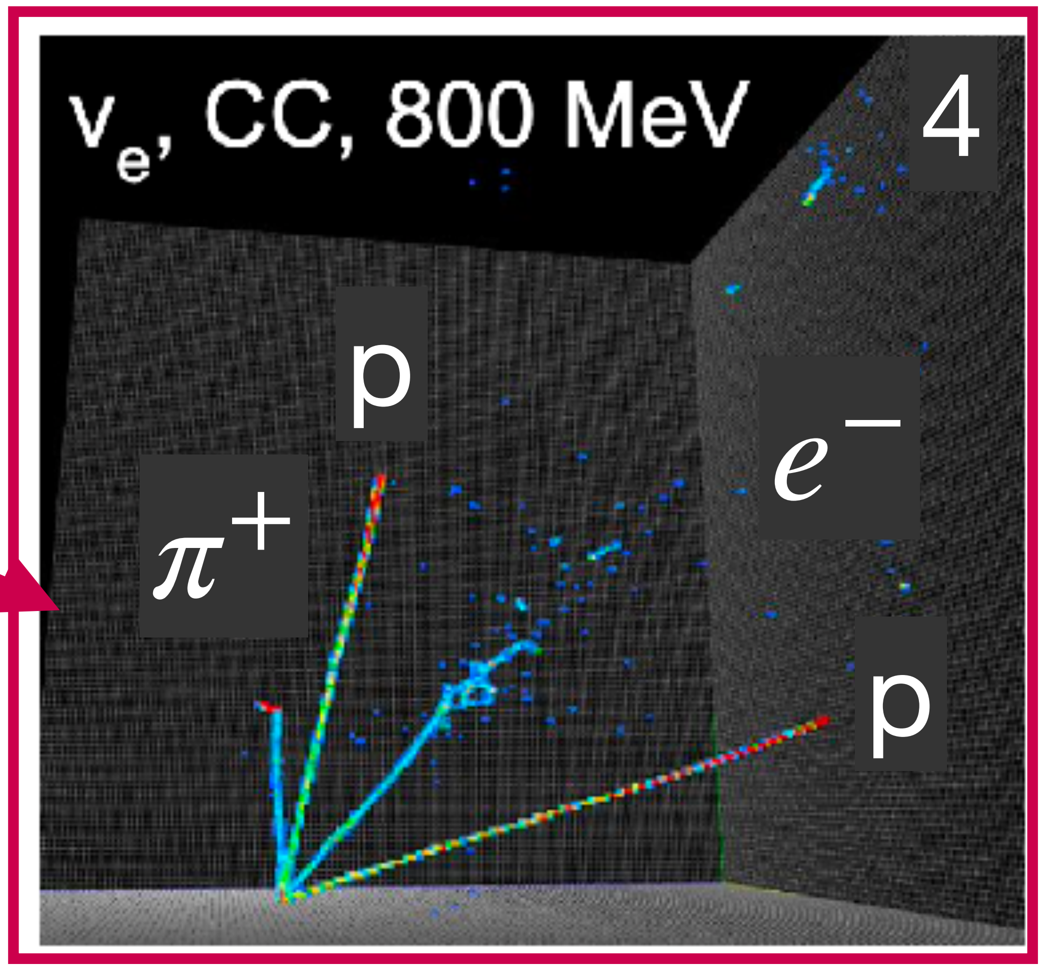
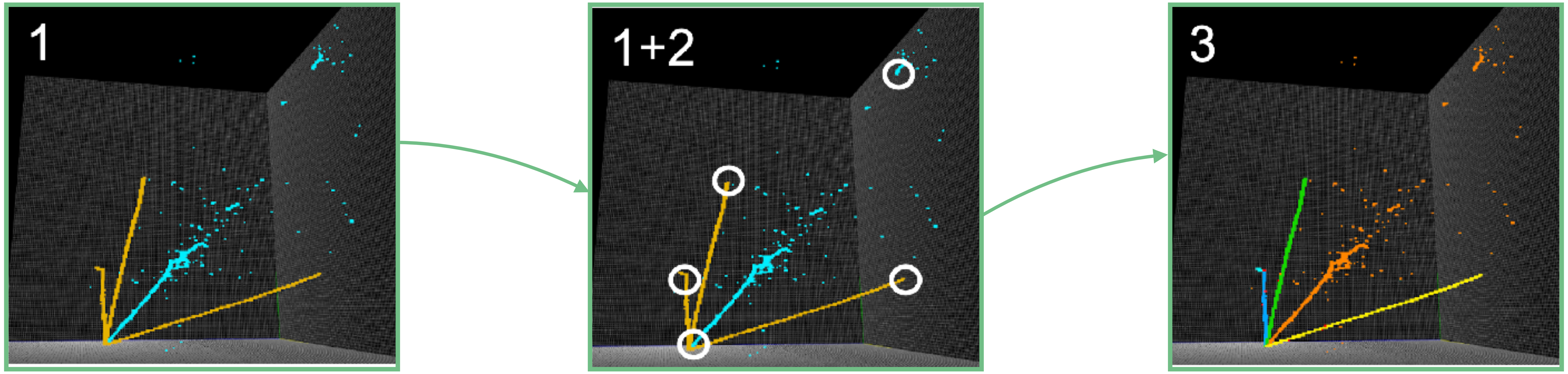


Image classifier

Convolutional Neural Network



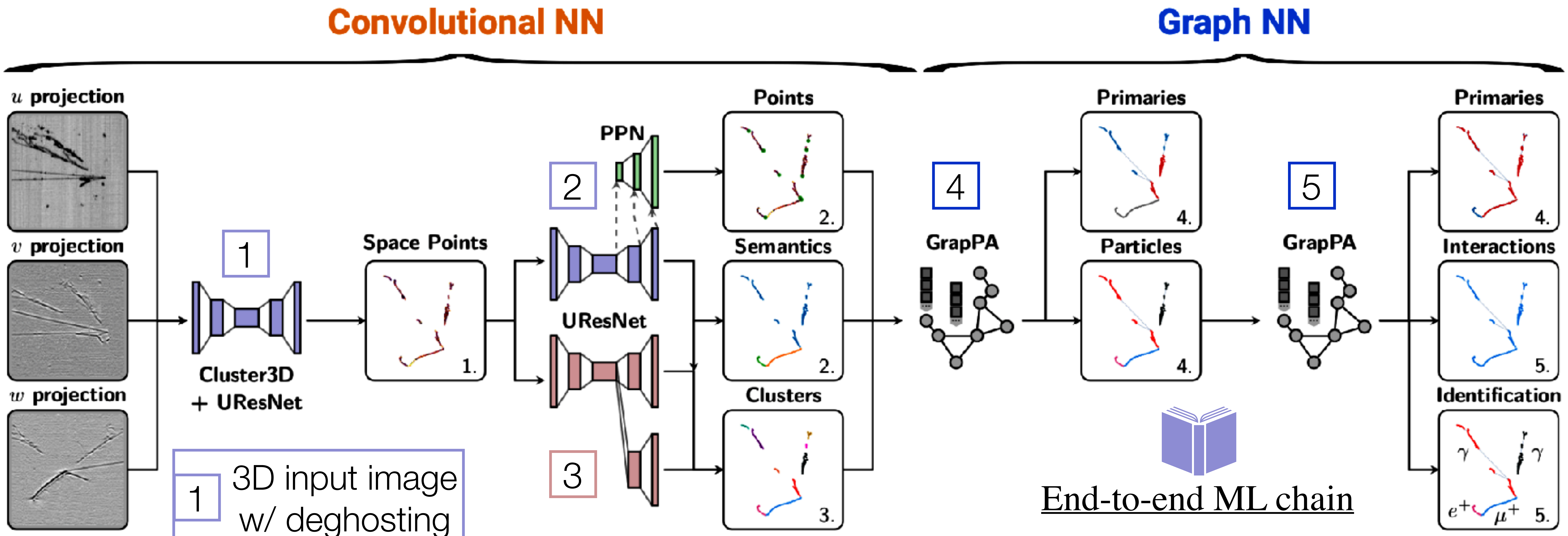
1	Separate *voxels* based on the **topology**
2	Find **important points** (vertex V, start/end P)
3	Cluster particles



ML-based LArTPC event reconstruction: end to end reconstruction chain

2 Voxels classified in different abstract particle classes + identification of the points of interest

4 Assemble shower objects and identify primary fragments



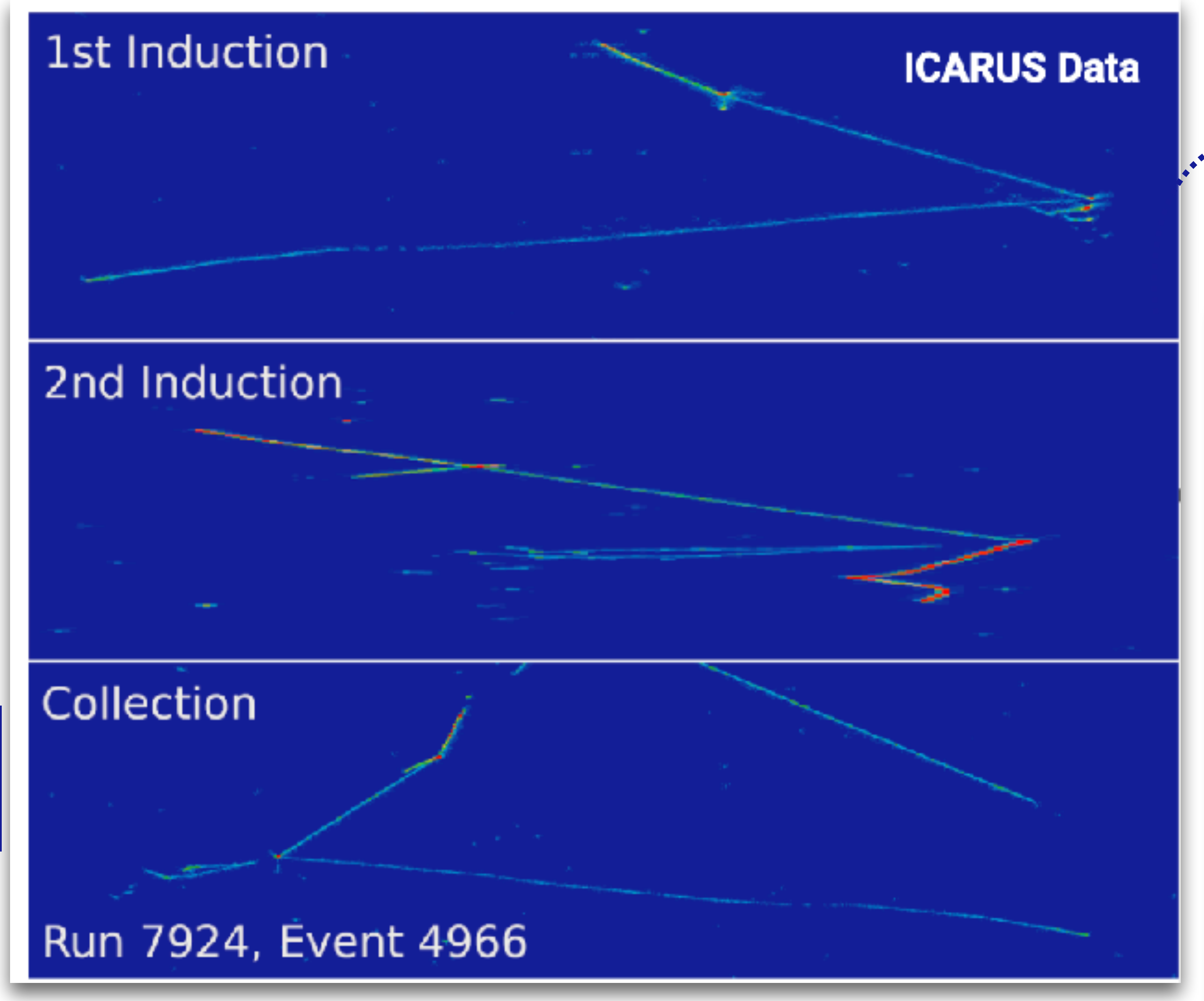
1 3D input image w/ deghosting

2D views from wire planes

3 NN to build individual dense particle clusters

5 Particles aggregation into interactions and ID

1 ML-based event reconstruction: hierarchical feature extraction

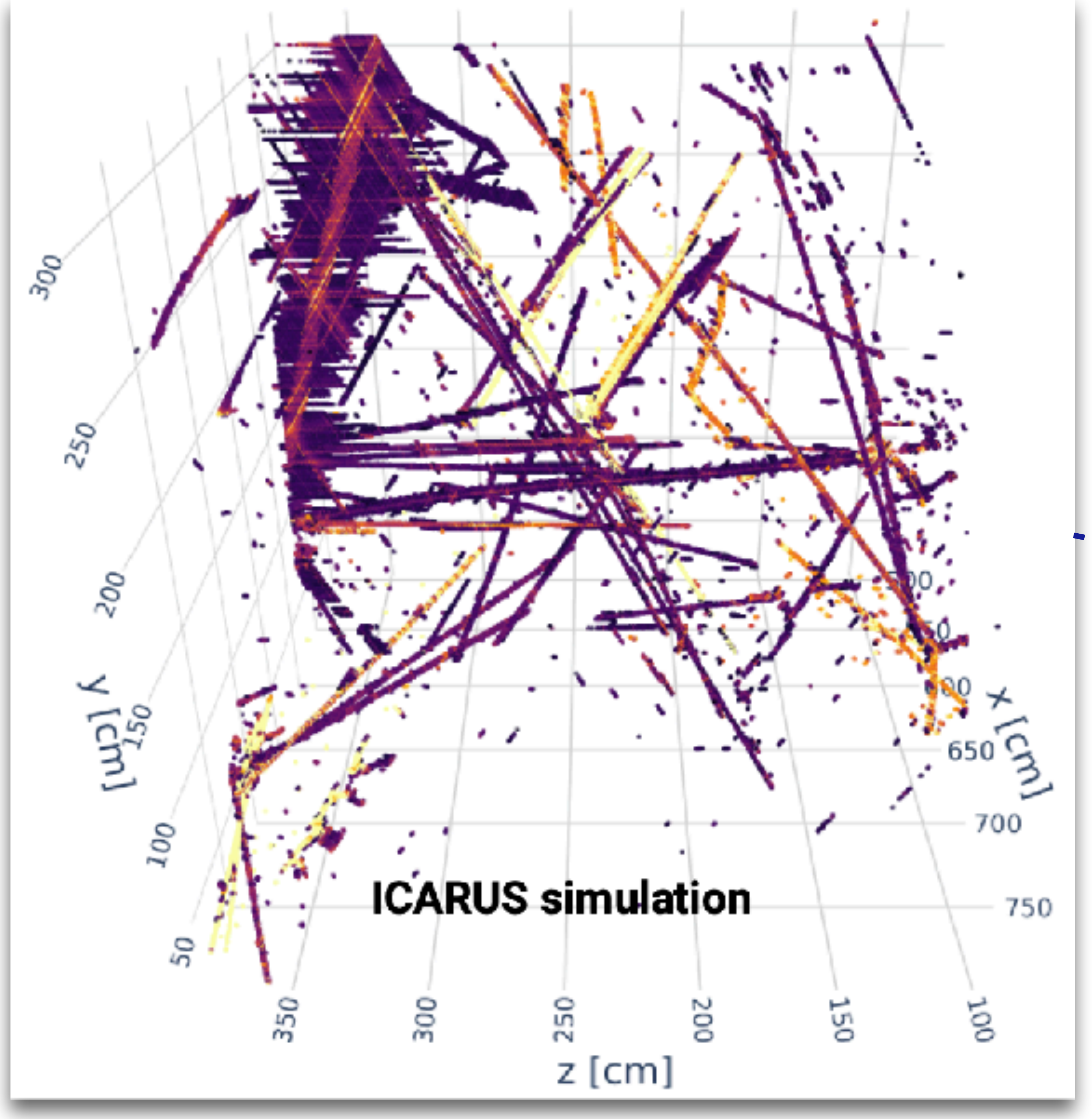


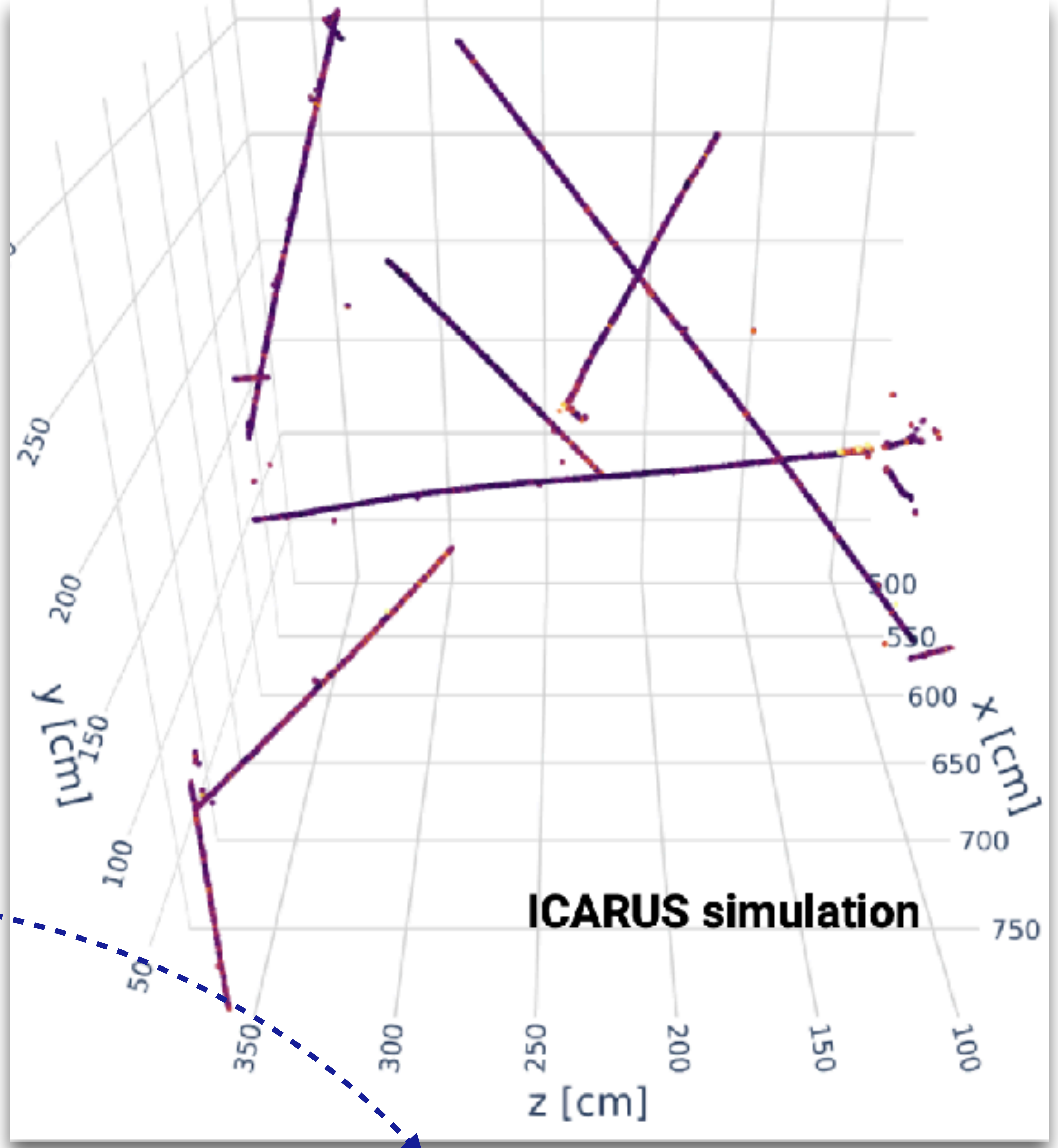
time

wire

Starting point:
3 wire planes ↔ 3 x 2D images

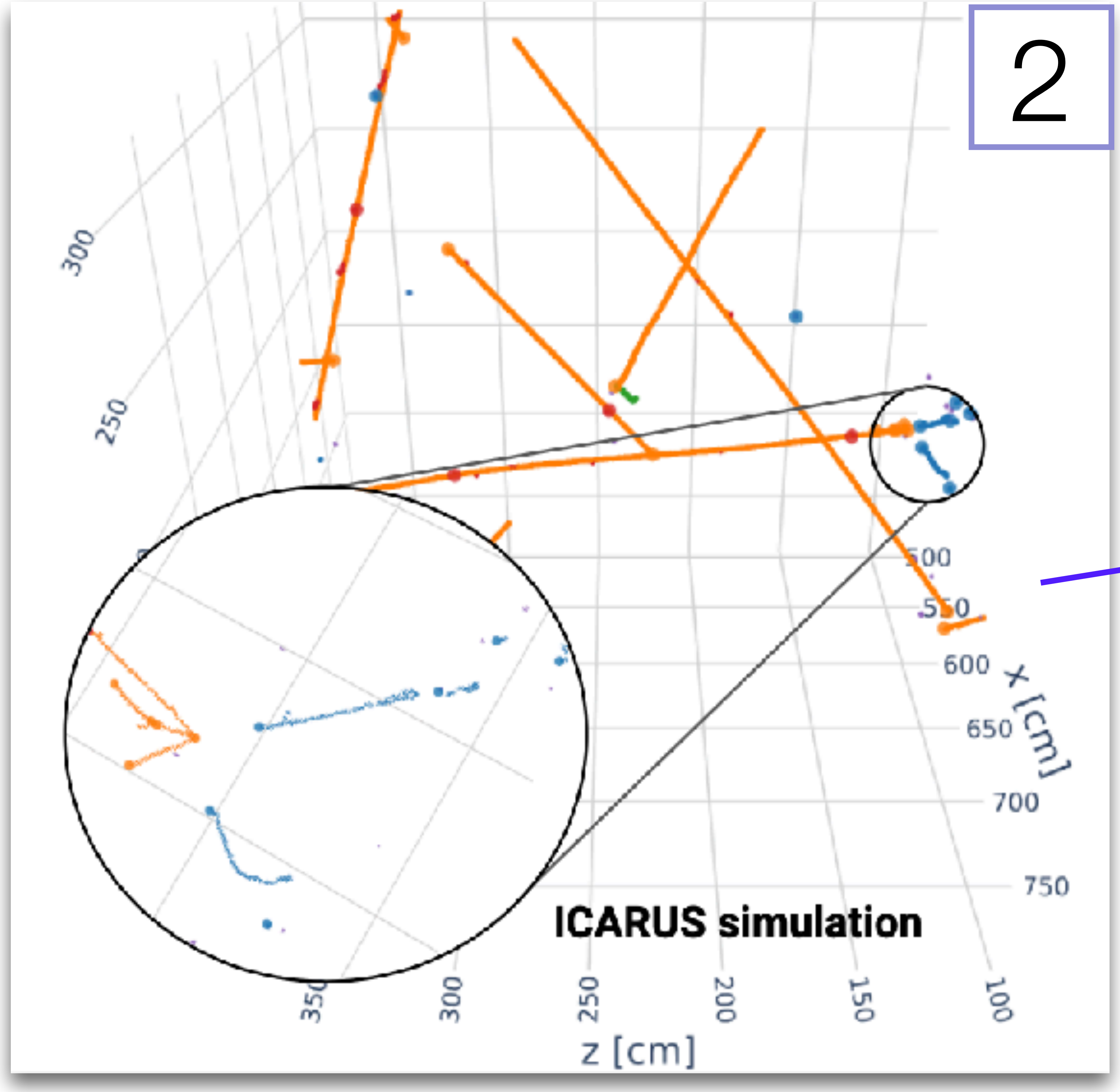
Cluster 3D: make all valid (time-compatible & intersecting) combinations of hits across 2 wire planes





