ML-Based Event Reconstruction in the CMS High Granularity Calorimeter

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ÉCOLE POLYTECHNIQUE

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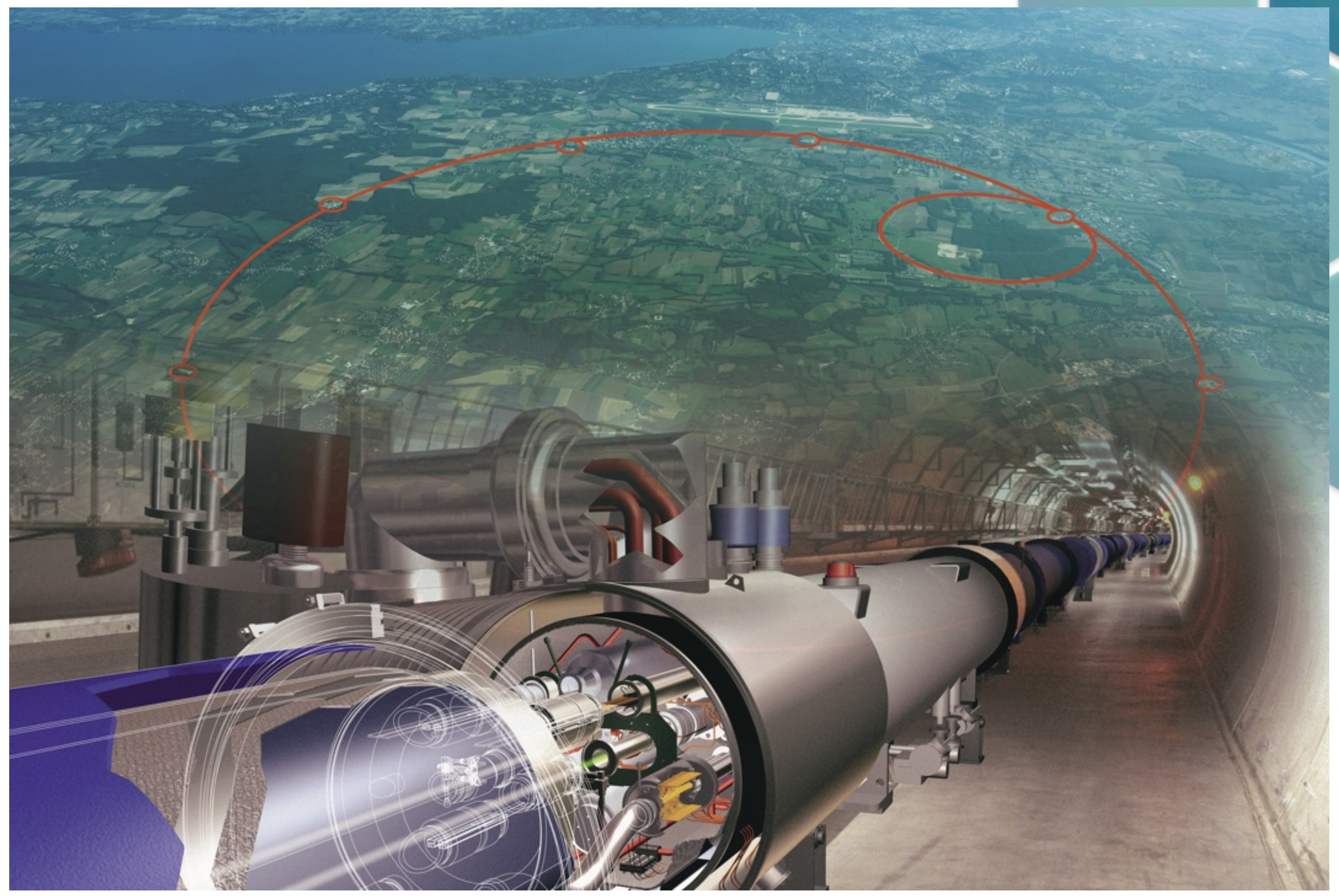
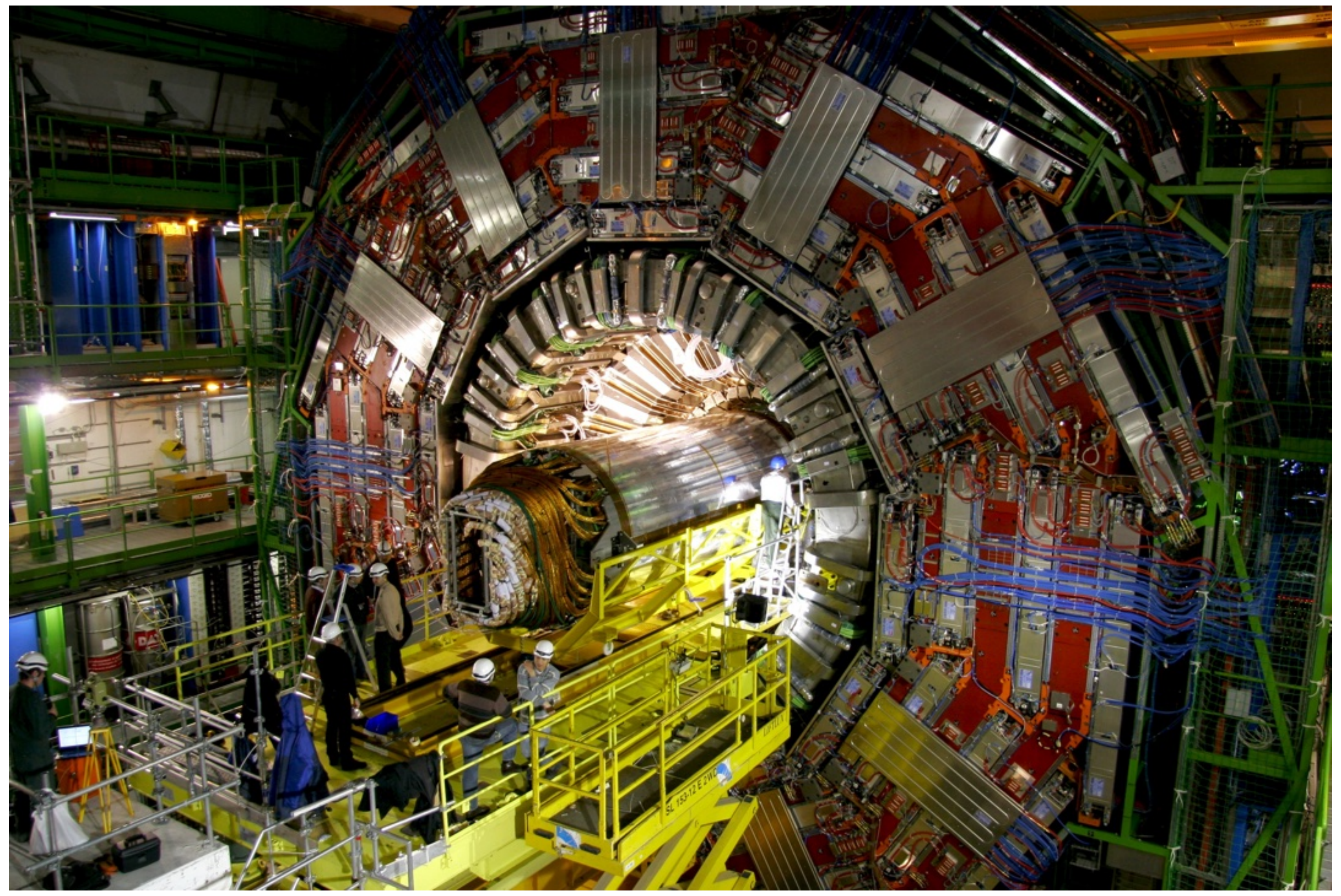
CMS

LHC and CMS in one picture

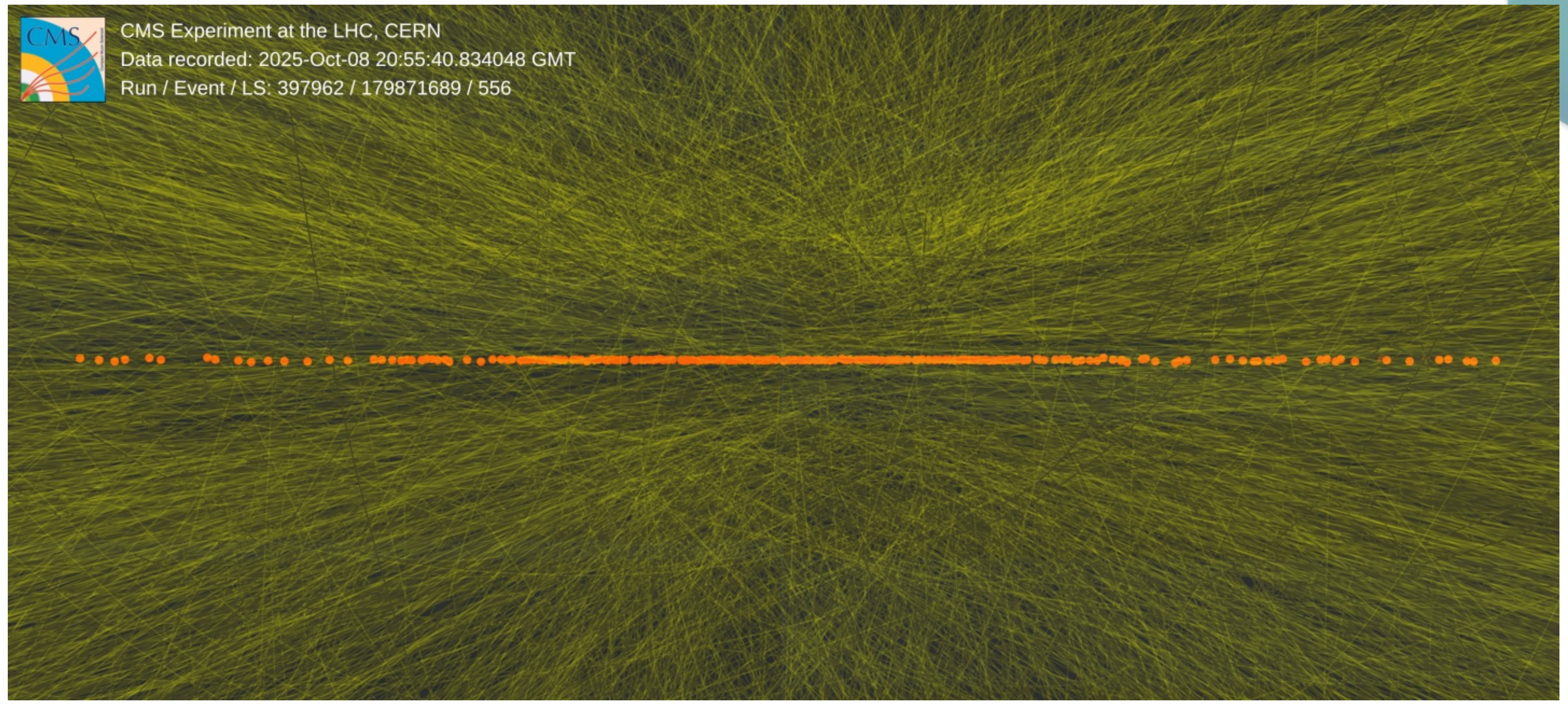
- Large hadron collider (LHC) is the largest particle accelerator,
  - producing proton-proton collisions at center-of-mass energies up to 13.6 TeV.
- Compact Muon Solenoid (CMS) is a large general purpose detector built around one of the LHC's interaction points. It combines:
  - a silicon tracker, electromagnetic and hadronic calorimeters, and a muon system inside a strong magnetic field.
- Accurate physics measurements rely on
  - precise tracking, detailed shower measurement, and clear separation of overlapping signals.





