Towards the optimization of a Muon Collider Calorimeter

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MODE

The collaboration

- IDEA: Use **Automatic Differentiation techniques** not for the optimization of a Neural Network, but rather for a **complex experimental system** such as a detector

- MODE (Machine-Learning Oriented Design of Experiments) aims at forming a **joint community** of physicists and computer scientists to help and propose alternative methods in experimental R&D

- Possibility for **global optimization studies**, sensitive also to the interconnection between subsystems

Toward the end-to-end optimization of particle physics instruments with differentiable programming

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[a] MODE Collaboration[1]

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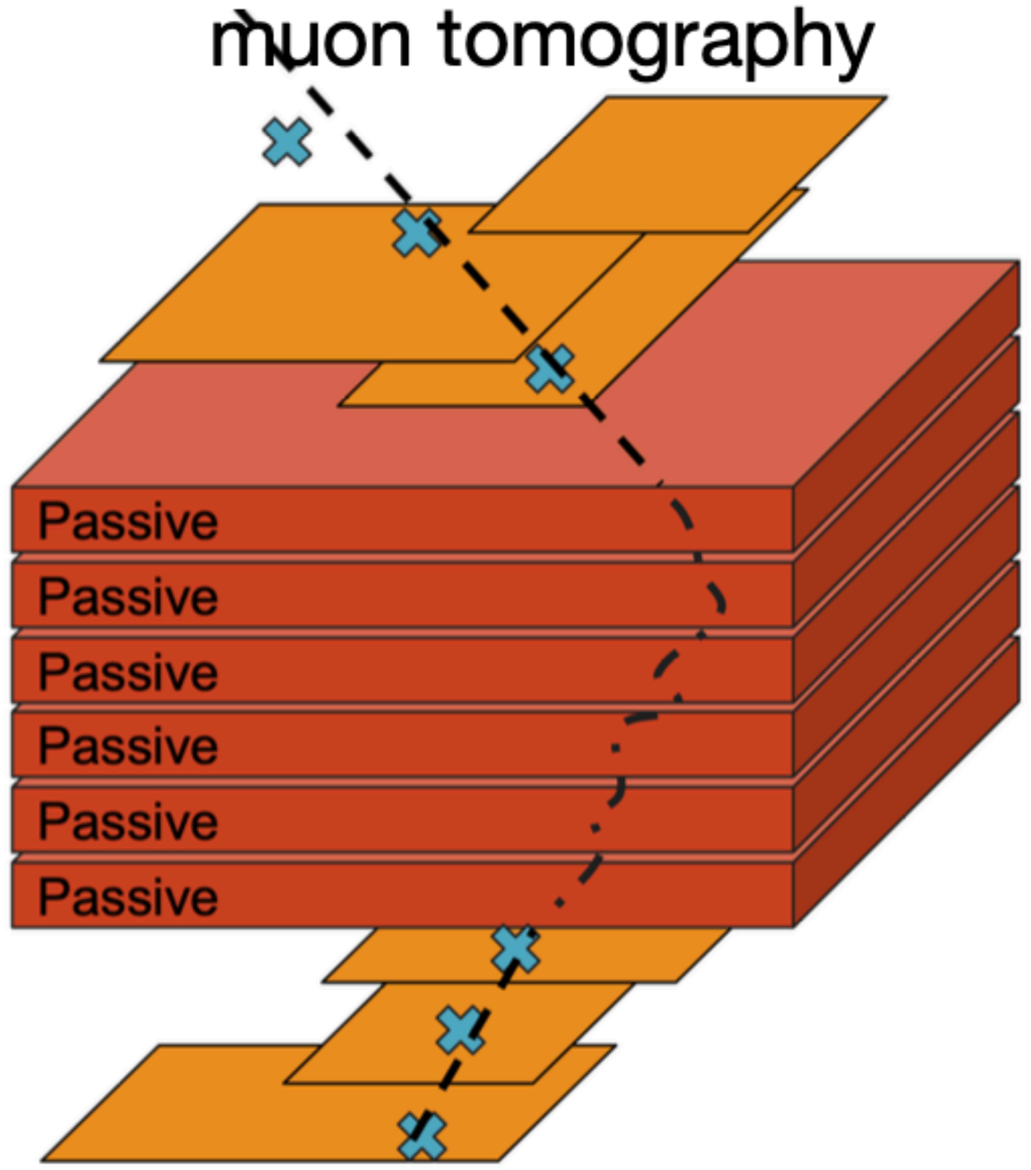
MODE