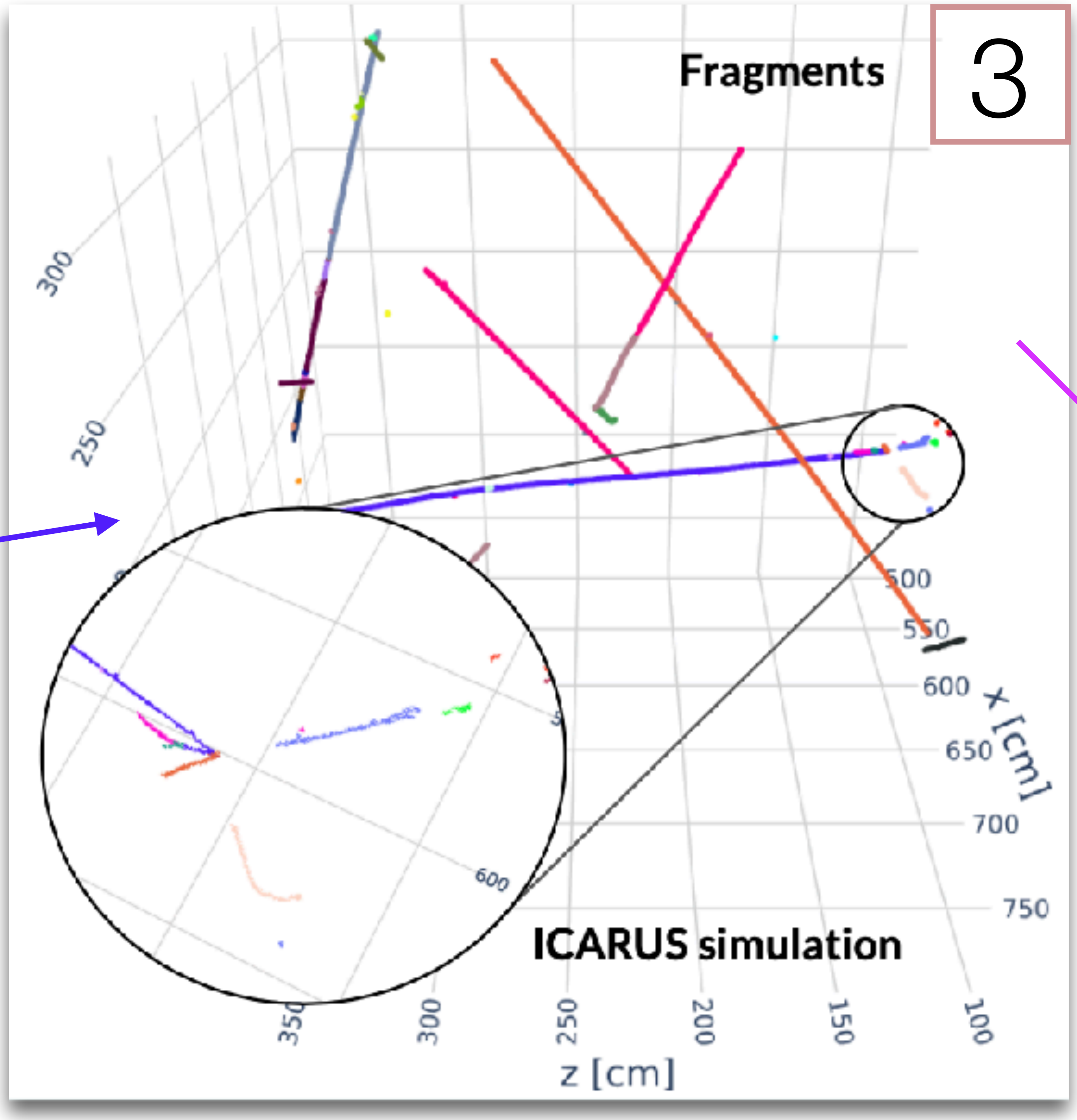
Deghosting: use **U-ResNet** to identify and remove *artifacts* of the reconstruction

ML-based event reconstruction: hierarchical feature extraction



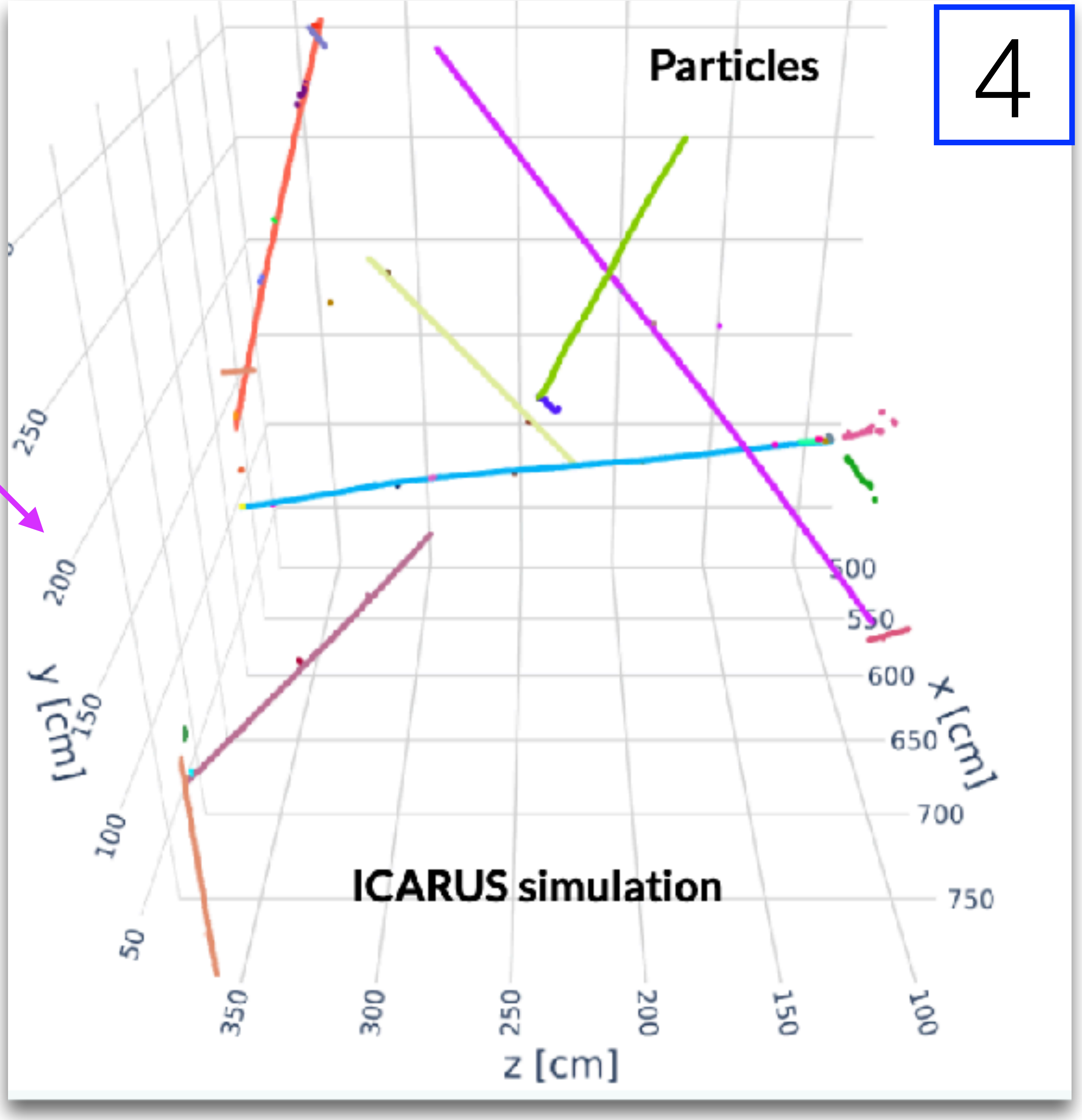
Semantic segmentation & Point of interest (PPN)

Distinguish different particle types based on topological features and identify vertex, start/end points



Particle clustering

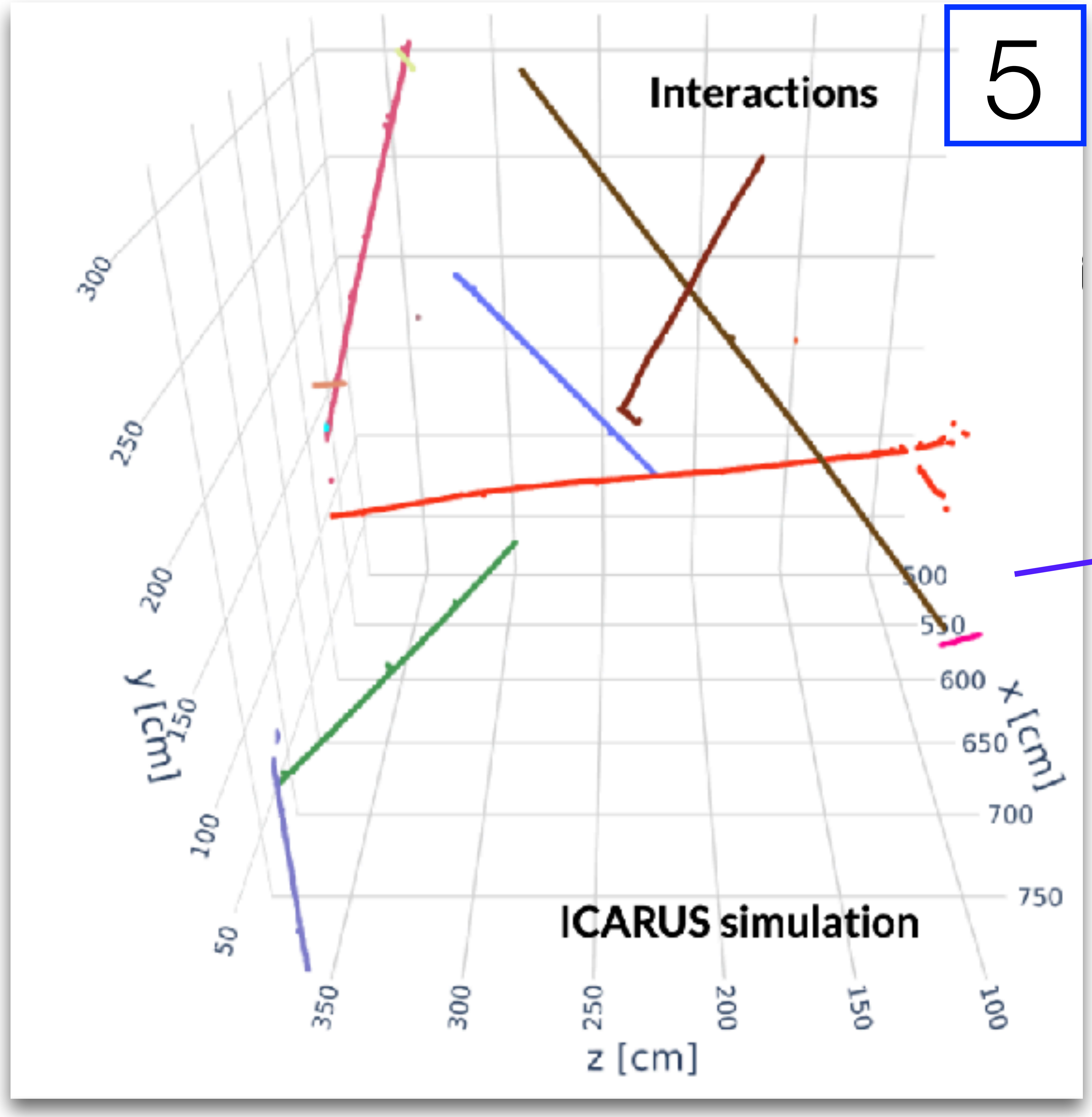
Cluster particle fragments that belong to a common *semantic* class, i.e. break track/shower fragments at PPN

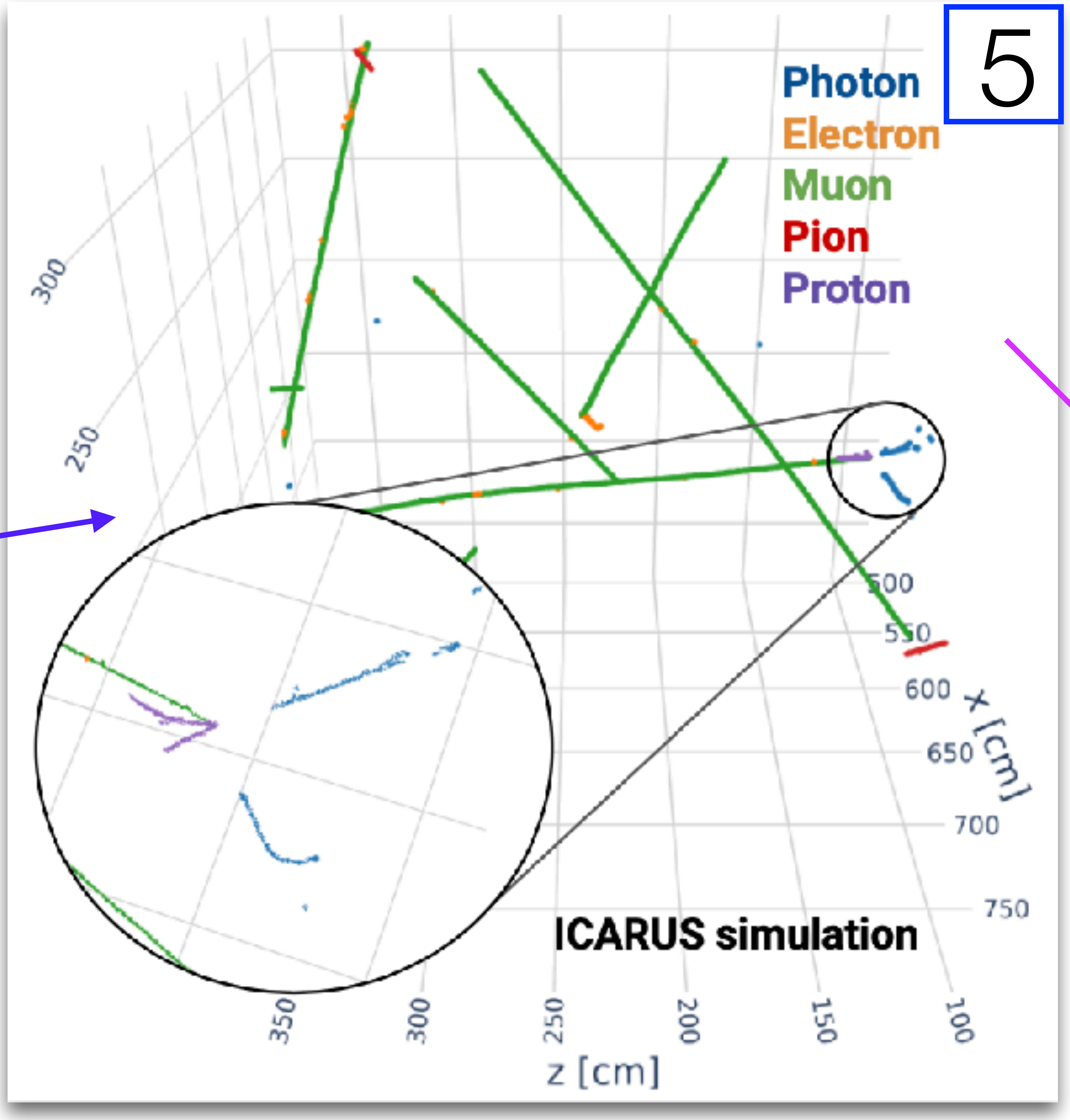


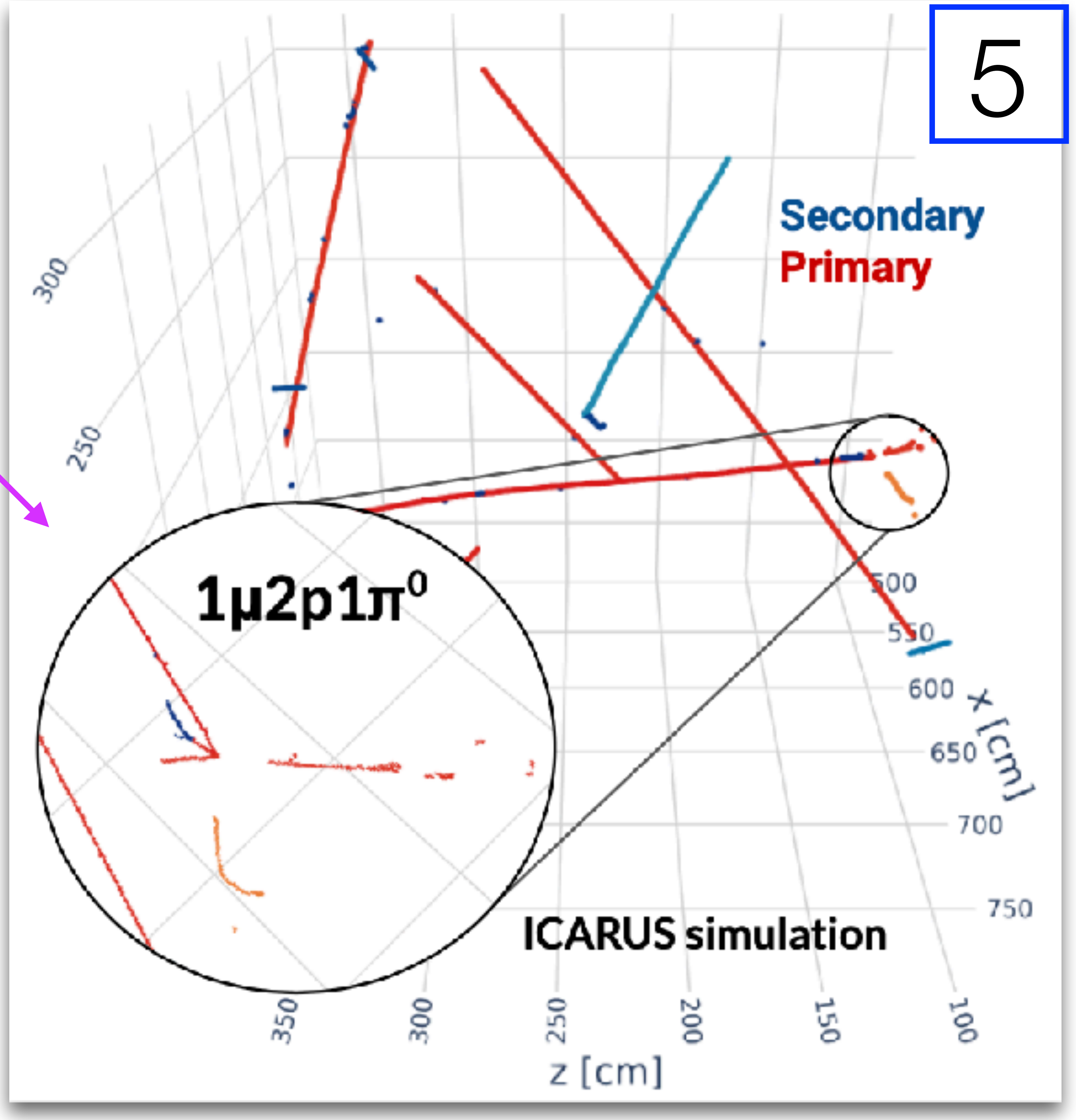
Particle aggregation

Use a Graph Neural Network (GNN) to aggregate fragments and form particles

ML-based event reconstruction: hierarchical feature extraction







Interaction aggregation

Use a Graph Neural Network (GNN) to aggregate particles and form interactions

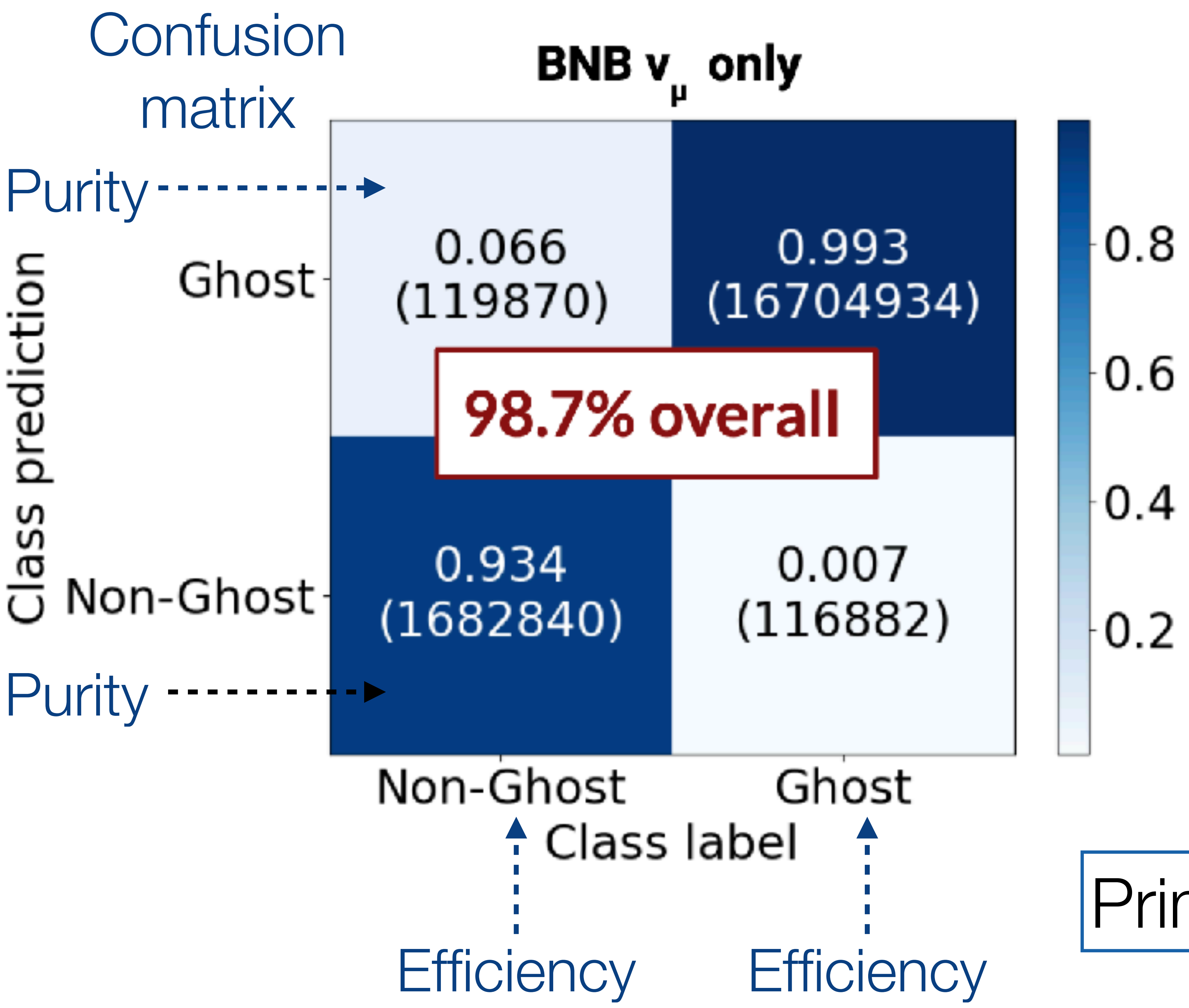
Particle identification

Use GNN to identify particles e, γ, μ, π, p in context

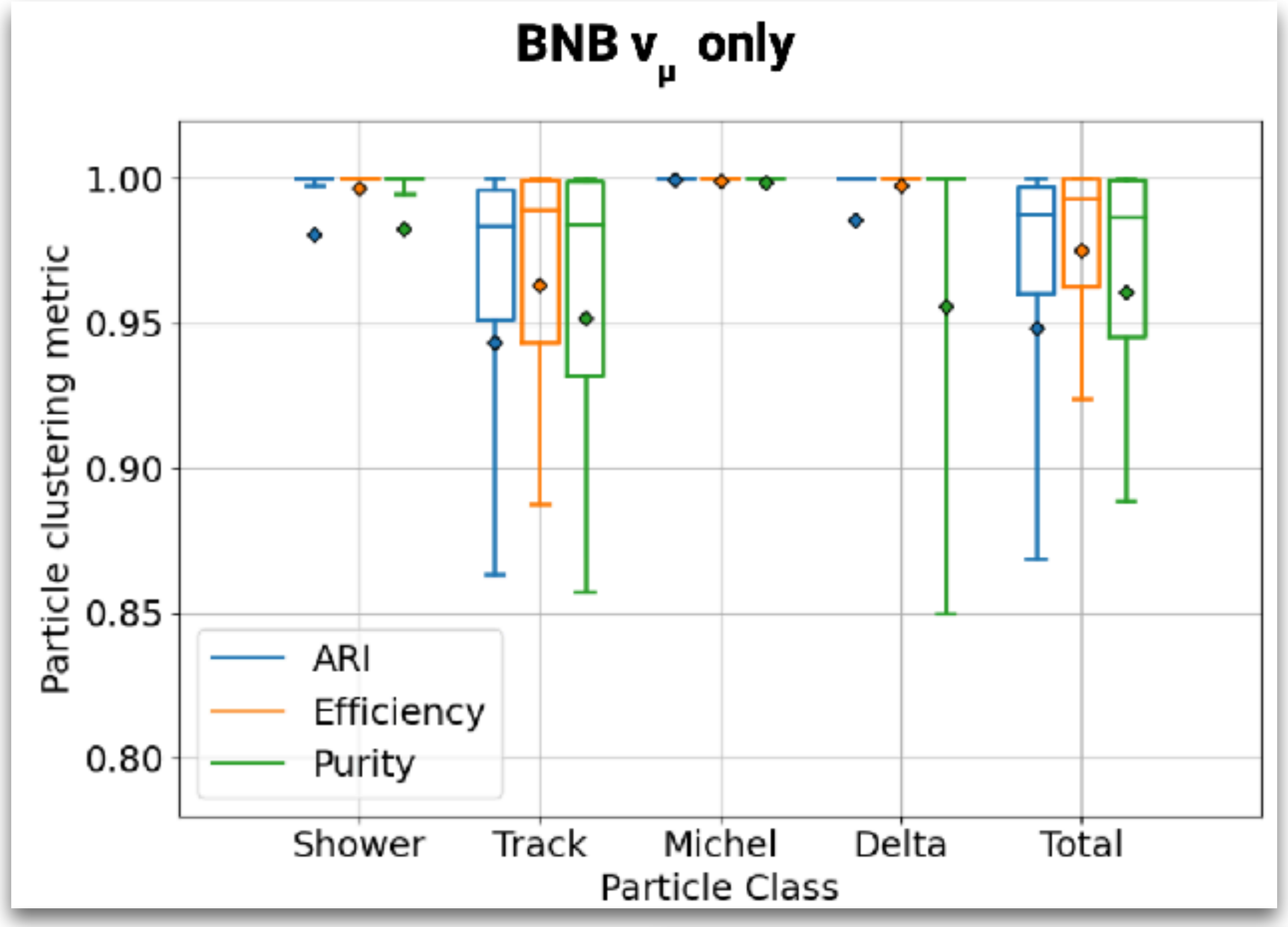
Primary identification

Separate particle(s) which originate from the **vertex**. This is fundamental for analyses.