The HL-LHC challenge

- The LHC is entering its High-Luminosity phase (HL-LHC) to significantly increase the amount of collected data,
    - enabling more precise measurements and searches for rare or new physics processes.
- It will deliver about 10 times more integrated luminosity, with up to 200 simultaneous proton–proton collisions per bunch crossing (pileup).
- This results in heavily overlaid events:
    - calorimeters see overlapping energy deposits, and the tracker records dense track environments.
- The main challenge is to maintain precise energy and position resolution, suppress pileup, and preserve efficient, accurate particle reconstruction.



Visualization of a high PU event (≈ 140) recorded by CMS on 2025-10-08.

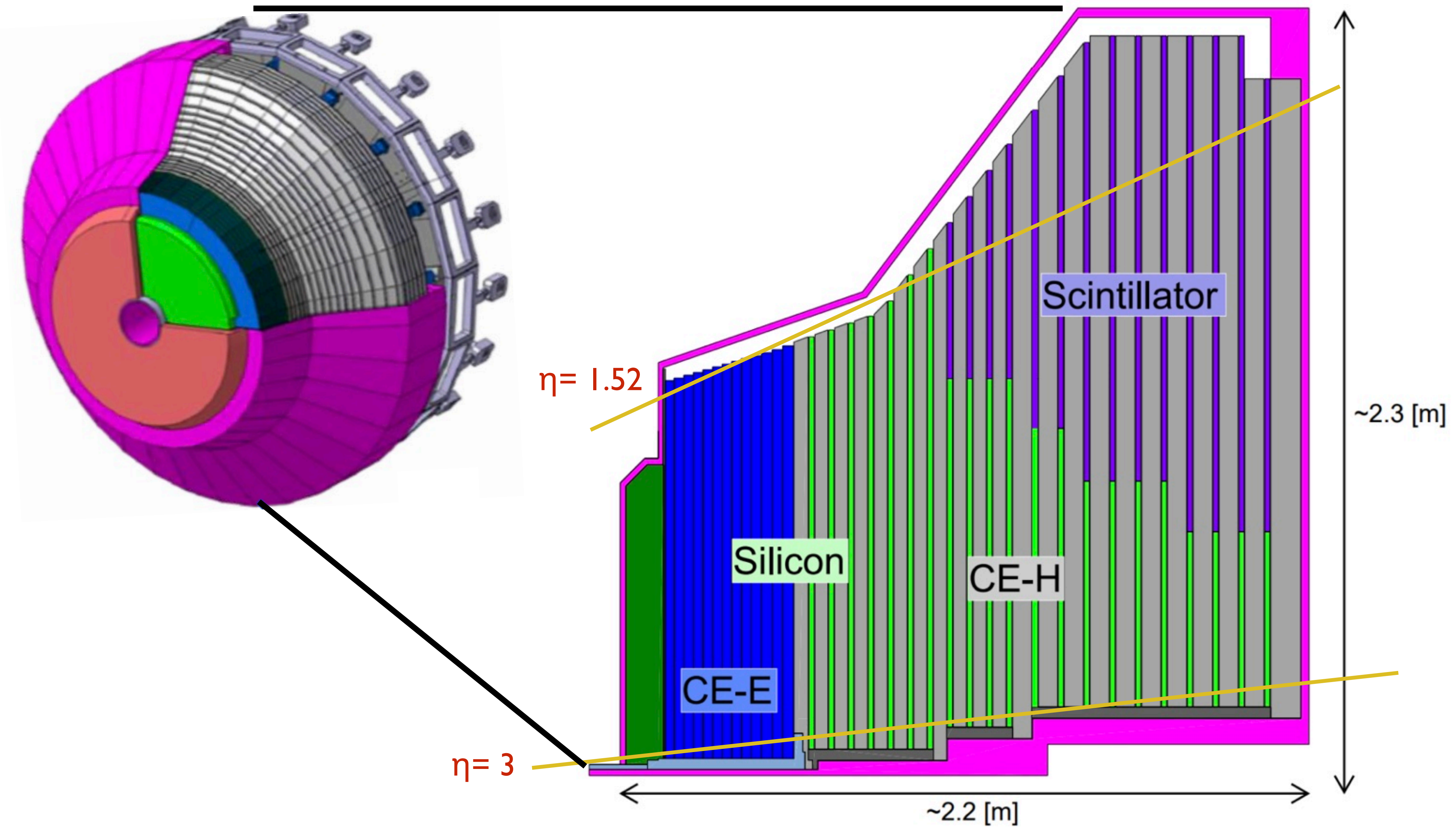
https://cds.cern.ch/record/2945596

HGCAL – the new CMS endcap calorimeter

- CMS is therefore undergoing a major upgrade program by replacing its current endcap calorimeters with the High Granularity Calorimeter (HGCAL) to cope with the HL-LHC conditions.
- A 5D calorimeter covering $1.5 < |\eta| < 3.0$, providing spatial, energy, and timing information.
- Extremely fine 3D granularity enables precise shower imaging and energy measurement.
- Precision timing helps disentangle overlapping interactions in high PU environments.

The 3D and longitudinal views showing the finely segmented structure of the two sections of HGCAL;

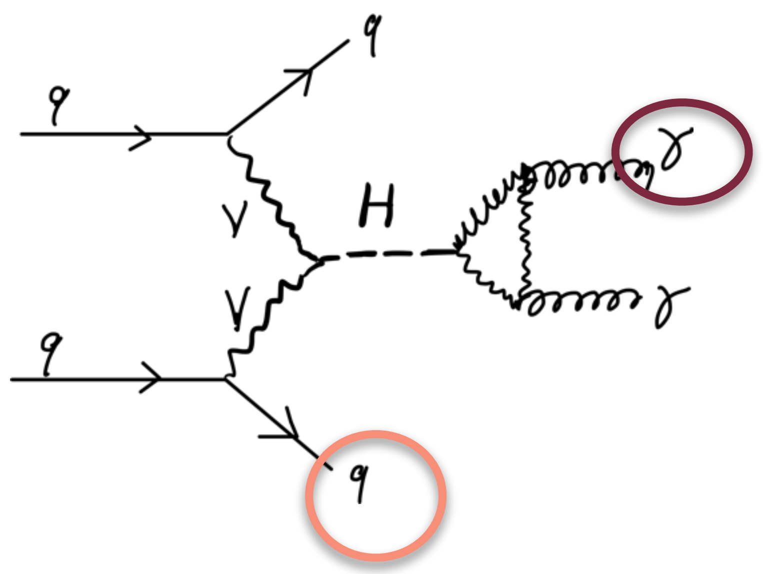
- CE-E (26 silicon layers)
- CE-H (21 layers combining silicon and scintillator sensors)



The power of high granularity

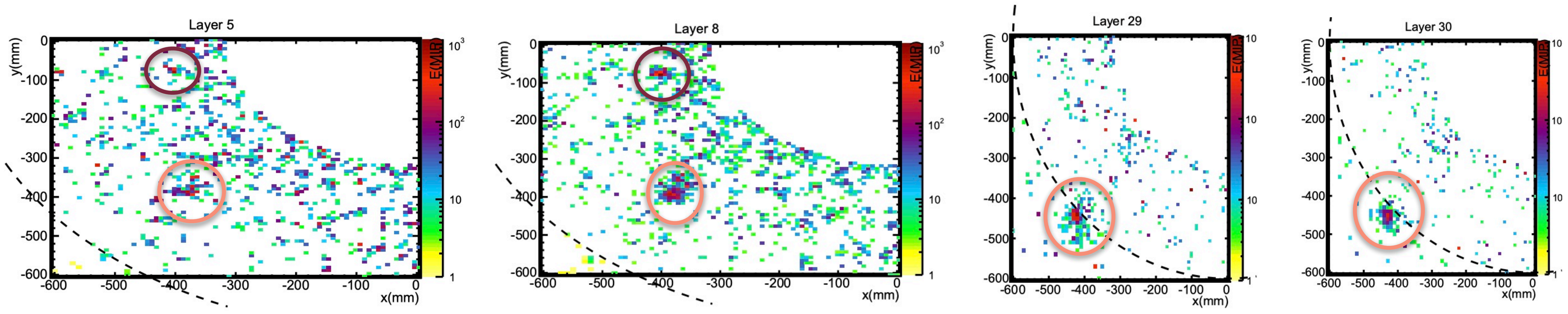
Full 5D calorimeter information with granularity and time allows to handle dense environments (140-200 PU)