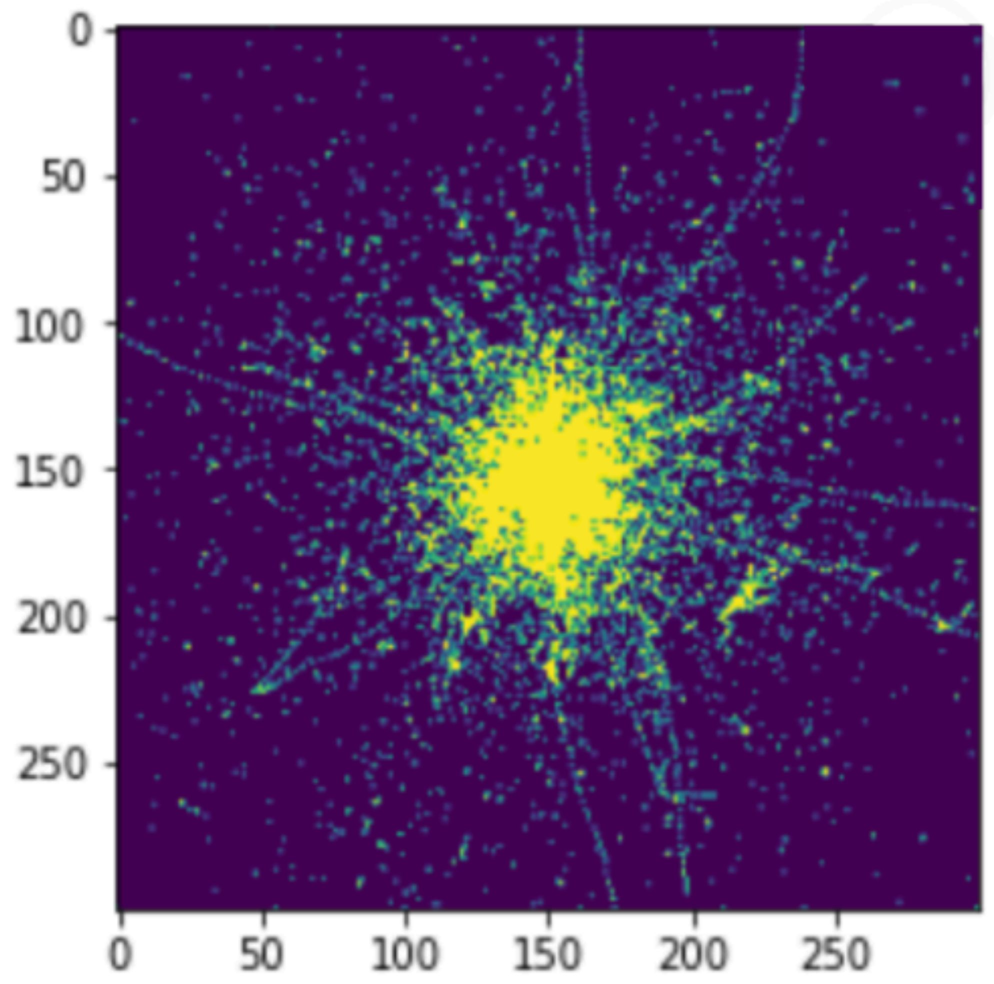
Activities

TomOpt: detector optimization for muon tomography

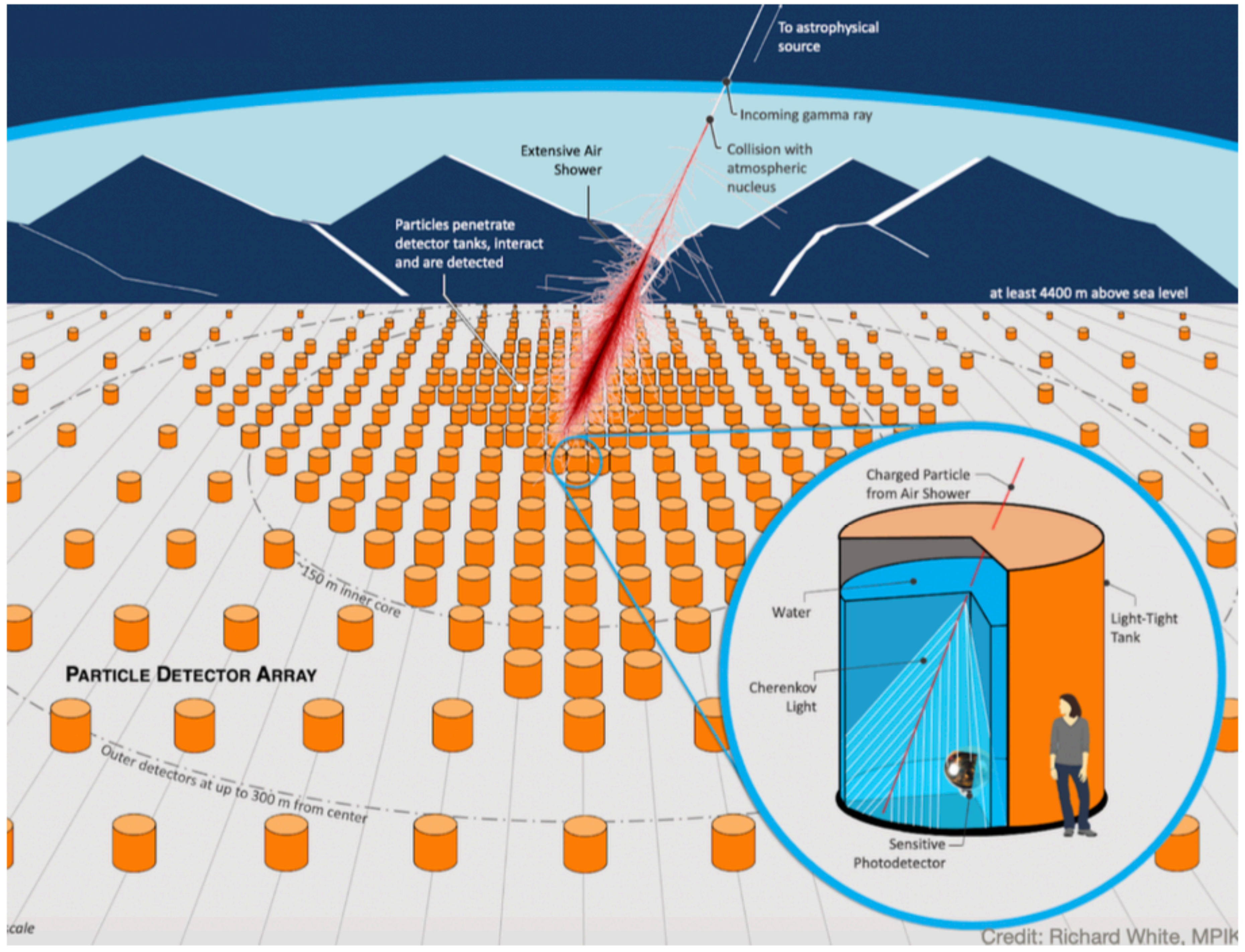


LHCb calorimeter optimization

Hybrid calorimetry - how coarse granularity allows us to perform particle ID



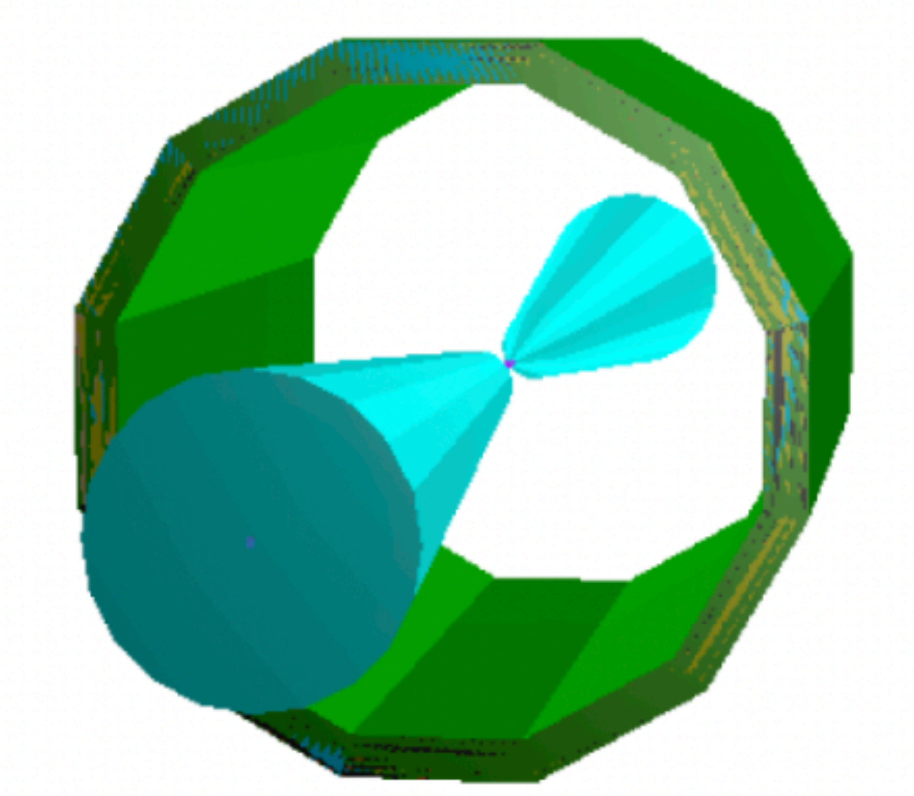
Array configuration for SWGO telescope

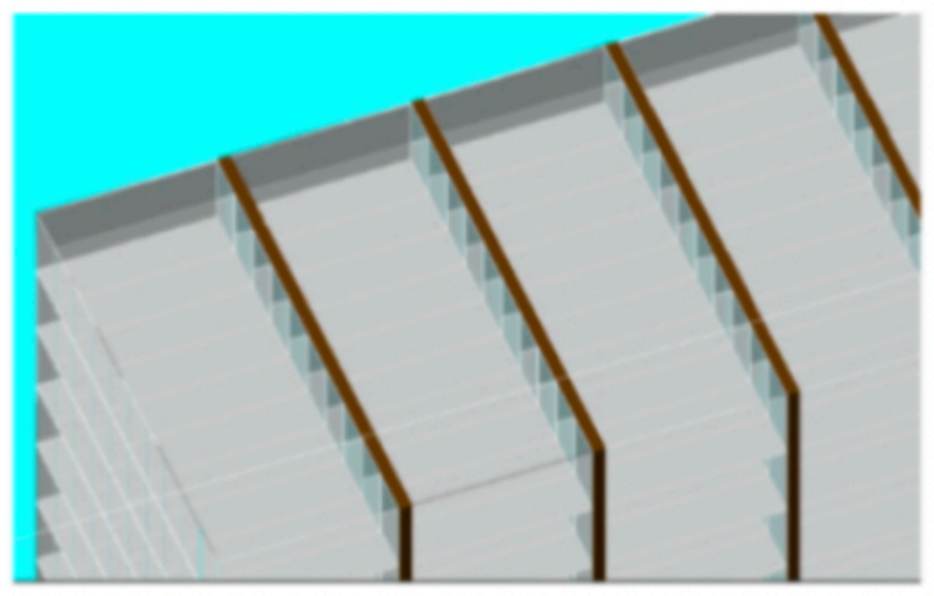


… And more!
https://mode-collaboration.github.io/#papers

Our study at the Muon Collider

- Development of a full differentiable pipeline to propose an optimized ECal design
- Starting from reference Crilin geometry
- Maximise energy and position reconstruction efficiency (and material budget)