ML-based event reconstruction: performance

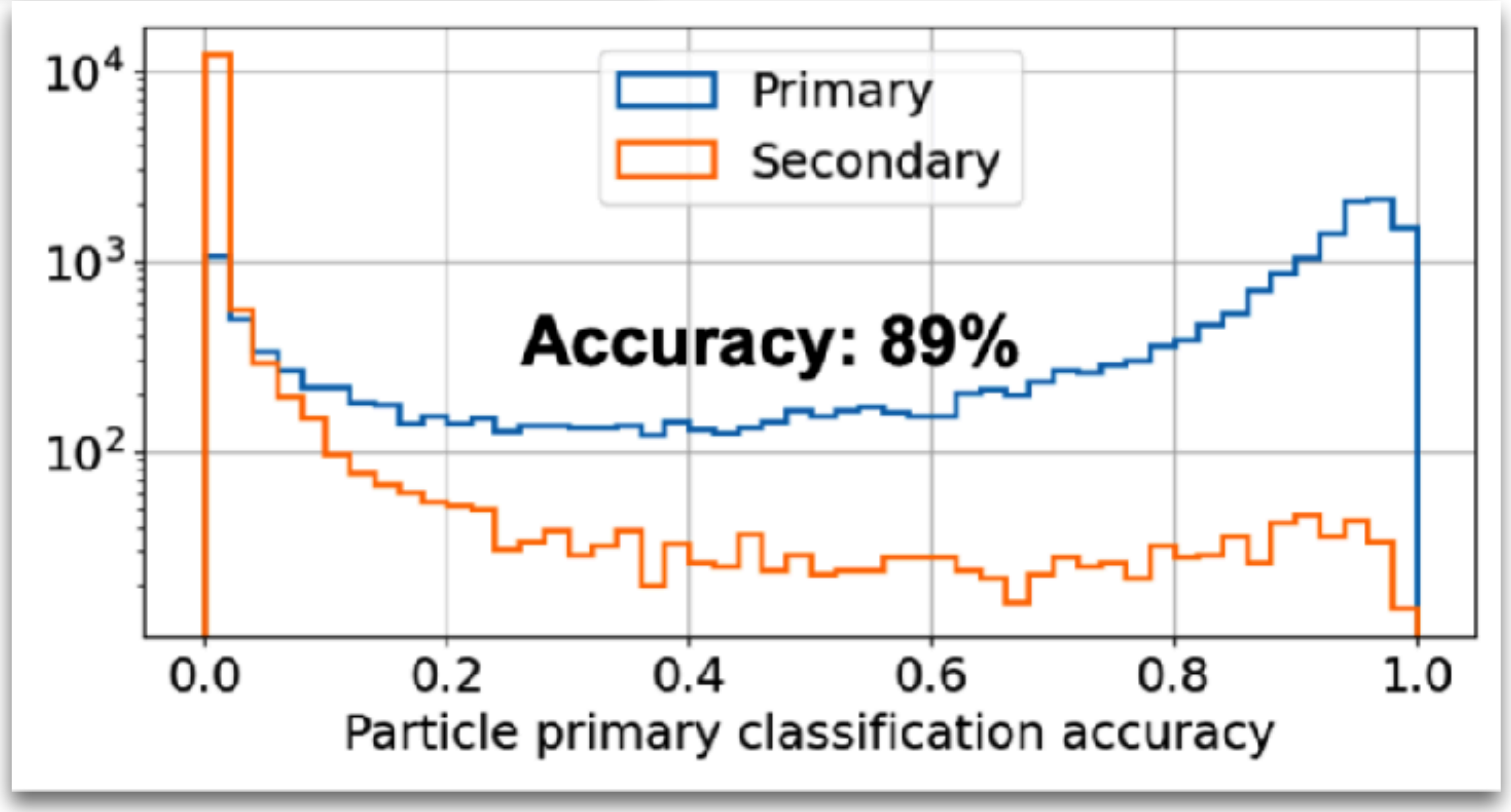


Deghosting



Particle clustering

Primary identification



ML-based event reconstruction: current effort and next steps

- Continuous effort to improve the performance of the end-to-end ML-based reconstruction chain as a whole exploiting both MC simulations and visual scanning info

- Several physical analyses underway in ICARUS using ML-based reconstruction:

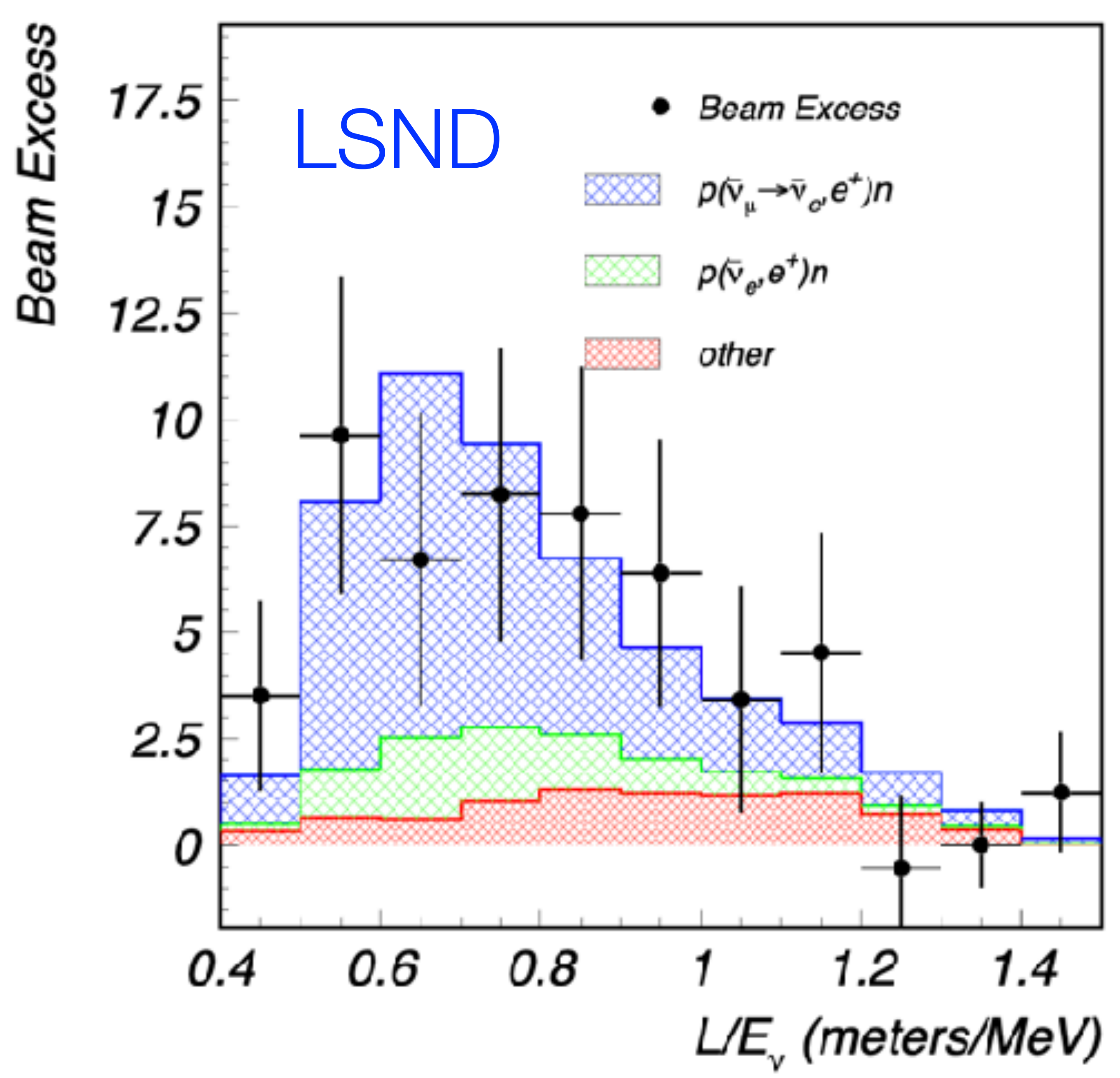
  - Beyond Standard Model physics: Higgs-portal scalar decays, $S \to ee$, (J.Dyer) see her talk tomorrow!

Thank you for your attention!

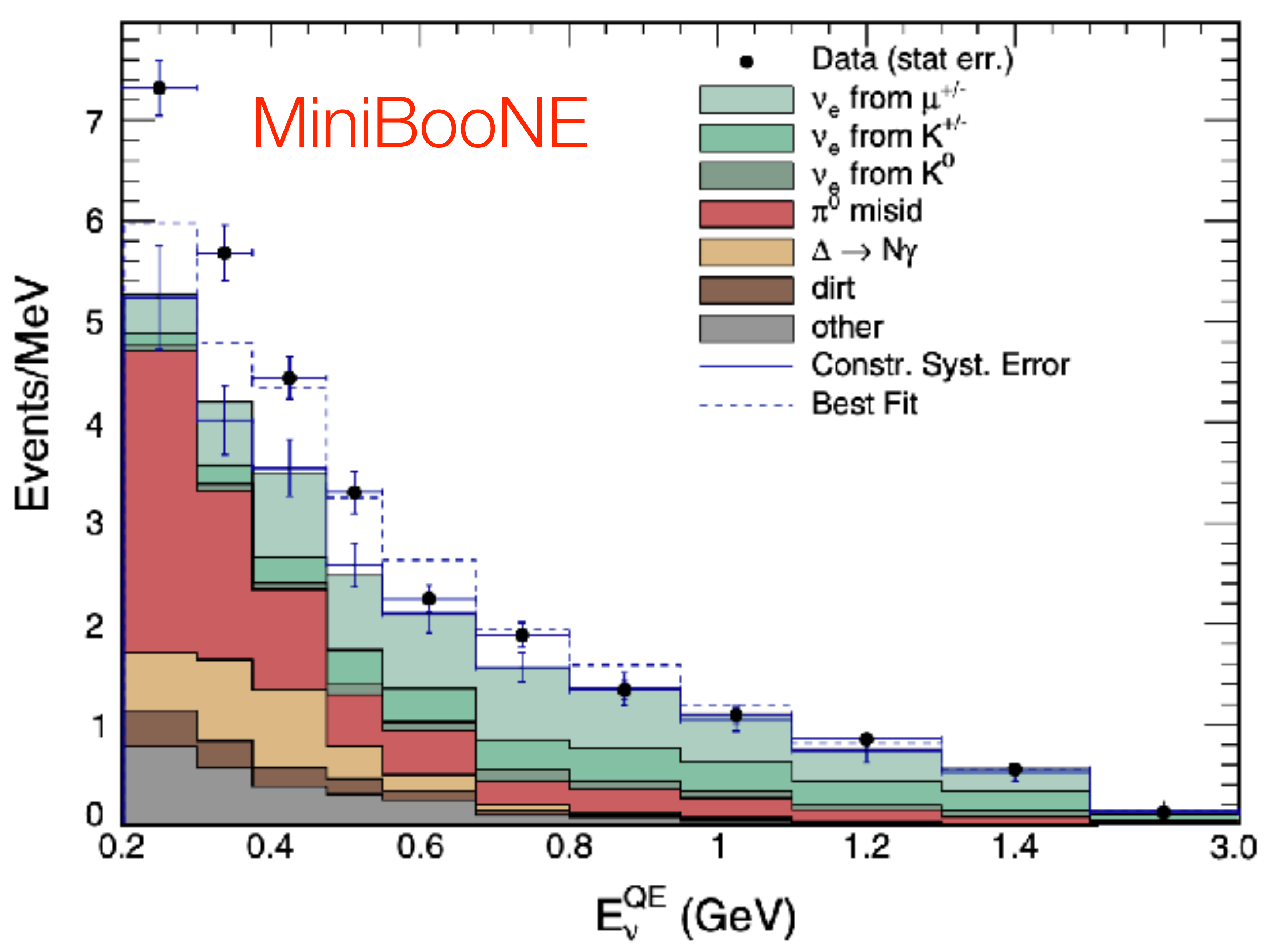
Back-up slides

Neutrino physics: oscillations and the sterile neutrino puzzle

- **LSND** and **MiniBooNE** reported anomalous signals of ν_e excess at low E: this could imply an additional term $\Delta m^2_{\rm new} \sim 1.0 \text{ eV}^2$ driving $\nu_\mu \rightarrow \nu_e$ oscillations at small distances and pointing towards the possible existence of non-standard heavier sterile neutrino(s)



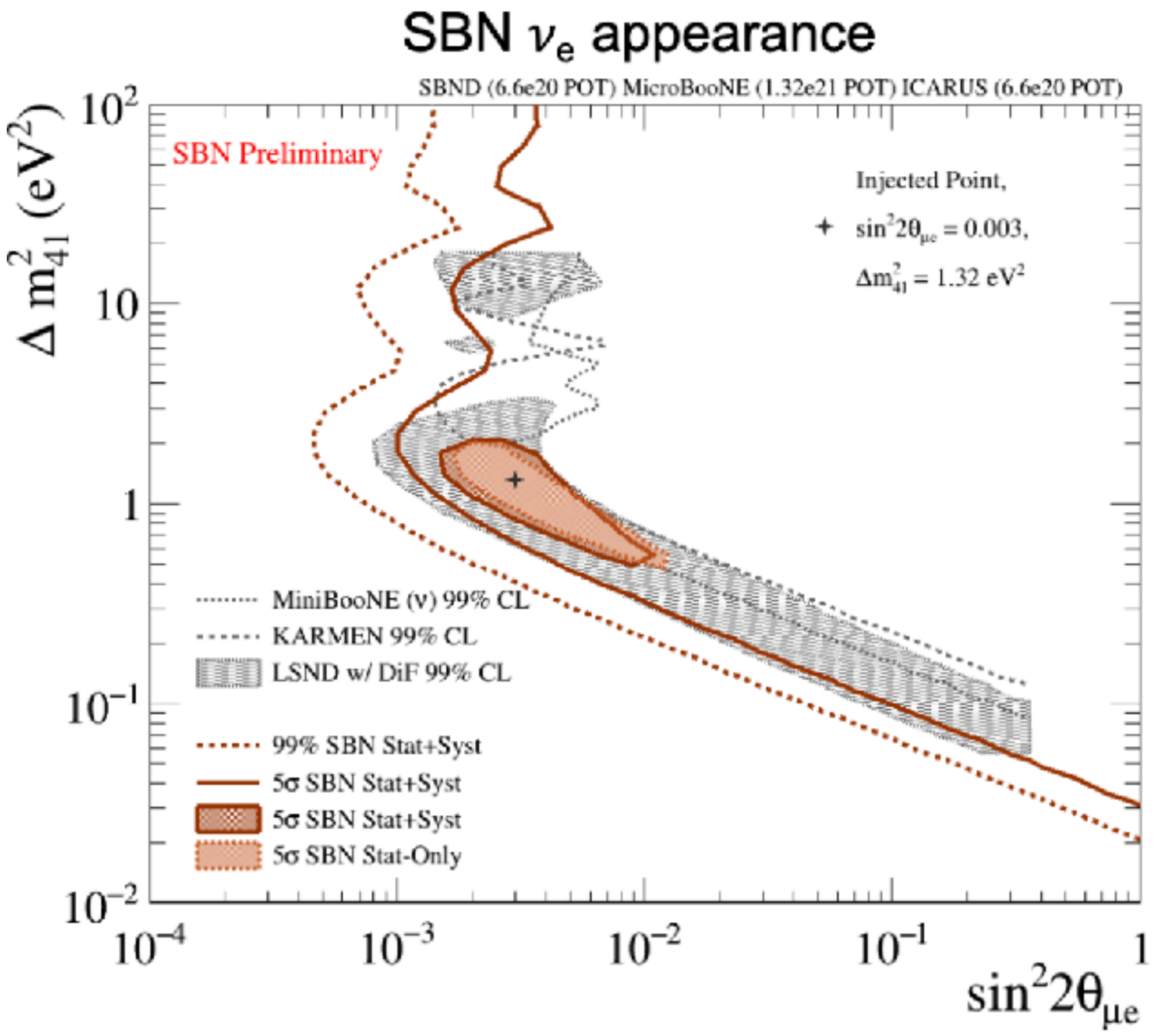
Phys. Rev. D 64, 112007 (2001)

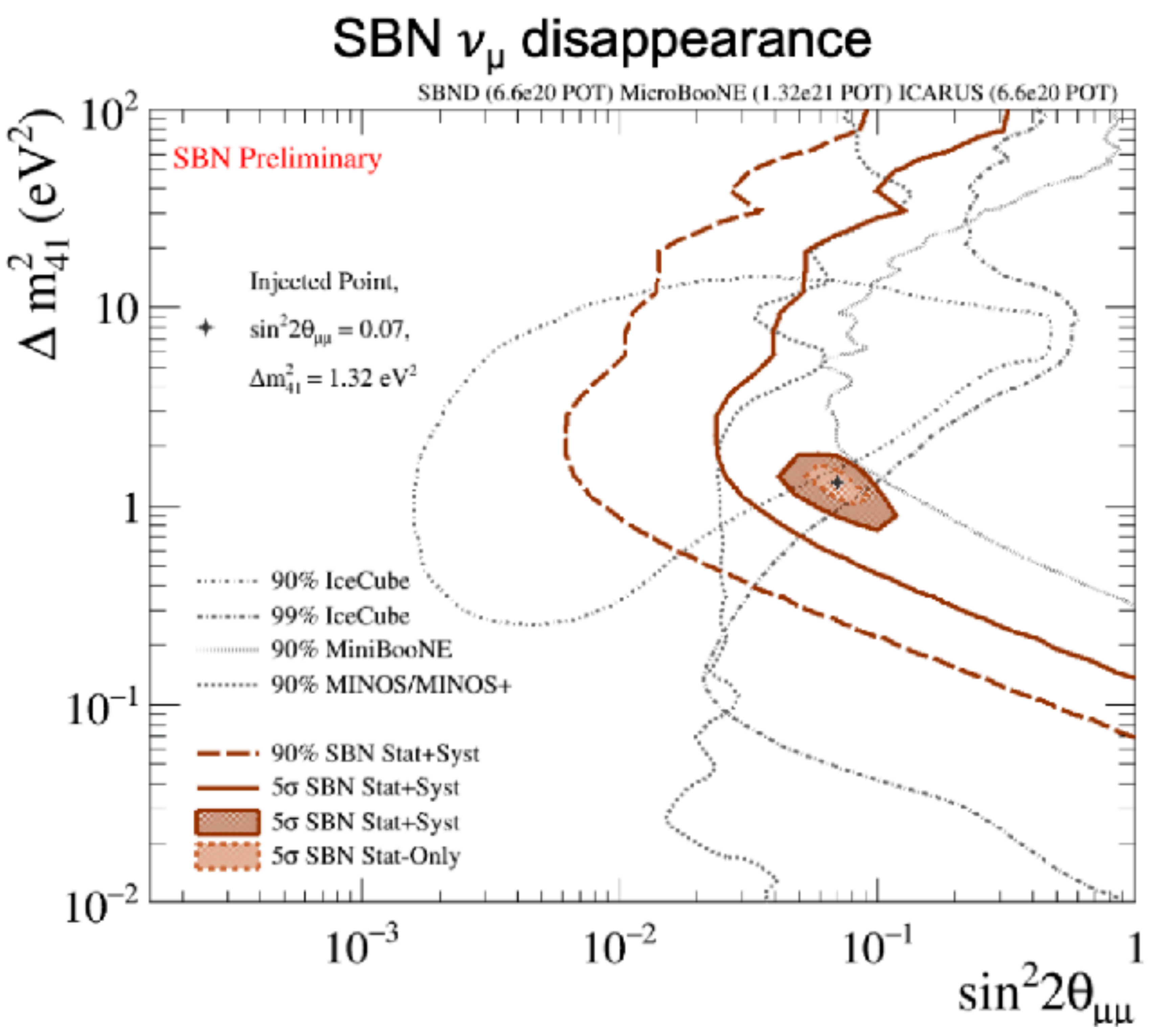


Phys. Rev. D 103, 052002 (2021)

- A clear tension between **appearance** and **disappearance** results is also observed so the possibility to measure both channels with the same experiment is extremely helpful to understand the current physics scenario

The Short Baseline Neutrino (SBN) physics program



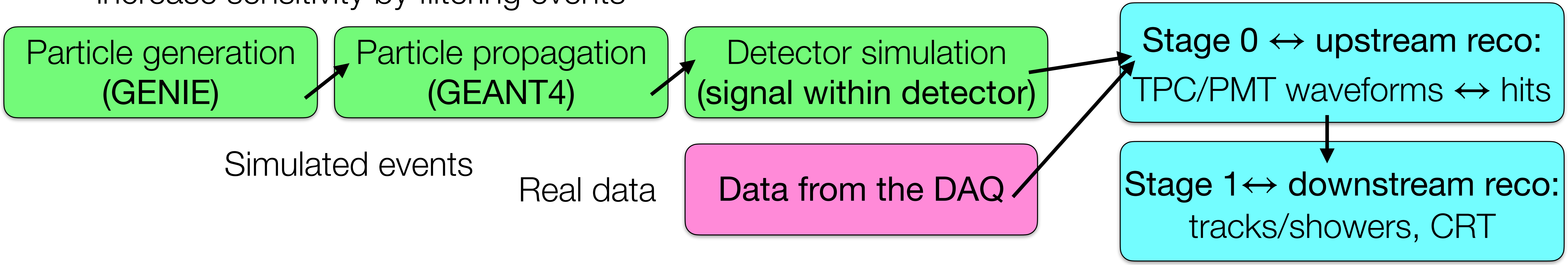


The combined analysis of near and far detector will allow a sensitive search with 5σ sensitivity in both appearance and disappearance channels in 3 years of data taking

Ann.Rev.Nucl.Part.Sci. 69 363-387 (2019)

Event reconstruction in LAr TPCs

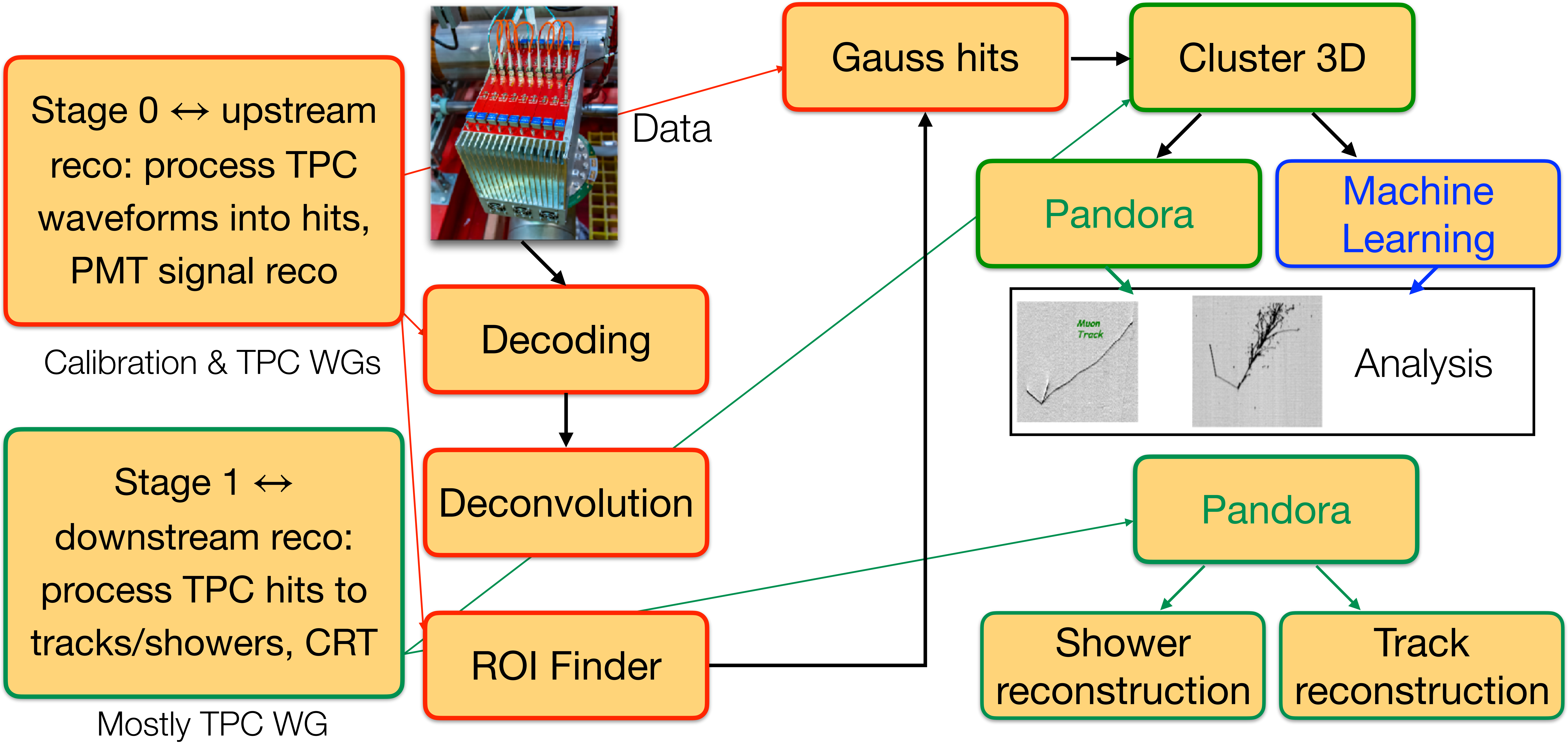
- **Goal**: take the electronic signals acquired by various subsystems and combine them to extract physical quantities related to neutrino interactions happened within the detector:
  - **TPC** readout signals go from waveforms on 3 wire planes to *showers* and *tracks*
  - Light detector (**PMT**) readout signals go from waveforms to *hits* clustered into *flashes*
  - Cosmic Ray Tagger (**CRT**) signals to reduce cosmic rays background are collected into *hits*
  - Tools to **match** info between TPC,CRT,PMT and fiducialize detector volume, mitigate background, increase sensitivity by filtering events