VBF jets + $H \rightarrow \gamma\gamma$ example



+ 200 PU

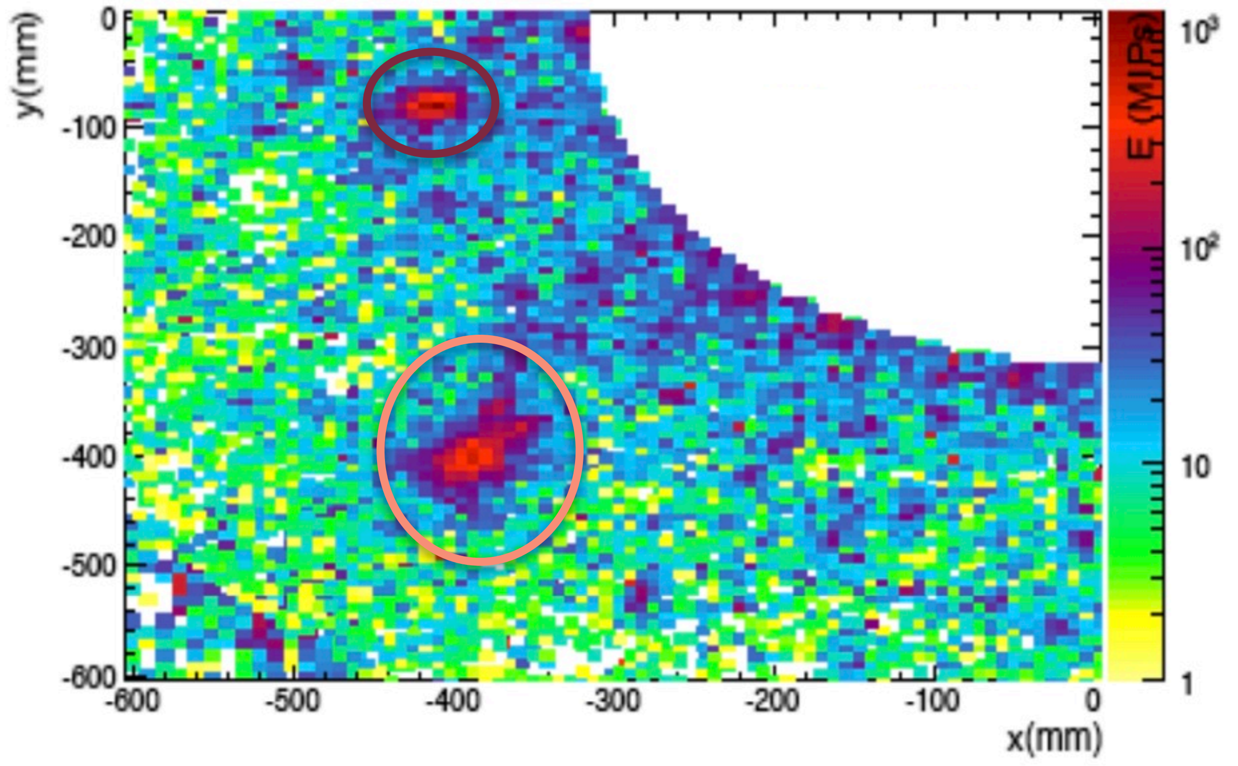
in HGCAL



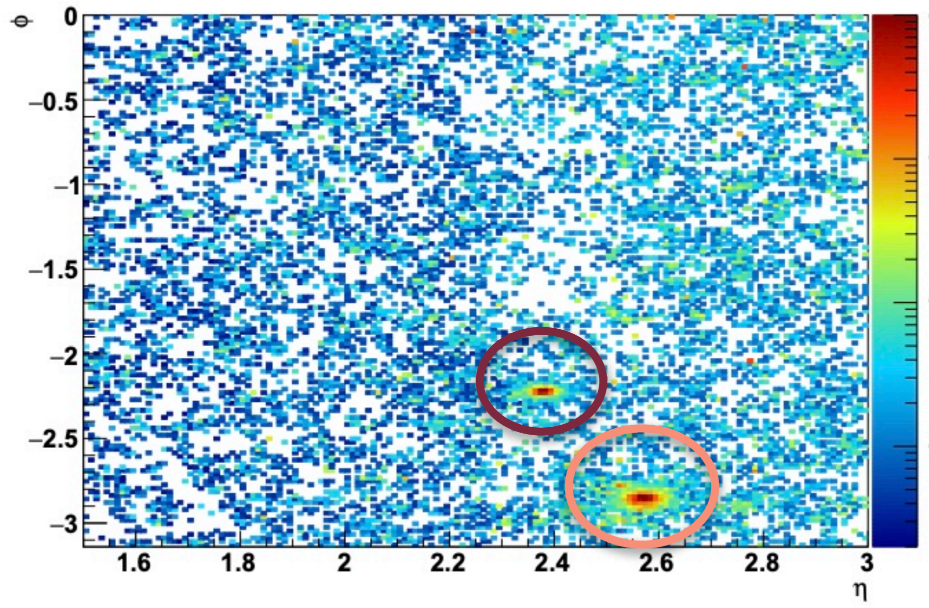
CE-E

CE-H

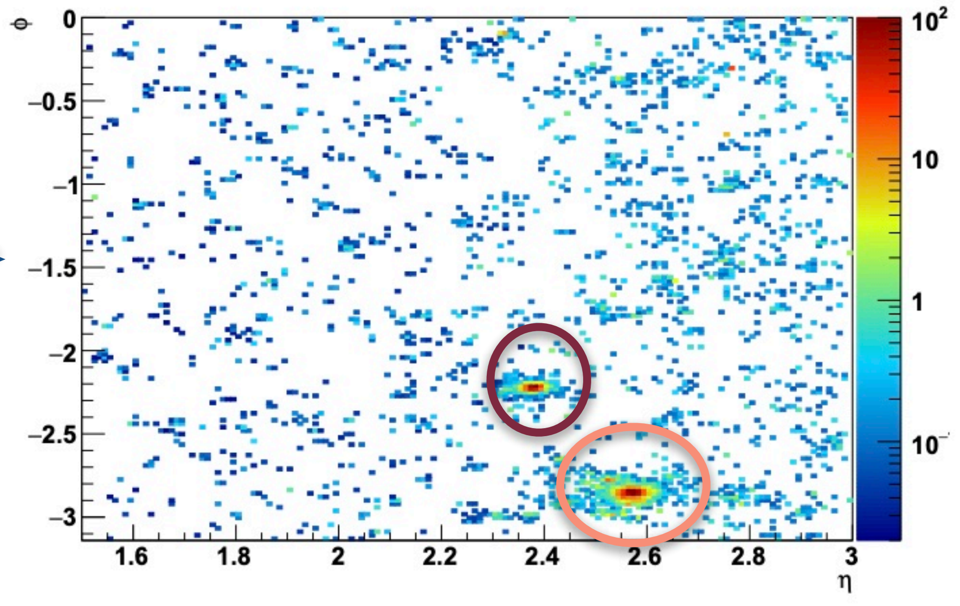
+ 140 PU



With the precision timing, identify high-energy clusters, then make timing cut to retain hits of interest



after removal of hits with |Δt| > 90 ps

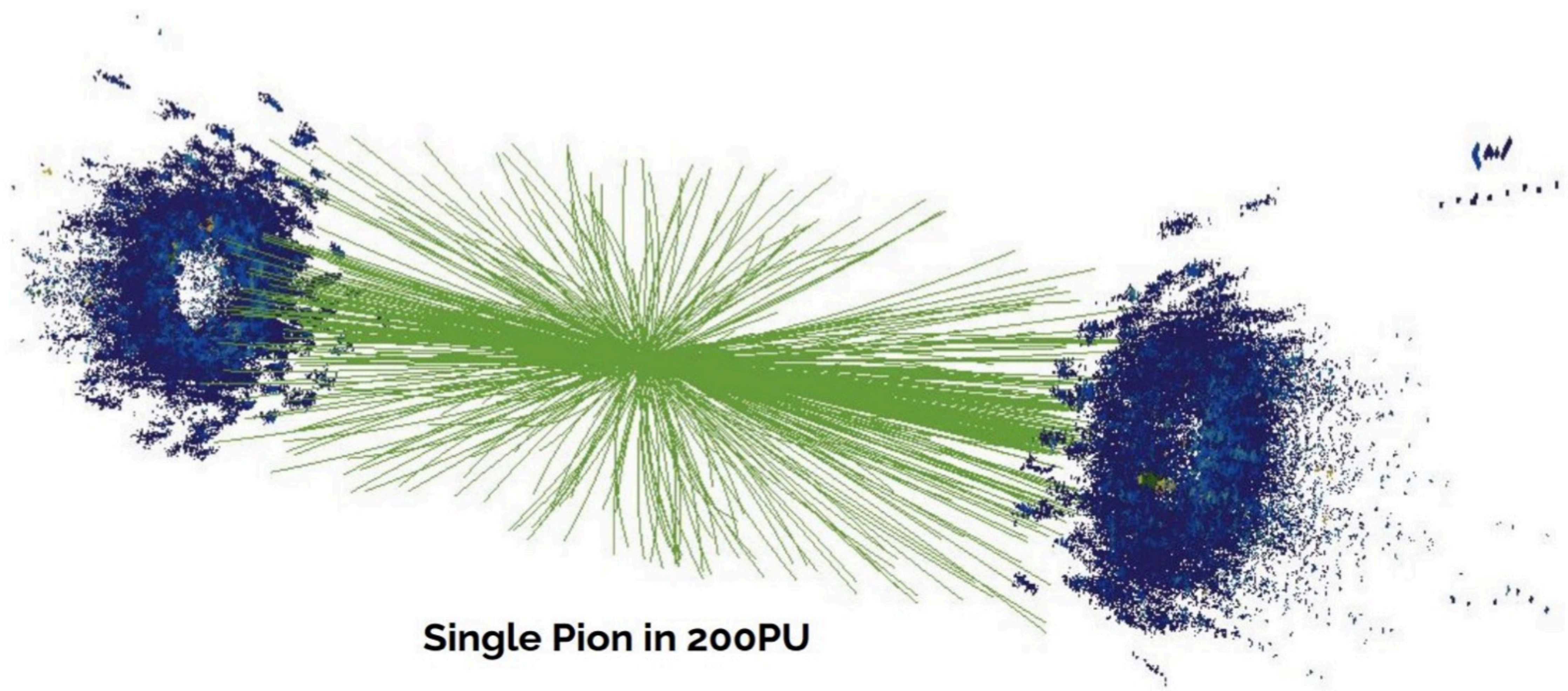


The HGCAL challenge

The price is complexity!

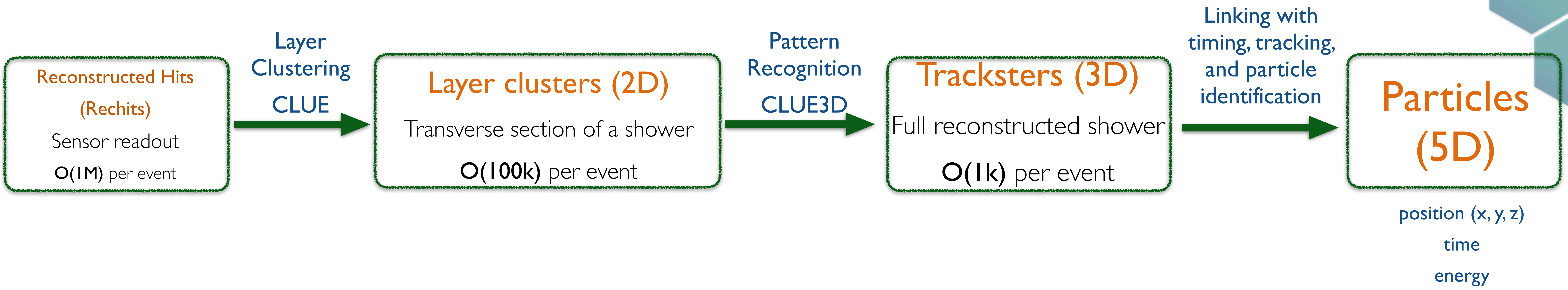
With millions of readout channels, HGCAL introduces a vast combinatorial challenge for clustering and reconstruction.