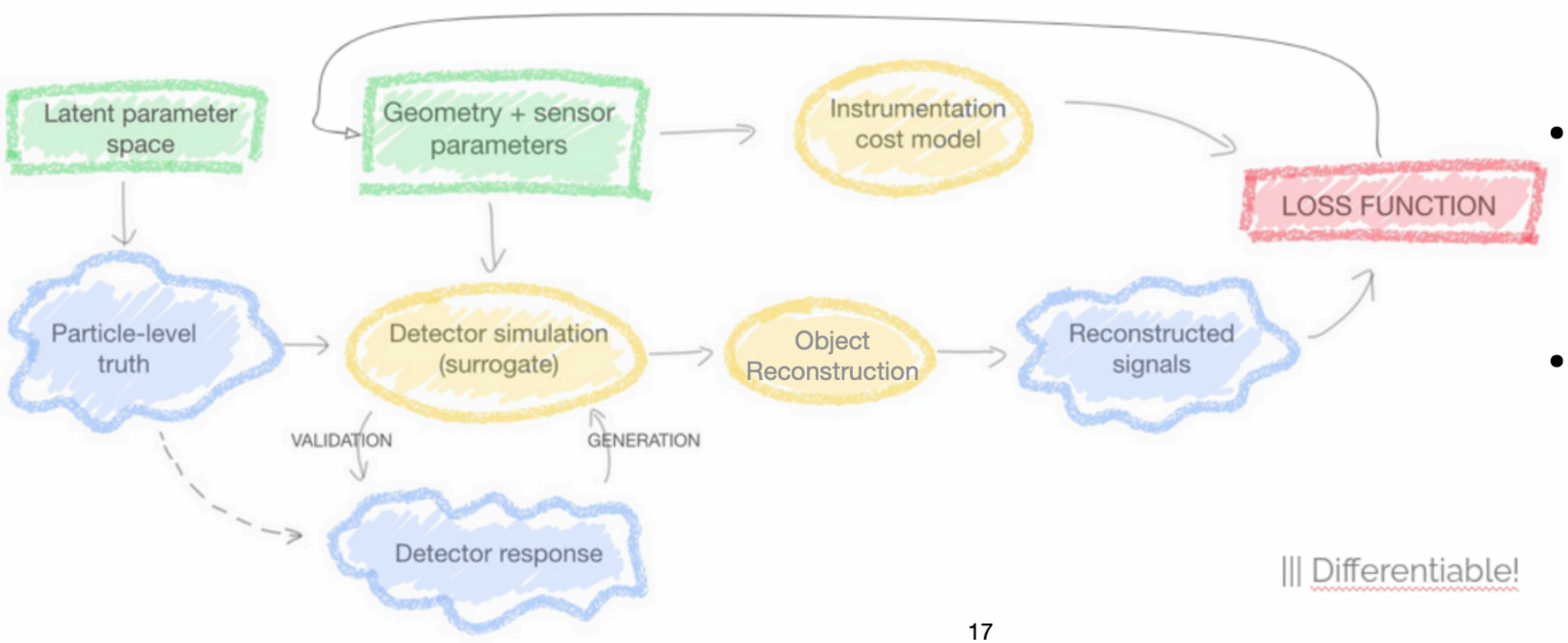




Muon Collider

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



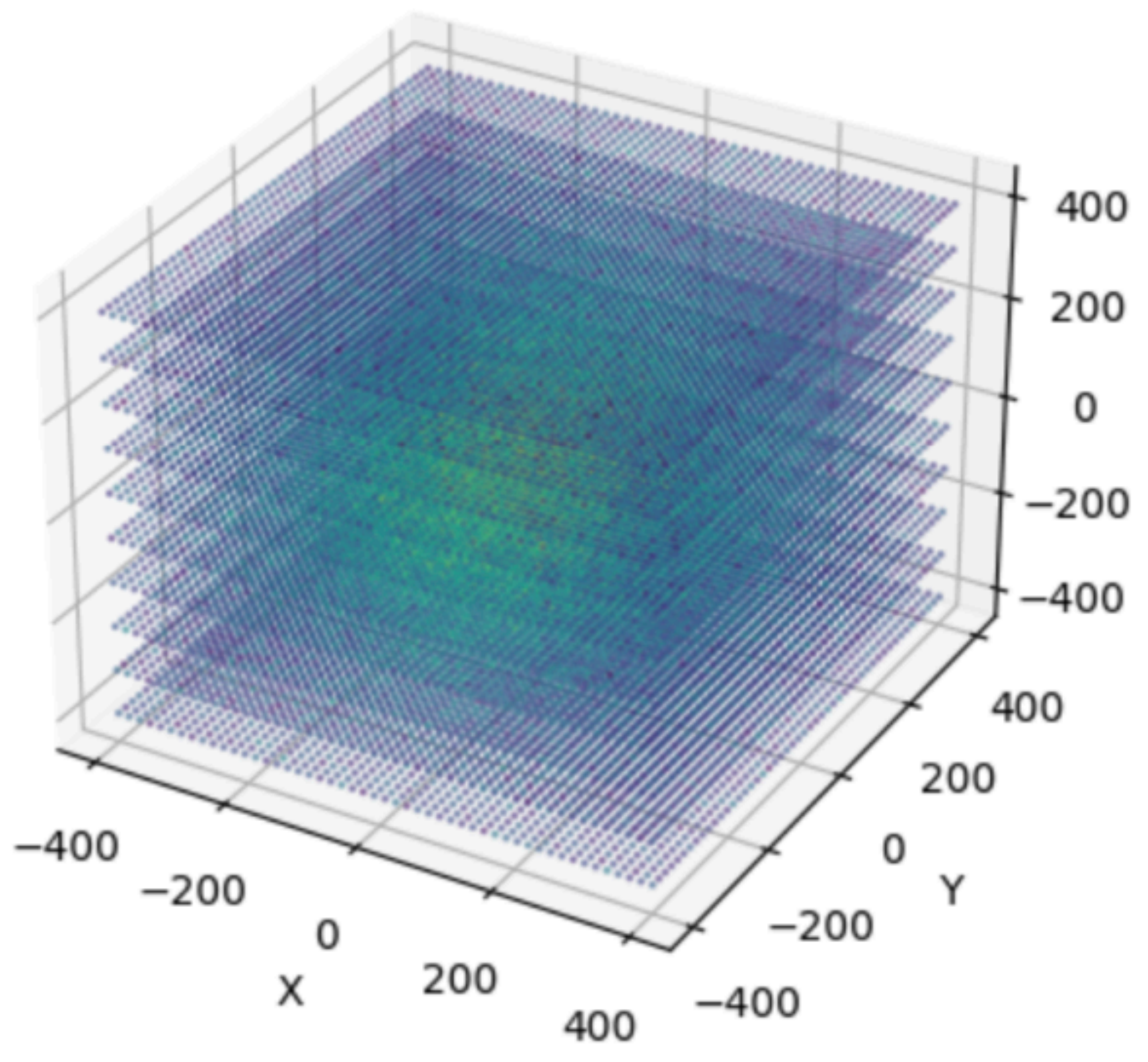
- Based on 3 main core methods
- Provide information encoded in a utility function
- Minimized using AD libraries (PyTorch, Tensorflow)