- Several activities: signal processing (*upstream* reconstruction), pattern-recognition, calorimetry, particle identification (*downstream* reconstruction)

Disclaimer: I'll mostly refer to **ICARUS** TPC **downstream** reconstruction

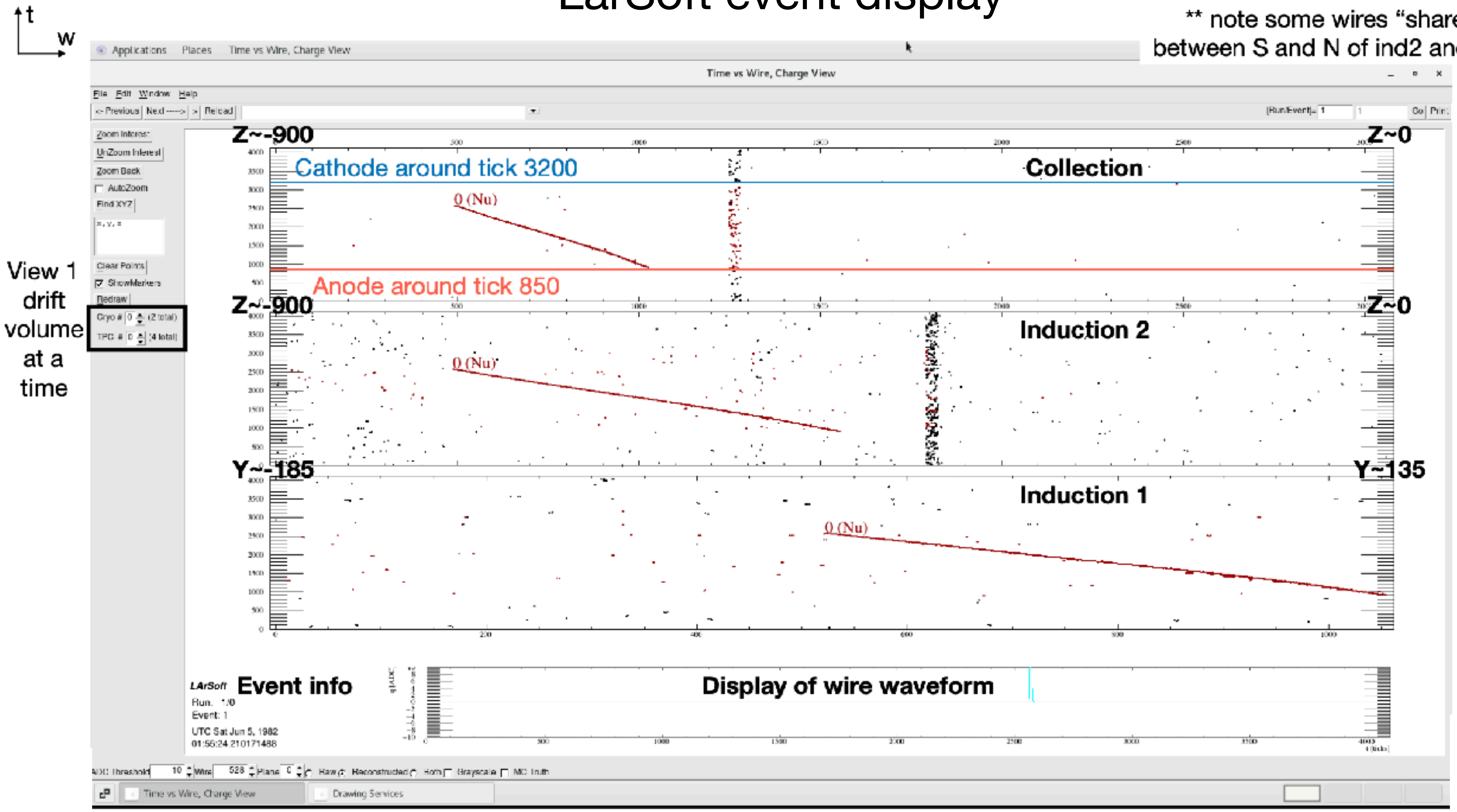
The ICARUS TPC reconstruction chain



LAr TPC images:
different event displays to help understanding reconstruction

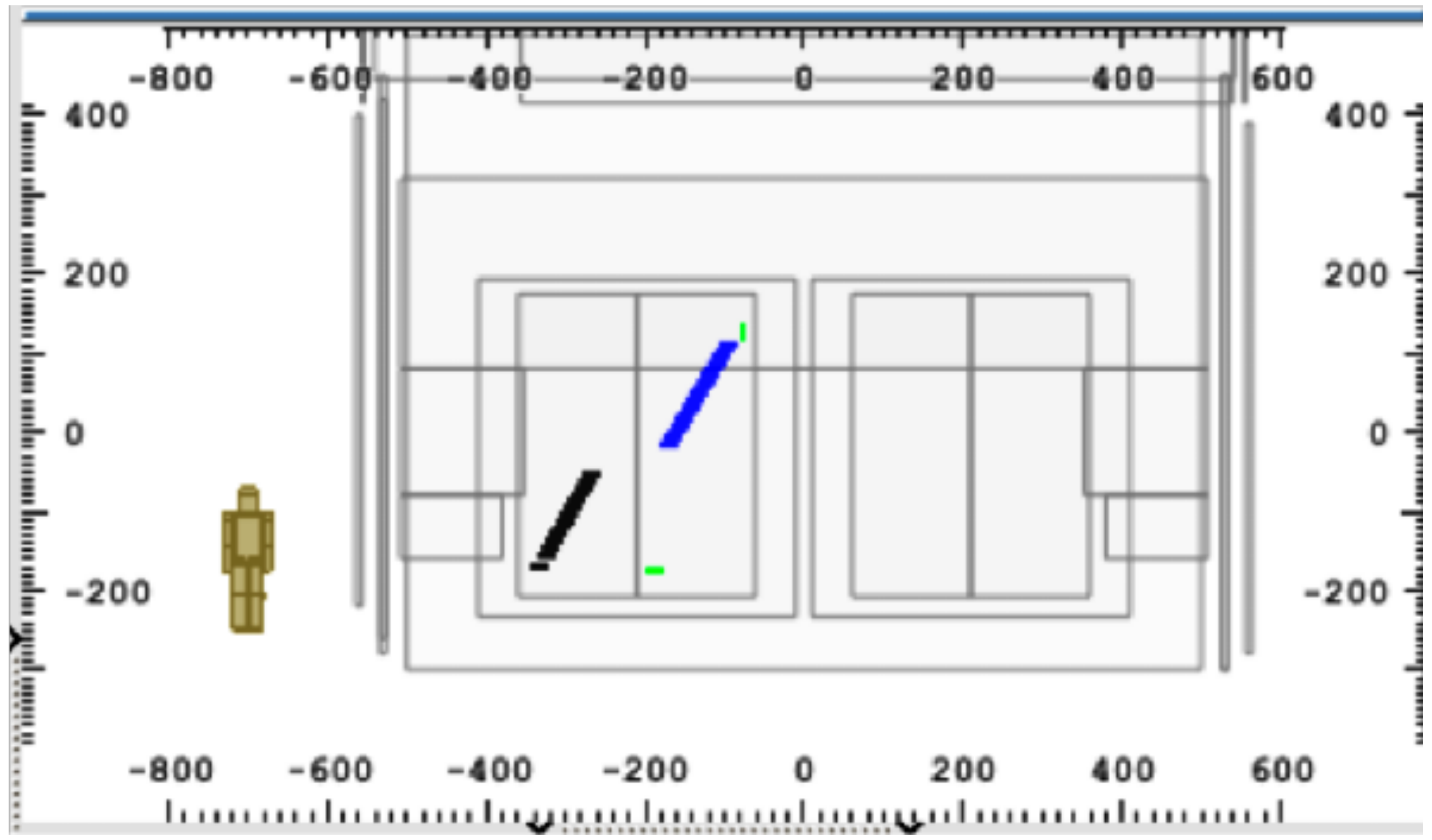
LarSoft event display

** note some wires "shared" between S and N of ind2 and cool



DECAF

Event display for **CAF** (Common Analysis Format) files - final output of the reconstruction chain



Possibility to see **3D points** in physical space, easier to study the interplay of **CRT, PMT, TPC** info (e.g. track splitting stitching algorithms)

Several event displays (**TITUS, LArSoft, DECAF**) to analyze 2D images of hits and reco objects and help understanding reconstruction (issues)

Signal processing: foreseen change from 1D to 2D deconvolution

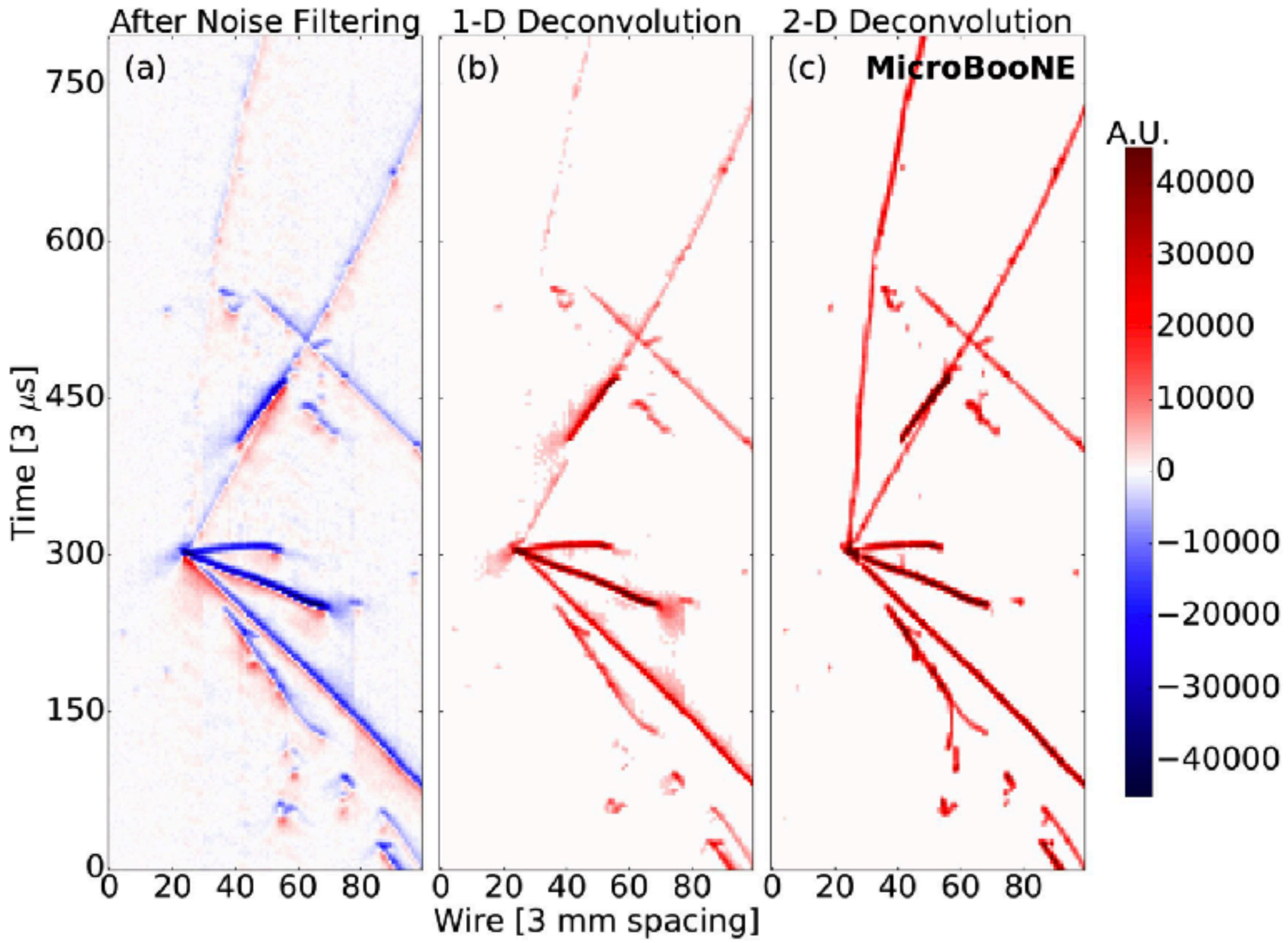
- Wire signals are a convolution of electric field and electronics responses:

$$M(t') = \int_{-\infty}^{\infty} R(t,t') \cdot S(t)dt$$

Measured signal   Response function   Original wire signal

- Original signal can be extracted (**1D deconvolution**) as the inverse Fourier transform of $S(\omega) = \frac{M(\omega)}{R(\omega)} \cdot F(\omega)$ with $F(\omega)$ a filter (noise + zeros of the response function)

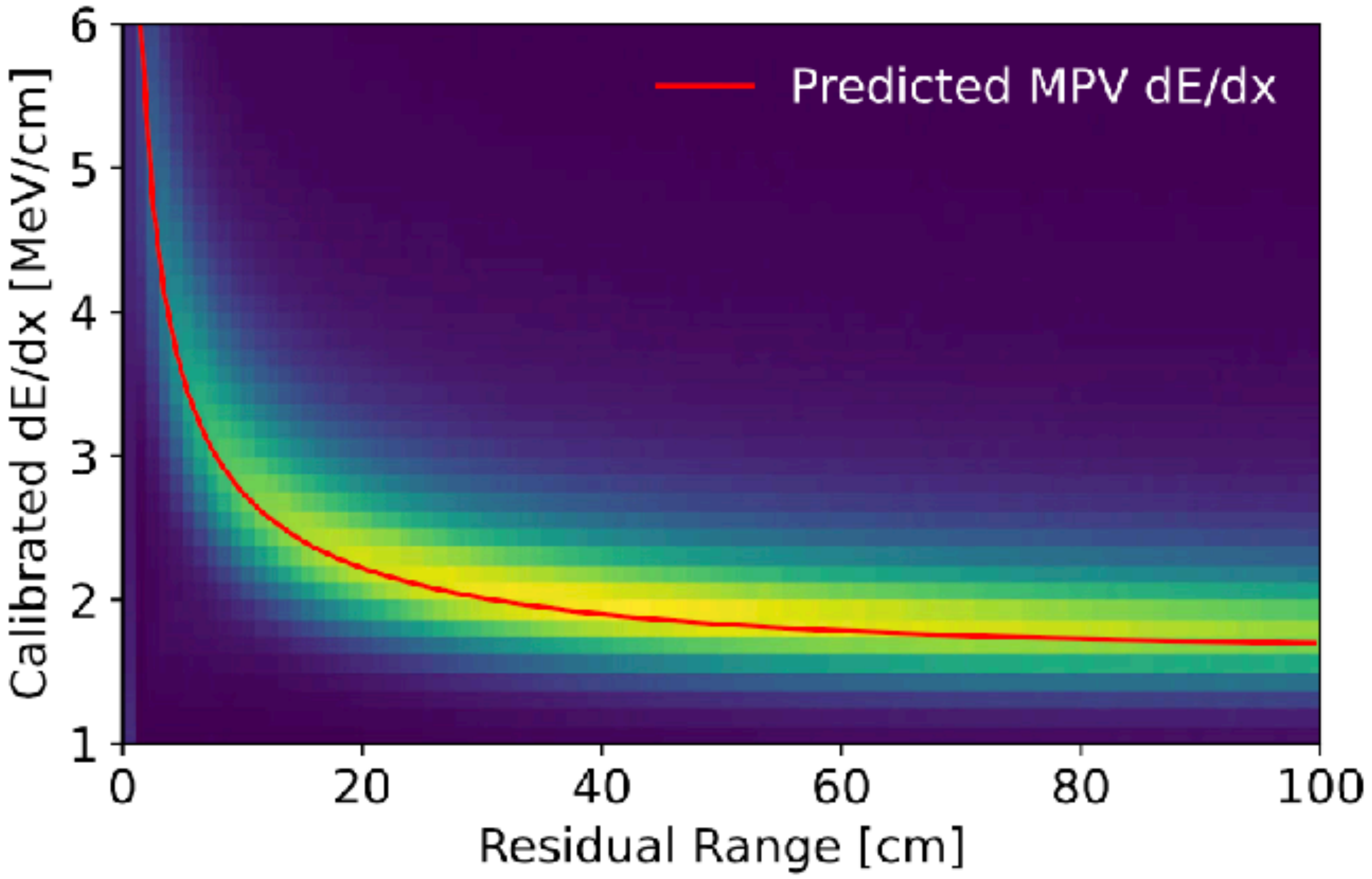
- **2D deconvolution** to account for induced charge effects of charge drifting in nearby sense wire regions: improvement of the charge resolution → higher ε on hits reconstruction for specific track classes



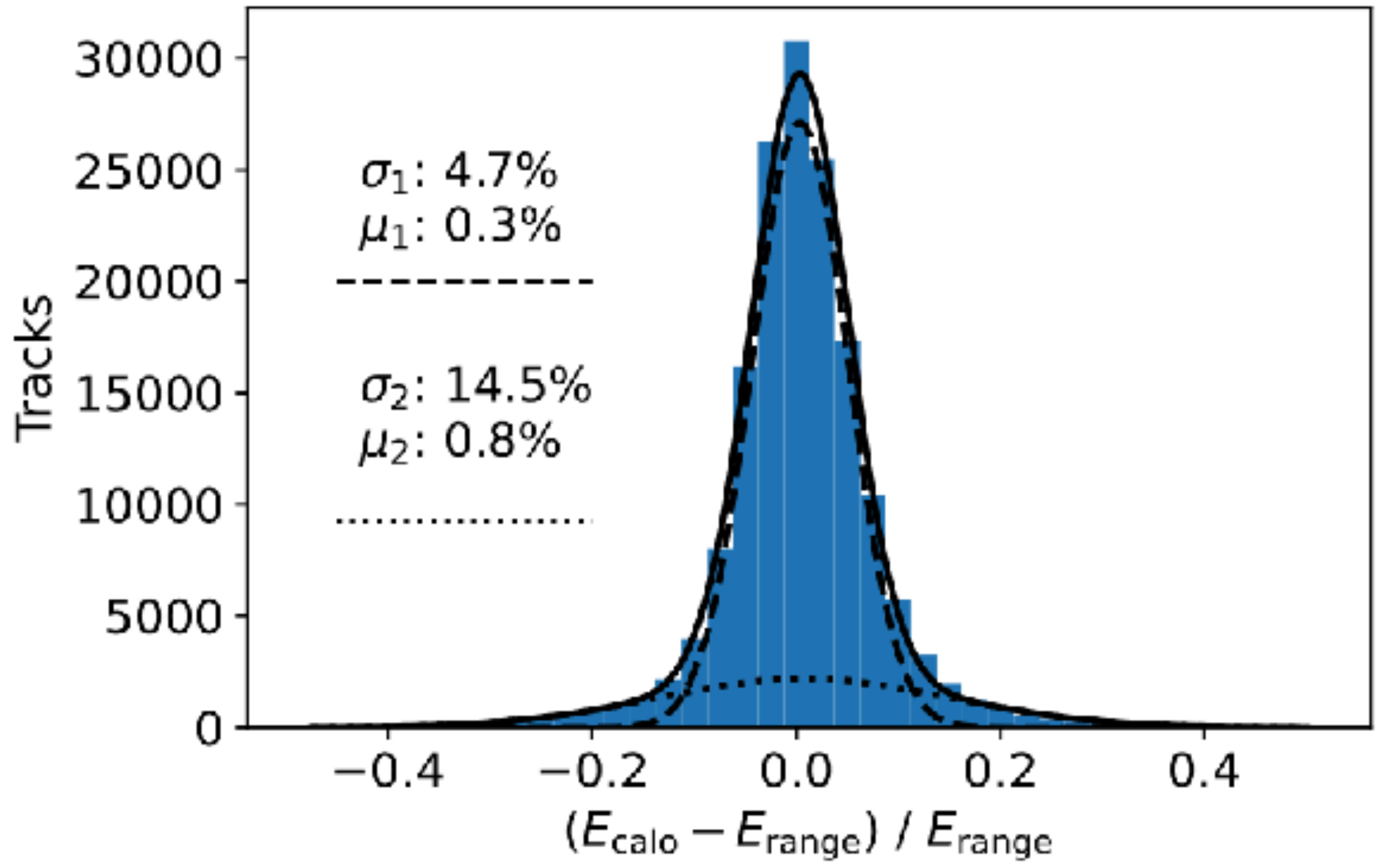
Example of charge recovery from MicroBooNE
Adams, C. et al. 2018 *JINST* 13 P07006 (ArXv link)

TPC signal calibration

- TPC calibration is based on the study of the ionization energy loss per unit length (dE/dx) versus residual range, i.e. distance from the end of the reconstructed TPC track, for cosmic muons (MIP) crossing the cathode and stopping/decaying in the active LAr volume



East TPC, West Cryostat - Collection Plane



- Ongoing effort to tune TPC signal response to improve data/Monte Carlo agreement and to include the spatial variations observed in detector response to CR muons

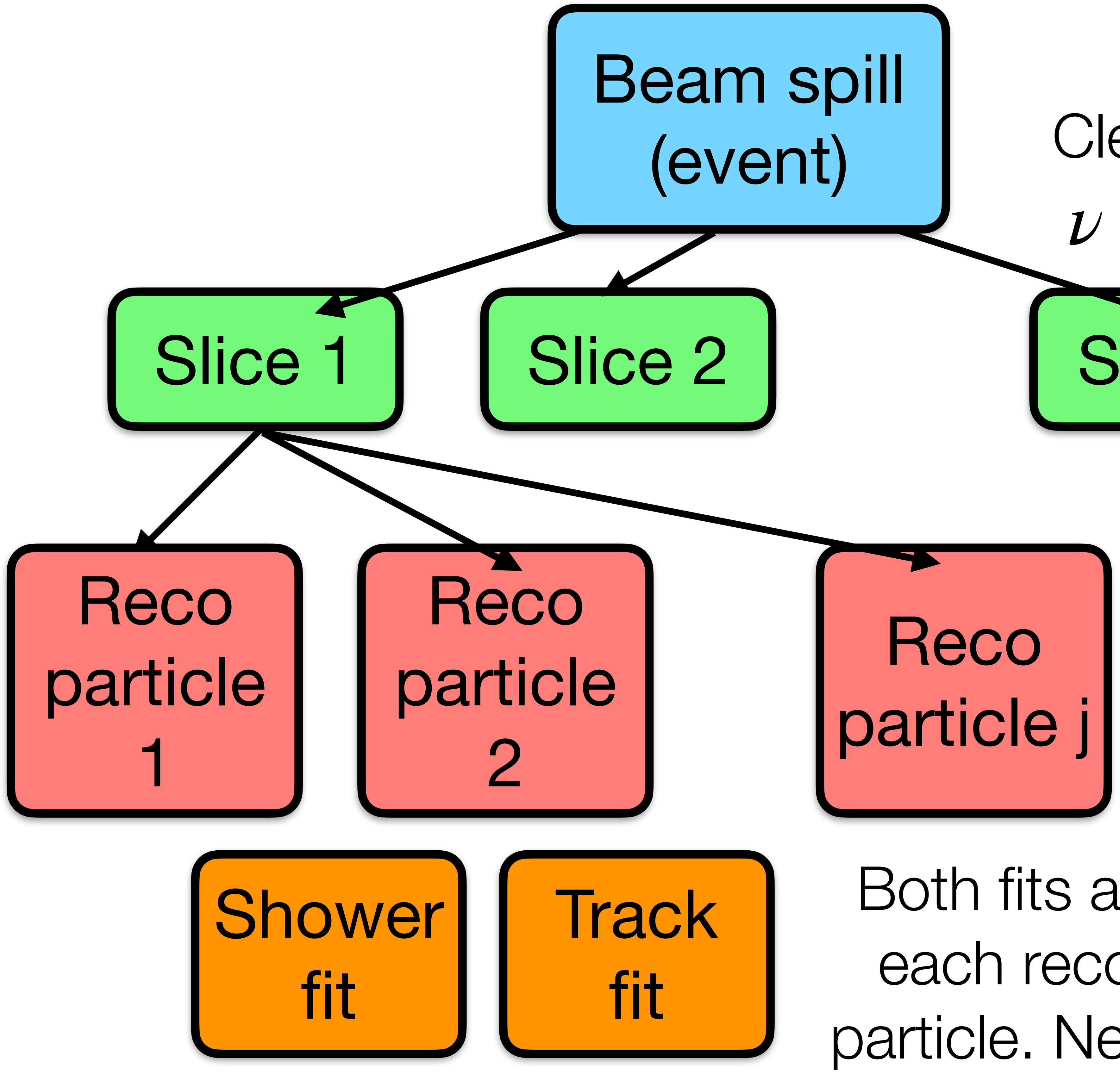
Further details in Eur. Phys. J. C 83:467 (2023)

Pandora-based event reconstruction

- Pandora (https://github.com/PandoraPFA) is a multi-algorithm pattern-recognition software with LArSoft interface (https://larsoft.org) commonly used in detectors based on LAr technology to:
  - **Cluster** the objects together into **reconstructed particles in 3D** by joining information (*hits*) from the TPC wire planes into a reconstructed interaction (i.e. a ***slice***);
  - Reconstruct the **interaction vertex**, i.e. the common point where reconstructed particles originate and thus the point where the ν candidate interacted;
  - Reconstruct **particle hierarchy** (parent/child particles);
  - Classifies particles as **track-like** (μ, p, $\pi^{\pm}$, …) or **shower-like** (e, γ…)
- There is a series of algorithms that one can alter/expand or replace with alternatives
- Machine Learning algorithms, e.g. Boosted Decision Trees (**BDTs**) are used in 3 steps of the chain:
  - **Slice identification** to separate candidate ν events from cosmics
  - **Vertex selection** from candidate important points
  - **Track vs shower discrimination**