This motivates the use of advanced machine learning techniques to efficiently perform pattern recognition and energy association.



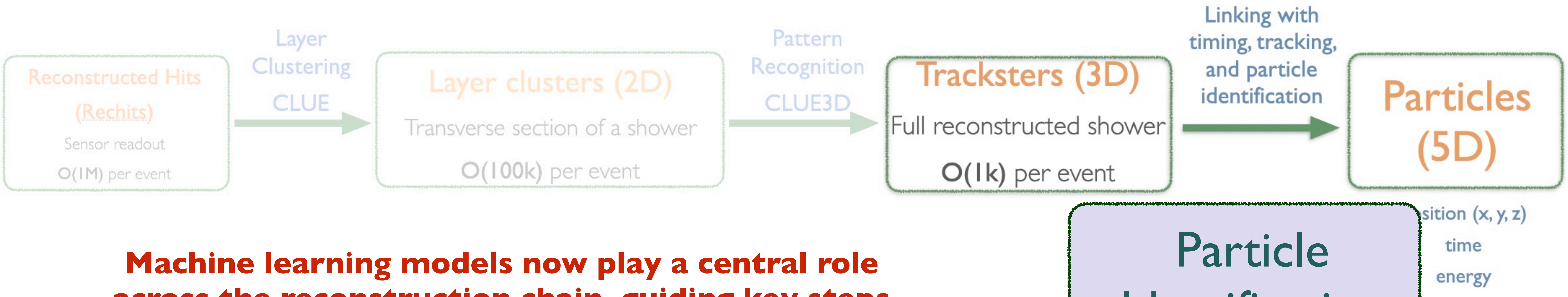
Simulated event display of HGCAL at 200 PU

TICL : The Iterative CLustering

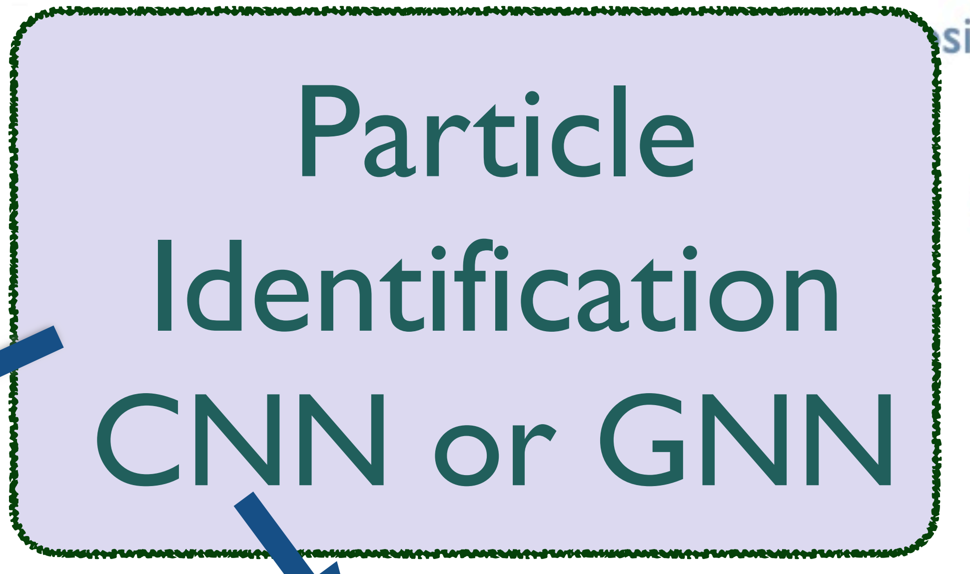


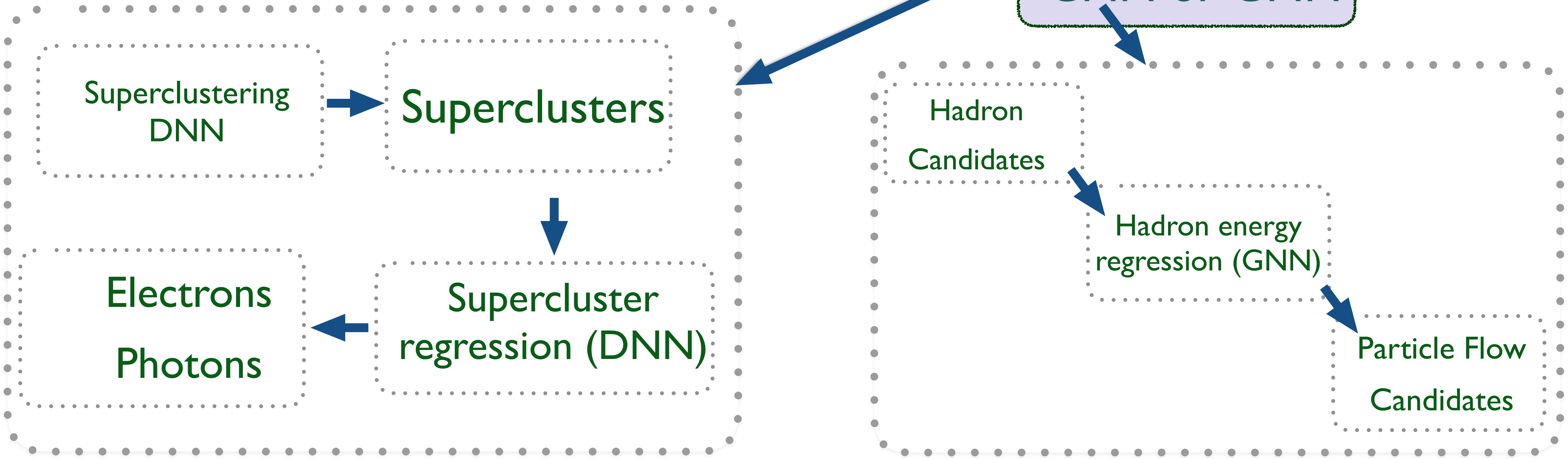
- TICL : The Iterative CLustering is a modular, iterative reconstruction framework
  - Each iteration targets a specific topology or object class and builds on previous results.
  - Full reconstruction starting from RecHits to particle properties and identification probabilities
  - Exploits full 5D calorimeter information: position (x,y,z), energy and time.
  - Handles large data rates efficiently on CPUs and GPUs.

TICL : The Iterative CLustering



Machine learning models now play a central role across the reconstruction chain, guiding key steps from clustering to particle identification!





Particle Identification

- Particle Identification (PID) aims to distinguish hadronic tracksters from electromagnetic (electron/photon) ones based on their shower development and energy distribution.
- Accurate PID is critical since electromagnetic tracksters seed the electron reconstruction, which is computationally expensive.
- To optimize between performance and processing time, especially under HL-LHC conditions, several approaches have been developed.

Classical Approach

- Uses high-level observables such as
  - Energy fraction in hadronic compartment
  - Longitudinal / transverse shower shape
- Very fast inference
- Limited discrimination power

Advanced ML-Based Approach

- Uses CNNs, DNNs, or GNNs depending on the input granularity
- Inputs: (x, y, z, E) of layer clusters or all raw hits
- Learns detailed shower topology
- Balances model complexity, accuracy, and computational efficiency

Particle Identification with GNN

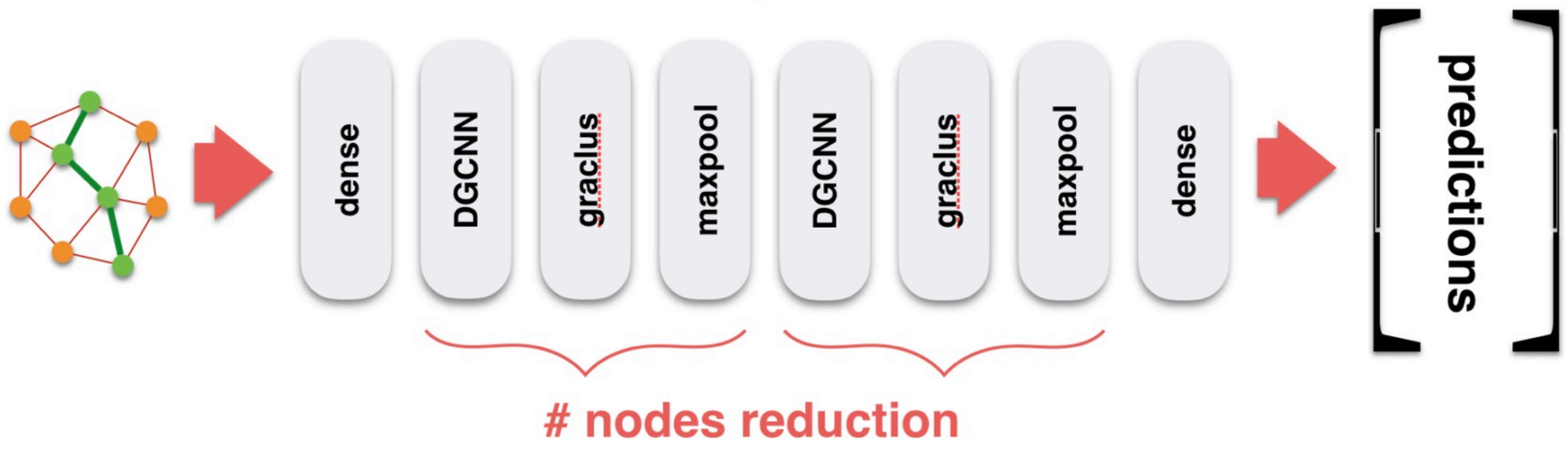
- Dynamic Reduction Network (edge convolution + graph pooling)
- Each shower in HGCAL is represented as a point cloud : a set of hits or clusters, each with coordinates (x, y, z, E).
- A graph is dynamically built, where nodes are hits/clusters and edges connect nearby ones
- Performs iterative node reduction to manage input size while retaining shower structure information.