Pipeline

A toy model

- Idea: represent calorimeter as a grid. Optimize the spacing (Δx,Δy,Δz) between the points.
- Initialize the **geometry**: 10 layers of 80x80 pixels
- **Simulation**: evaluate a distribution in each grid point
    - 3D gaussian with $\mu_x = \mu_y = \mu_z = 0, \quad \sigma_x = \sigma_z \neq \sigma_y$
- **Reconstruction**: infer parameters of the distribution from the grid
    - Use sample mean and standard deviation estimators $\hat{\mu}, \hat{\sigma}$
- **Loss:** Mean-squared-Error for gaussian parameters + regularizer to prevent collapse towards 0:
    - $\sum_{i=x,y,z} (\hat{\mu}_i - \mu_i)^2 + (\hat{\sigma}_i - \sigma_i)^2 + \frac{1}{\Delta x_i^2}$

```
Initial spacing:  [1.0   1.0   1.0]
```



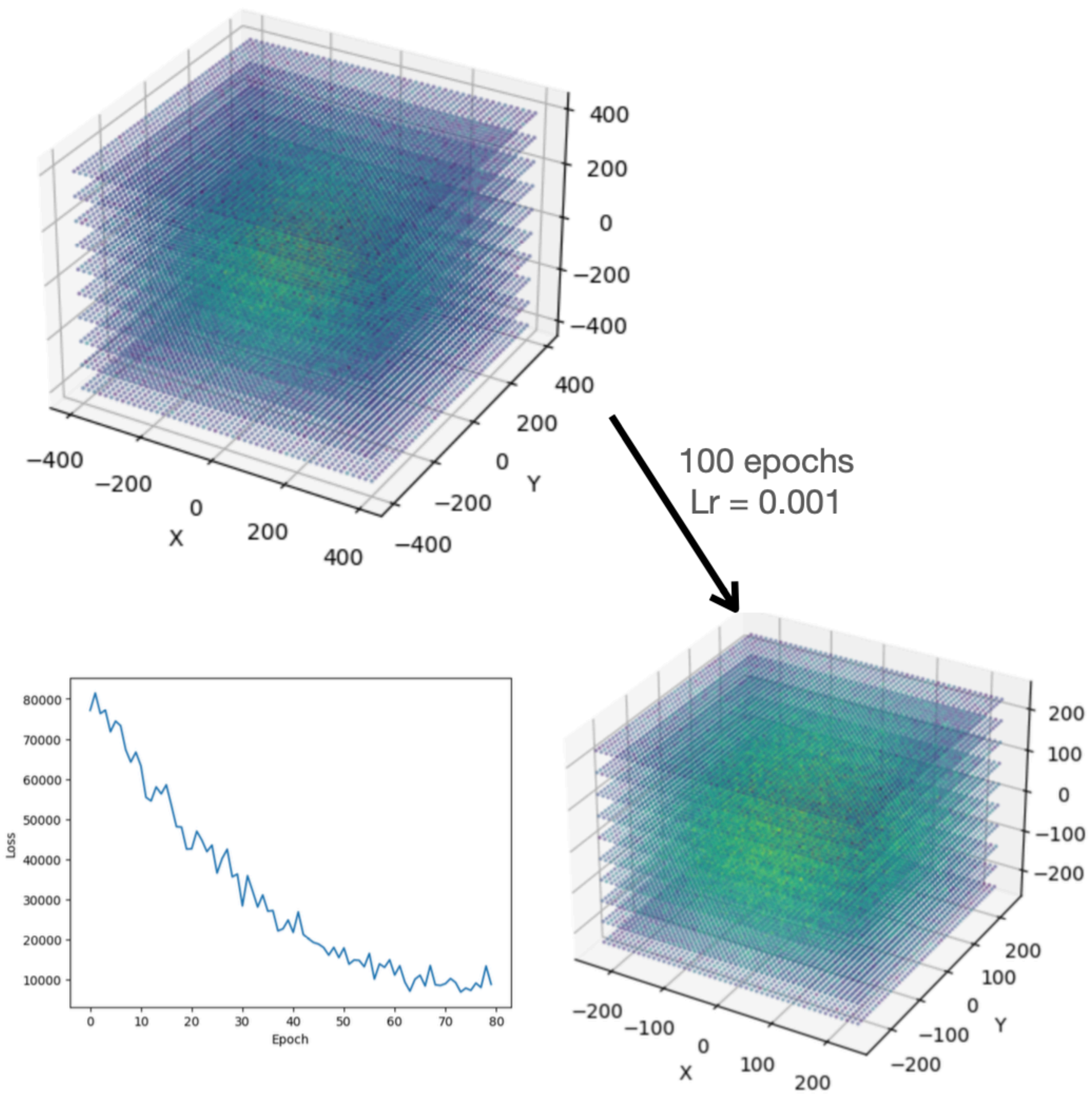

```
sigma_x = 100.
sigma_y = 120.
sigma_z = 100.
```

Pipeline

A toy model

- Use Automatic Differentiation to find (Δx,Δy,Δz) that **minimize** the loss
- Using proposed parameters, the grid adapts to the dimension of the gaussian ball
- Asymmetry in sigmas reflected by **different spacing values**

Initial spacing: [1.0 1.0 1.0]