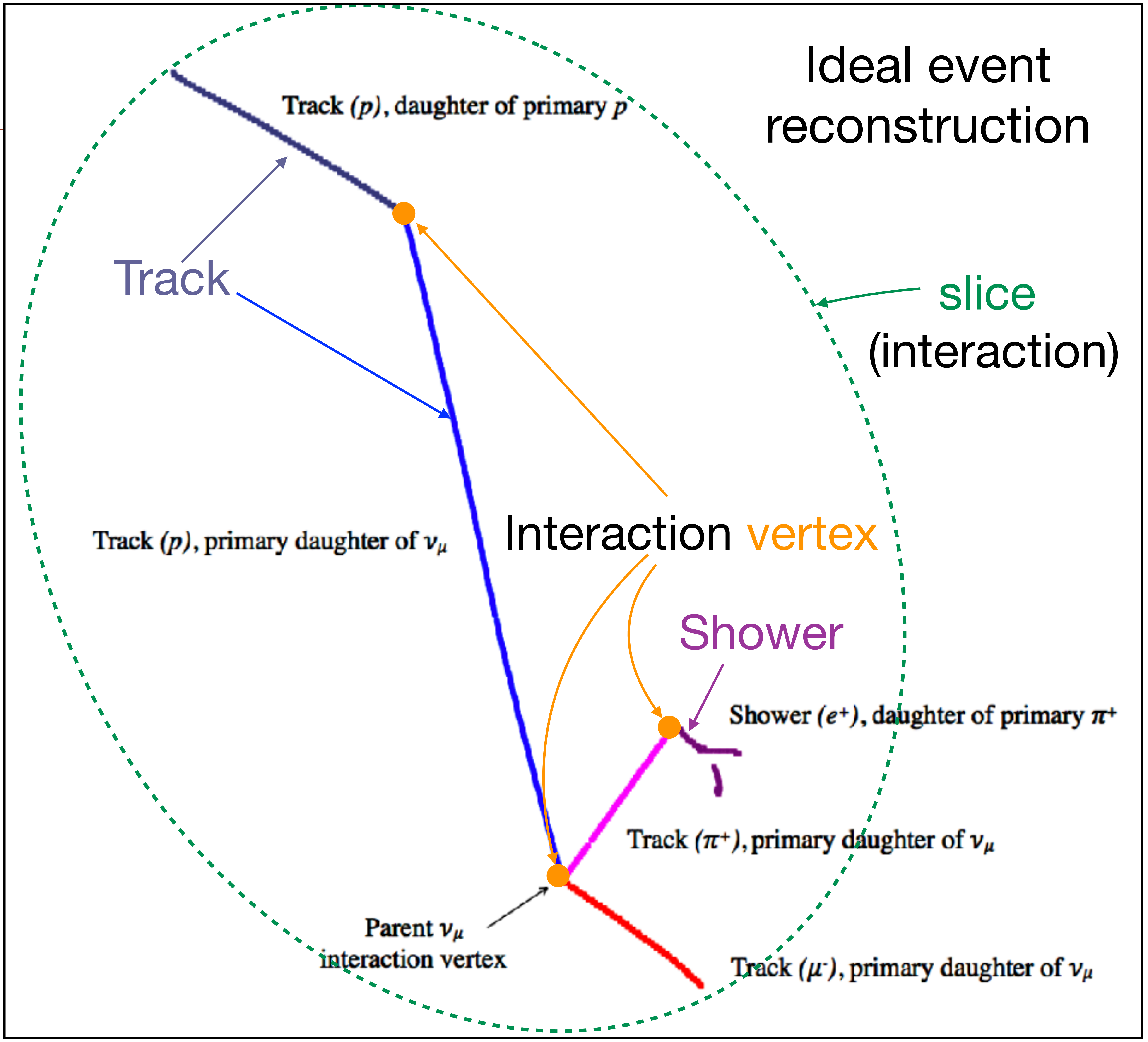
Pandora-based event reconstruction

- Ultimate output of Pandora is reconstructed **interaction hierarchies:**



Clear cosmics
ν candidates

Both fits are done for each reconstructed particle. Next steps are energy reconstruction, calorimetry, PID.



- https://github.com/PandoraPFA

Pandora-based event reconstruction: new BDT training to discriminate tracks and showers

- BDT based on a set of reconstruction variables: 8 **geometrical** (5 **calorimetrical**) from the 3D coordinates (charge) of the hits
- Output is a ***track score:*** parameter in range [-1,1] track-like (if ≥0), shower-like (if <0) particle

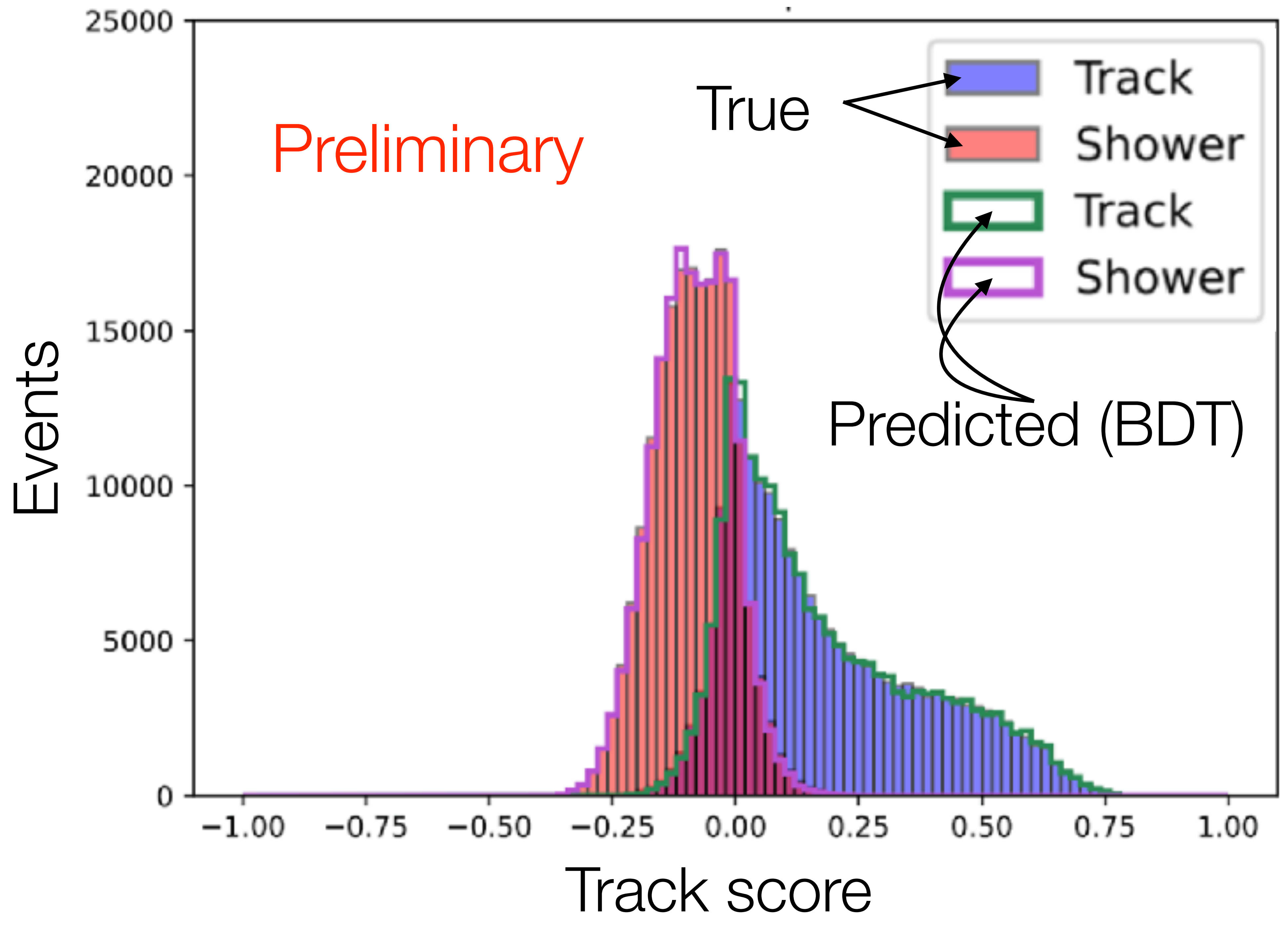
New training based on BNB ν-only ICARUS MC recently introduced

- 3 additional charge variables to improve the discrimination capability
- Cross-Validation strategy to maximize the classification efficiency
- training sample with $\mathrm{n_{tracks}} = \mathrm{n_{showers}}$
- good events: only events from ν interactions with $\mathrm{n_{hits}} \geq 15$ for $\mathrm{n_{views}} \geq 2$

Test sample

Training sample: $\varepsilon_{\mathrm{classification}}$	ν only	ν + cosmics good events
ν only	81.8%	81.4%
ν + cosmics good events	81.5%	82.0%
old training	72.0%	71.8%

Preliminary



Pandora-based event reconstruction: new BDT training to discriminate tracks and showers

- Validation to exclude **bias** on the event selection, i. e. dependence on $E, \theta_{xz}, \theta_{yz}, L_{track}$
- Sample: $\mathcal{O}(5 \cdot 10^4)$ MC events BNB ν_μ, ν_e only, NuMI ν only w/ (w/o) good reconstruction [**]

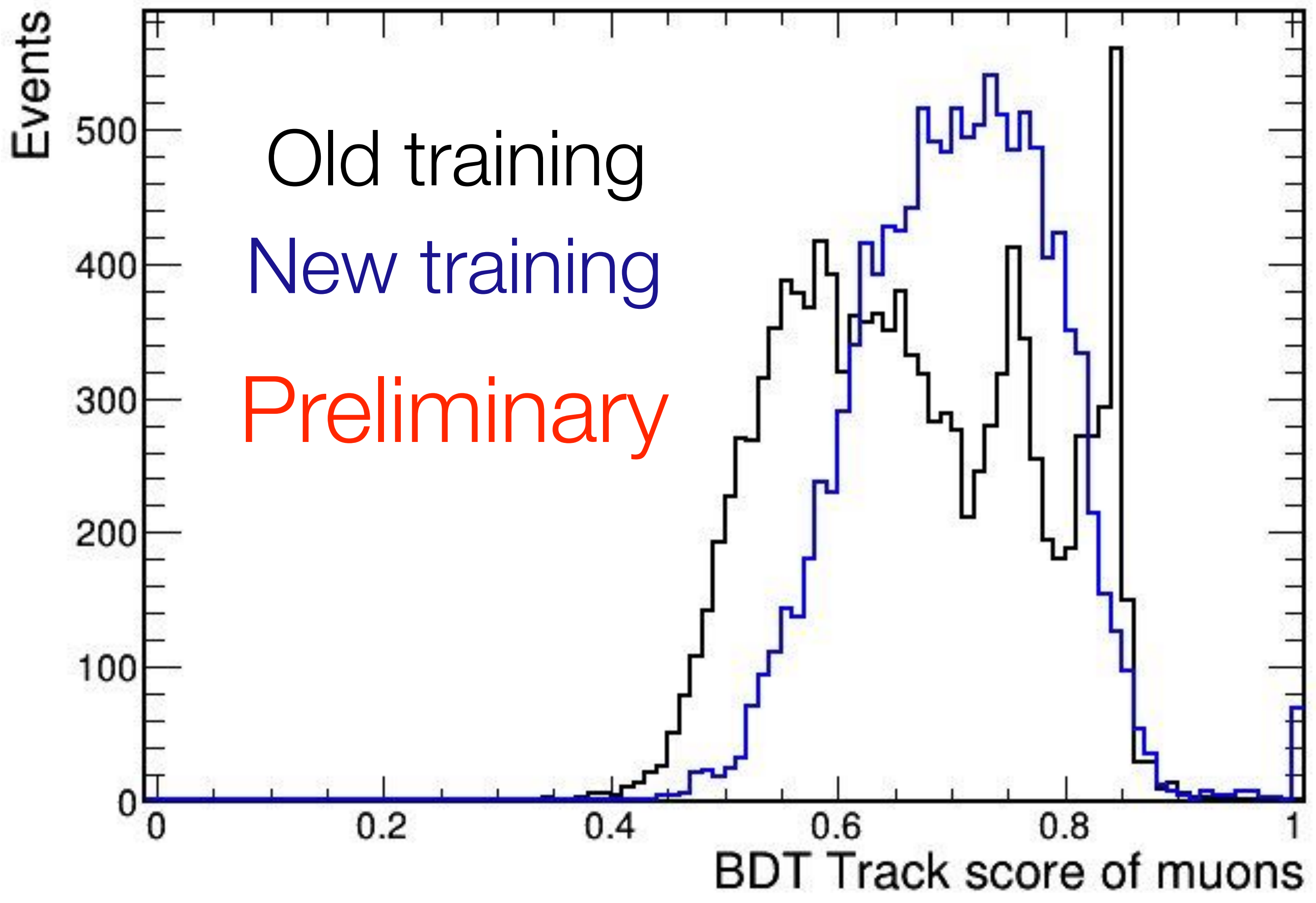
$$\varepsilon_{\text{classification}} = \frac{(\mu + \text{p} + \pi^\pm) \text{ in trks } + \text{e}^- \text{in shws}}{(\mu + \text{p} + \pi^\pm + \text{e}^-) \text{ reco}}$$

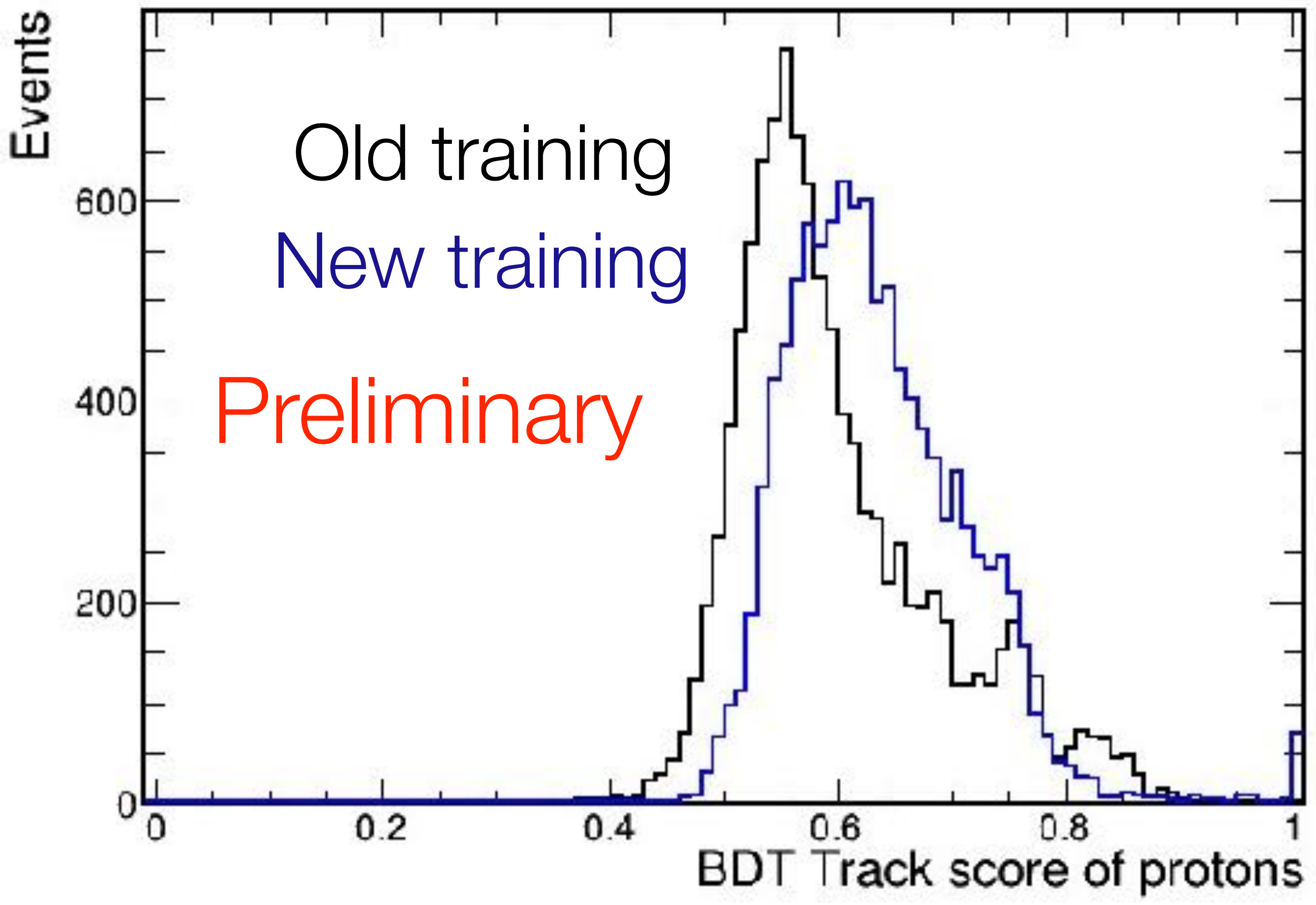
Good events	Old training	New training	Δ
BNB ν only	94.6%	97.8%	3.2%
NuMI ν only pre-tuning [*]	82.9%	96.9%	14.0%
NuMI ν only tuned [*]	89.6%	95.4%	5.4%

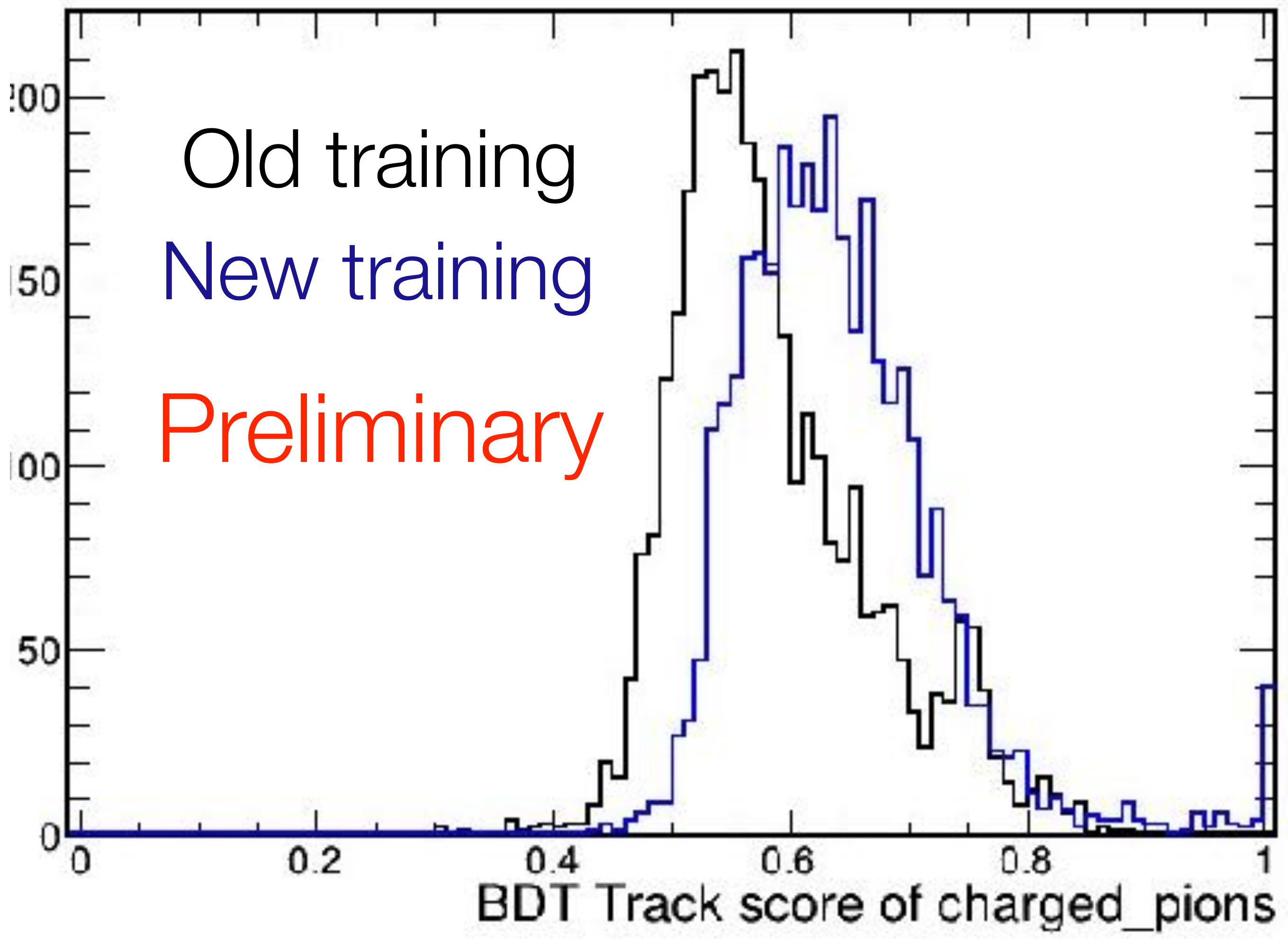
Preliminary

All events	Old training	New training	Δ
BNB ν only	72.3%	80.3%	8.0%
NuMI ν only pre-tuning [*]	67.8%	79.9%	12.1%
NuMI ν only tuned [*]	66.7%	79.2%	12.5%

Preliminary







Track score BDT variables for track/shower discrimination

- The BDT uses 10 input variables:

1. Length: estimate of length of the reconstructed particle
2. Sliding linear fit: Estimate of difference with respect to a straight line averaged over planes (divided by length so it's a fraction and not length correlated)
3. Sliding linear fit: Estimate of the largest gap averaged on planes (again divided by length)
4. Sliding linear fit: Estimate of the RMS averaged on planes (divided by length…)
5. Vertex distance: distance from the interaction vertex to the start of the particle
6. Difference in beginning and end direction of the reconstructed particle: computes an angle relating to a few points at the beginning and at the end of the particle

Track score BDT variables for track/shower discrimination

- The BDT uses 10 input variables:

7. Principal Component Analysis: secondary eigenvalue / primary (estimate of how linear the particle is)

8. Principal Component Analysis: tertiary eigenvalue / primary (estimate of how linear the particle is)

9. Charge variable 1: fractional spread of charge values calculated as follows:
$C_1 = \frac{\sigma/\sqrt{N}}{\mu}$ where $\mu = \sum_{hit} q_{hit}$ (mean charge) , $\sigma^2 = \sum_{hit} (q_{hit} - \mu)^2$, $\sigma/\sqrt{N}$ an RMS/mean

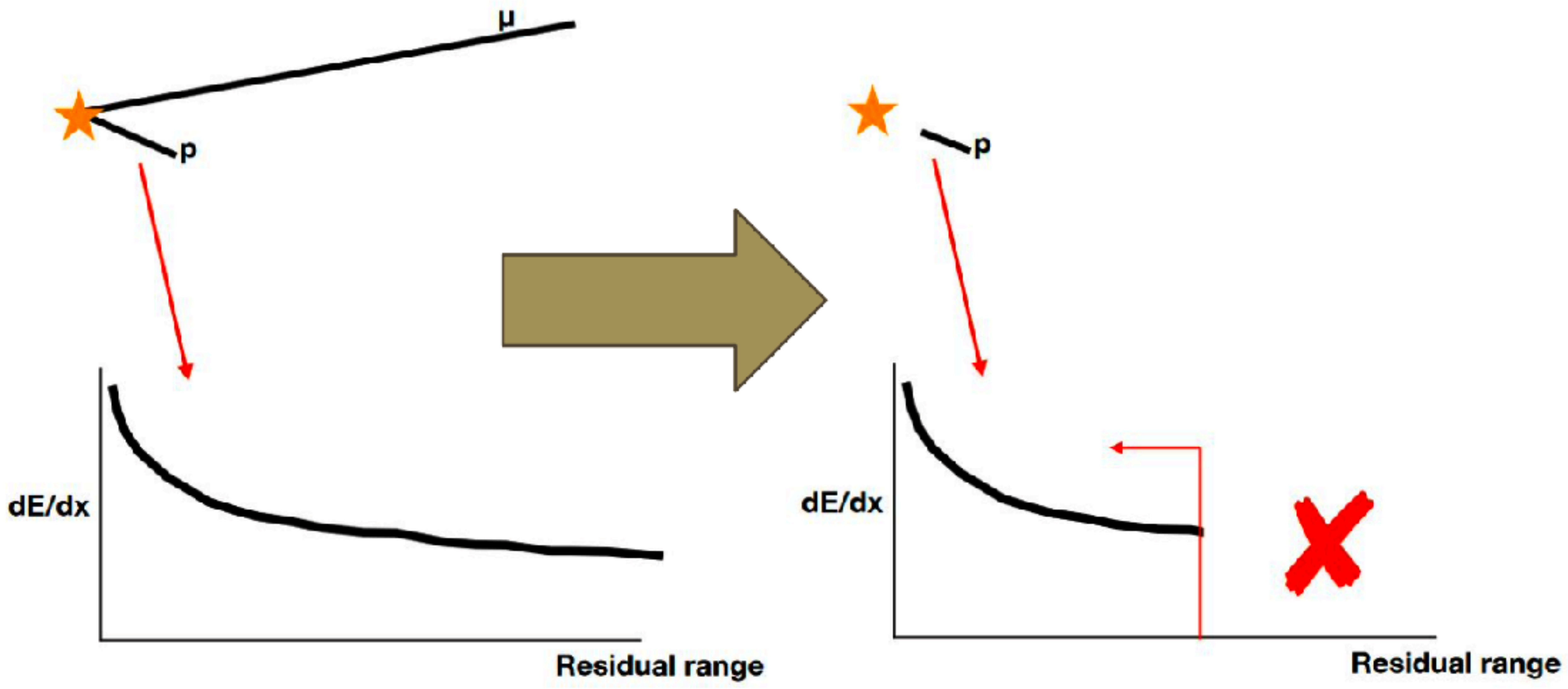
10. Charge variable 2: fraction of the total charge that is near the end of the particle
$C_2 = \frac{q_{end}}{q_{tot}}$ where q_{tot} is the total charge, q_{end} the charge of the $10\,\%$ hits near the end

Track score BDT variables for track/shower discrimination

- **Halo total ratio**: in the shower hypothesis, the fraction of charge in the external halo, evaluated summing the energy of the hits whose transverse distance (R_T) to the cluster direction (outcome of PCA) is above 20% of the Moliere Radius (R_M = 10 cm);
- **Concentration**: in the shw hp, the ratio between the concentration and the total charge, where concentration is the sum of E/R_T for all the hits and the total charge is halo + cone charge, cone (halo) includes hits with R_T < (>) 0.2 R_M;
- **Conicalness**: in the shw hp, this variable quantifies the how the charge is distributed in the cone and increases if the charge is concentrated in the final part of the cone, it is computed as the ratio between charge in the final part/charge in the initial part of the cone (weighted by R_T^2) normalized to the ratio total end charge/total start charge.

