Towards the optimization of a Muon Collider Calorimeter

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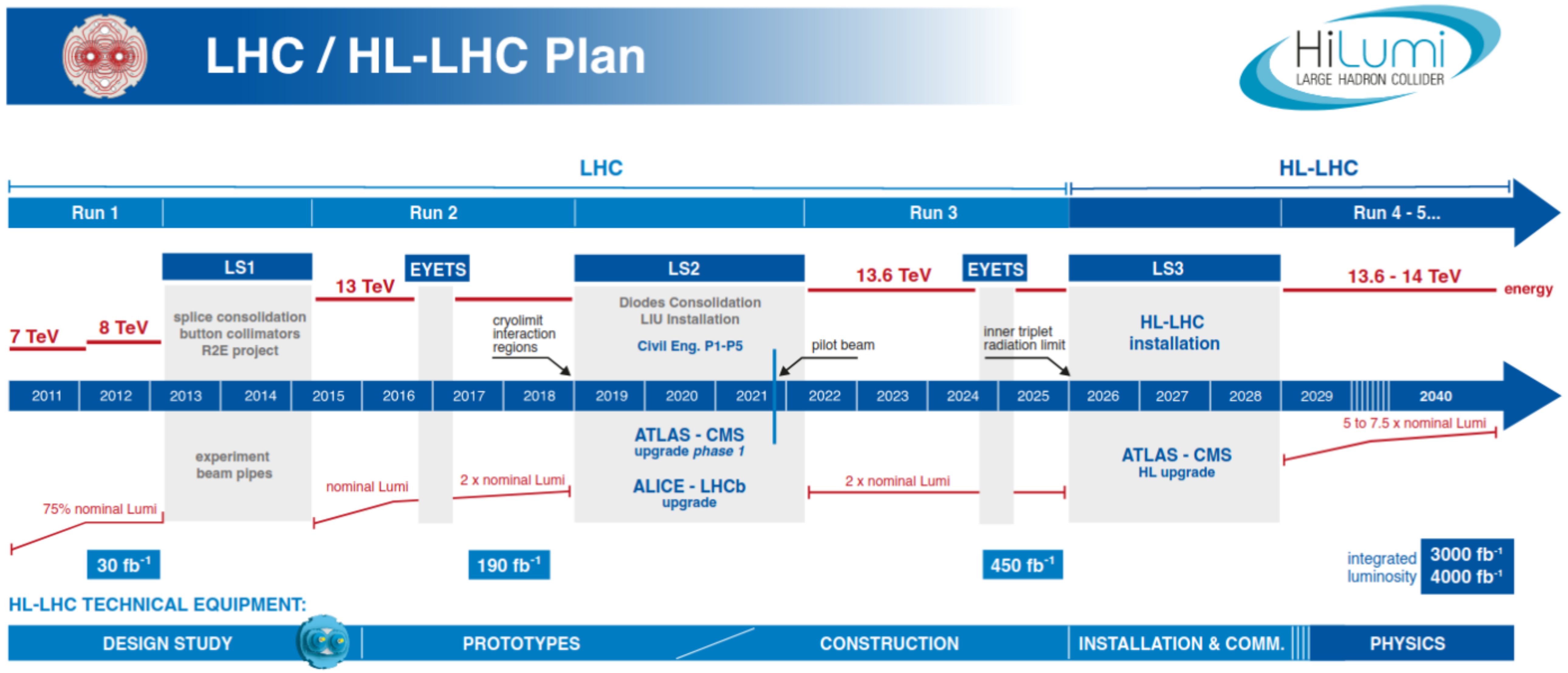
Introduction

Why a Muon Collider?

- Discovery of the Higgs -> 3 main directions
  - Precision Higgs measurements
  - High Luminosity -> Reach high enough sensitivity for EFT effects to be visible
  - High Energy -> Expand the phase space to explore for direct searches

LHC programme is not over yet…

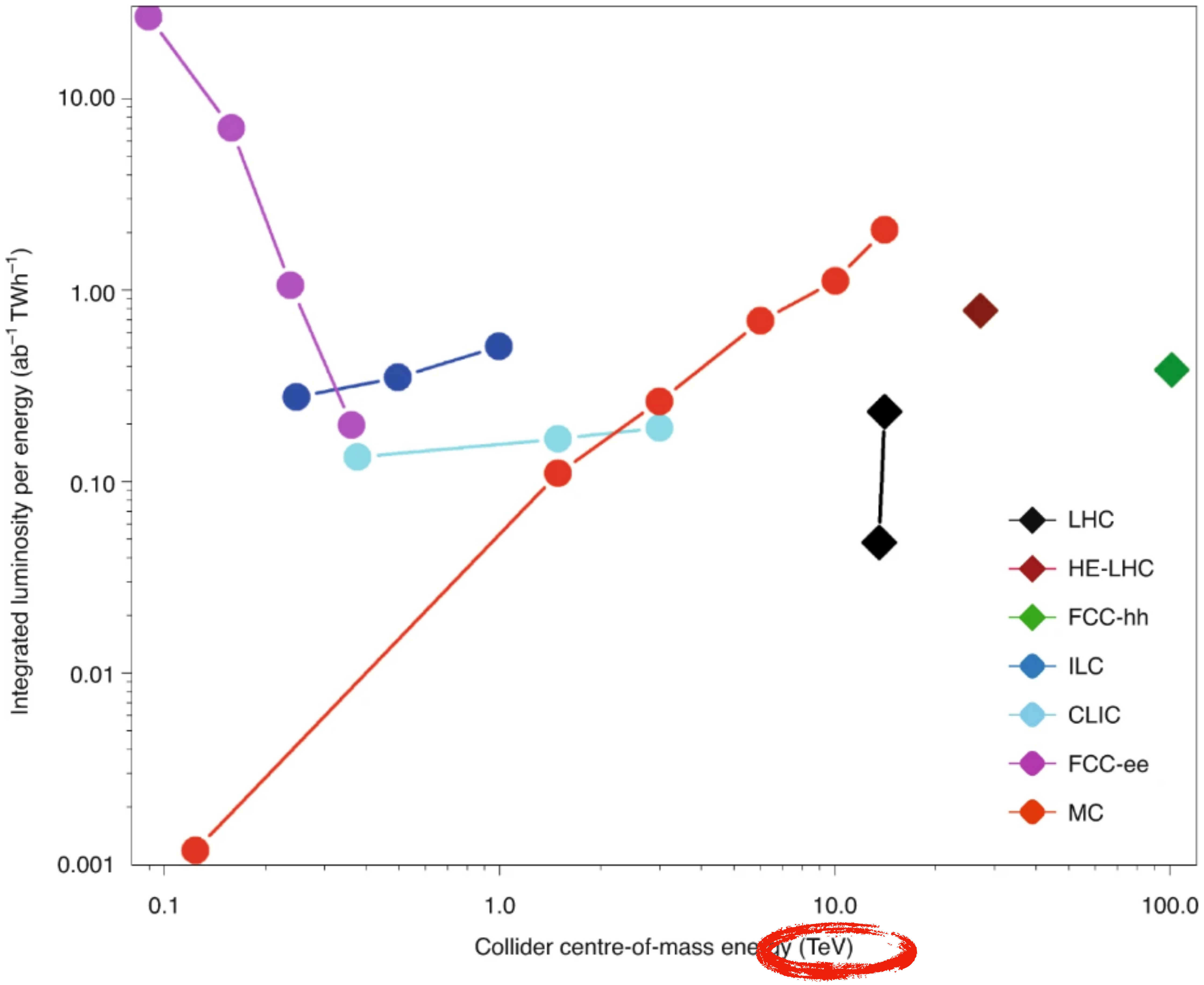


… but it is not a bad time to start thinking about what's next!

Introduction

Why a Muon collider?

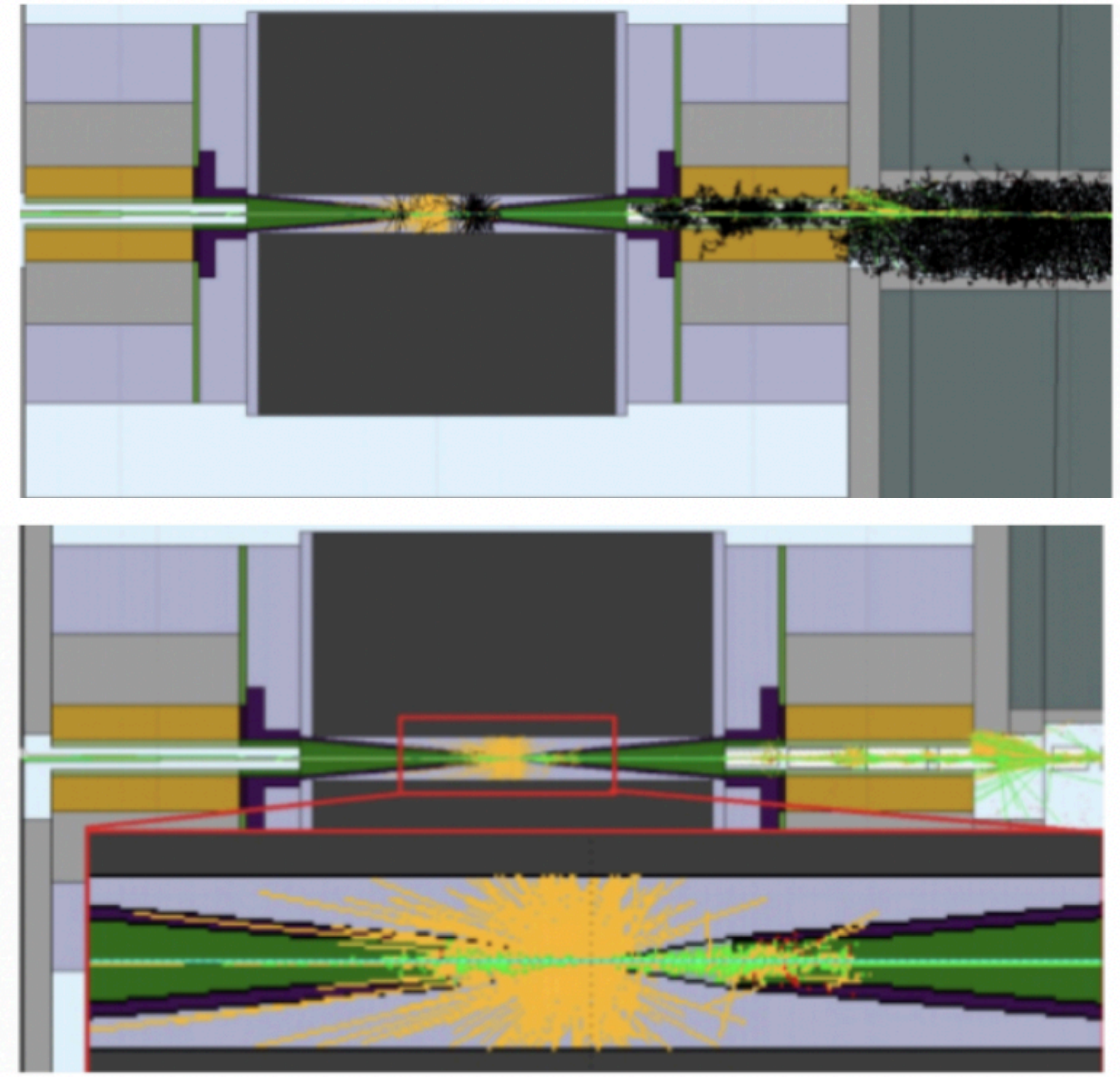
- Luminosity increases with center-mass energy
    - Competitive with LINACs
    - Most ‘physics-per-dollar’ potential
- Heavier than electrons: less radiative losses
- Lepton Collider: no pile-up effects
- Rather old concept, regained interest with the Snowmass Process
- Higgs Factory
    - $\sigma(\mu\mu \rightarrow H) \simeq 40000\ \sigma\ (ee \rightarrow H)$
- Dark Matter portals



Muon Collider

The BIB problem

- TeV-scale Muon Collider as strong candidate among proposed Future Colliders (no pile-up, access to DM portals, Higgs factory)
- Finite lifetime of the muon (2.2μs) implies a cloud of high-energy decay product along the beamline, which interferes with the instrumentation (Beam-Induced Background - BIB)
- During preliminary Machine-Detector Interface design, a double-cone nozzle has been included to shield the detector from BIB radiation