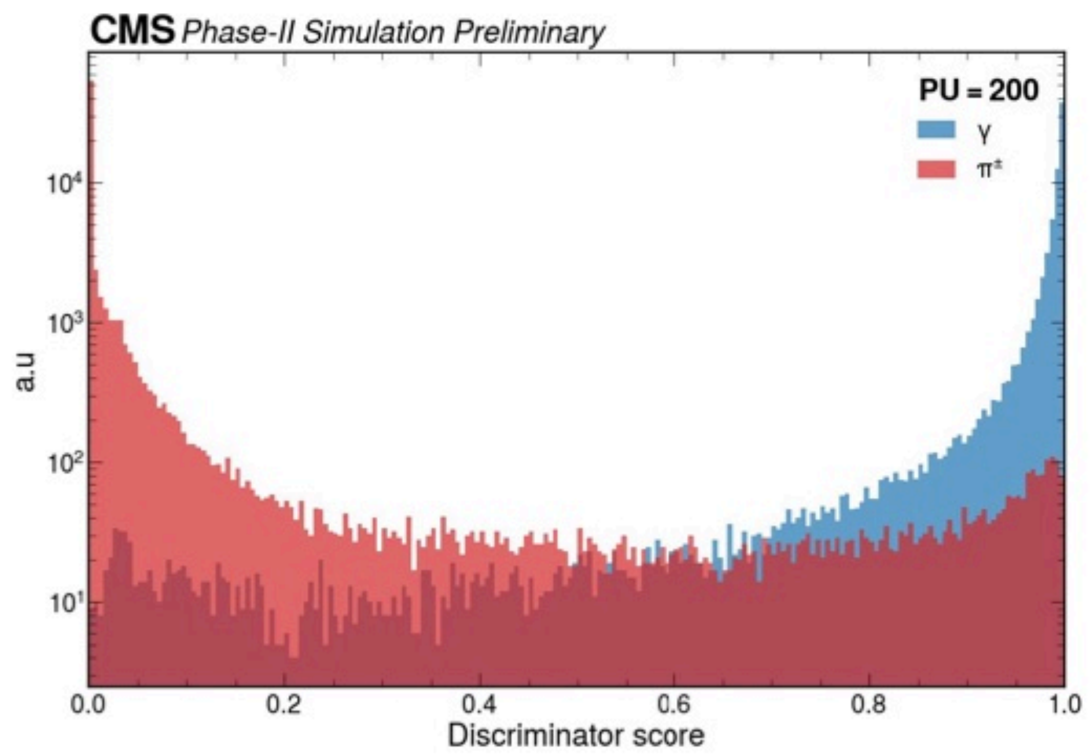
Dataset:

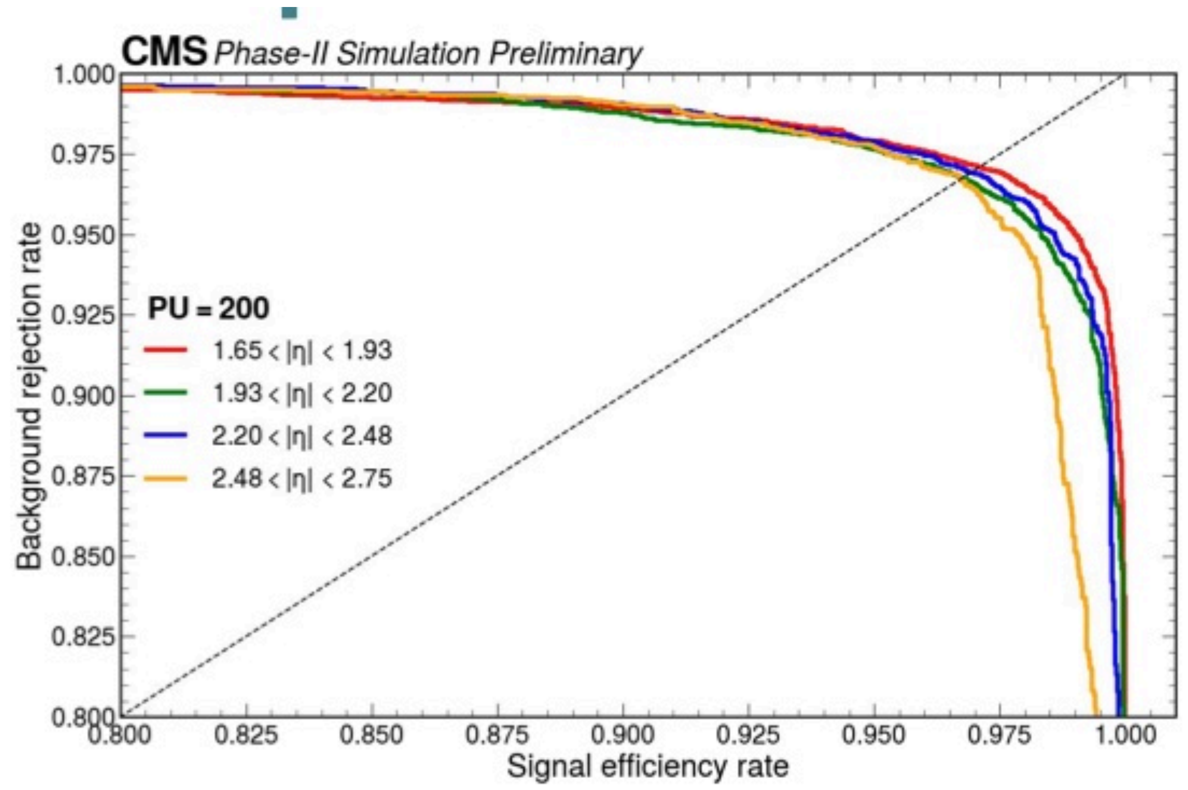
- Unconverted photons (γ) and early-showering pions ($\pi^{\pm}$)
- Energy range: 10 GeV – 1 TeV with PU = 200

Results:

- Good separation between pions and photons
- ROC curves show > 95% signal efficiency with strong background rejection
- Slight performance drop at high η due to pileup contamination