Pandora-based event reconstruction: study of systematics and performance

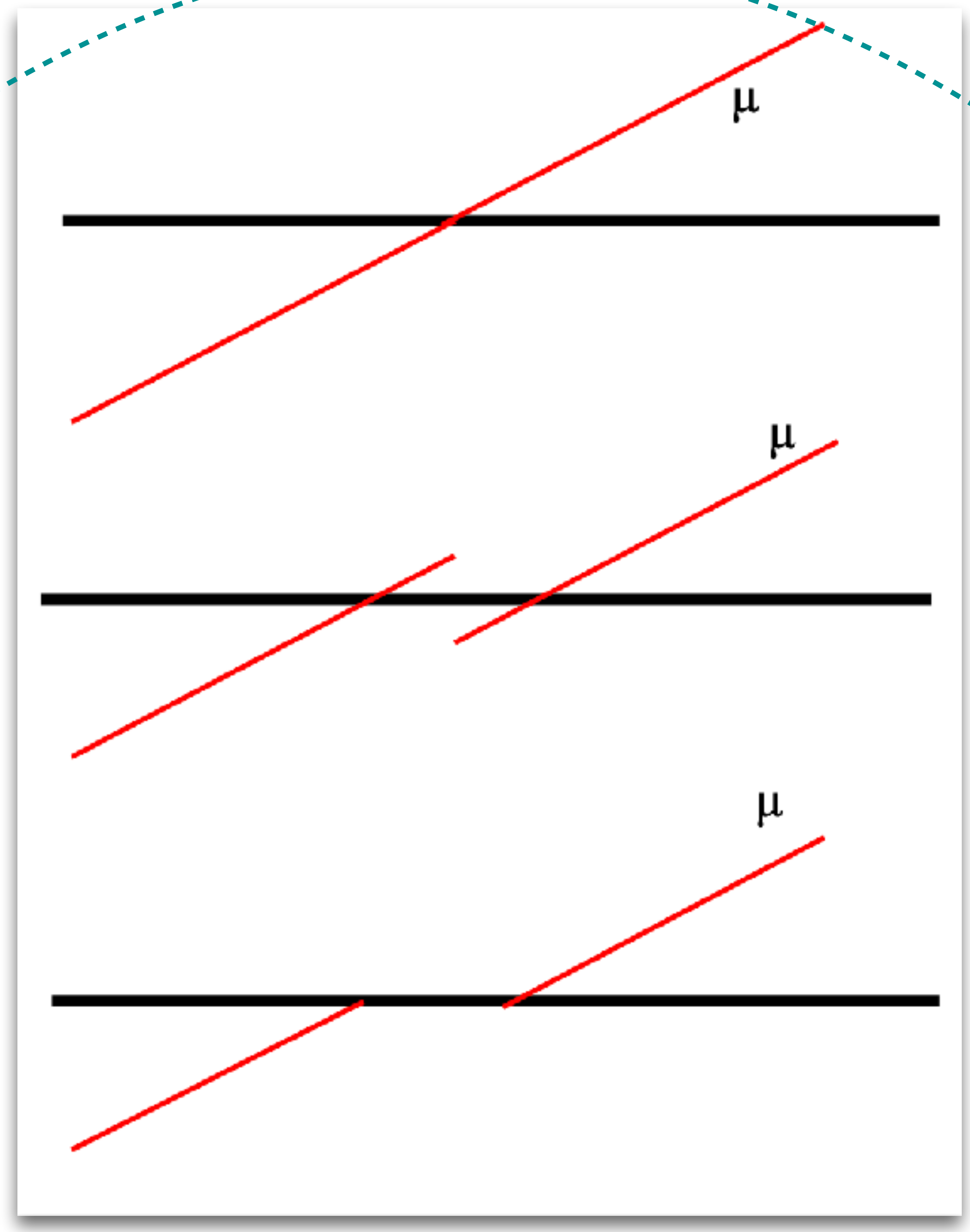
- Goal: understand and account for differences in reconstruction between data and MC
- *Hit Activity Removal from Particles for Systematics* (HARPS): the basic idea is to operate on picked particles and reduce their size (e.g. take a long, clear proton and make it shorter by removing hits at the beginning of the track ↔ similar to starting with a lower energy proton) and analyse the impact on reconstructed quantities - data driven validation of ML algorithms



Example: HARPS on a sample of **protons** from ν+cosmics MC

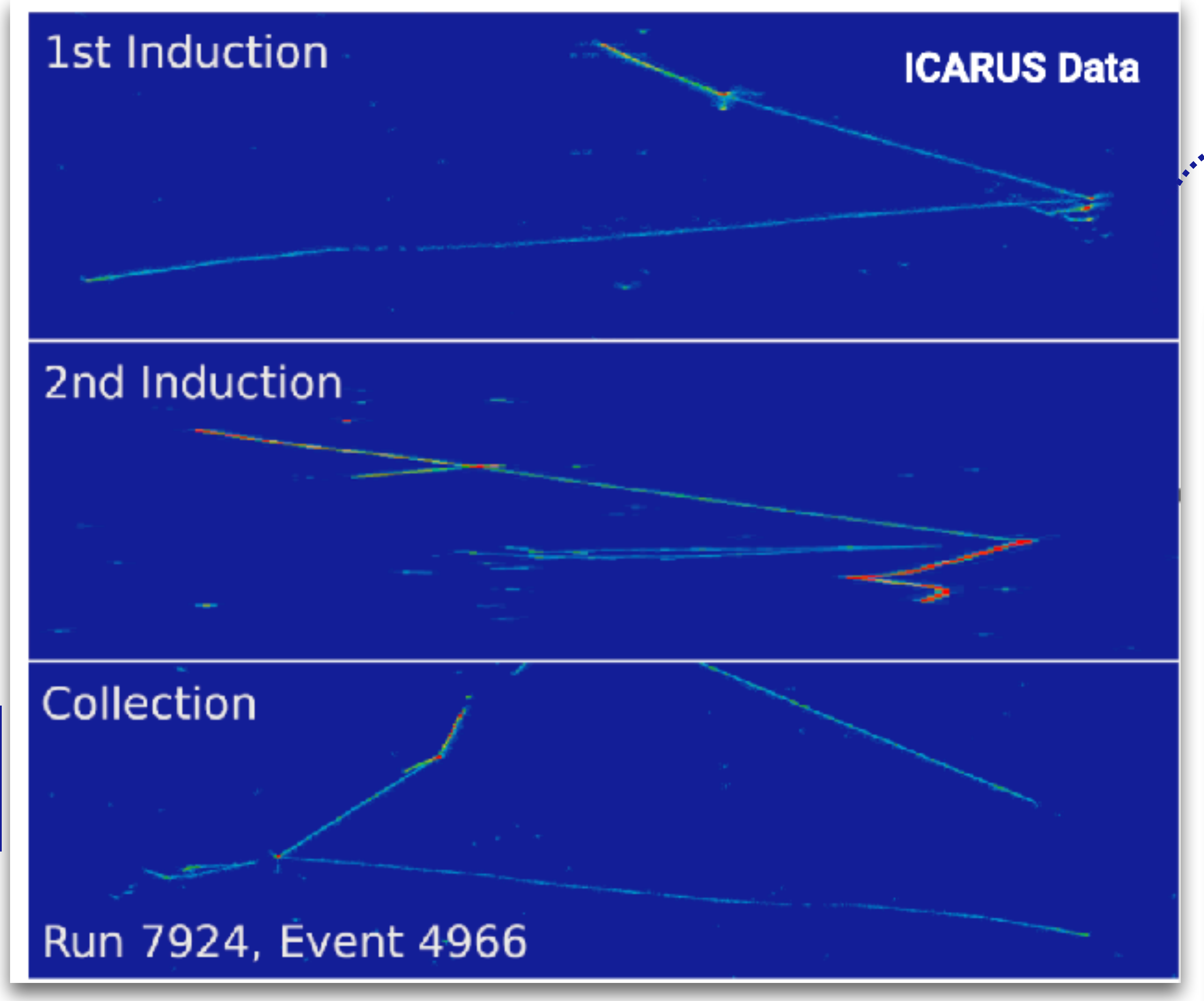
Pandora-based event reconstruction: improvements to MC simulations

- Difference in data and MC: $t = 0$ in an event was different:
    - In data: time of the trigger
    - In MC: start of the beam time
- Can lead to the effect of splitting the tracks if the event start at $t > 0$, particularly relevant for NuMI (beam duration of the beam spill is 9.6 μs) as shown in the cartoon



- New module to emulate the trigger added to the simulation tools improving the vertex reconstruction

1 ML-based event reconstruction: hierarchical feature extraction



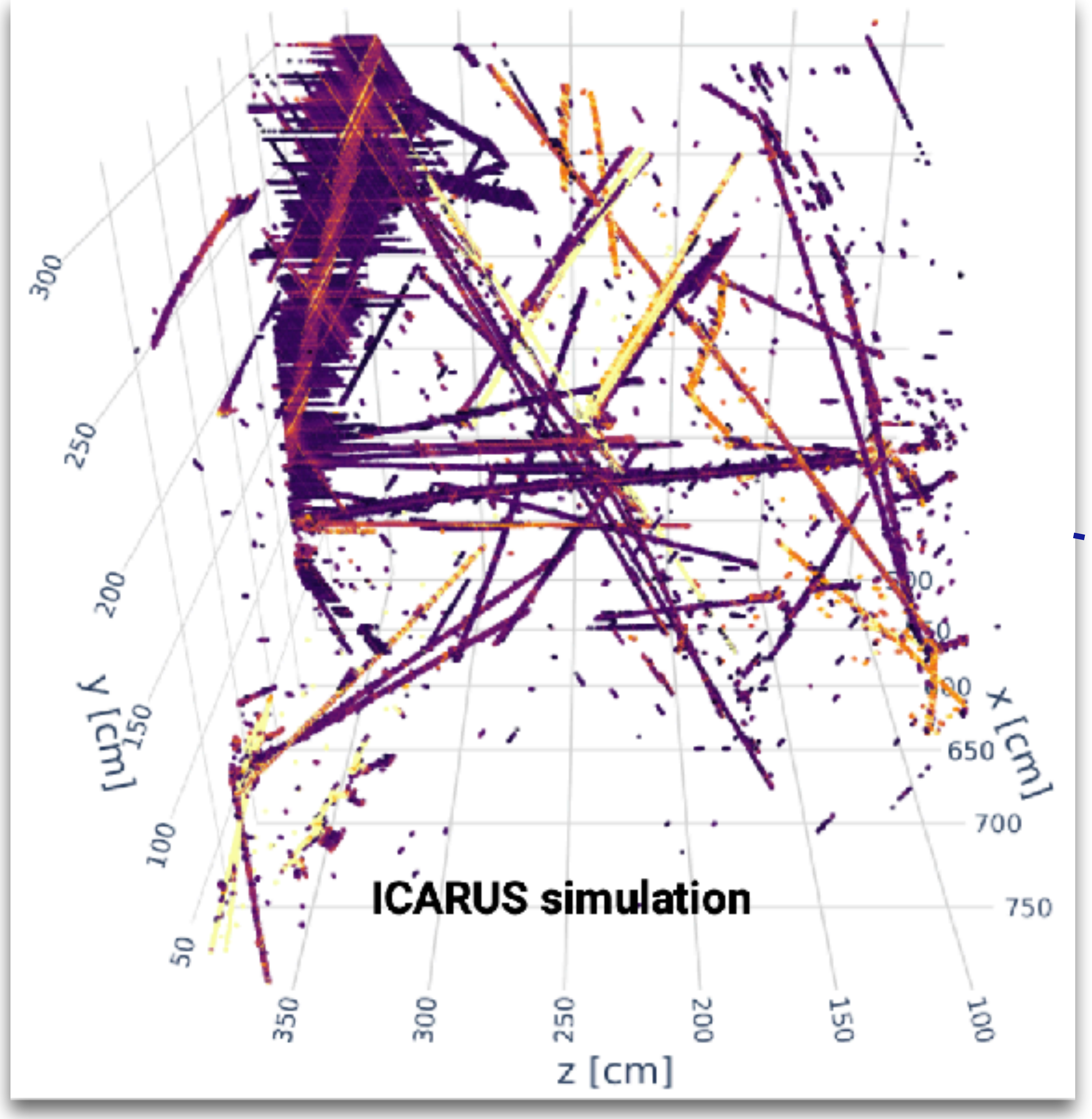
time

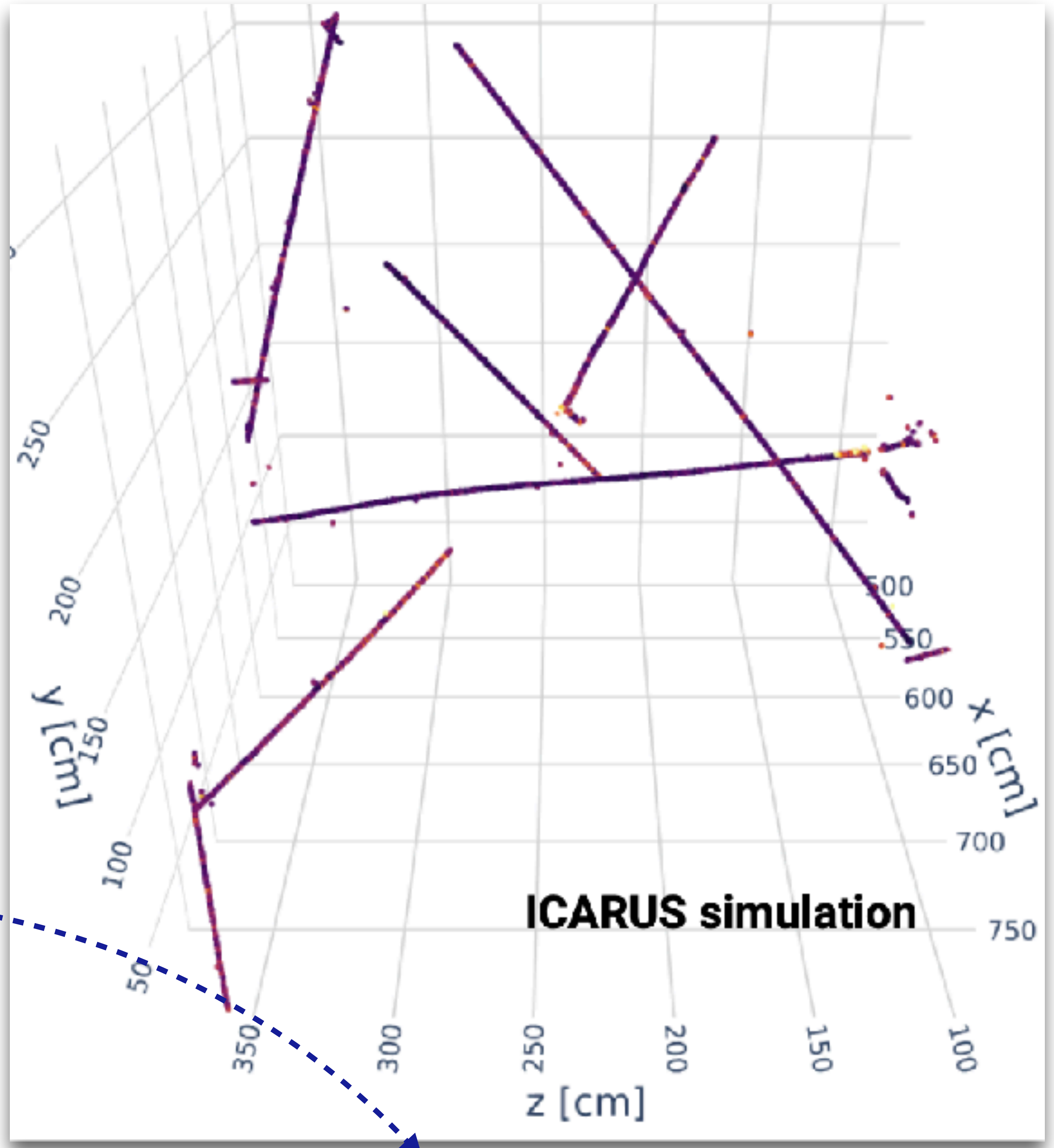
wire

Starting point:

3 wire planes ↔ 3 x 2D images

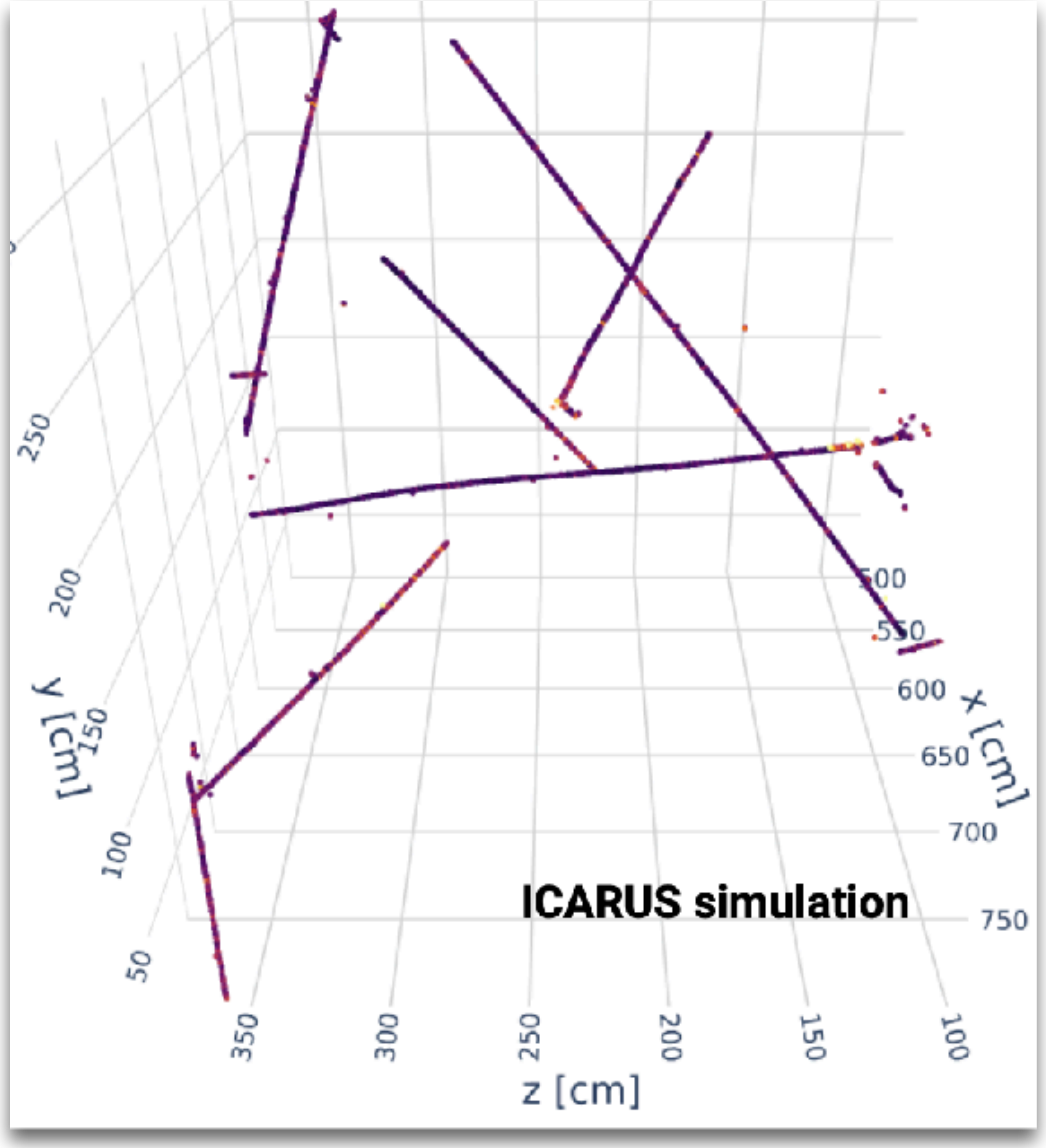
Cluster 3D: make all valid (time-compatible & intersecting) combinations of hits across 2 wire planes

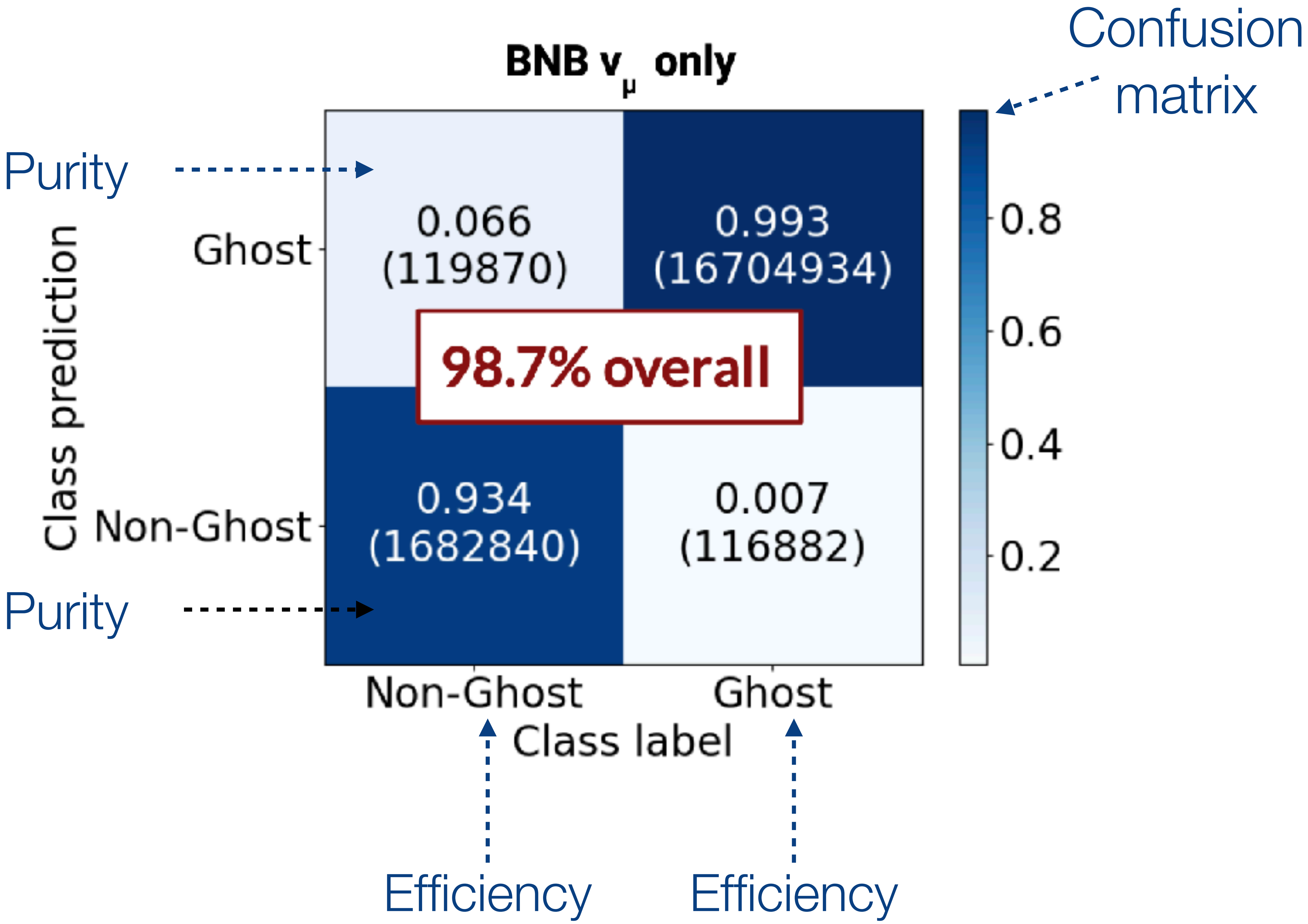




Deghosting: use U-ResNet to identify and remove *artifacts* of the reconstruction