Visualizations from FLUKA BIB simulation. Black: neutrons, other: photons

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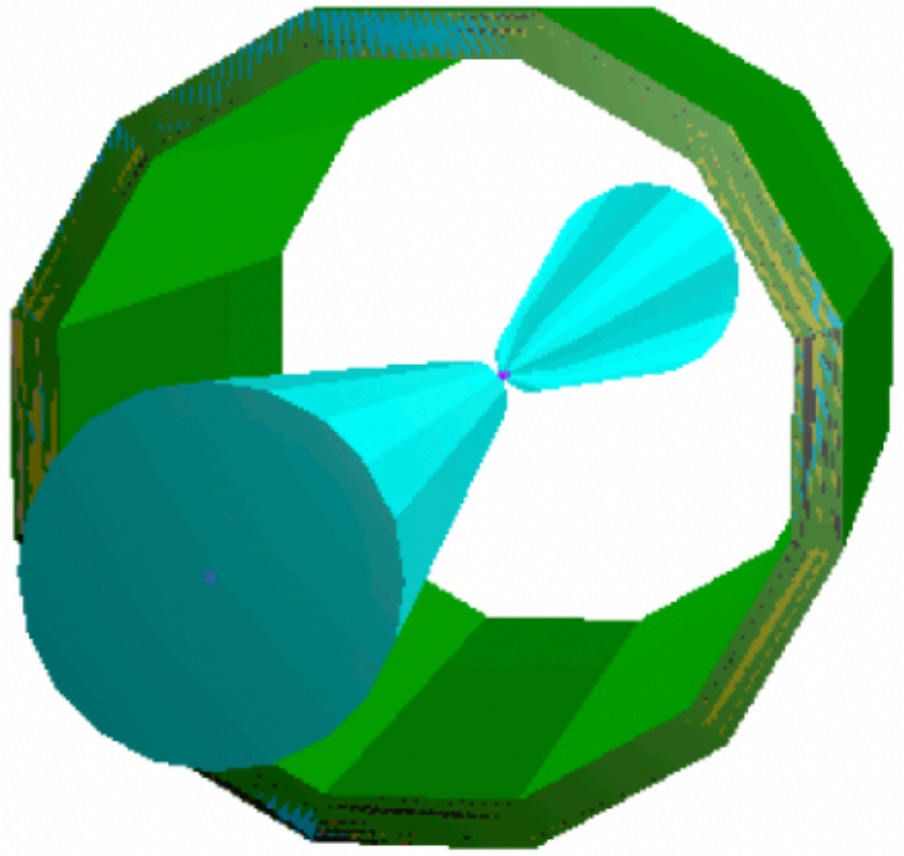
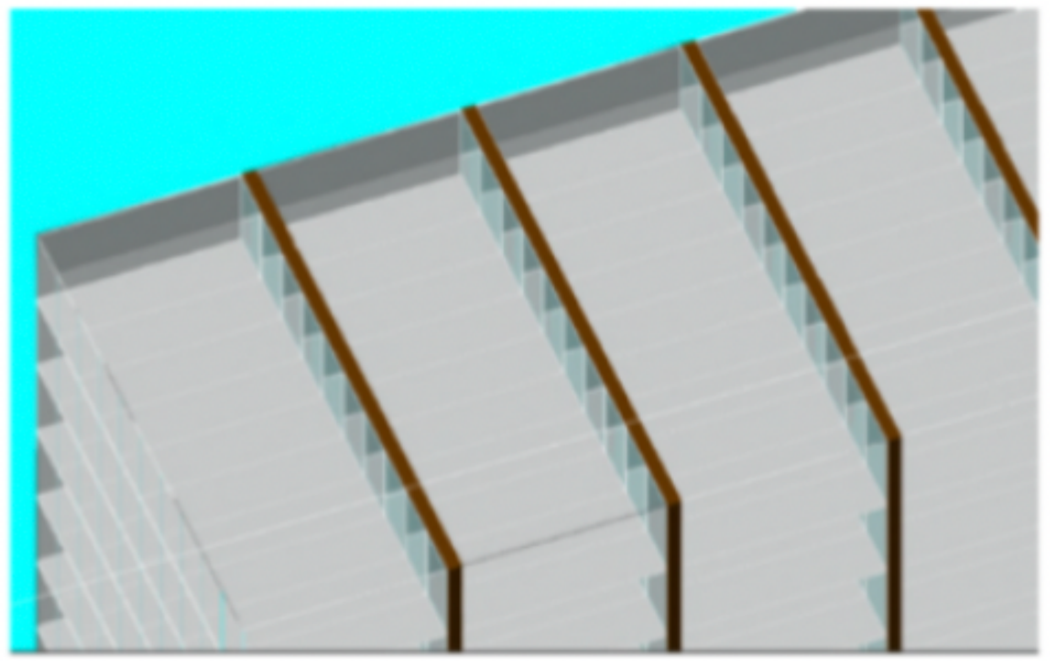
CRILIN: reference design

- Reference design chosen for our studies is CRILIN for the Electromagnetic Calorimeter (ECal)
- Array of 1x1x4.5cm^3 PbF_2 voxels, arranged in a dodecahedron
- 5 layers per wedge
- Modular design, easy to modify and rearrange





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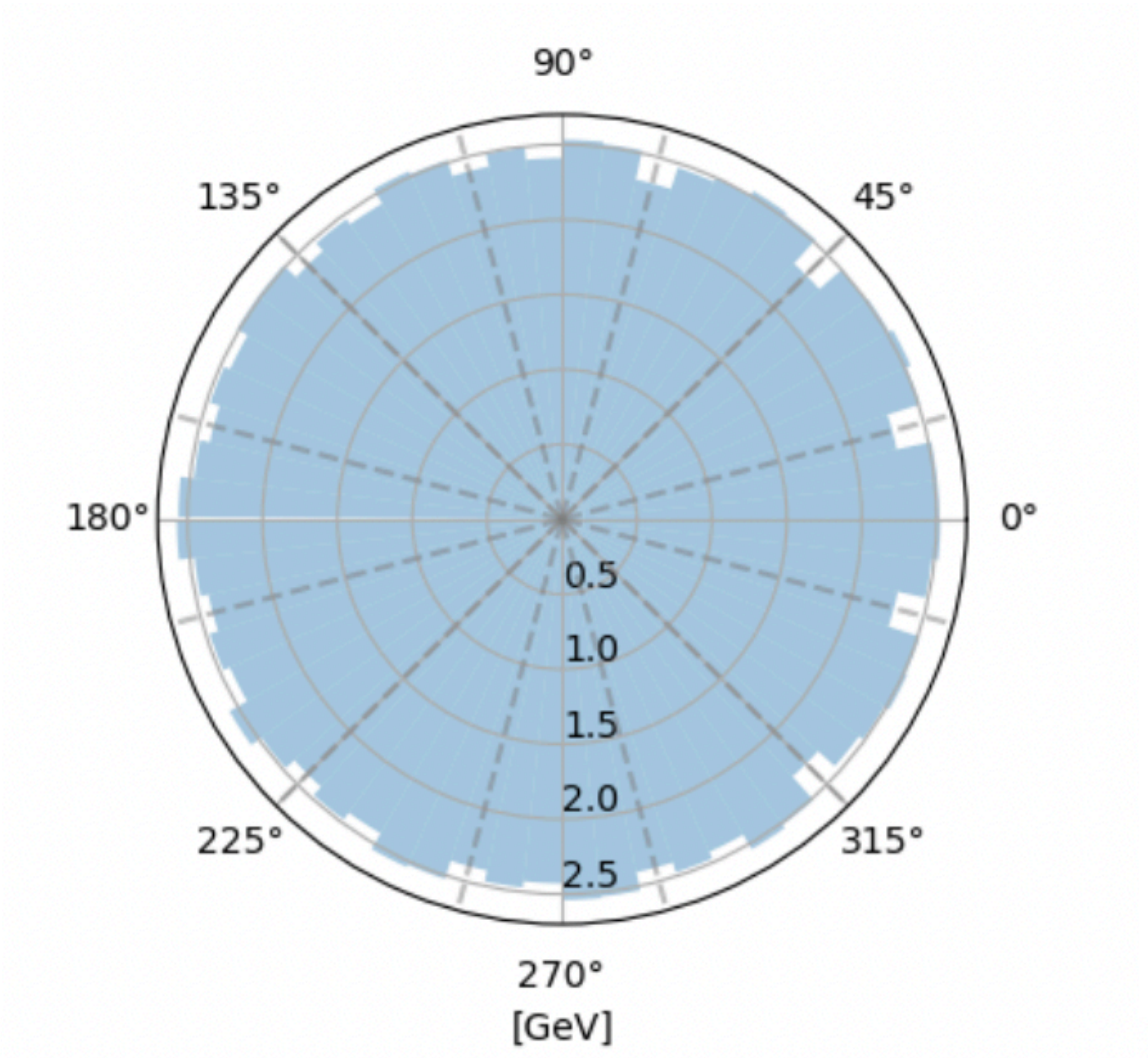
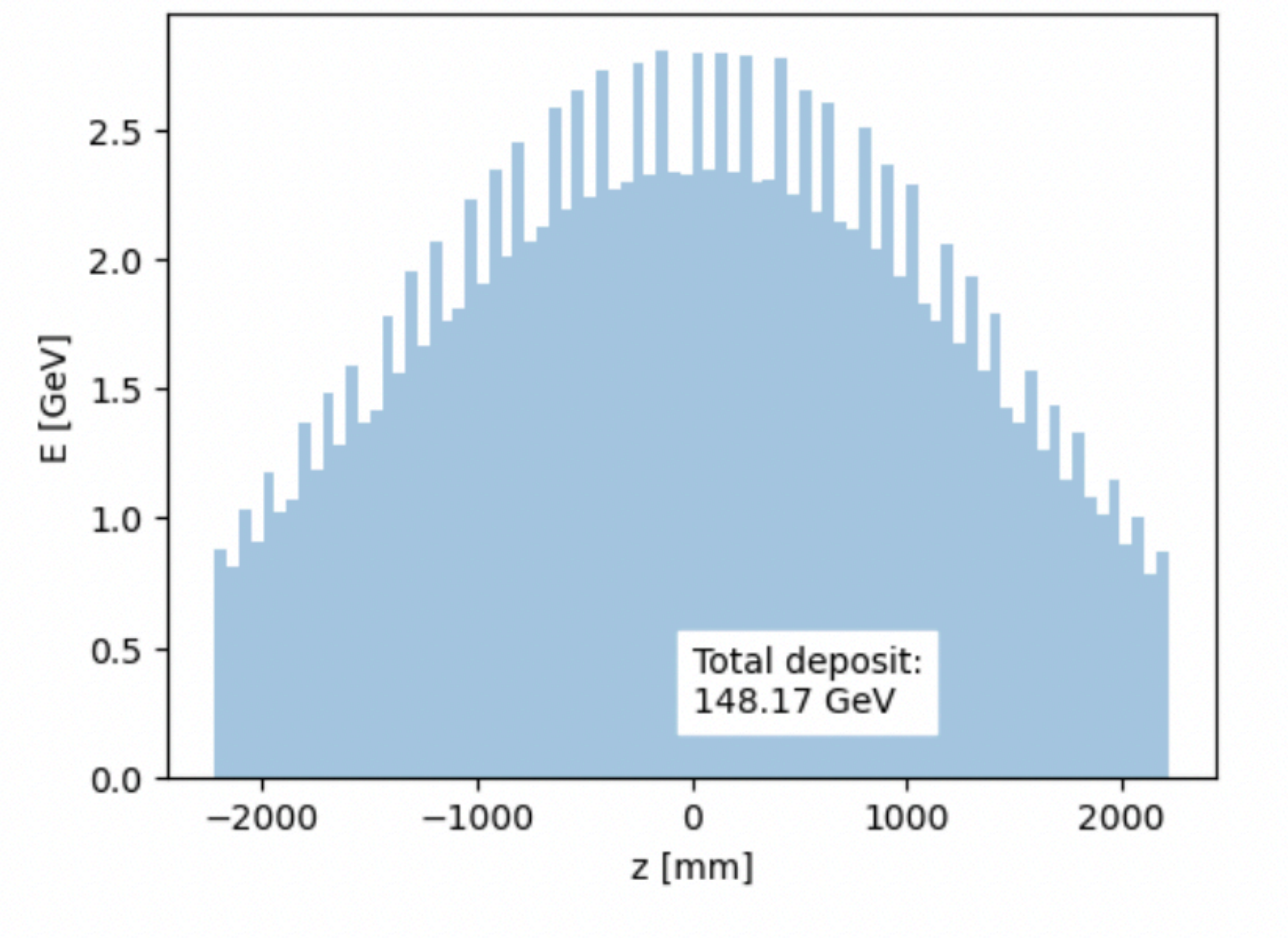
BIB characterization