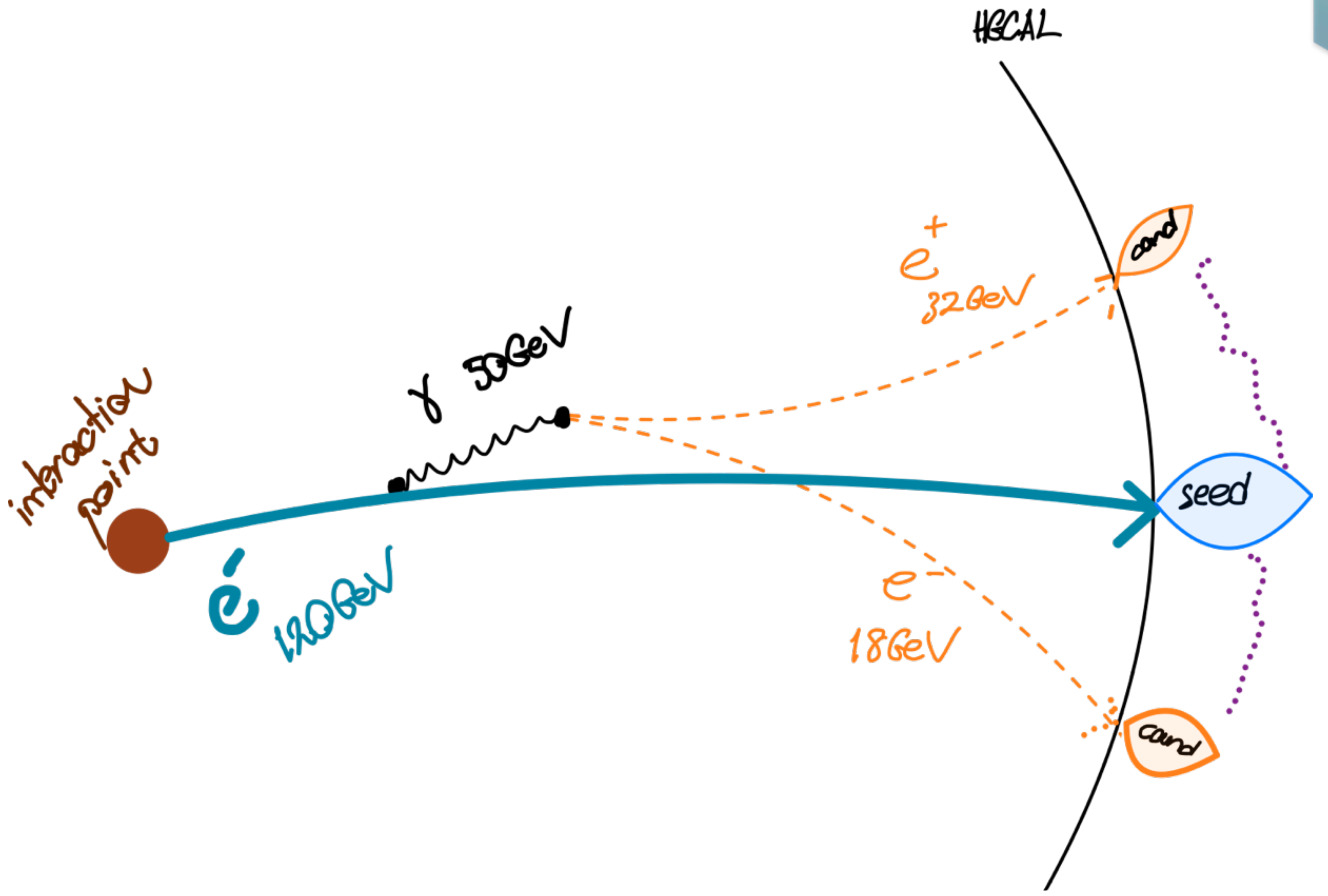


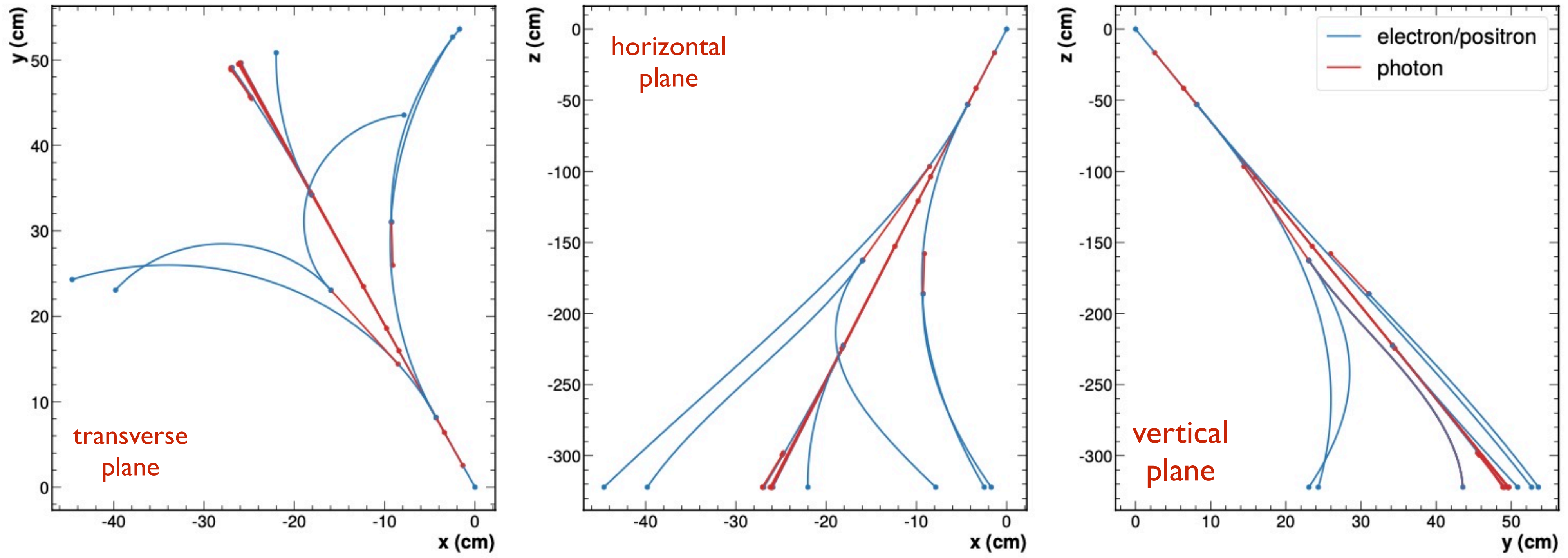




Electron reconstruction

- As an electron traverses the tracker, it emits multiple bremsstrahlung photons.
- These photons and the electron enter the calorimeter, spreading in ϕ due to the magnetic field.
- For an accurate reconstruction, all related energy deposits must be re-associated with the original electron, enabling:
  - Energy recovery from all associated particles
  - Suppression of pileup contributions





Representation of the trajectories of electron emissions before reaching the HGCAL.

Electron reconstruction

So how do we group all these scattered deposits together?

- In the current electromagnetic calorimeter, the Moustache algorithm;
  - The shape mimics how bremsstrahlung photons and the electron spread under the magnetic field, forming a moustache-like pattern in η–ϕ space.
- With HGCAL, several new reconstruction complexities arise:
  - Much finer granularity → showers fragment more.
  - Longitudinal segmentation → showers stretch in depth.

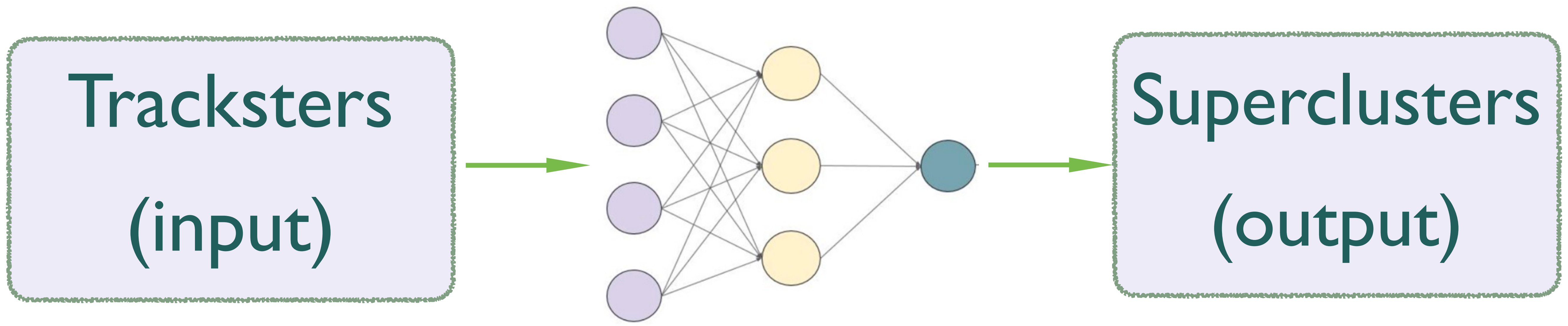
The upgraded detector demands more adaptive and sophisticated clustering strategies.

We leverage machine learning to learn these complex patterns and accurately associate all shower fragments to their parent electron.

Electron reconstruction

- Showers originating from the same electron are expected to exhibit:
  - angular alignment and correlated energy and kinematics
  - unlike those from pileup or unrelated sources
- We extract a rich set of features for each shower:
  - angular variables, kinematic quantities and timing information — used for the first time in superclustering studies
- A neural network predicts the probability of association between showers.
  - Showers with high mutual scores are iteratively grouped to form superclusters.

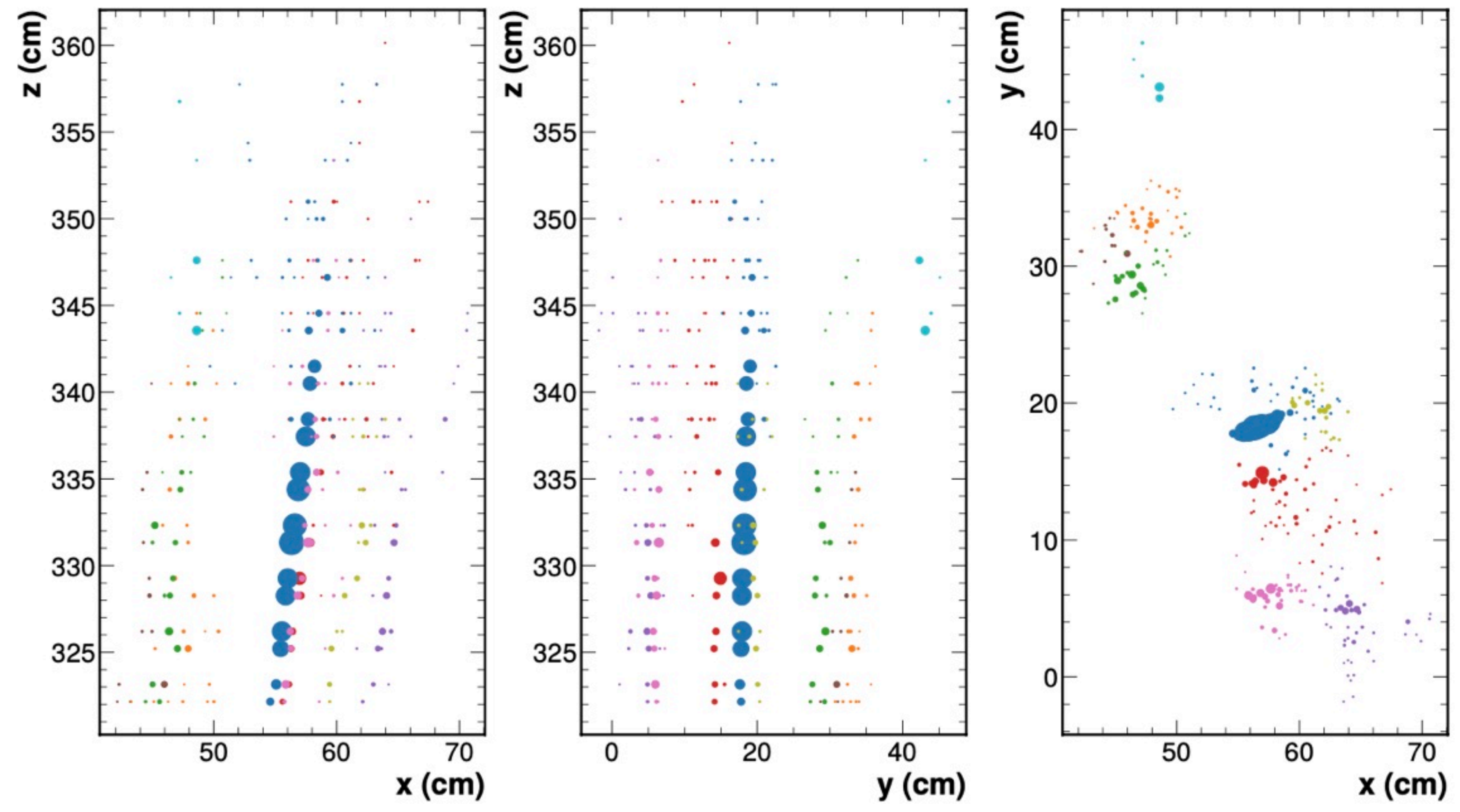
Electron dataset in 200 PU is used.



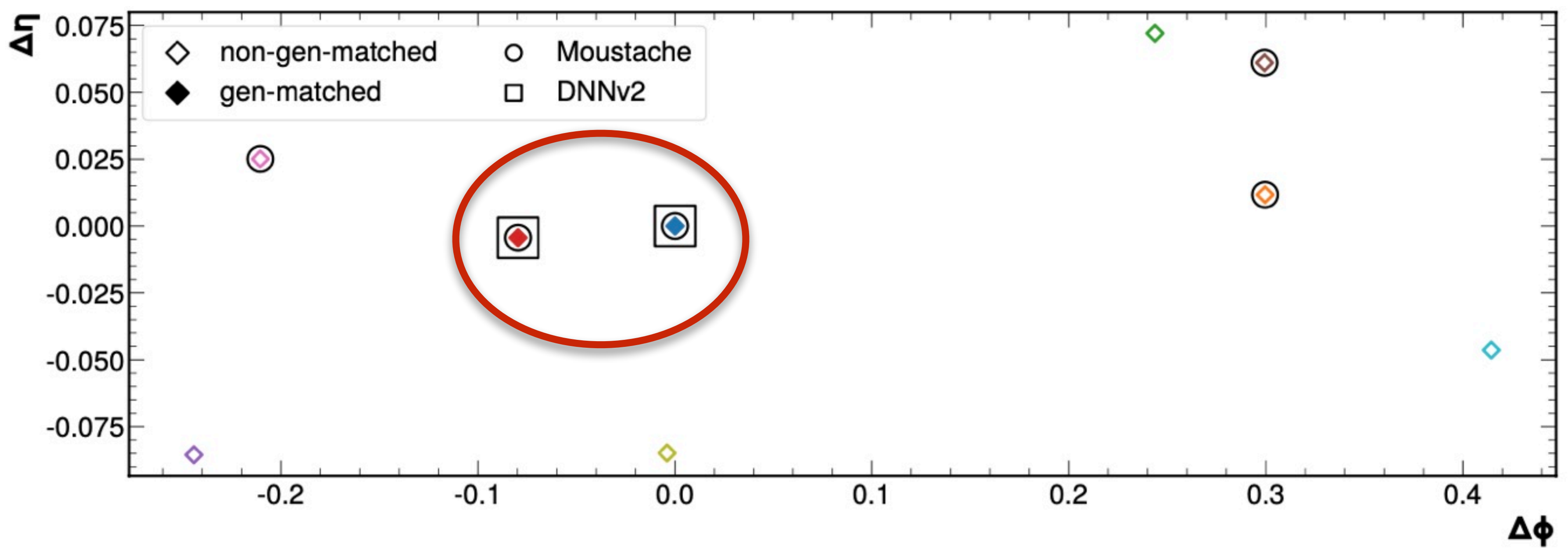
Tracksters : 3D shower candidates built by linking per-layer clusters across depth in HGCAL.