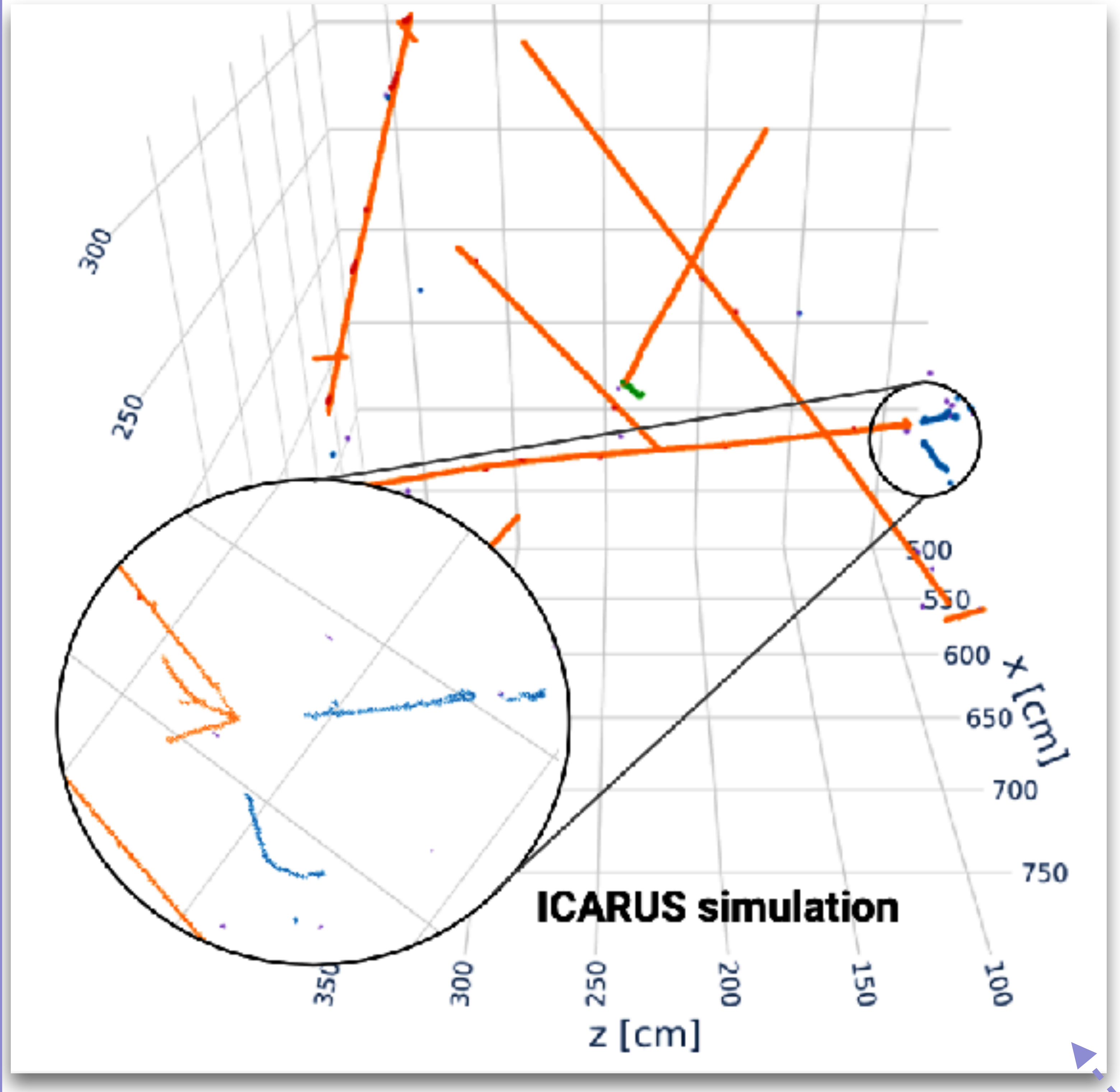
1 ML-based event reconstruction: hierarchical feature extraction





Deghosting: use **U-ResNet** to identify and remove *artifacts* of the reconstruction

2 ML-based event reconstruction: hierarchical feature extraction



A **score** for each target particle class, EM shower, track-like, Michel electron, delta ray, low energy (LE), is predicted

Semantic segmentation

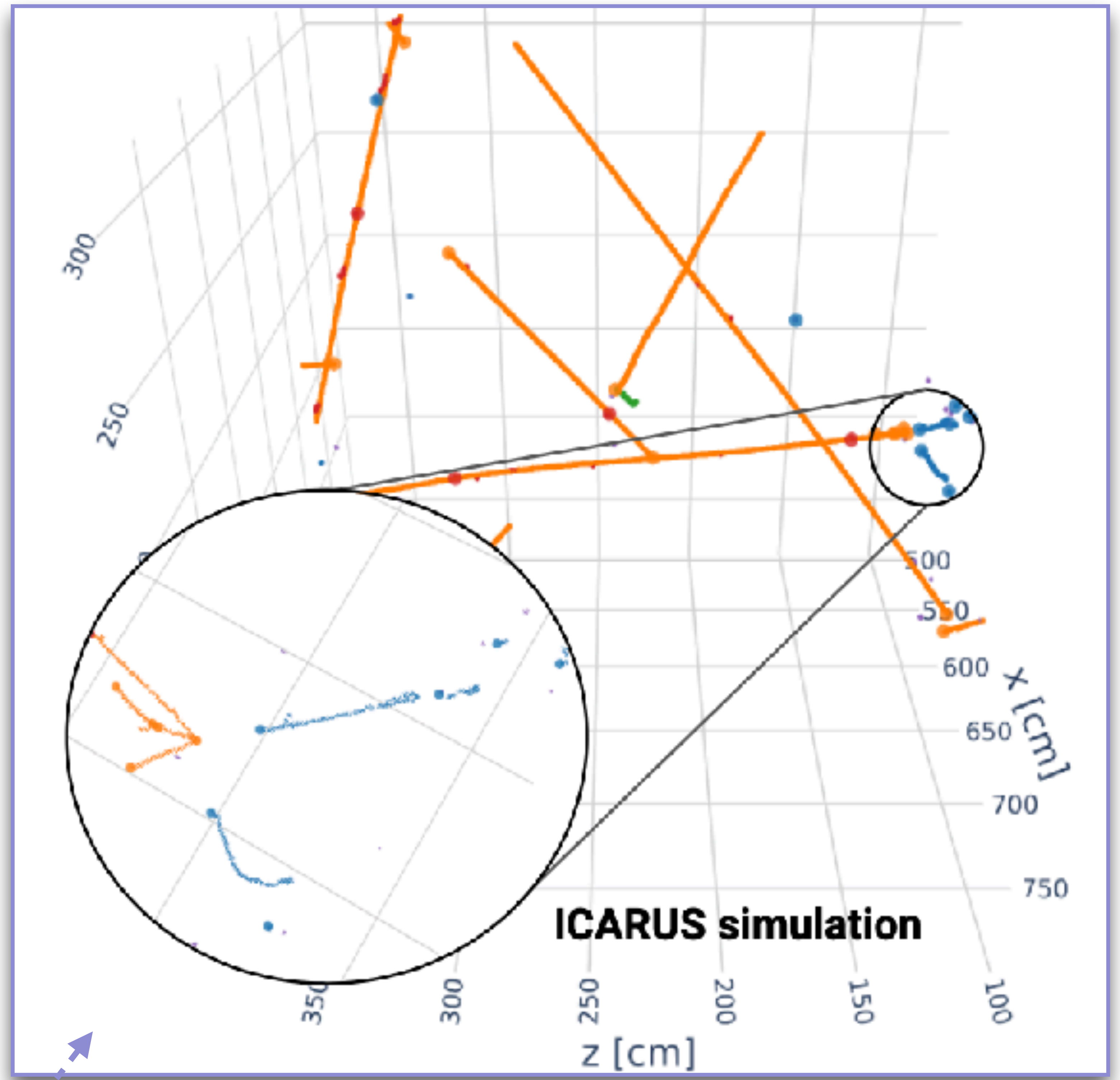
Distinguish different particle types based on topological features

BNB ν_μ only

Class prediction \ Class label	Shower	Track	Michel	Delta	LE
LE	0.011	0.000	0.001	0.001	0.850
Delta	0.001	0.001	0.007	0.851	0.001
Michel	0.003	0.000	0.877	0.005	0.001
Track	0.005	0.997	0.038	0.121	0.055
Shower	0.981	0.002	0.077	0.023	0.094

99.1% overall

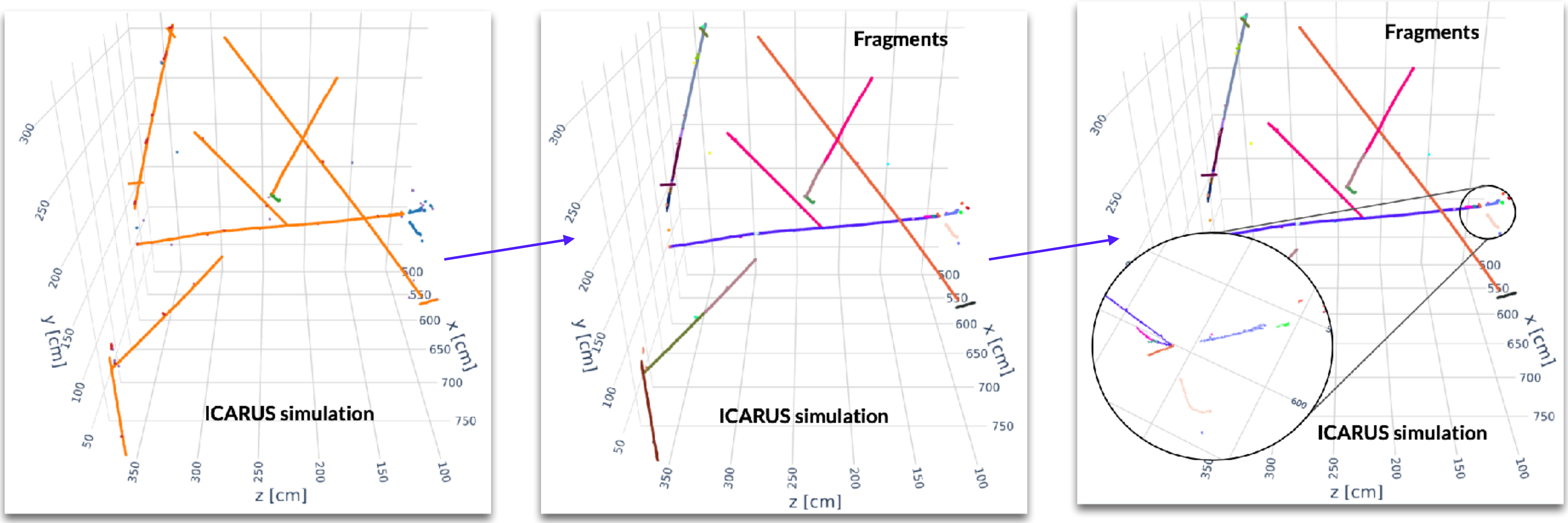
Sparse convolutional network (U-ResNet)



Point of interest (PPN)

Progressively narrow down a region to a single point with successive masks: 96% of points are found within 0.7 cm

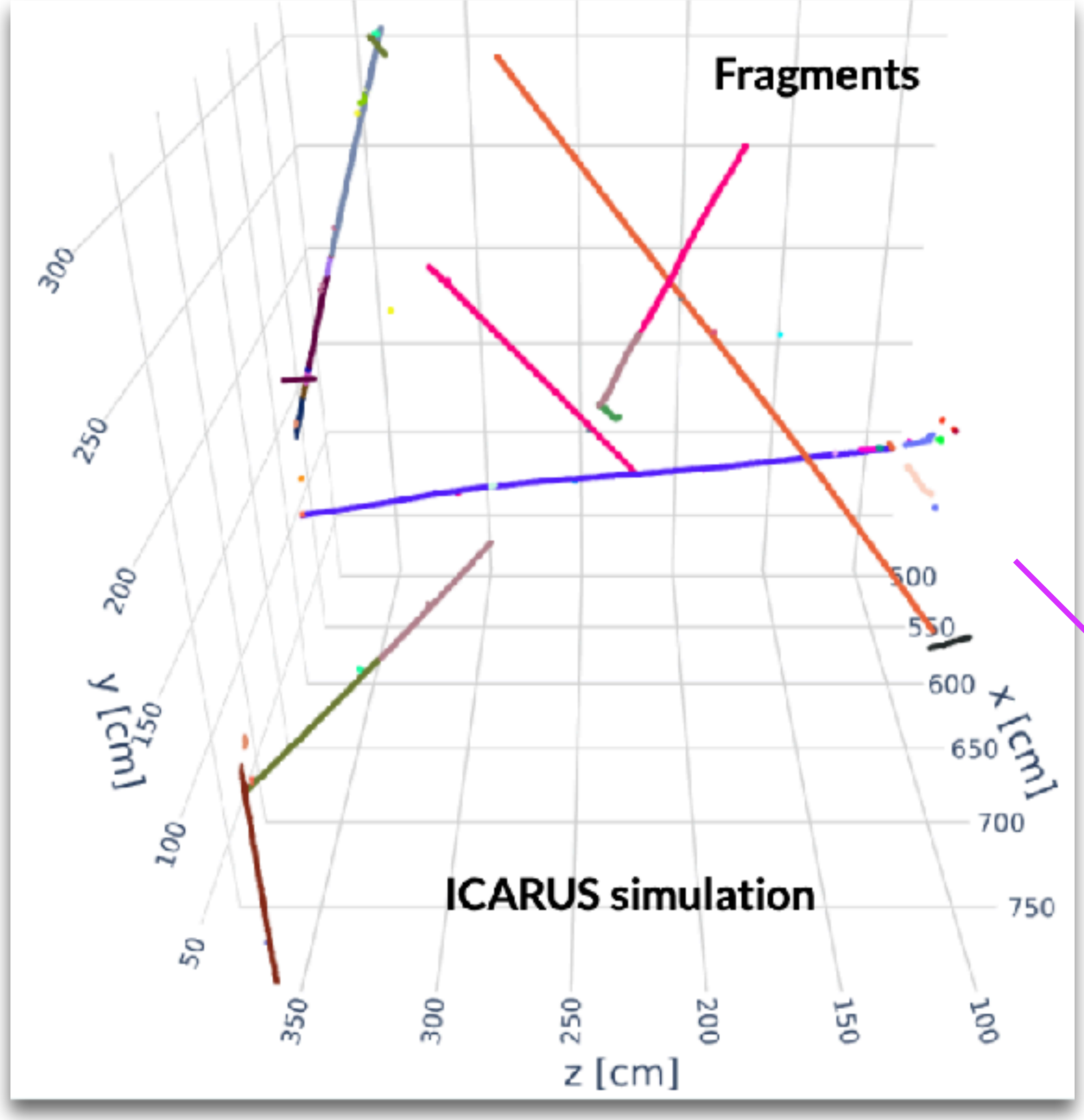
3 ML-based event reconstruction: hierarchical feature extraction



Dense clustering

Density based clustering (DBSCAN) used to cluster particle fragments that belong to a common semantic class, i.e. break track/shower fragments at PPN/where they touch

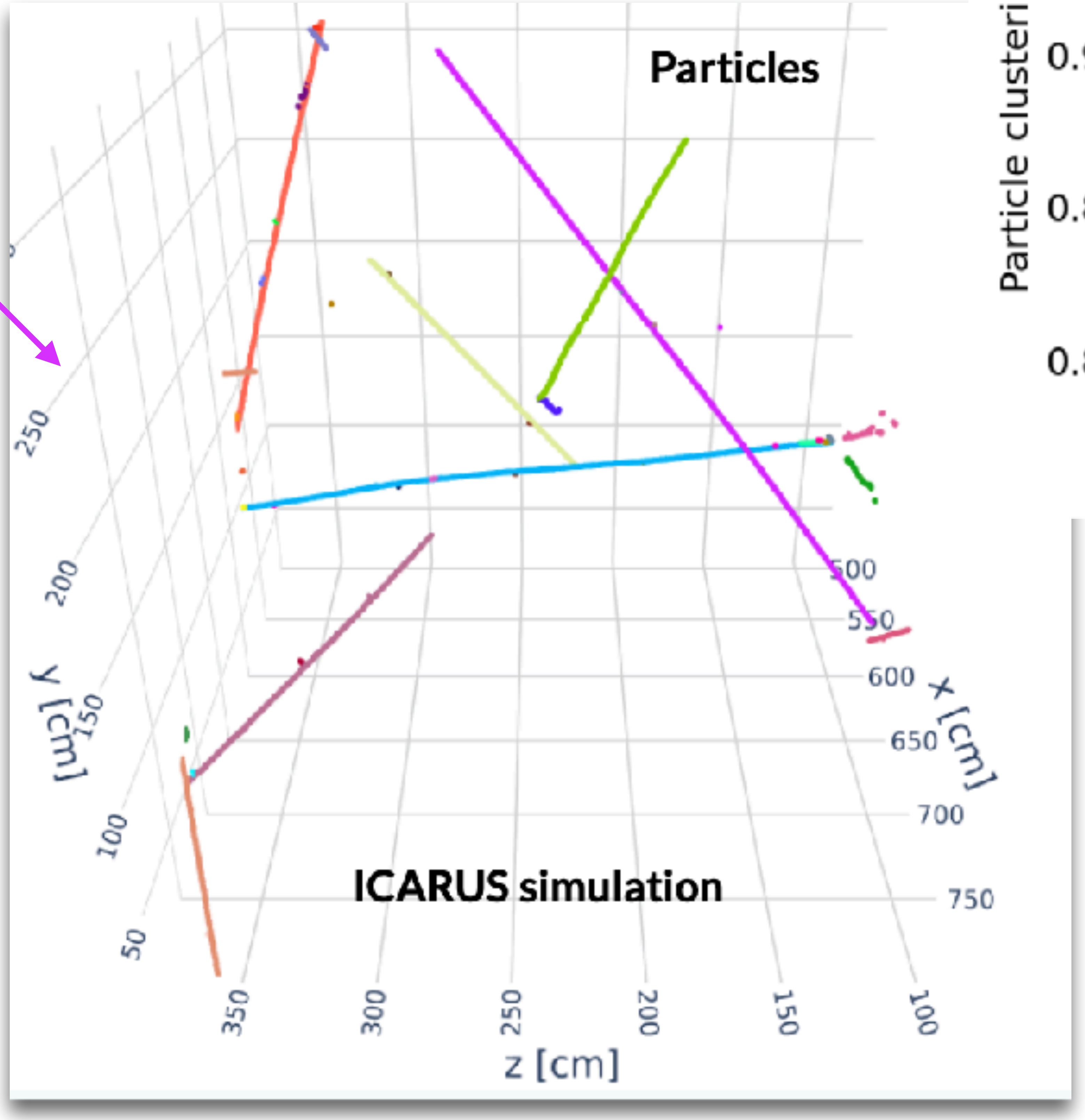
4 ML-based event reconstruction: hierarchical feature extraction

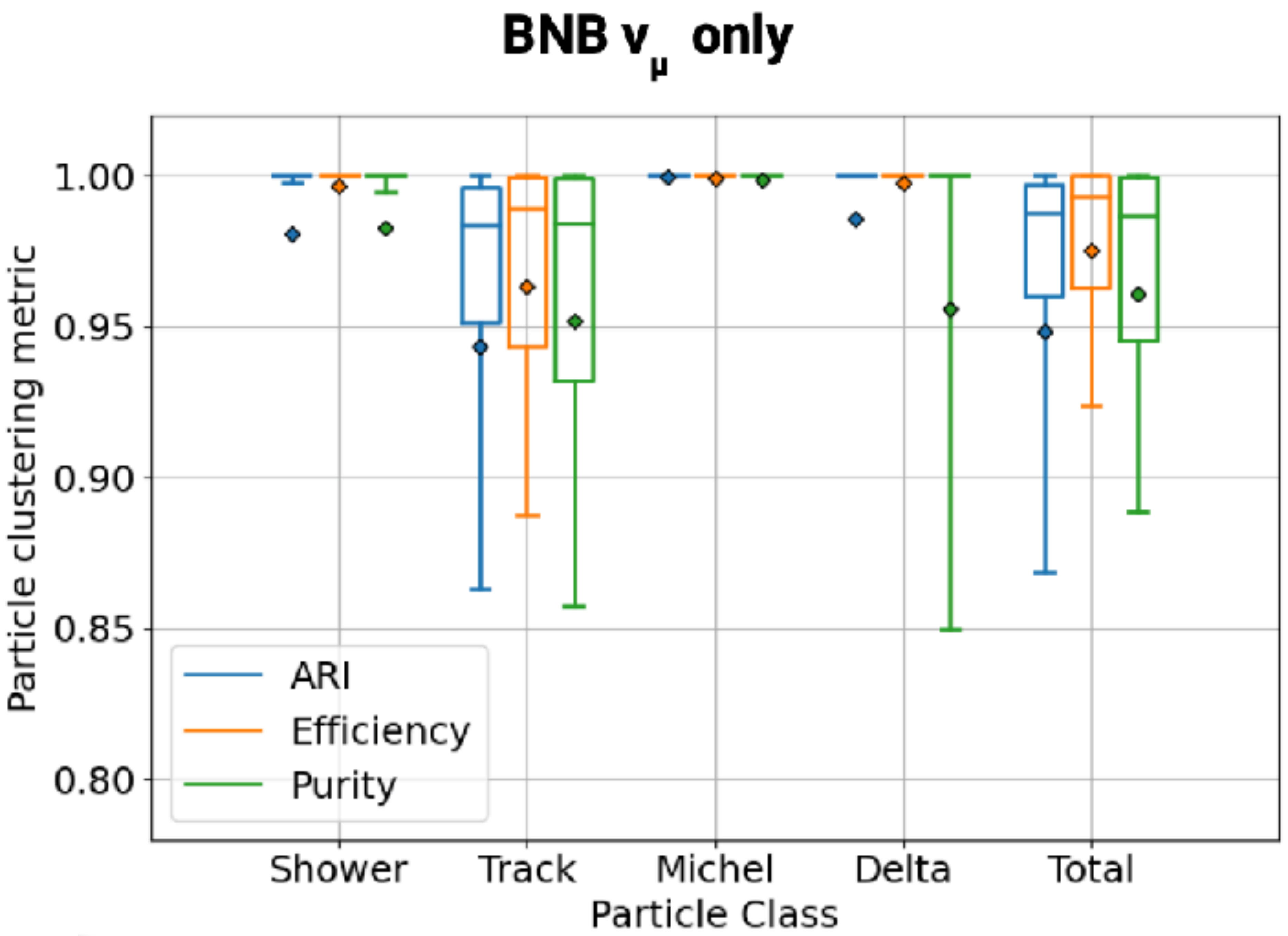


Represent the set of fragments as a set of *nodes* in a graph and connect them. *Edges* represent correlations between them.