- Nozzle shields most radiation from endcaps, but area around interaction point remains unshielded
- BIB simulation at 1.5TeV center-of-mass energy. Energy deposits in ECal
- Still a considerable amount of energy deposited inside
- Non-uniform distribution alongside z-axis suggests that homogeneous voxels might be suboptimal





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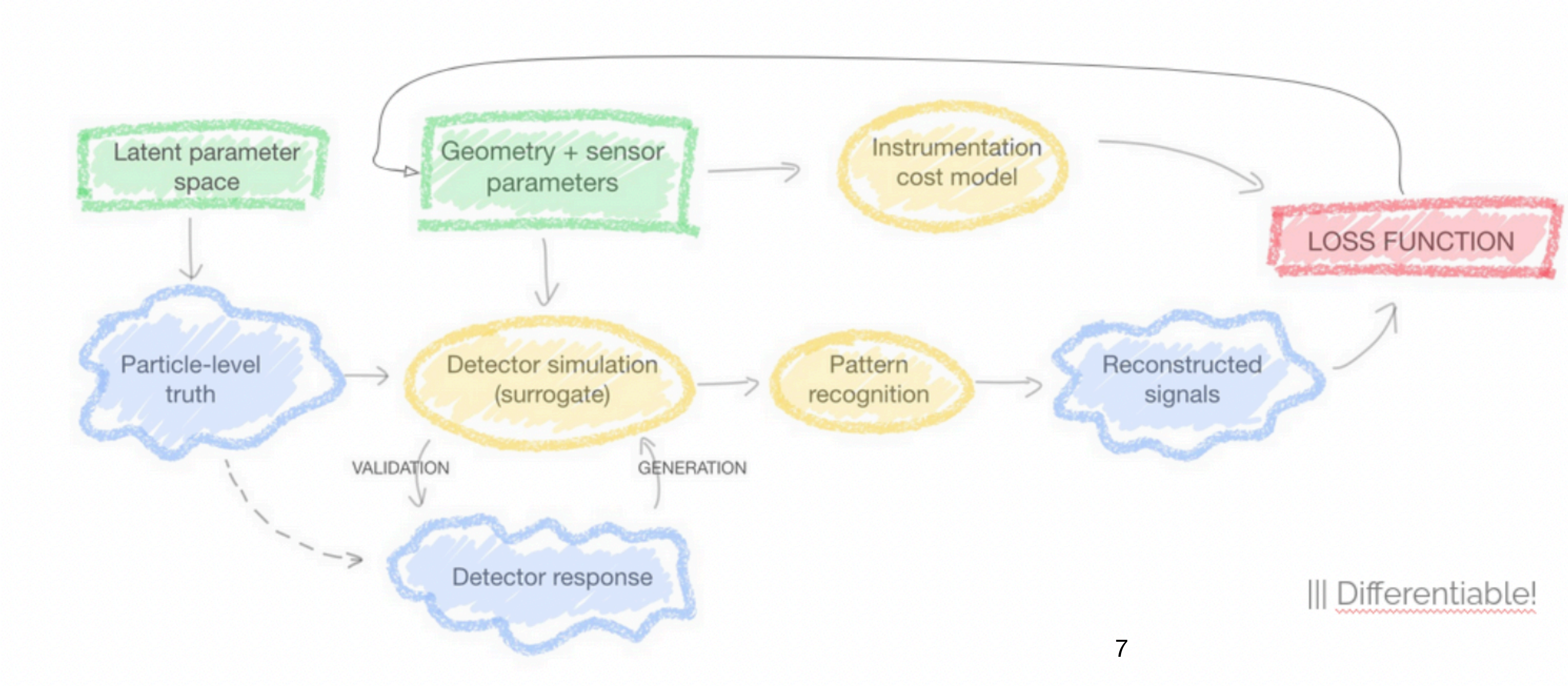
Optimization Workflow

- End objective: design optimization study approached with AD techniques
- Development of a pipeline to propose an optimal configuration in terms of signal-to-background discrimination and instrumentation cost



- Based on 3 main core methods
- Provide information encoded in a utility function
- Minimized using AD libraries (PyTorch, Tensorflow)

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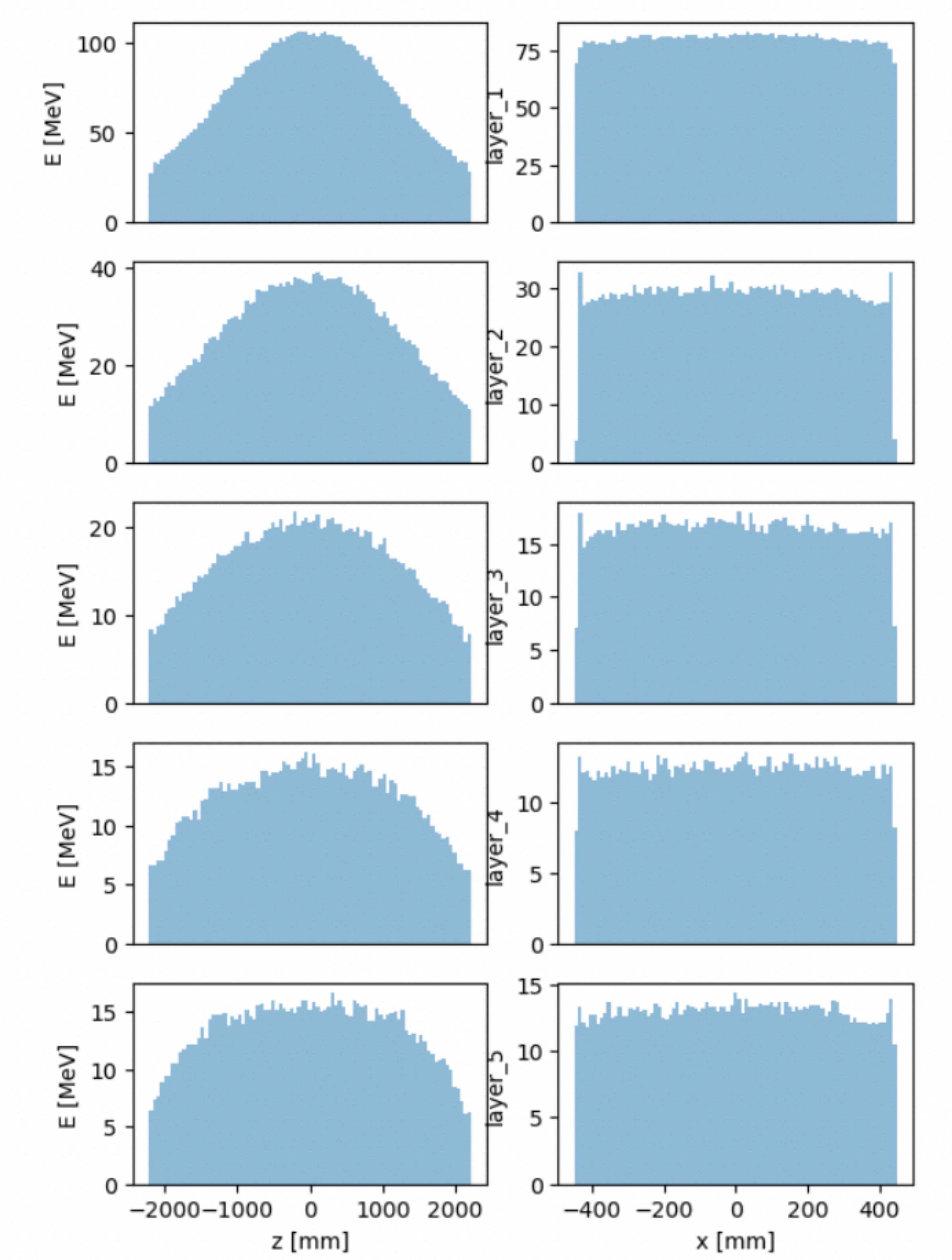
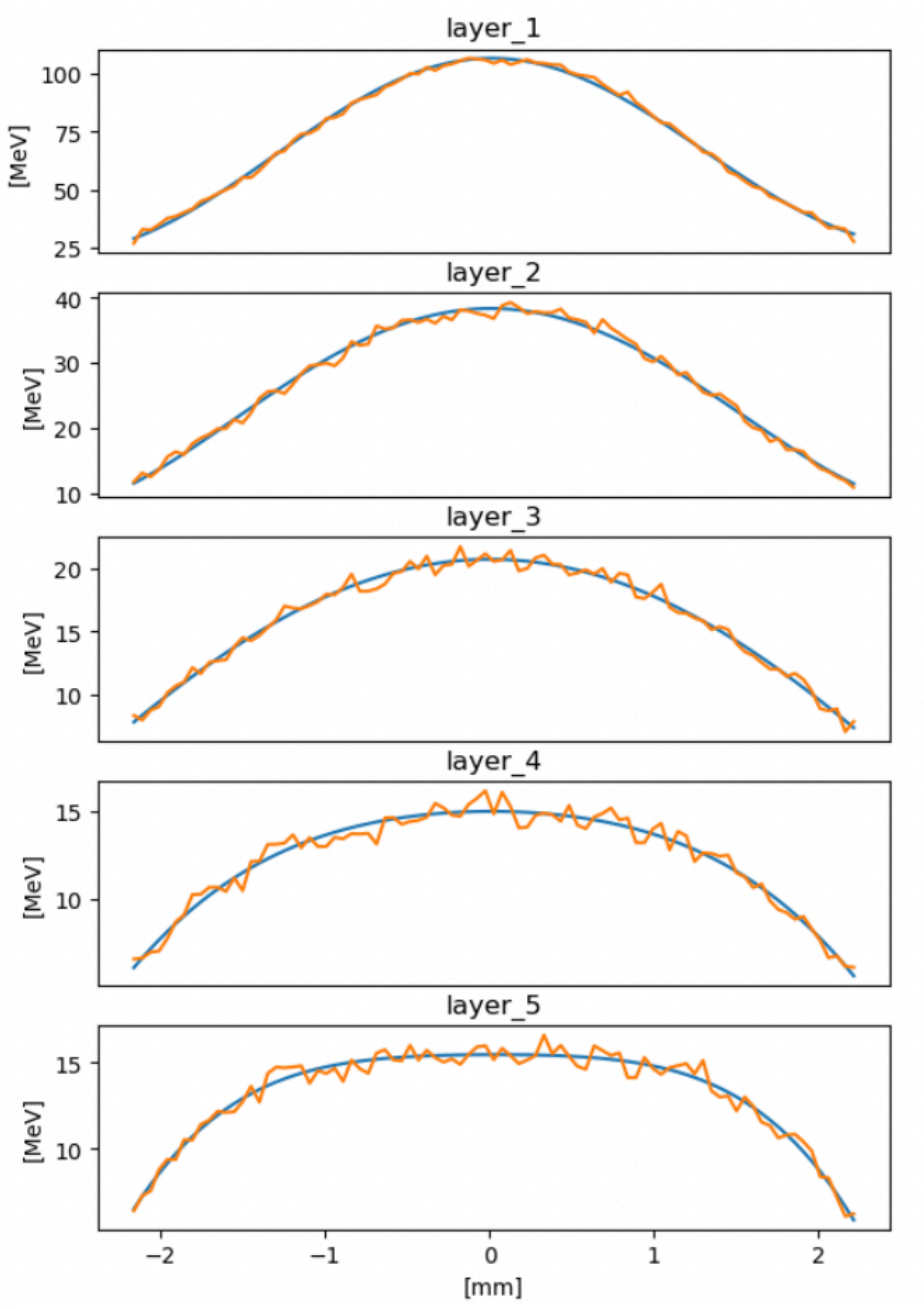
Fitting BIB distribution