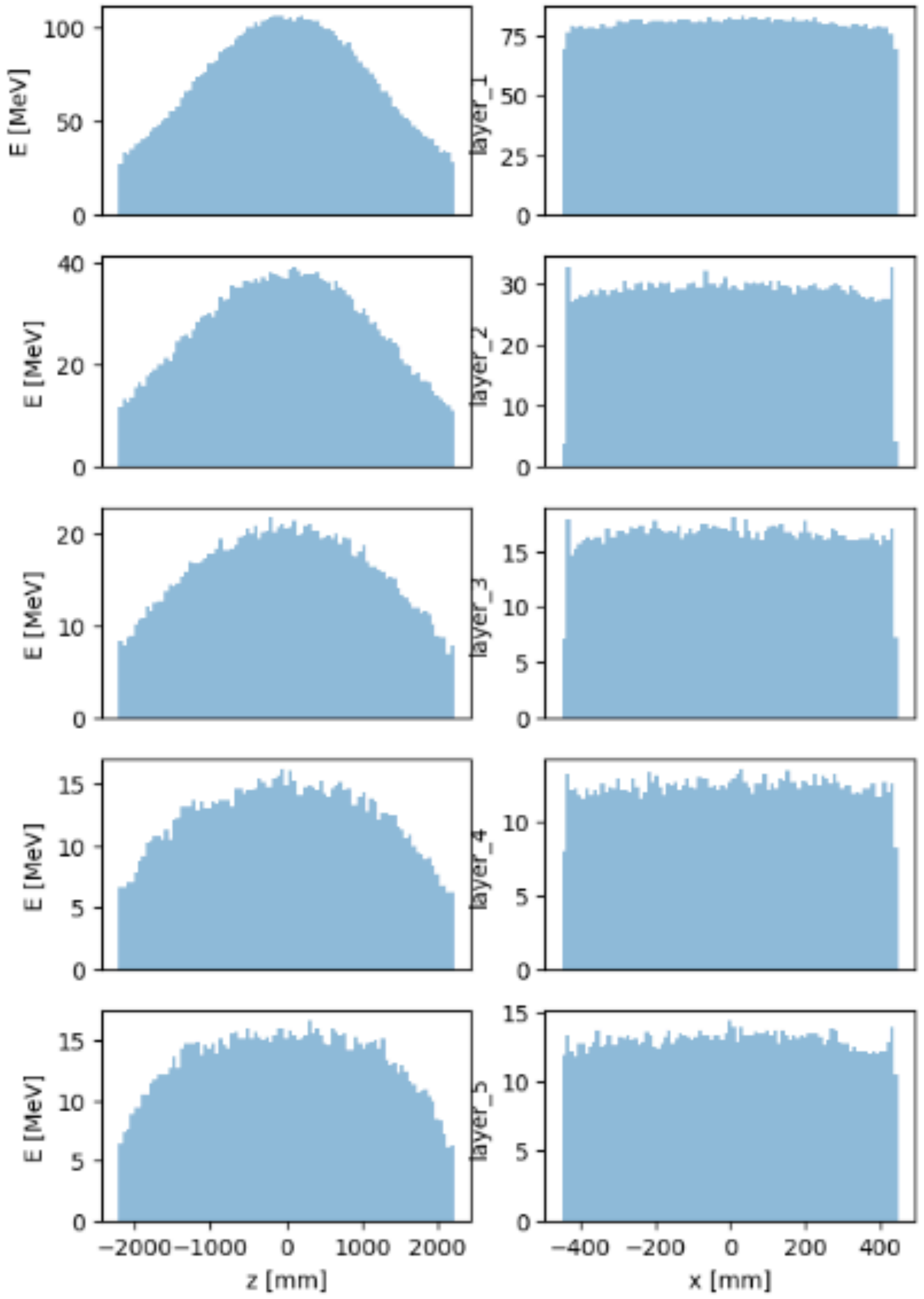


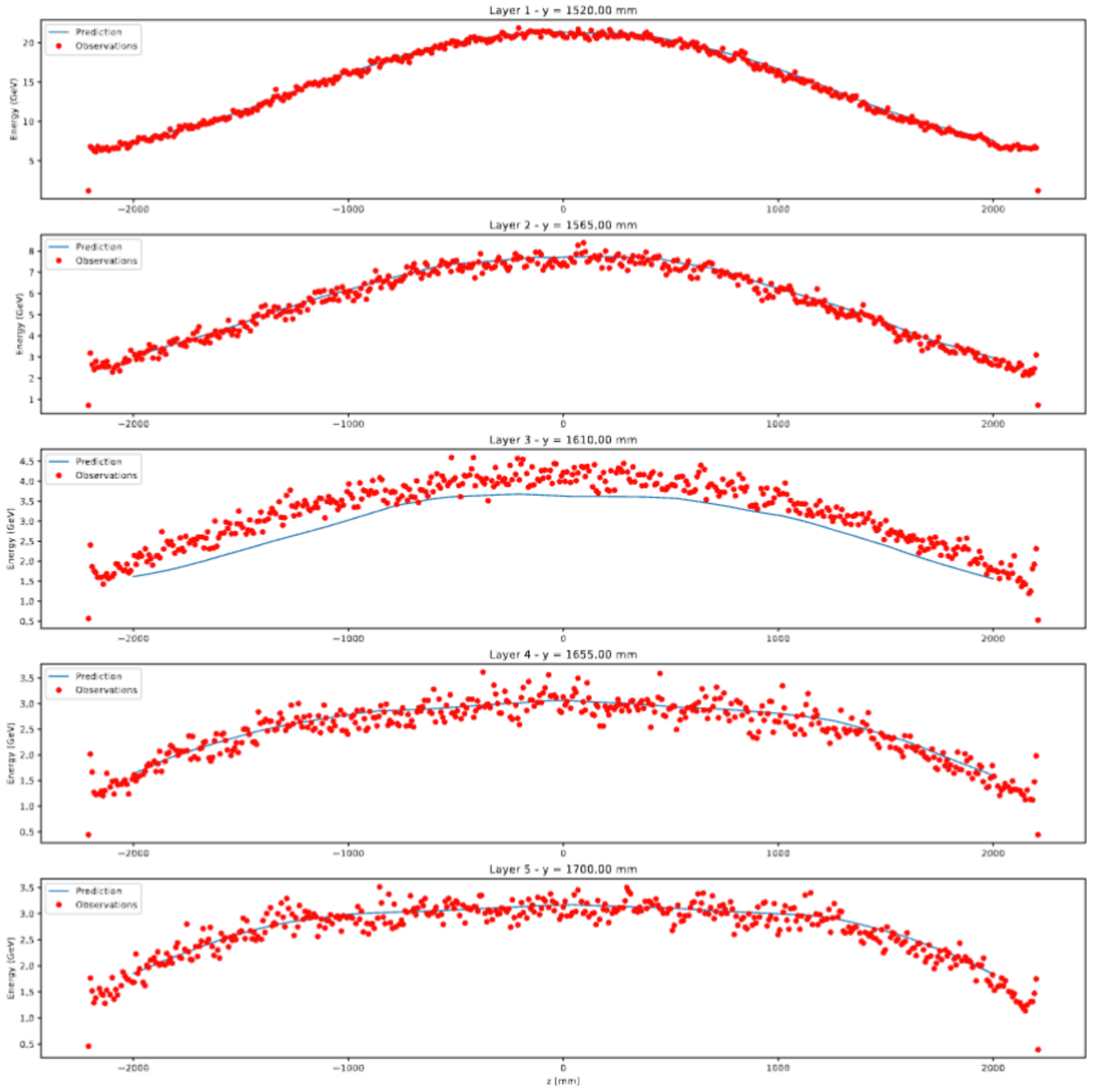
Final spacing: [0.47563136 0.5433373 0.44885612]

Surrogates

BIB generator

- Isolated a single wedge, with 1.5TeV BIB event
- Trained a Neural Network to replicate BIB flux on each wedge
- Possibility for intra-wedge interpolation to be able to resolve smaller crystals