Particle aggregation

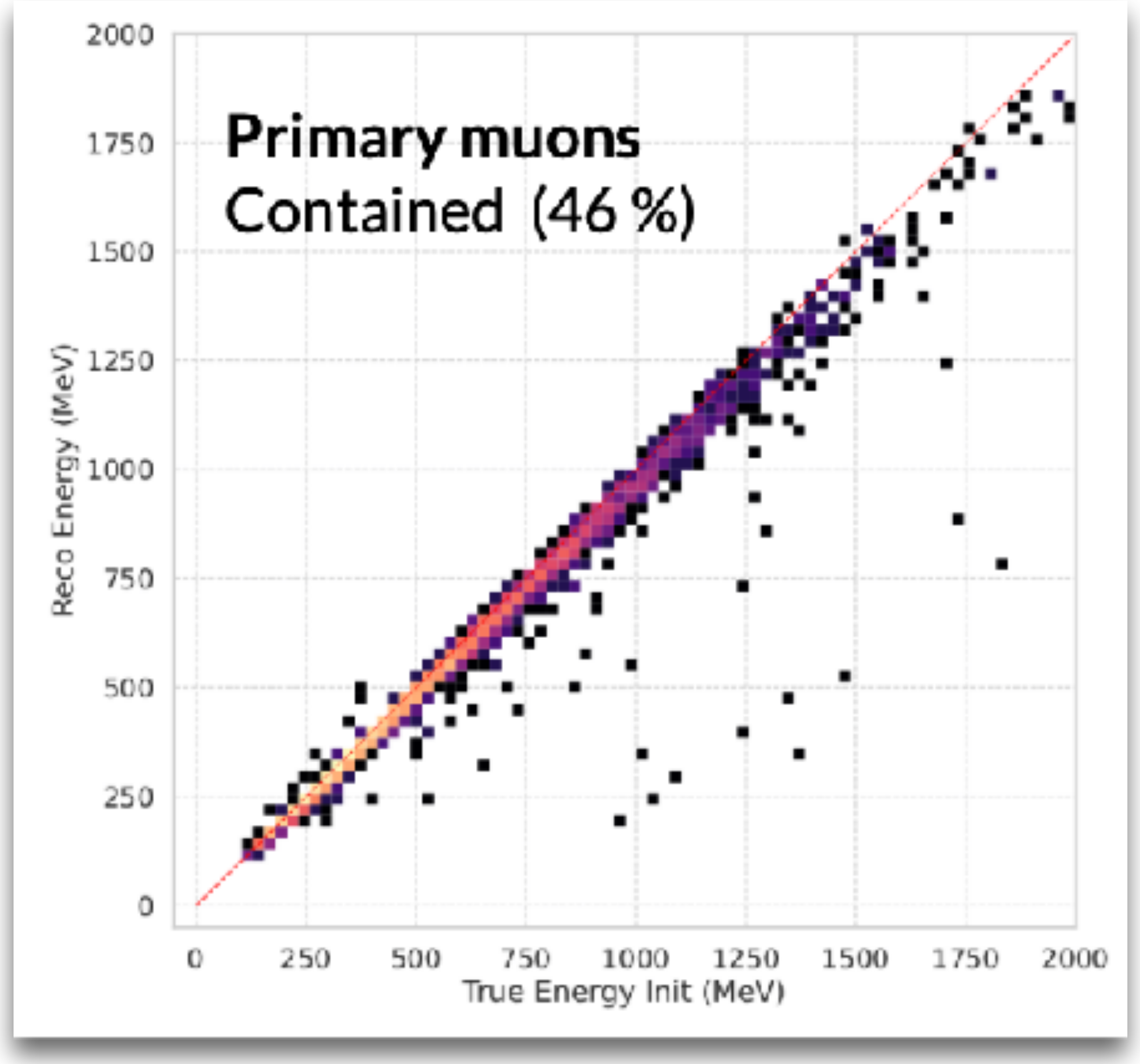
Use a Graph Neural Network (GNN) to aggregate fragments and form particles





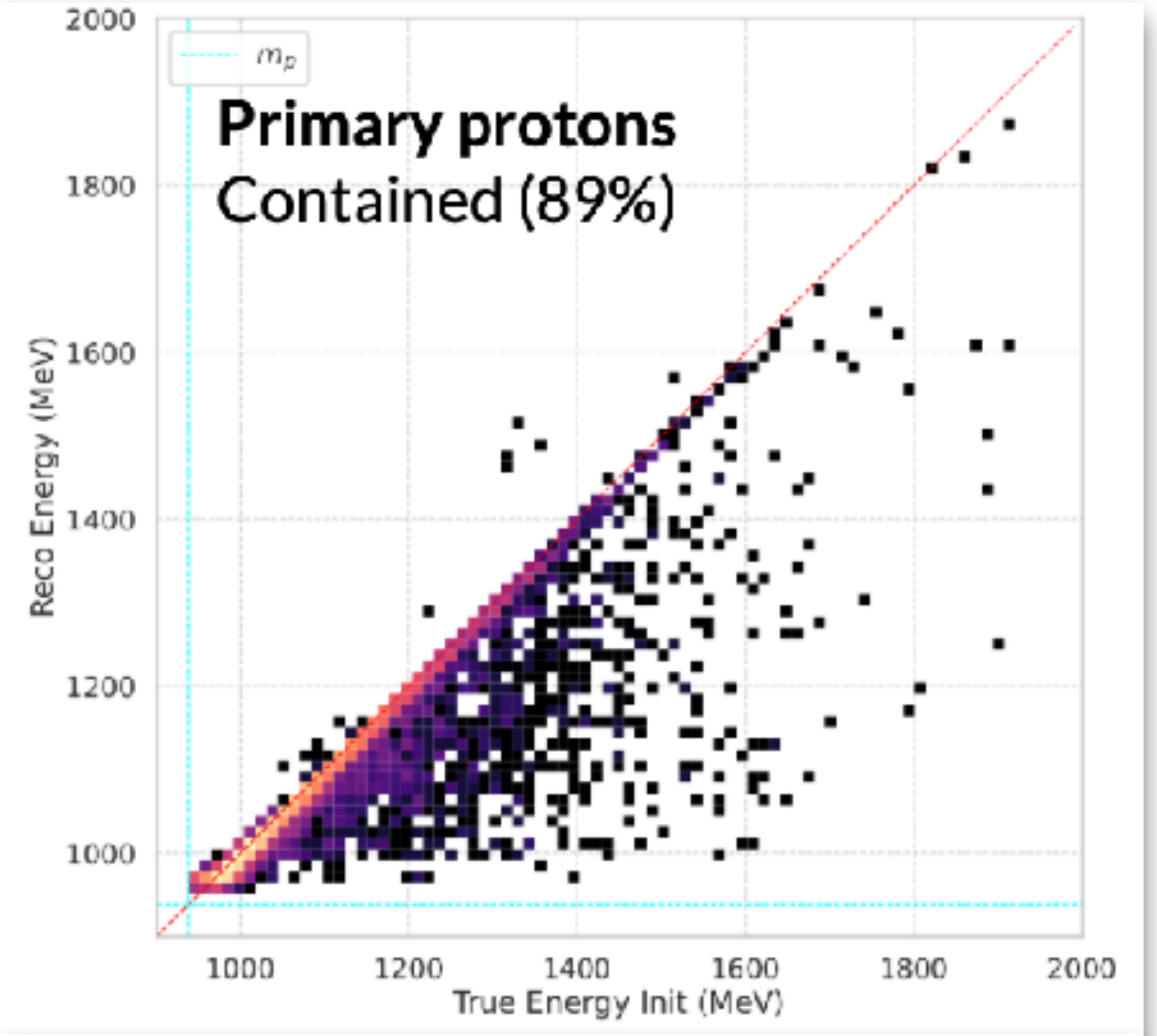
Three metrics to characterize clustering performance:
efficiency (in both/true) [*]
purity (in both/predicted) [*]
ARI (Adjusted Rank Index)
[*] in both = pred & true

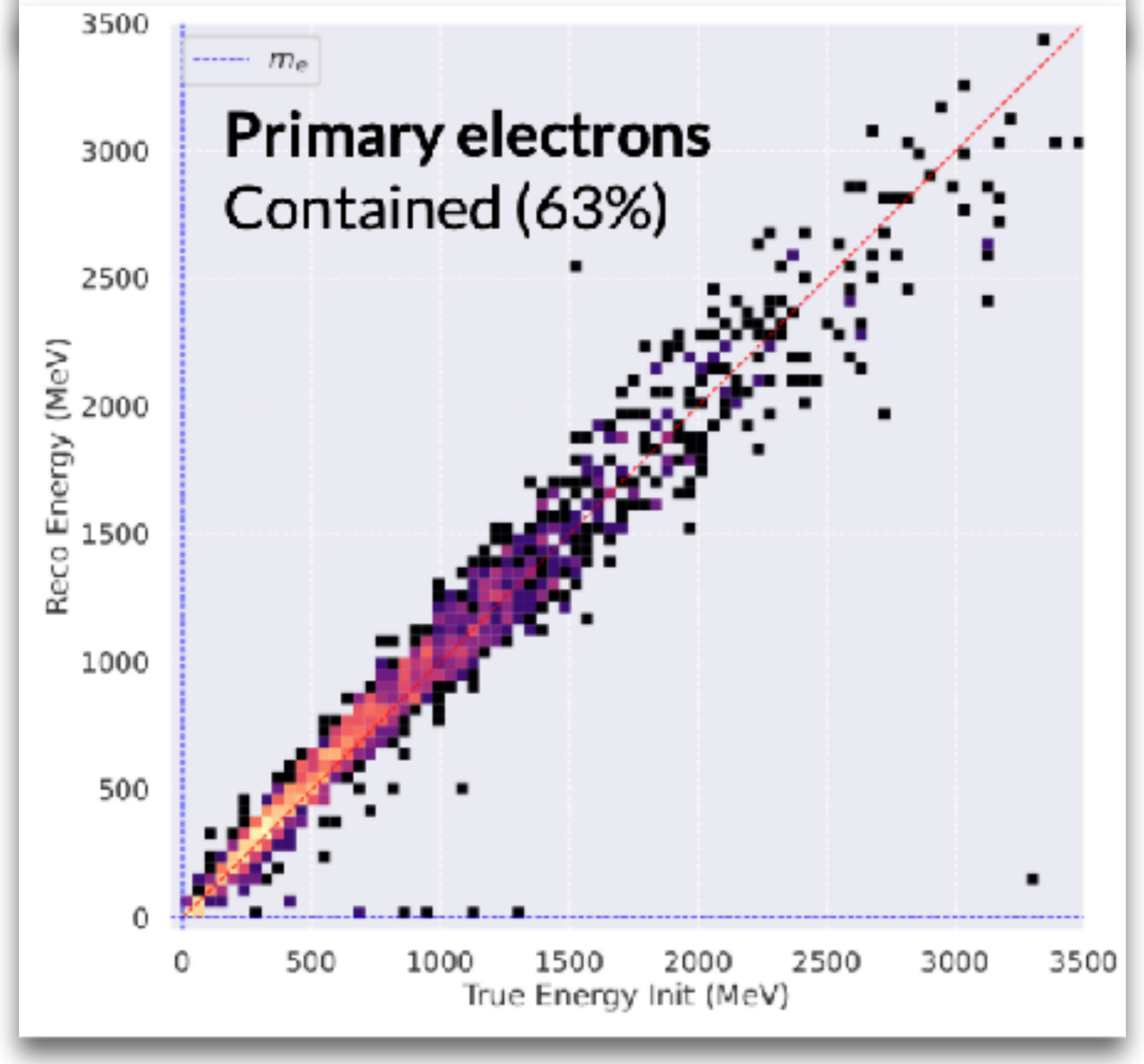
5 ML-based event reconstruction: hierarchical feature extraction



Traditional energy reconstruction

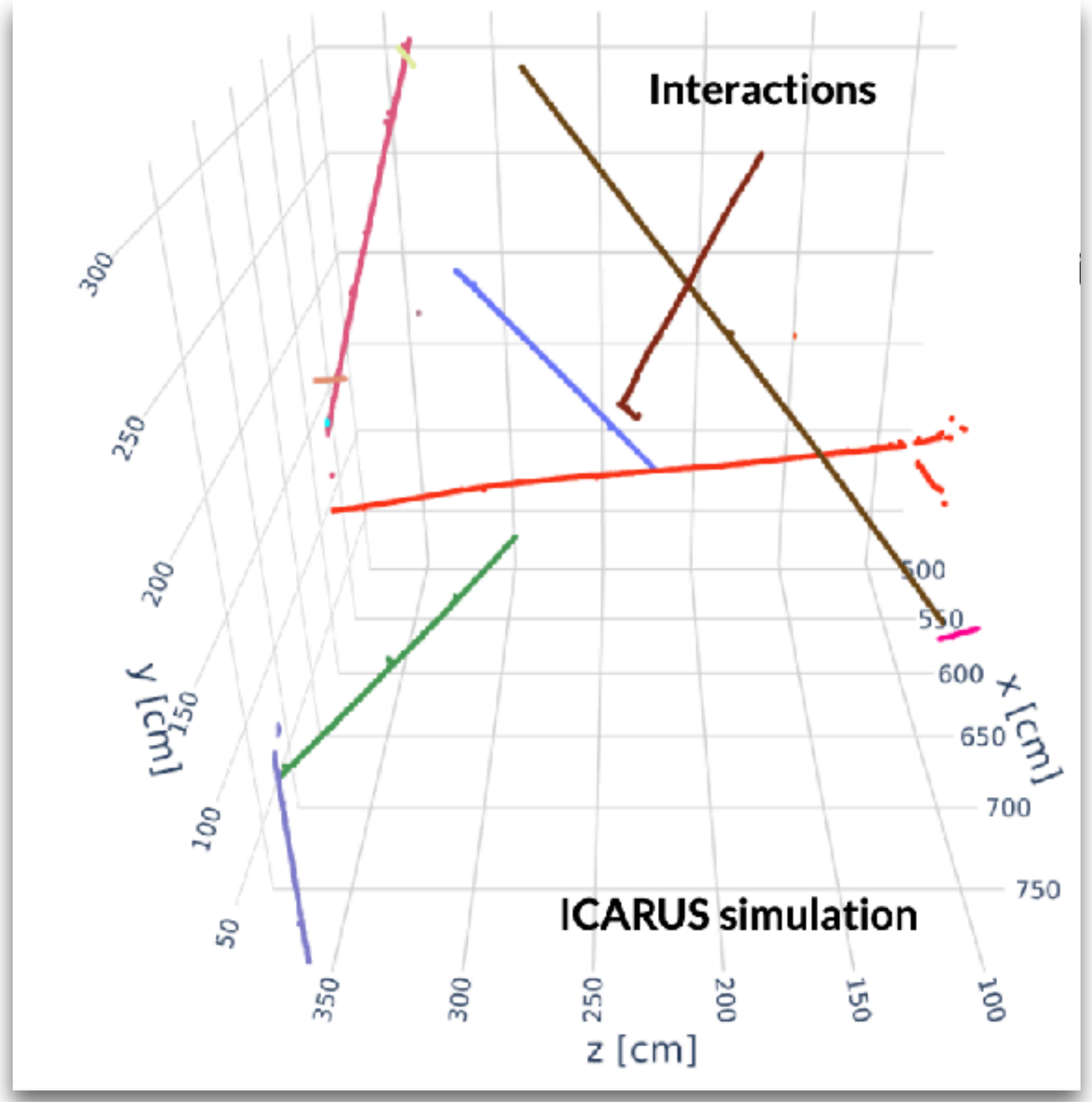
- range-based reconstruction for muons and protons
- calorimetric approach for electrons



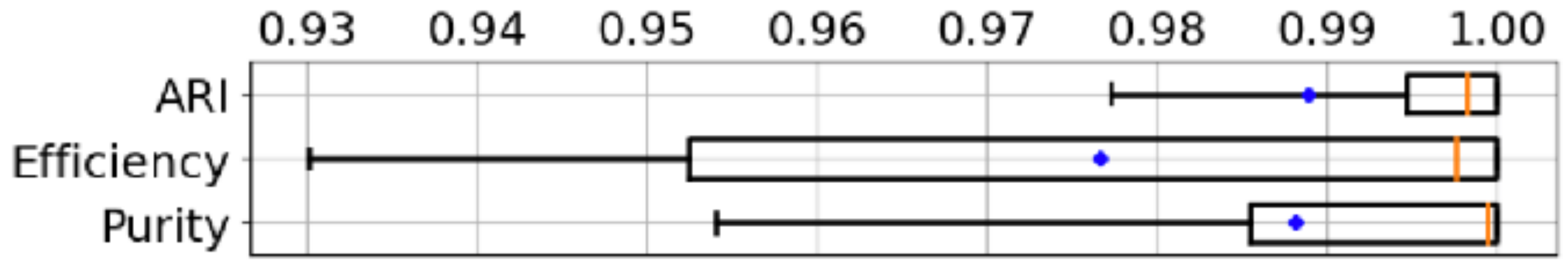


Interaction aggregation

Use a Graph Neural Network (GNN) to aggregate particles and form interactions

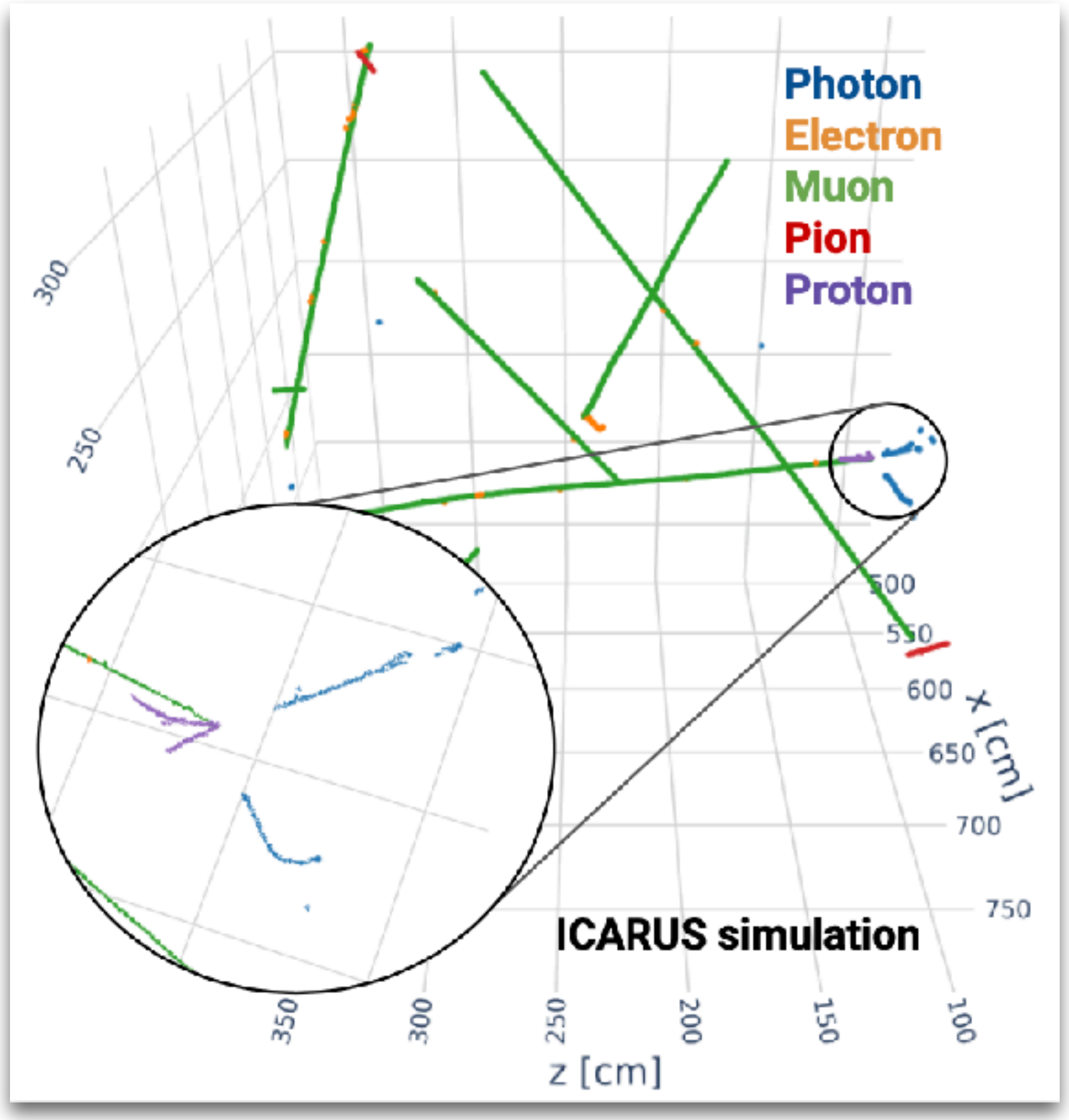


BNB ν_μ + Cosmics



5 ML-based event reconstruction: hierarchical feature extraction

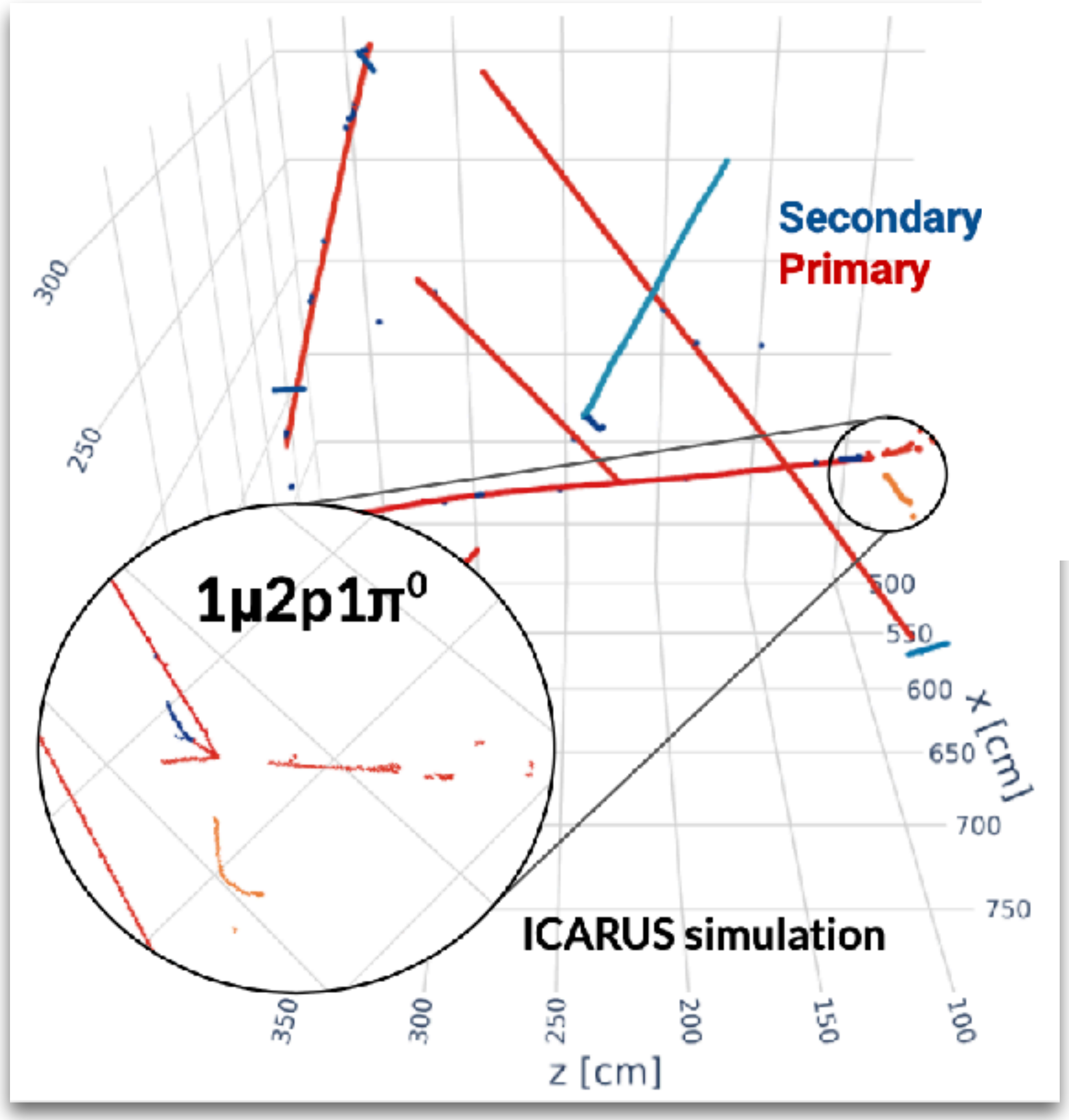
Particle identification

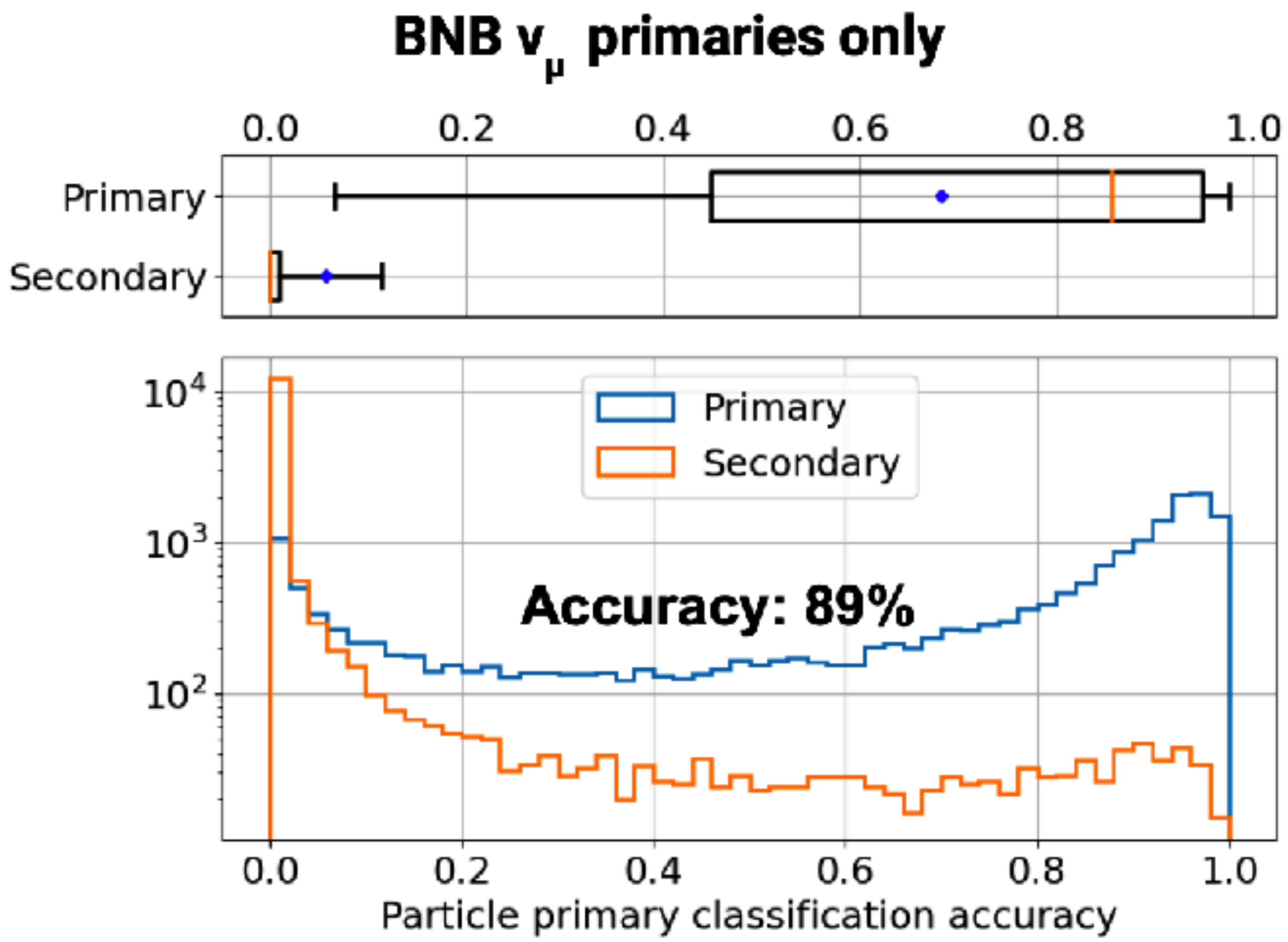


Use again GNN to identify particles e, γ, μ, π, p in context

Primary identification

Separate particle(s) which originate from the **vertex.**





Use GNN to distinguish **primary** particles from secondaries. This is fundamental for any analysis studying a **specific interaction channel.**