- Starting from 1.5TeV BIB simulation
- Cylindrical symmetry lets us neglect transverse direction: focus on a single wedge and model component along beam axis.
- 5-parameter fit to a gaussian superimposed to a 2nd order polynomial



$$f(z) = p_1 e^{-\frac{z^2}{p_2^2}} + p_3 z^2 + p_4 z + p_5$$



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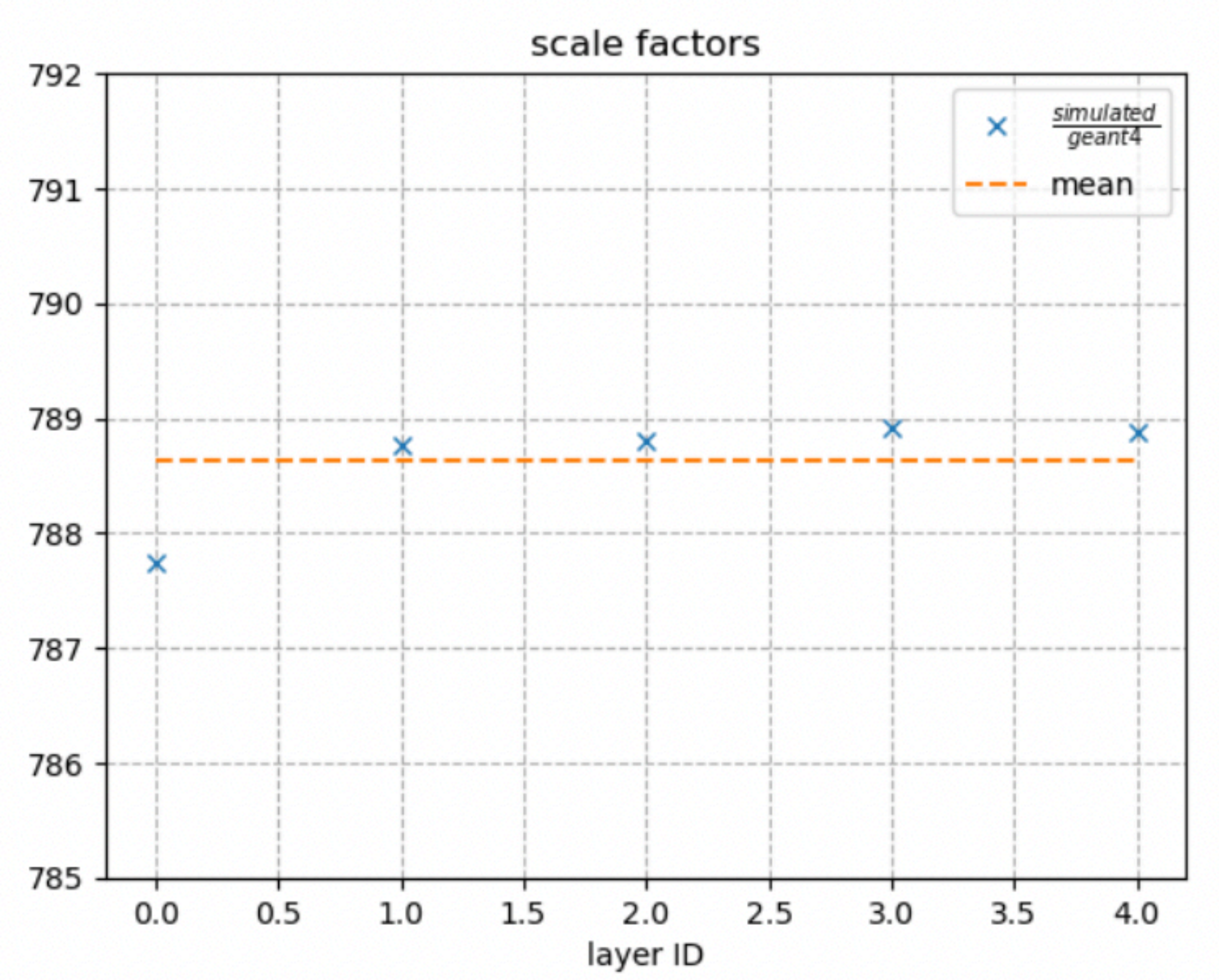
BIB simulation and checks



- Evaluate parametrization in a grid. Since we have neglected transverse direction, parametrizations will be accurate up to a normalization constant
- Constraint: parametrized deposition match layer-by-layer the Geant4 deposition
- Normalization constant can be explained by the transverse bin multiplicity (~80) times a bin width geometric factor (10mm)

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Object Condensation for reconstruction

- To reconstruct signals in ECal we test DeepJetCore, a package developed for the reconstruction of jets in the High-Granularity Calorimeter developed for the CMS upgrade for the High-Luminosity LHC runs

- Core is a Graph Neural Network that clusters the data, whose dimensionality has been reduced by filter layers.

- Clustering performed through the identification of one condensation point for each object, and the subsequent minimization of a loss function

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DeepJetCore loss for Object Condensation

- In DeepJetCore the condensation loss is interpreted as a physical potential.
- A scalar $\beta_i \in [0,1]$ is predicted for each GNN vertex i, representing a likelihood for it to be a condensation point.
- From this a charge q_i is defined through a monotonic function (ensuring a definite minimum)
- A force pushing each vertex towards object k can be derived introducing potential V:

$$q_i \nabla V_k(x_j) = q_j \nabla \sum_{i=1}^{N} \delta_k^i V_{ik}(x_i, x_j)$$

Attractive term

Repulsive term

$$L_V = \frac{1}{N} \sum_{j=1}^{N} q_j \sum_{k=1}^{K} \left(\delta_{jk} ||x_j - x_\alpha|| q_{\alpha k} + (1 - \delta_{jk}) \max(0, 1 - ||x_j - x_\alpha||) q_{\alpha k} \right)$$

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OC: Dataset Generation

- The dataset chosen to test the algorithm is 1000 monochromatic photon events for each energy point: (10,25,50,75,100,125,150,175)GeV
- Photons generated with Geant4, with rapidity 0 and uniformly distributed in the transverse angle ϕ
- BIB parametrization superimposed
- Geometric cuts:
  - 2σ of total signal deposition in ϕ
  - 40cm band along z-axis

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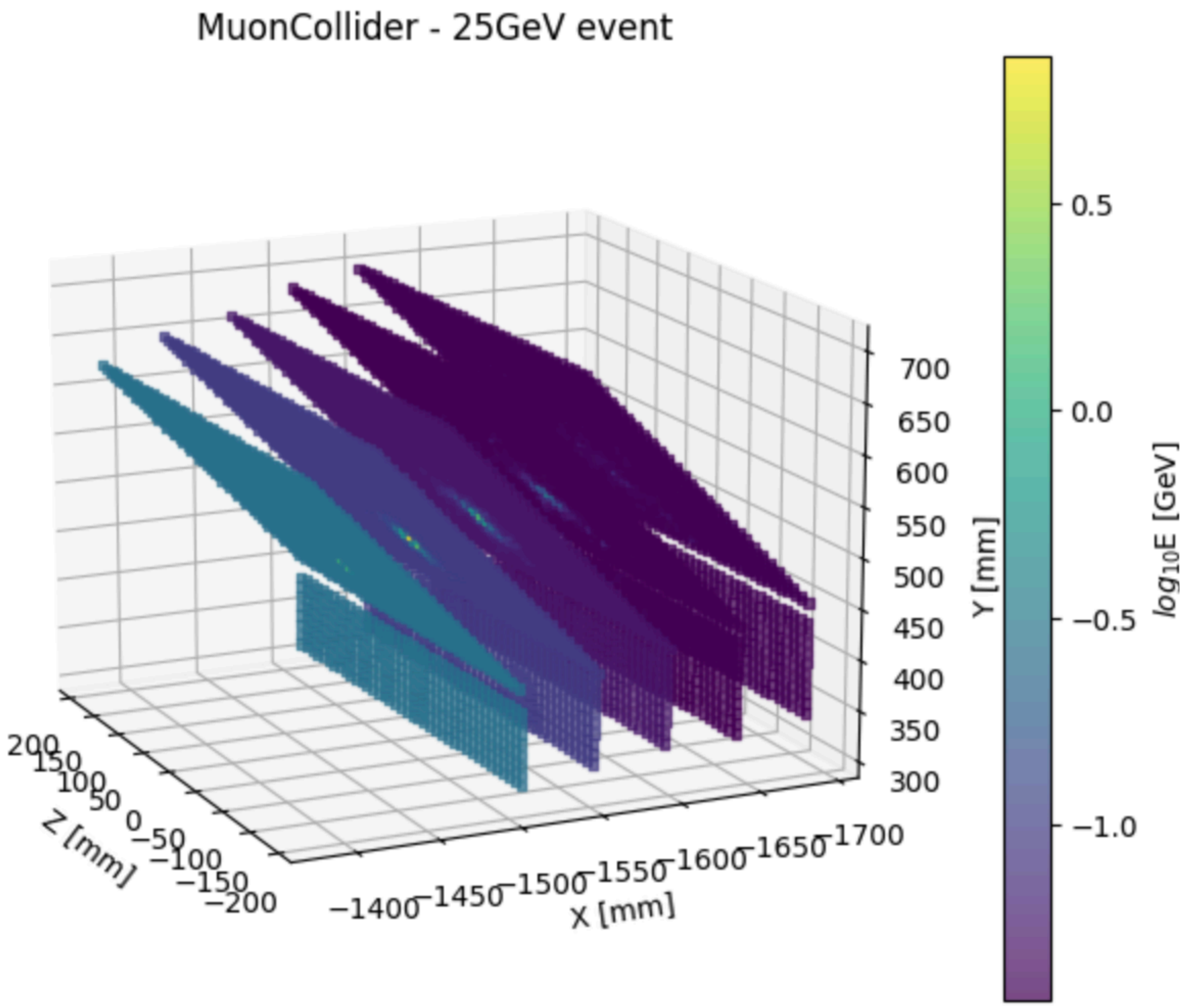
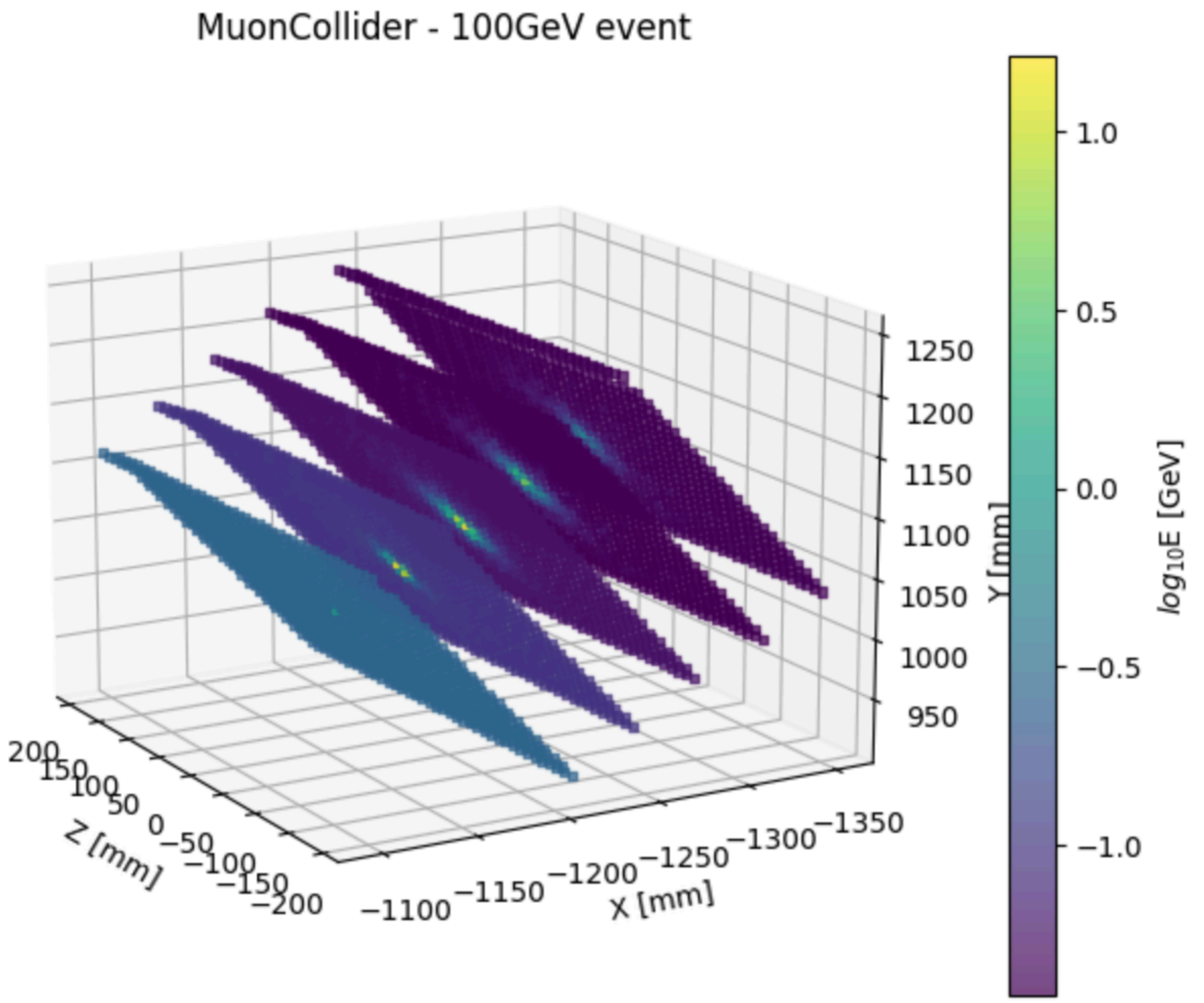
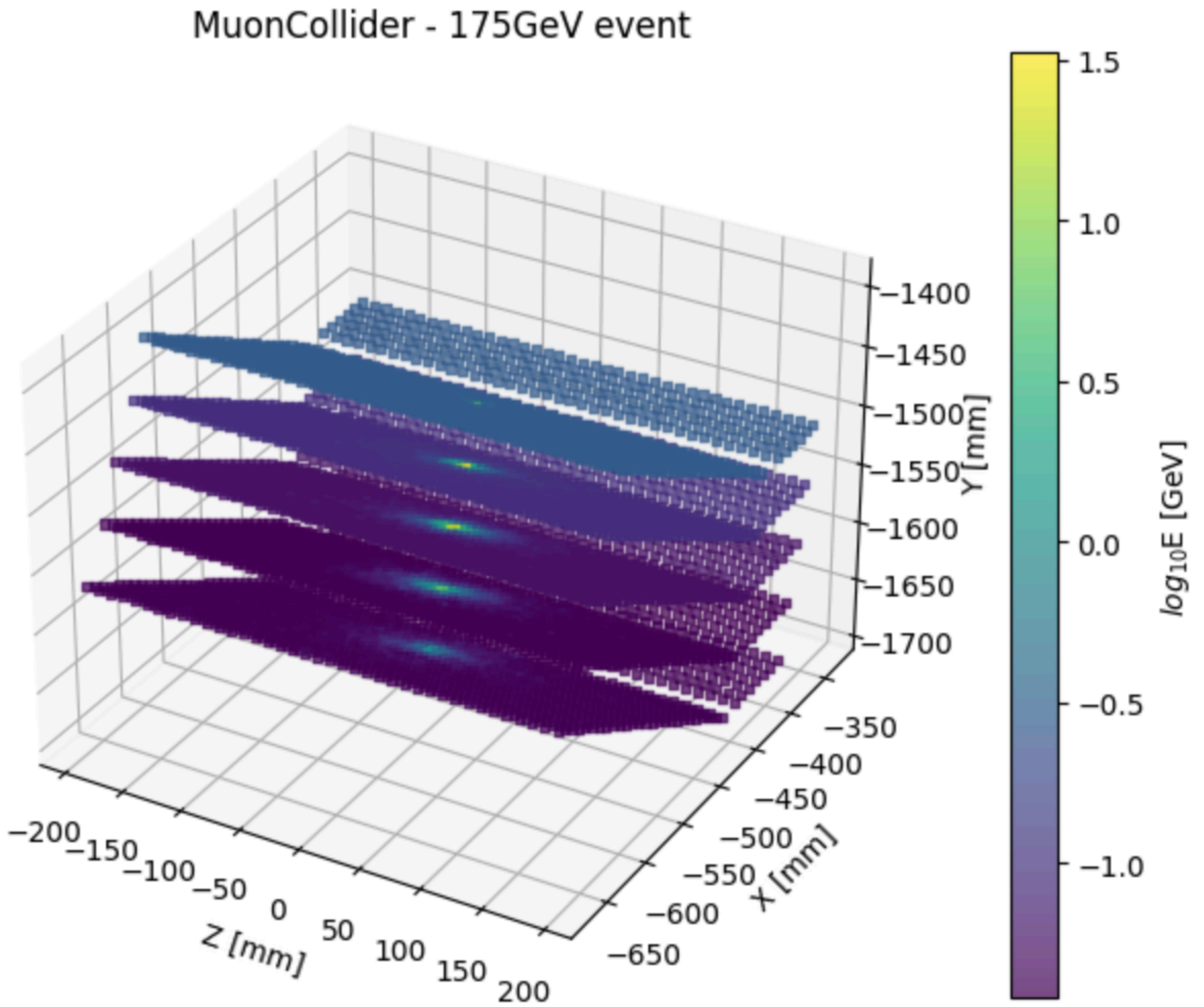
OC: Dataset Generation