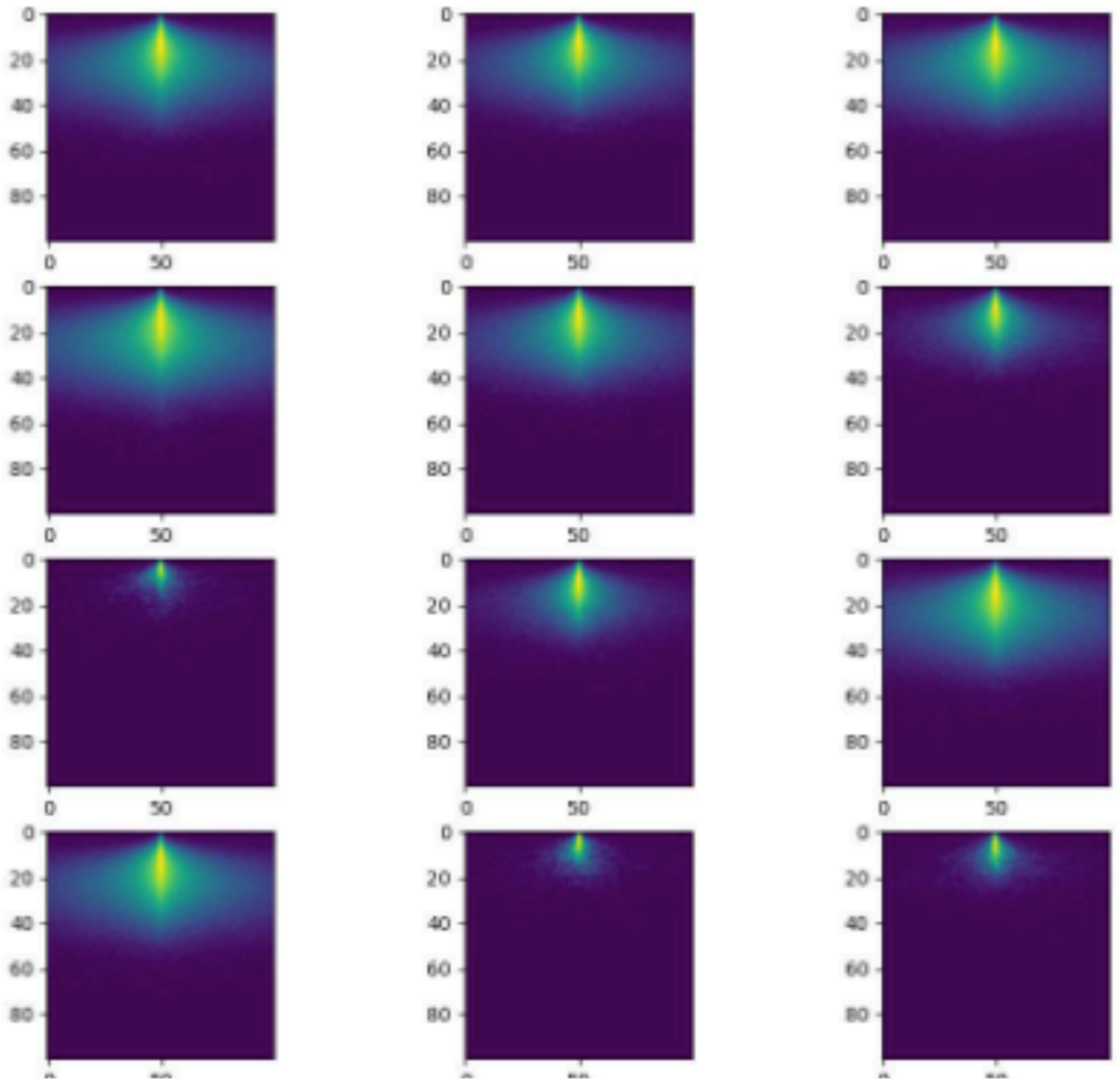


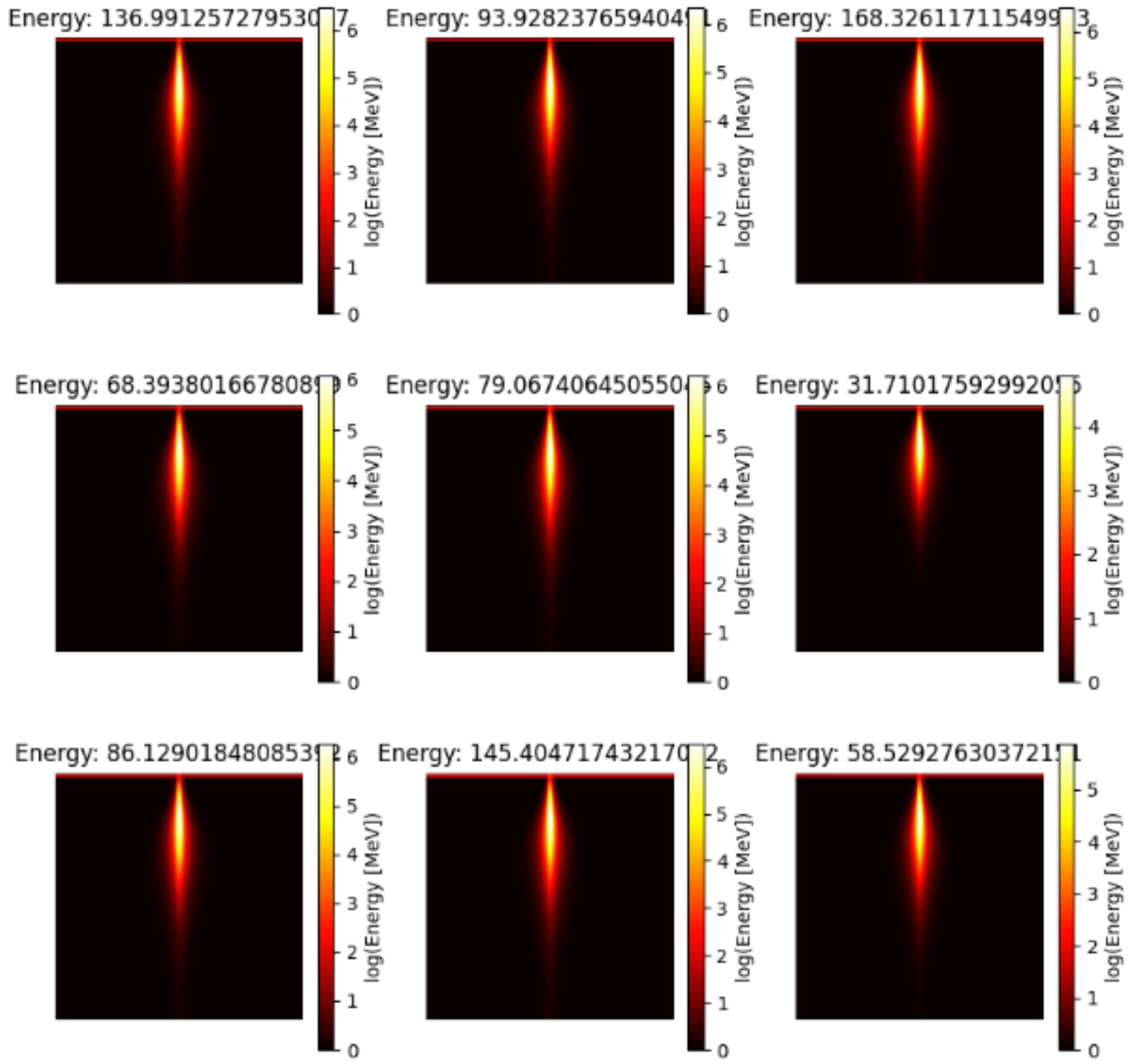


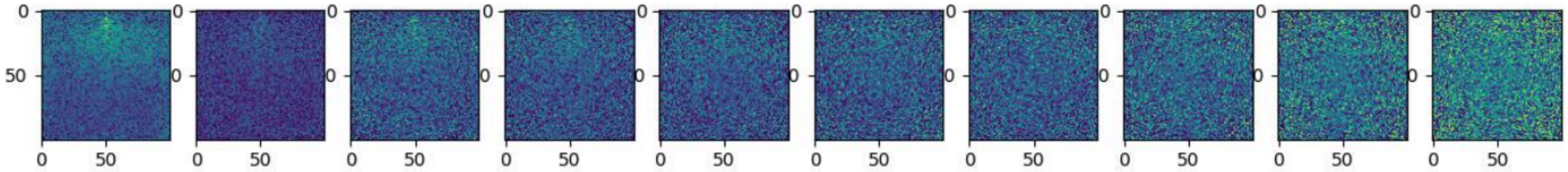
Surrogates

Shower generation

- Generated a set of monochromatic photon events with Geant4
- Fitting images to differentiable functions to describe showers
- Also,training of a DNN in progress