Superclusters : groups of tracksters corresponding to a single calorimeter electron, including its bremsstrahlung photon deposits

Electron reconstruction performance



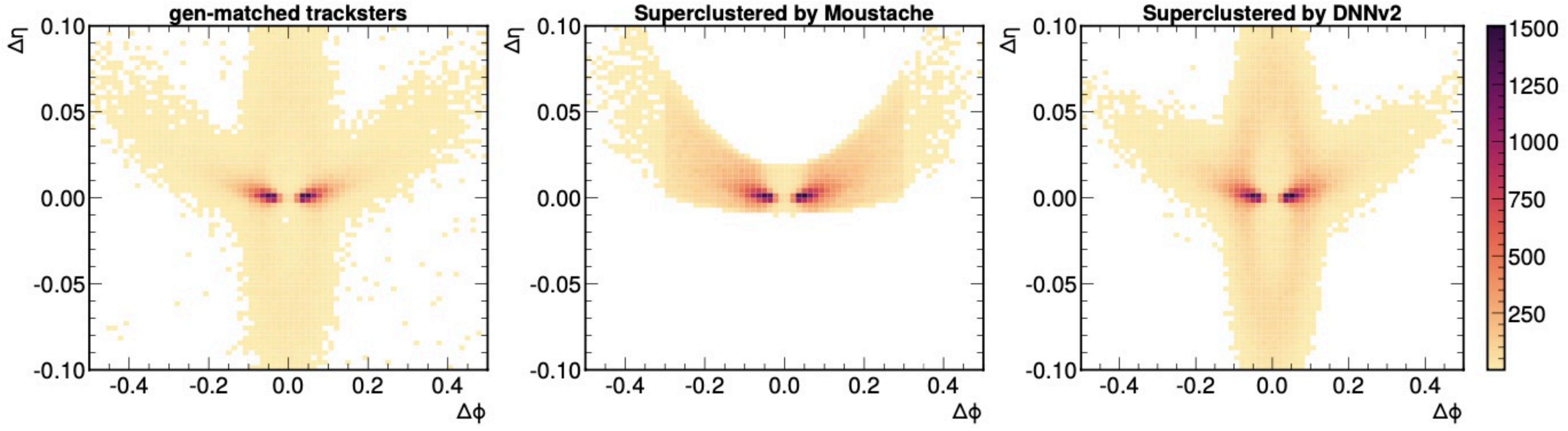
An example of an electron shower. Each circle corresponds to a layer cluster, with size proportional to its energy, and clusters belonging to the same trackster are shown in the same color.

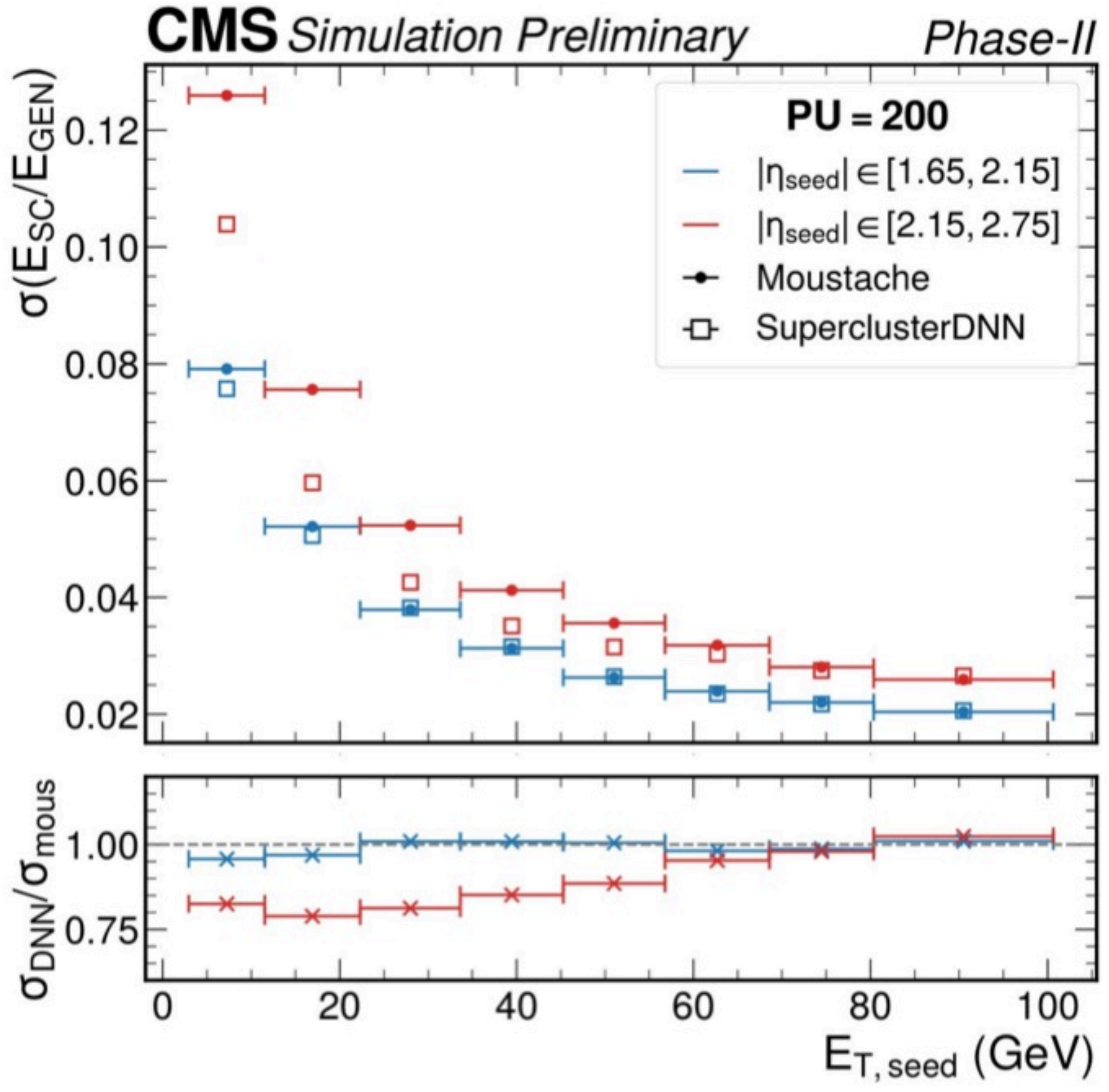


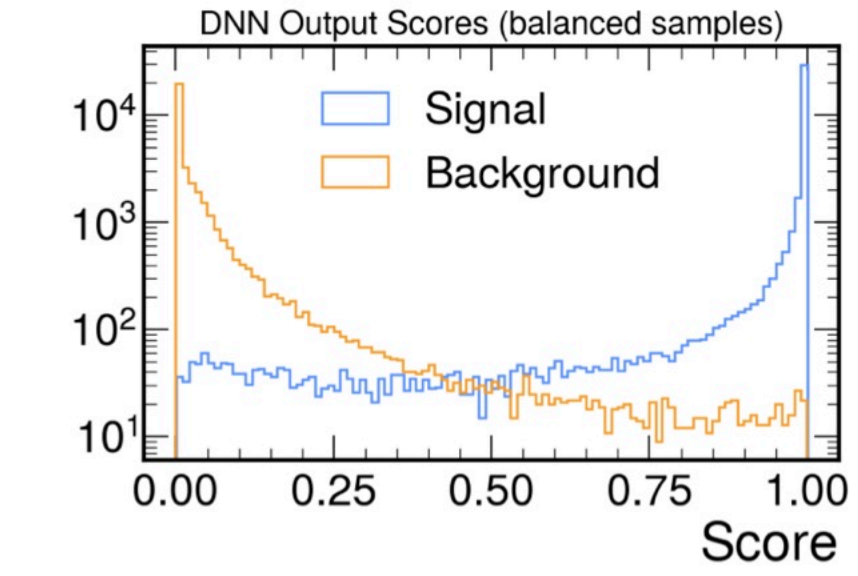
The Moustache shows more spreads

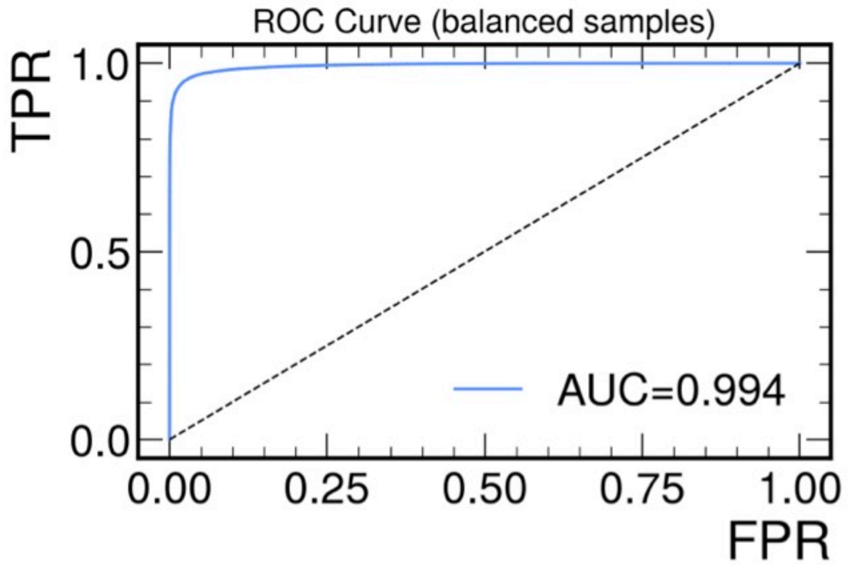
In contrast, the DNN remains focused on the true shower area, effectively rejecting uninteresting contributions.

DNN is very efficient with gaining back all the clusters.