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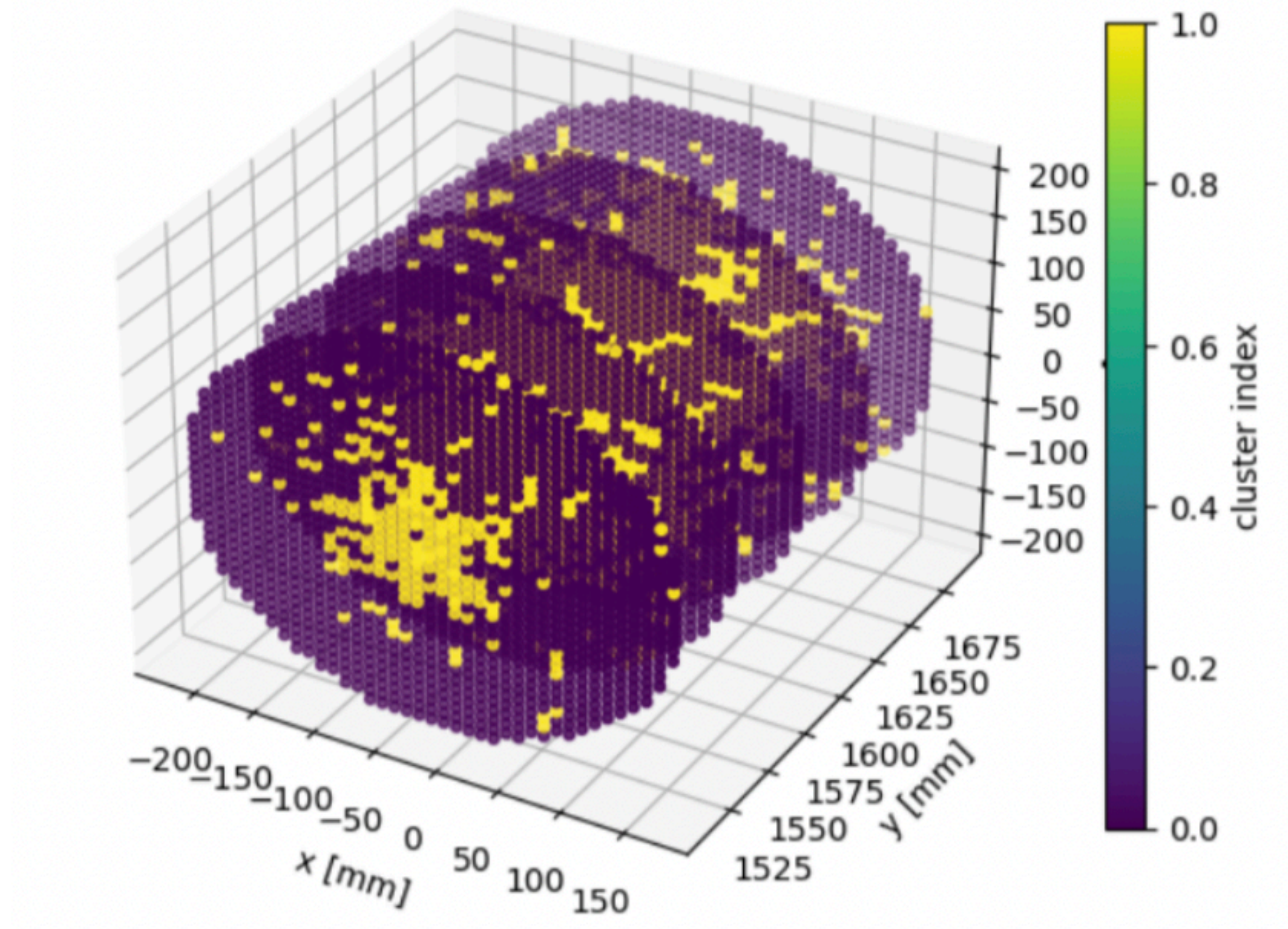
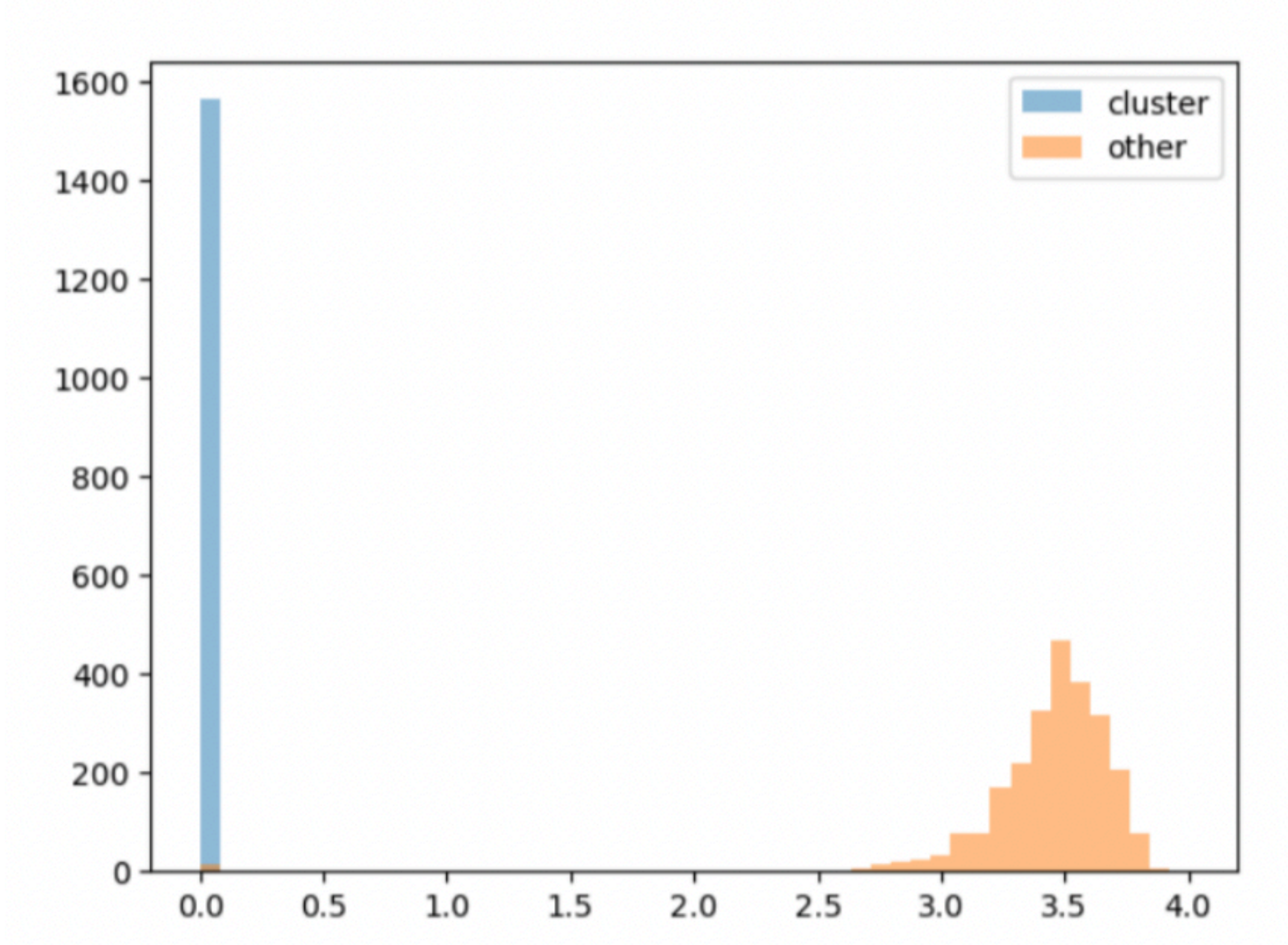
OC: Run 1 - Clustering