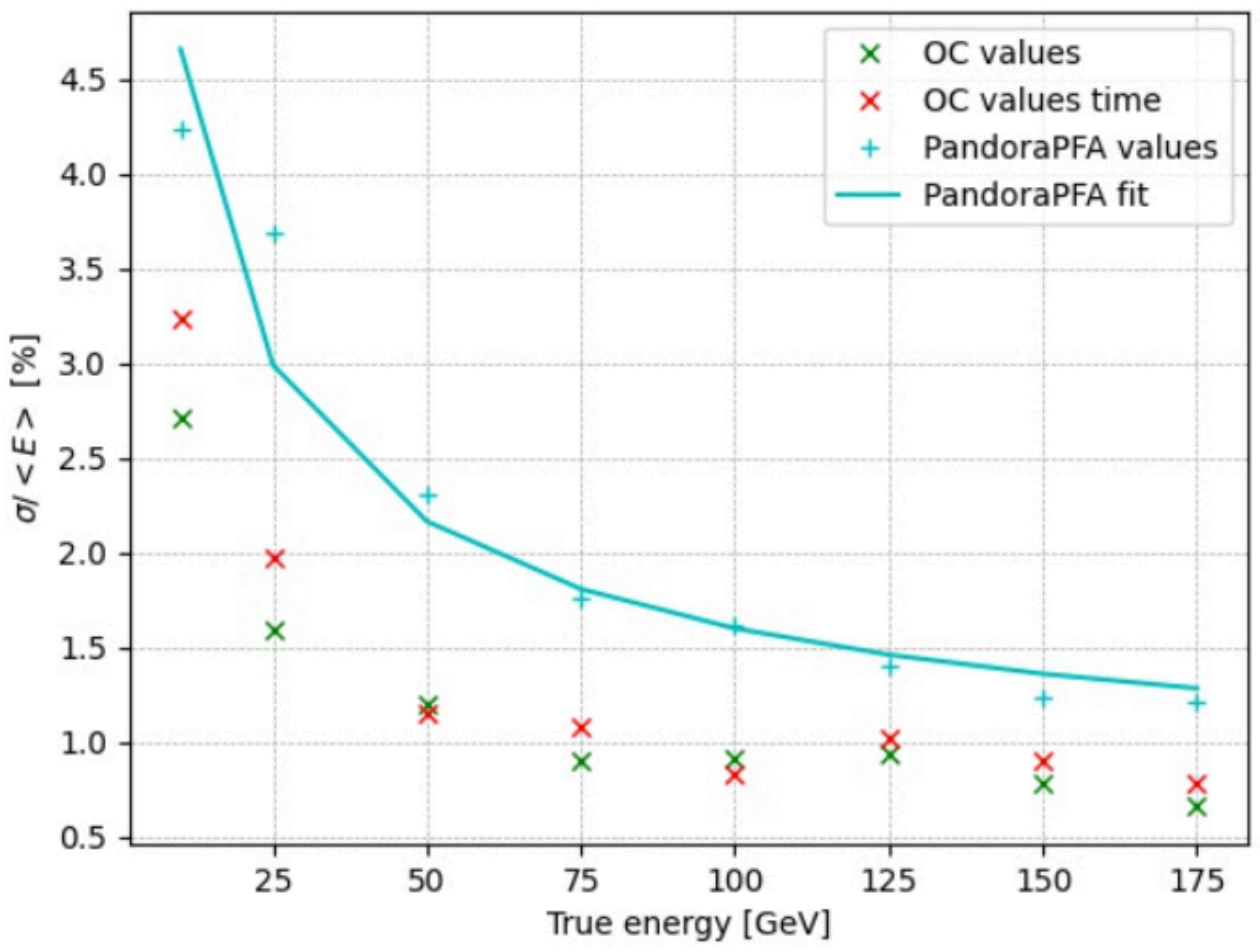






Reconstruction

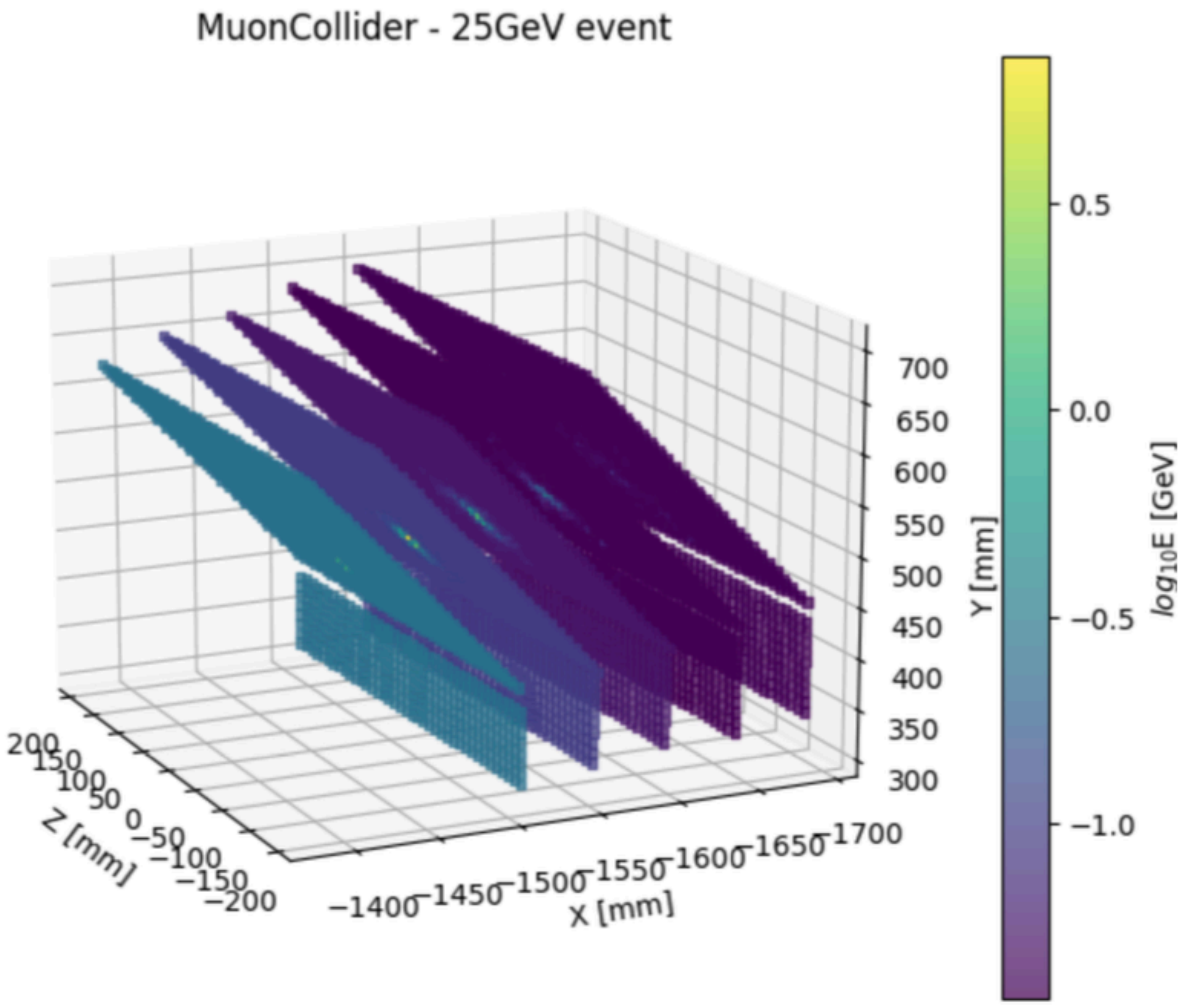
- Reconstruction based on DeepJetCore, a Graph Neural network developed originally for the HGCal of CMS to perform clustering on jets
- Adapted for our single-photon case
- Compared reconstruction resolution with respect to traditional algorithm (Pandora+ParticleFlow)