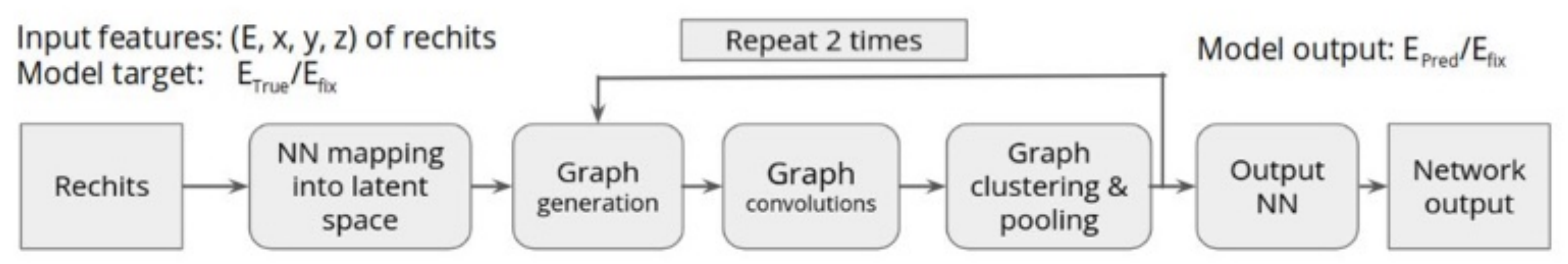




Hadron Energy Regression

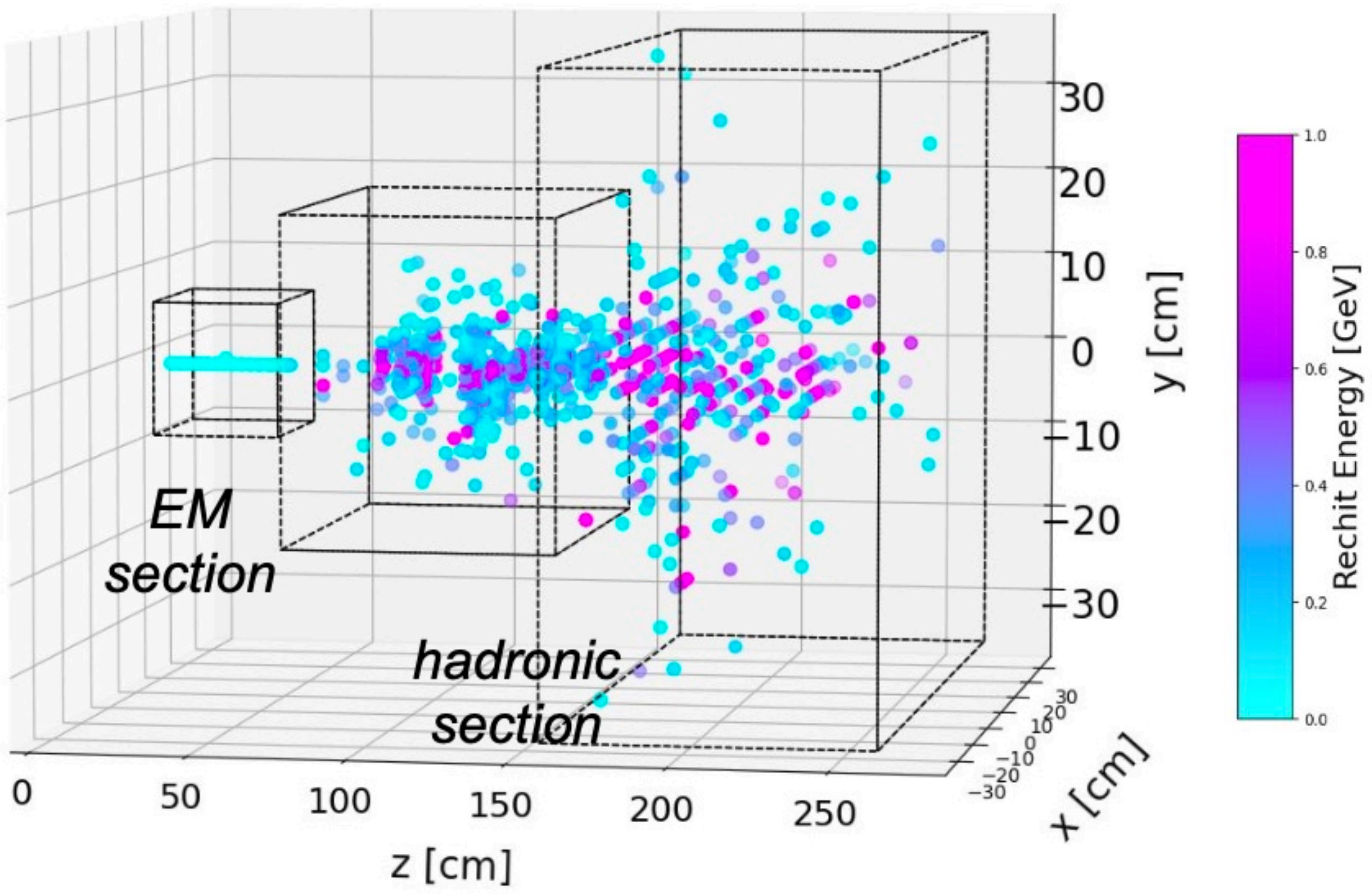
https://cds.cern.ch/record/2815404/files/

- For hadronic tracksters, the energy resolution of the calorimeter can be considerably improved with ML based regression.
- GNN is used for the PID studies —> very promising outcomes
    - hence trained on simulation and tested on test beam data (pion beam)

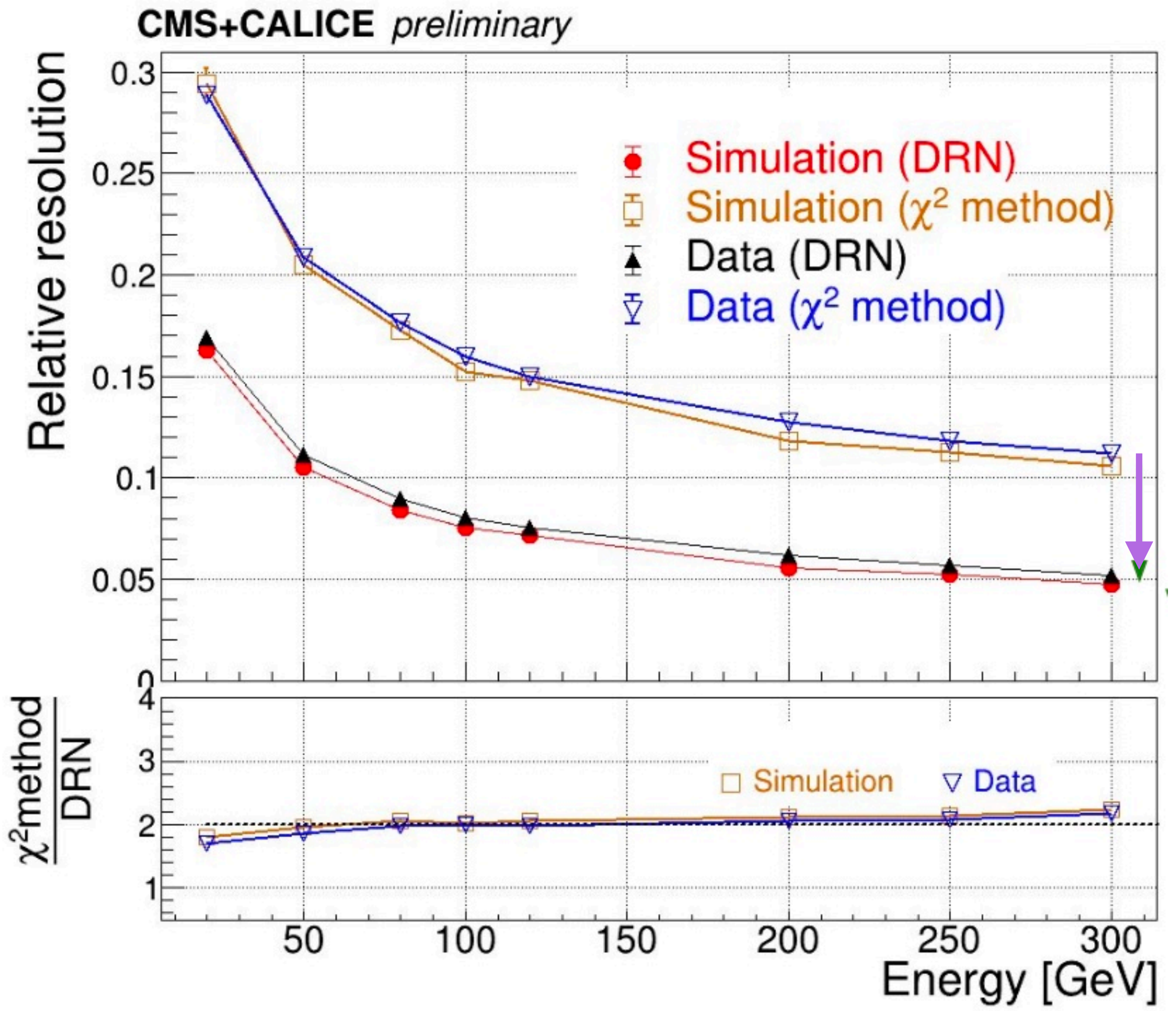


where E_{True} is the true energy of particle, E_{fix} is reconstructed energy using detector level calibration and E_{Pred} is the energy reconstruction using DRN weights.

Arxiv : 2003.08013v1



Display of the input reconstructed hits to the GNN.



significant resolution improvement with GNN

Energy resolution comparing classic calibration ($\chi 2$ method) and GNN regression, on test beam data and simulation.

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Future directions of ML in HGCAL

Timing-based pileup rejection:

Integrating precise timing ($\approx$ 60 ps for a hit, $\approx$ 20 ps for a full shower) into ML models to improve discrimination of overlapping interactions.

Full-hit GNN architectures:

Employing Graph Neural Networks that use the entire set of reconstructed hits, capturing the detailed 3D shower structure for advanced event understanding.

ML-driven Particle Flow:

Using ML to associate tracks with calorimeter tracksters, resolve ambiguities, and enhance the overall reconstruction performance.

Conclusion

- The HL-LHC era demands reconstruction techniques that can handle extreme event complexity and data density beyond traditional algorithms.
- HGCAL's fine granularity, energy, and timing information provide an ideal environment for ML-driven reconstruction.
- The TICL framework leverages ML at multiple stages:
    - GNNs for particle identification, learning from irregular hit topologies.
    - DNNs for superclustering, associating fragmented showers into coherent objects.
- These models learn directly from detector geometry and physics patterns, improving accuracy and flexibility.
- ML is now central to CMS reconstruction
    - enabling precise, scalable, and intelligent event understanding, essential for exploiting the full HL-LHC physics potential.