Cluster-space distance from condensation point

- Lighter data version: 15cm radius around maximum deposition. Only main wedge kept
- Quite sharp separation between signal (ID=1) and background (ID=0) hits
- Index of good clustering performance
- Recover shower-like pattern when transforming back to physical ECal space

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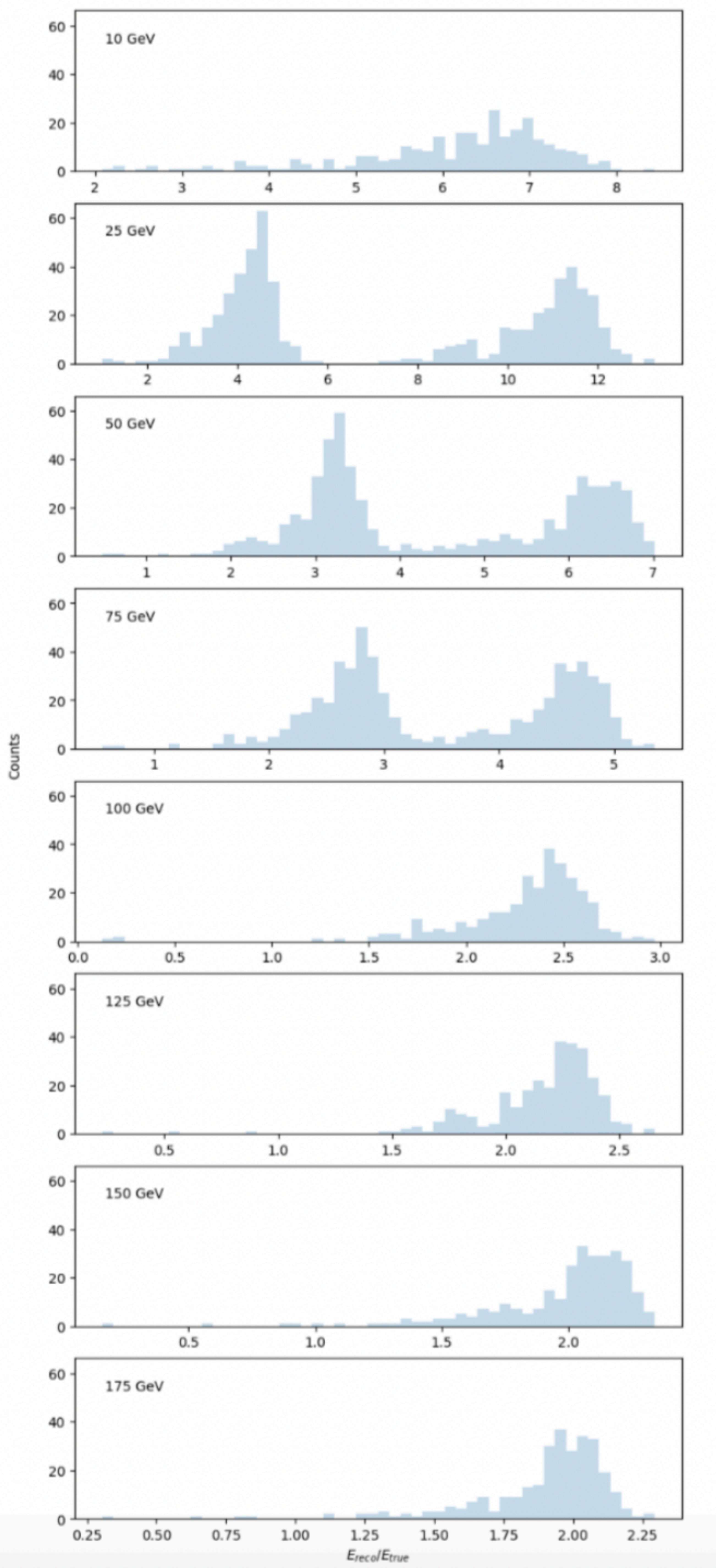
OC: Preliminary results - Energy reconstruction

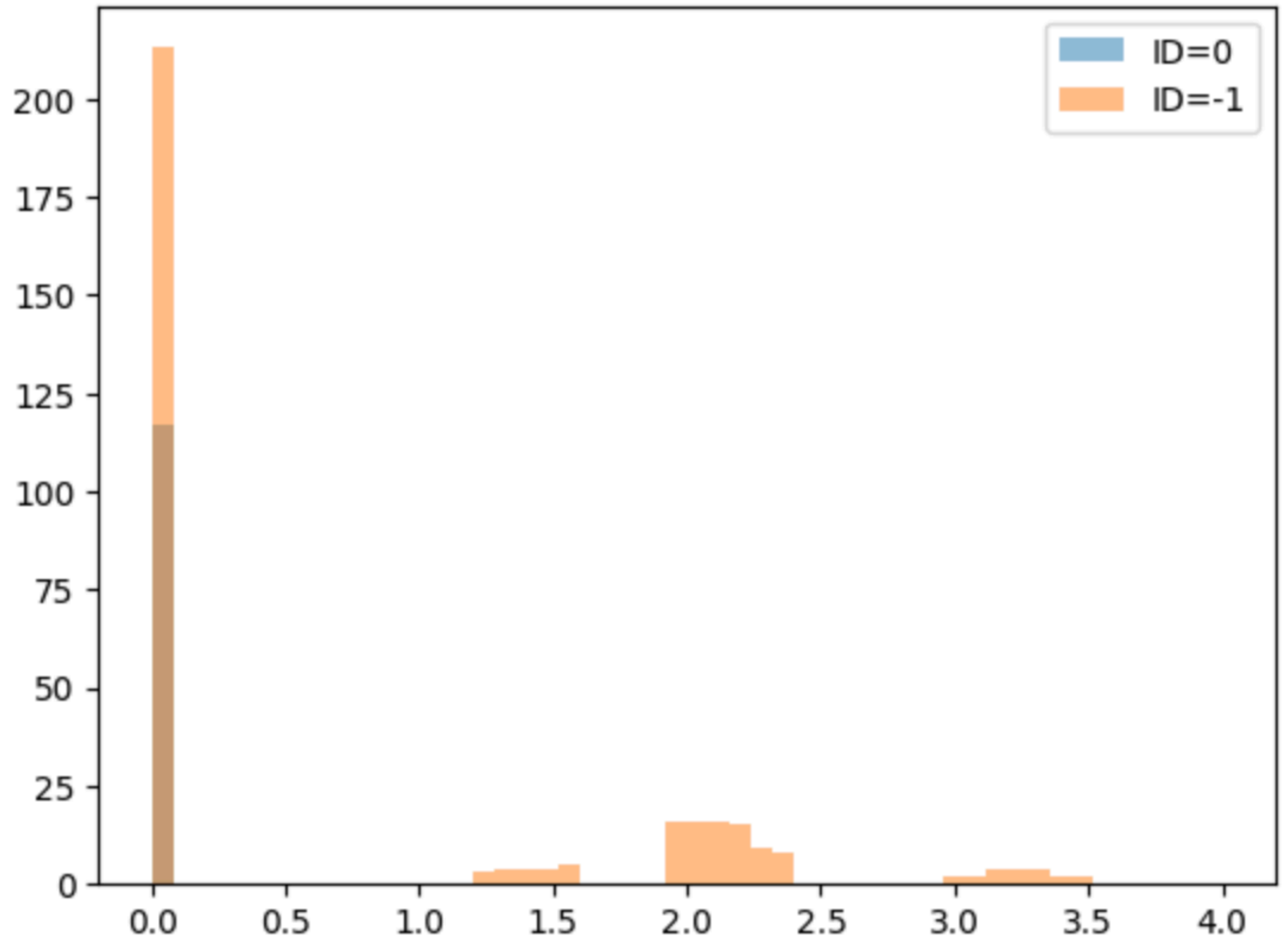
- However, issues in reconstructed energy inference
- Network trained to predict an energy deposit value for every hit associated to an object, given the true energy of the incoming photon and the total calorimeter deposit
- Predicted deposit summed for all photon hits and plotted
- Clear overestimation. Issues in the way a hit is assigned to either signal or BIB in the data generation. Truncated showers at the origin of the multiple peaks