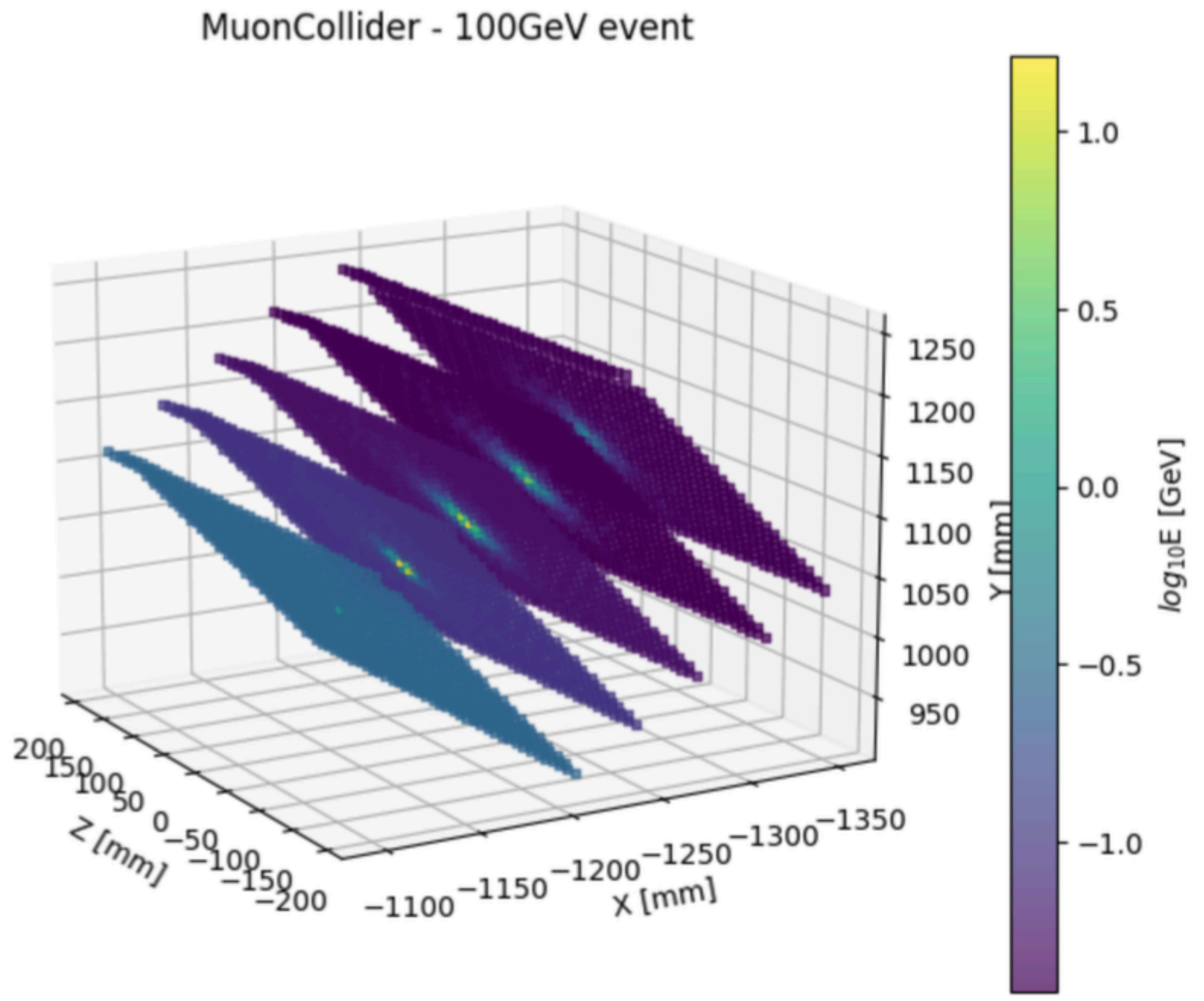
Reconstruction

Signal photons

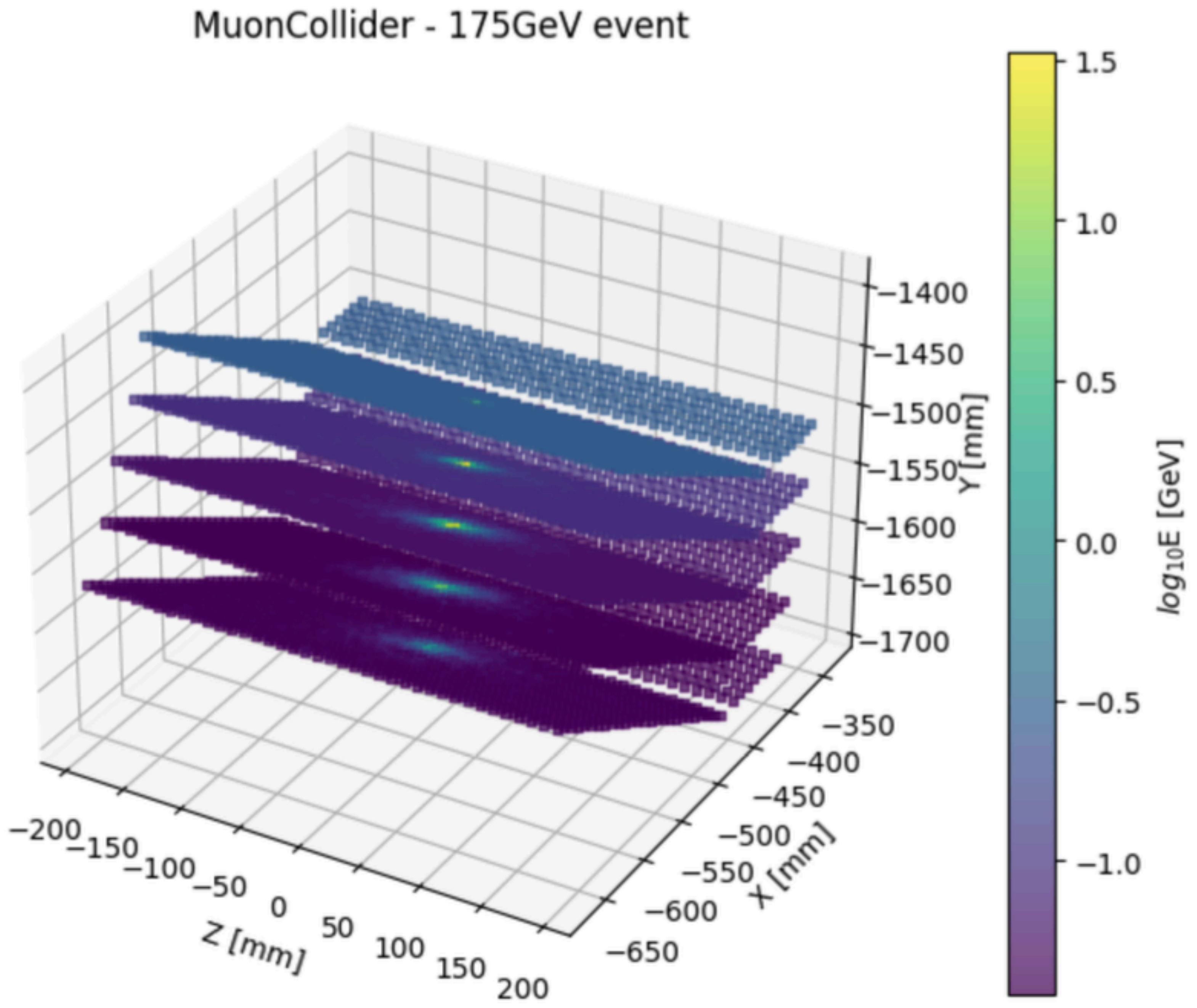
Overlay of 1.5 TeV BIB and single-photon
events generated with Geant4



ϕ=0.38rad



ϕ=0.75rad



ϕ=-1.91rad

Summary

- Developed and tested surrogates
- Developed basic pipeline
- Need to finish implementation of all elements and run full simulation
- Final results TBA!

Backup

Muon Collider

OC: Energy reconstruction

- Primary **energy** inferred by summing the energy **deposits for signal-labeled hits**
- **Degrades at lower energies**, where signal and BIB deposits become comparable
- To **evaluate resolution**, fit to a CrystalBall function. Extract gaussian parameters for mean and std.

$$f(x;\alpha,n,\bar{x},\sigma) = N \cdot \begin{cases} \exp(-\frac{(x-\bar{x})^2}{2\sigma^2}), & \text{for } \frac{x-\bar{x}}{\sigma} > -\alpha \\ A \cdot (B - \frac{x-\bar{x}}{\sigma})^{-n}, & \text{for } \frac{x-\bar{x}}{\sigma} \leqslant -\alpha \end{cases}$$