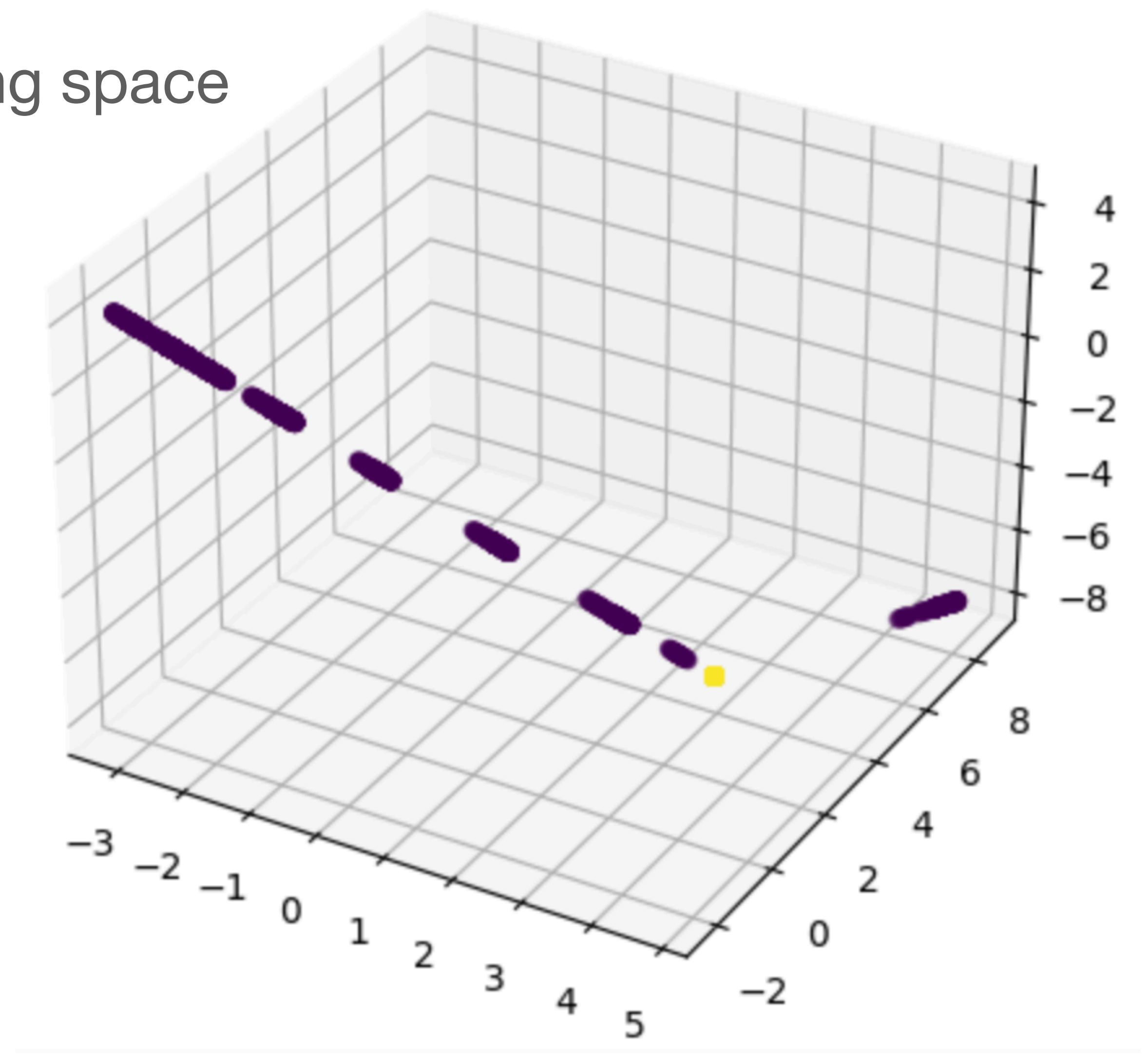
Muon Collider

OC: Run 2 - Clustering

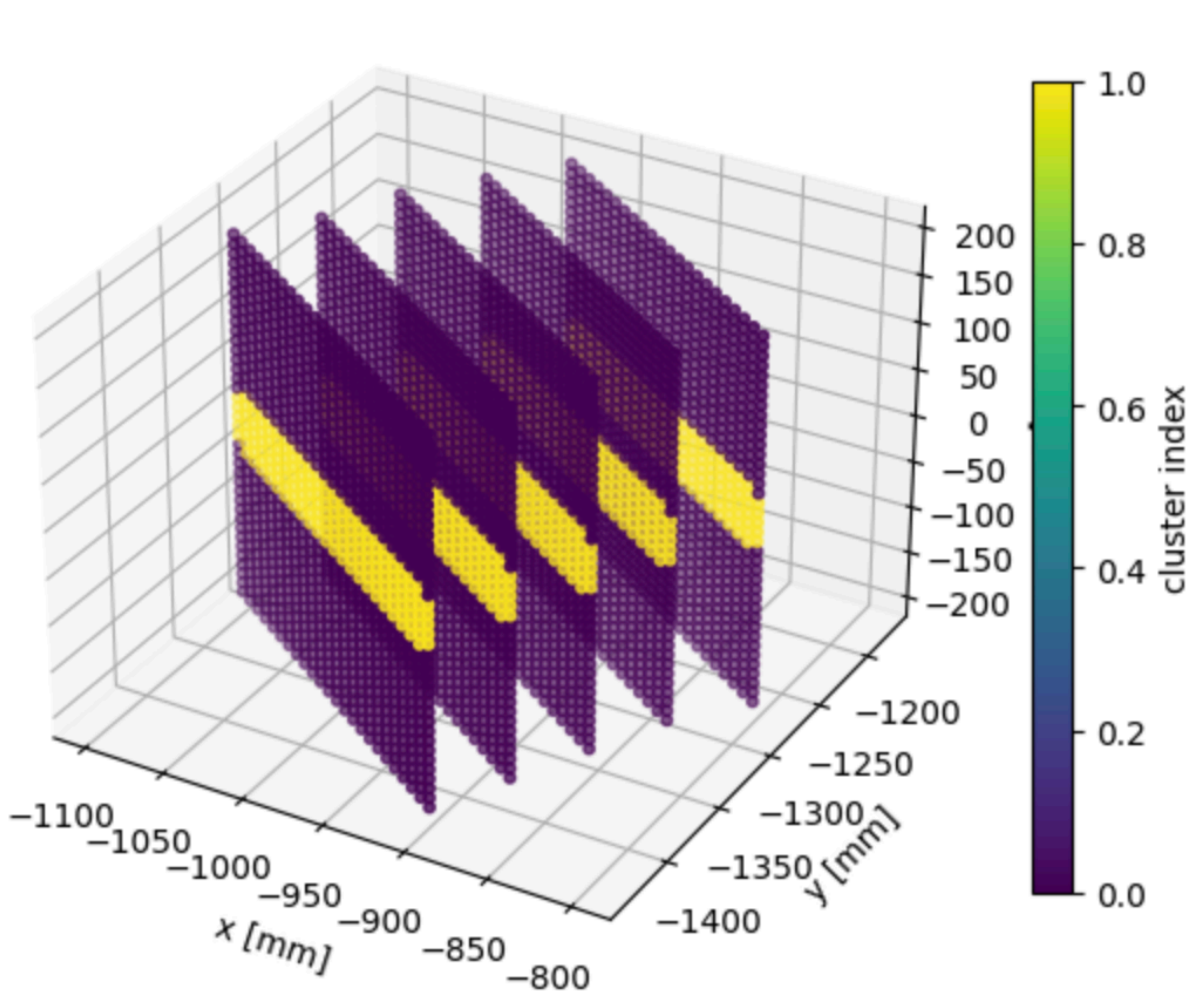
Cluster-space distance from condensation point



Clustering space



175 GeV photon



- Complete dataset
- Trained for 50 epochs at lr=1e-2, then 120 at 1e-3
- Deposit separation not net anymore
- Geometric features emerge, seems like the wedge separation is learned
- Running for more epochs might help solving the issue

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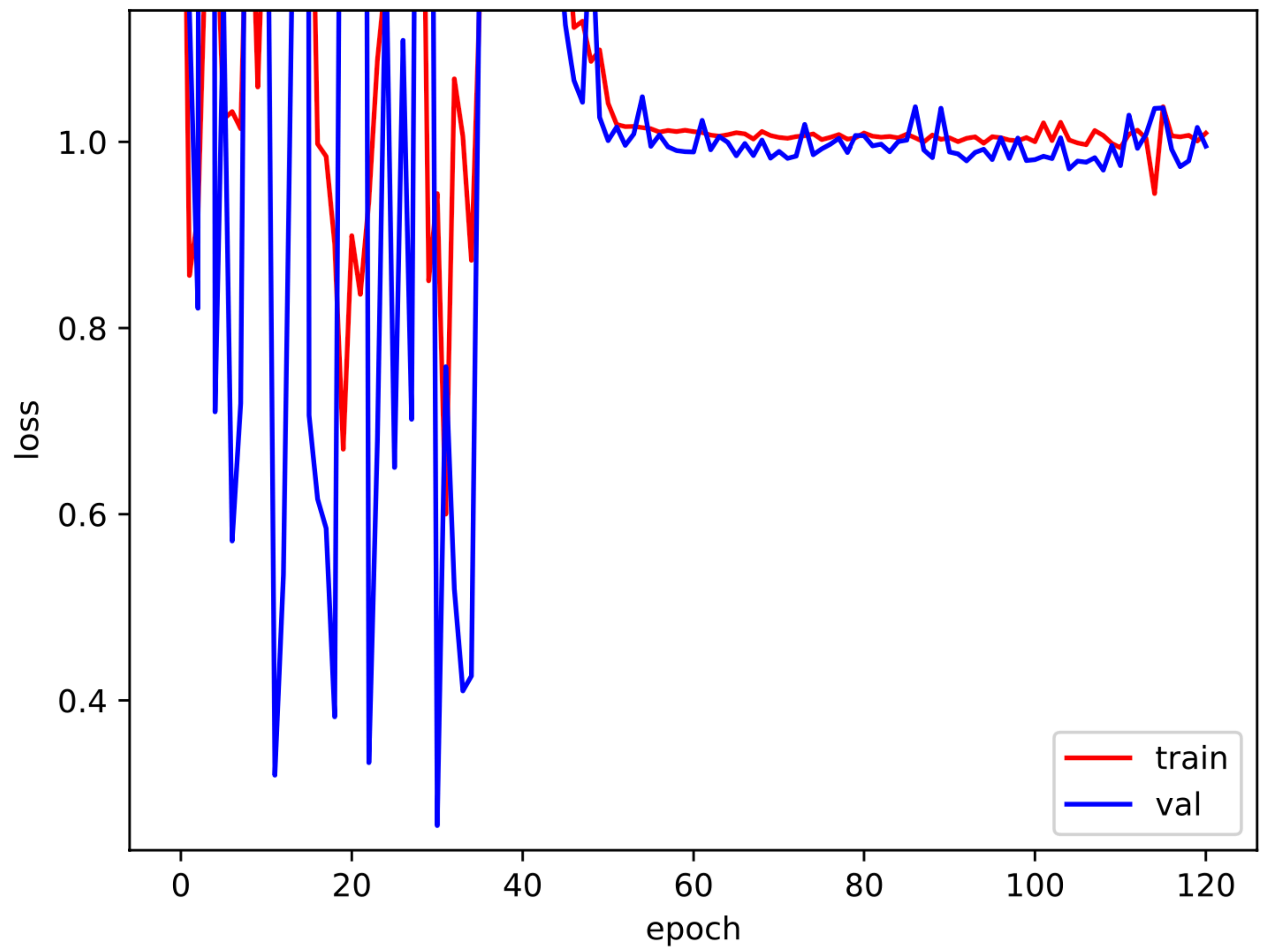
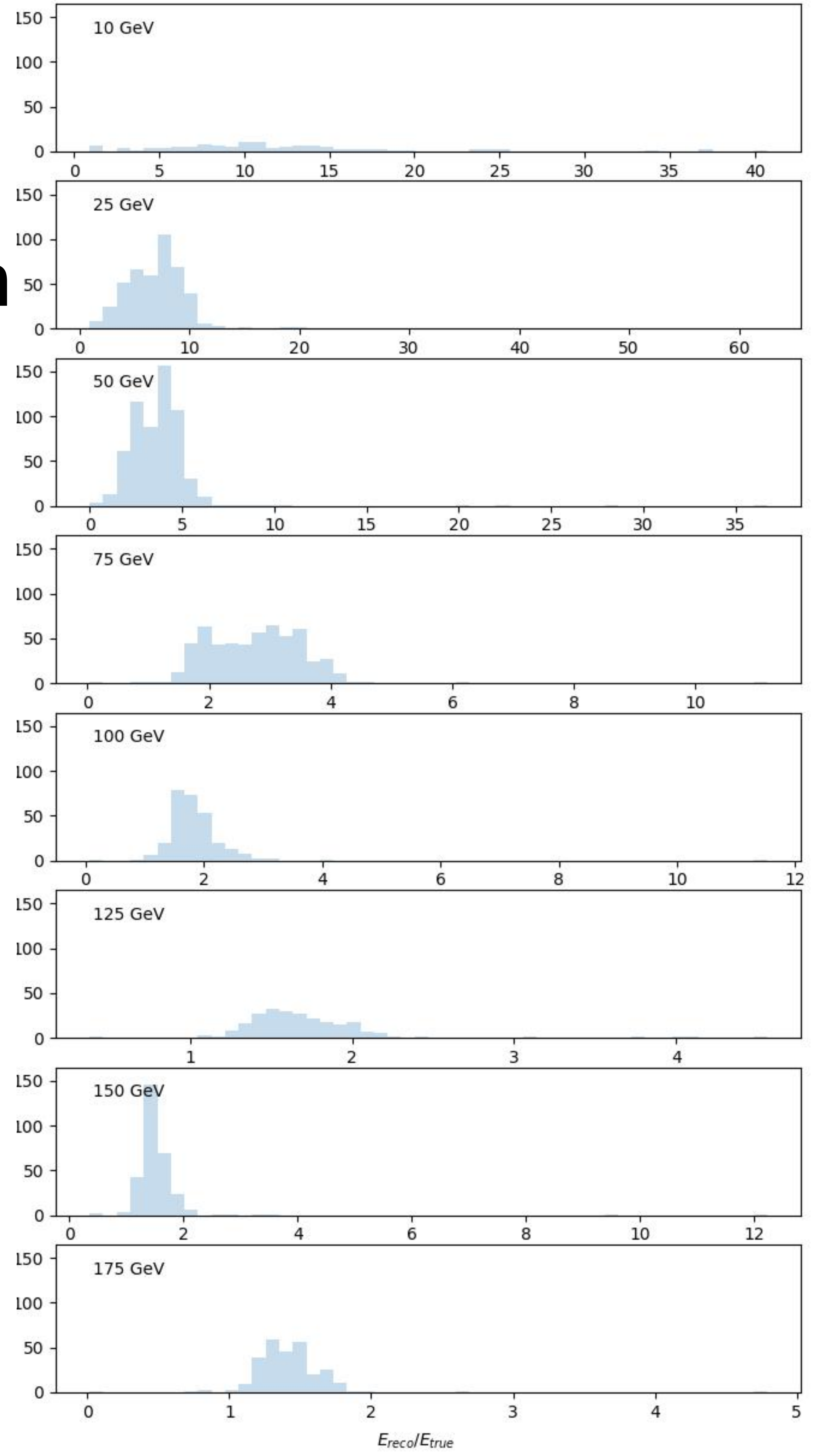
OC: Preliminary results - Energy reconstruction

- Resolved multiple peak issue in energy inference
- Overestimation however still remains, further index that not all dataset features have been learned



- Looking at the training curve, hints that we have not reached the minimum
- Too few epochs for all loss components to be optimized

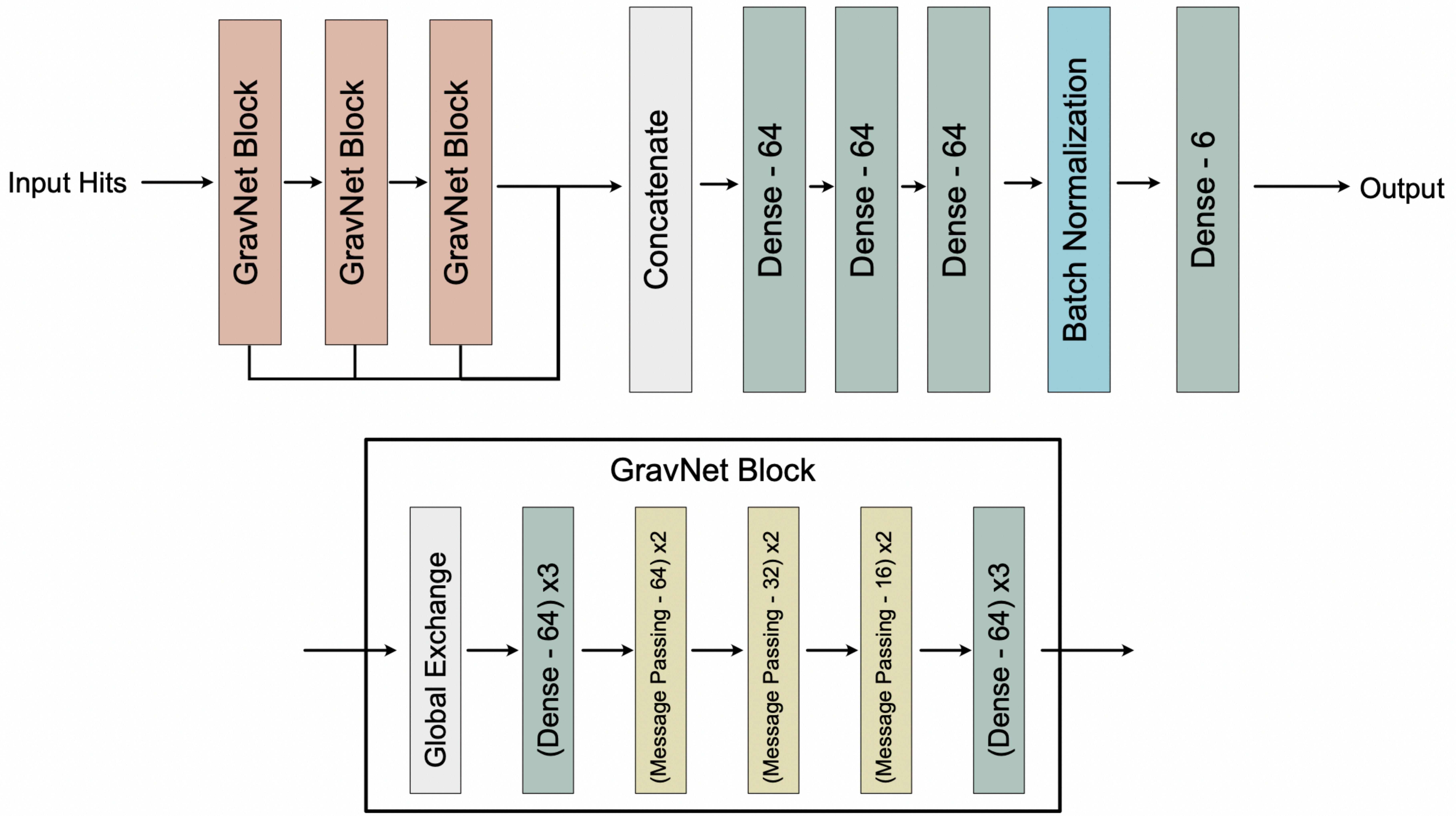


Summary

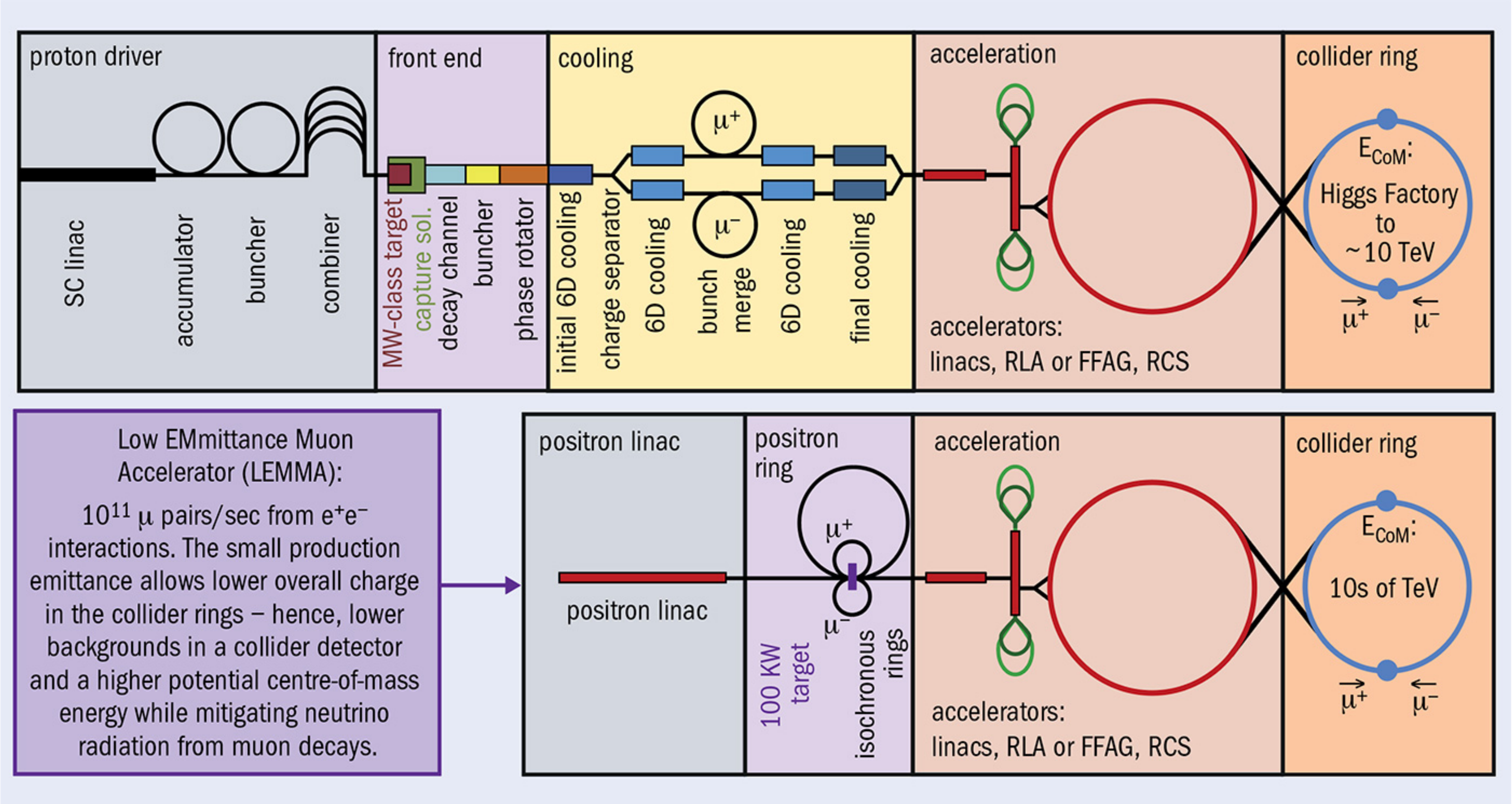
- Still work to do to come up with a design
- Differentiable blocks are however taking shape
- Data shape and quality is crucial for sensible and interpretable results
- Good momentum after Snowmass2022, further push towards a full optimization study

Backup

DJC Architecture



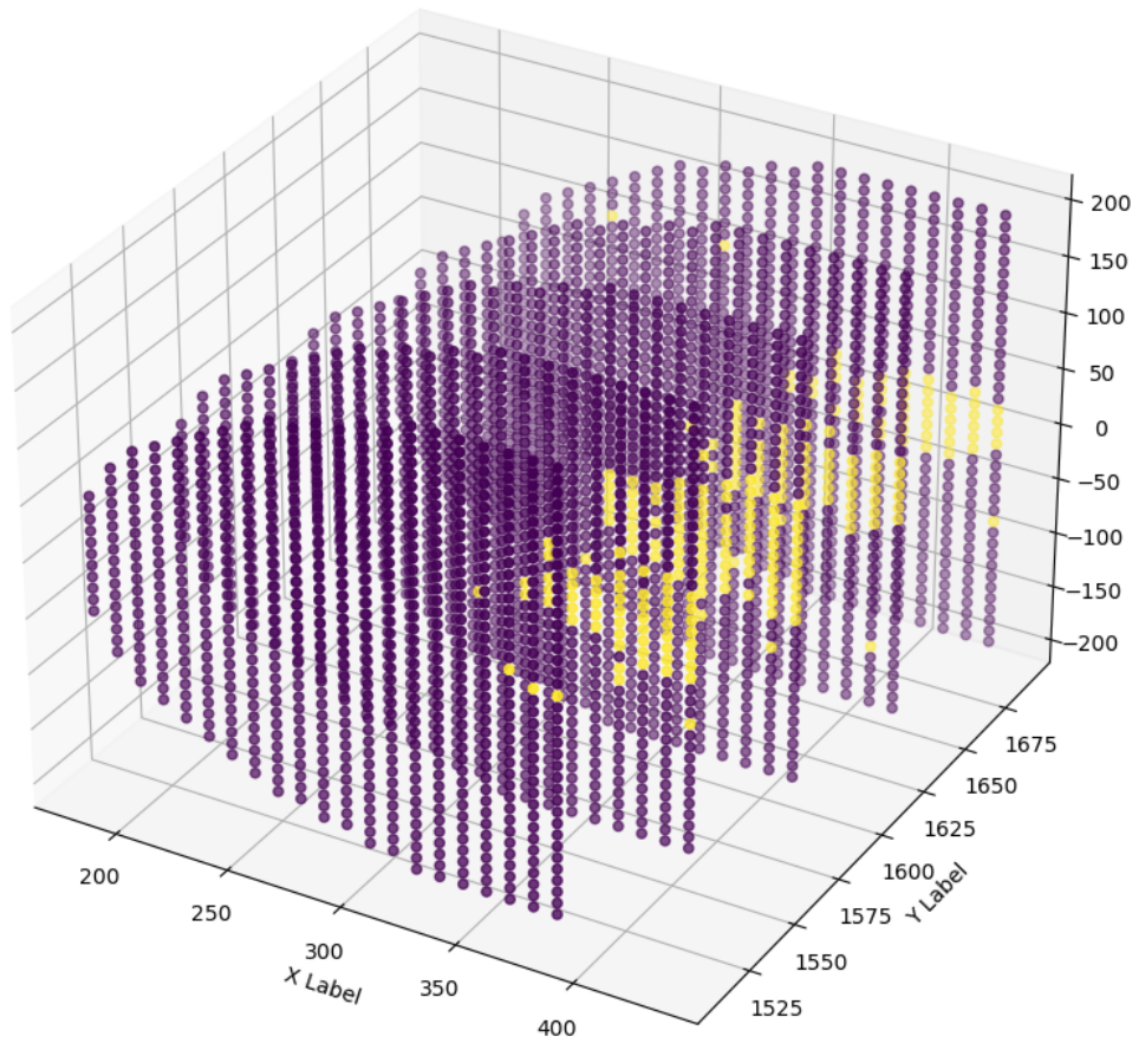
Muon Collider baseline



- Muon production - mMAo Muon Accelerator Program
  - Proton beam on a target, muons from pion decay
  - High emittance, advanced cooling needed
- Alternative - LEMMA

Run 1 dataset

- Reco IDX per hit



- Signal flag per hit