Towards the optimization of a Muon Collider Calorimeter

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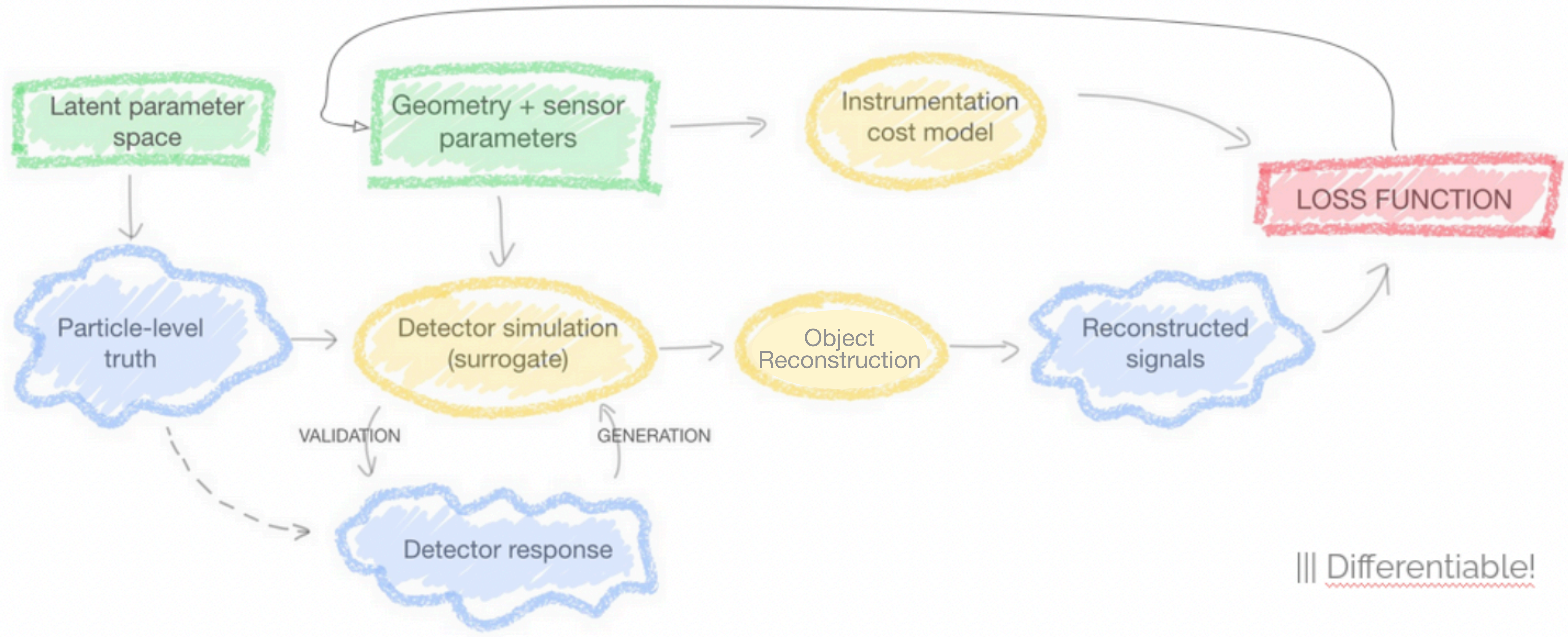
What

Pipeline scheme

- 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

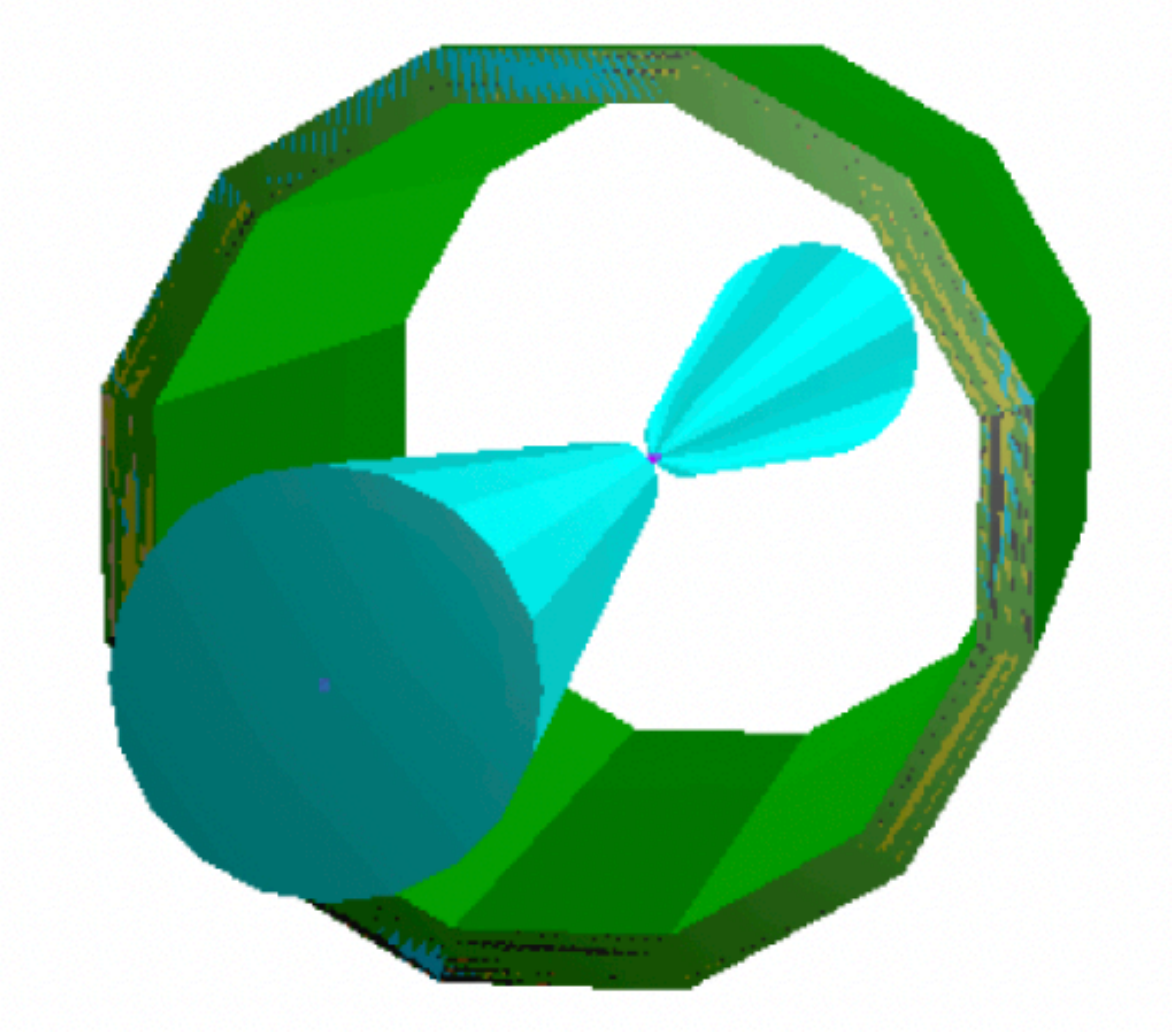


- Based on 3 main core methods
- Provide information encoded in a utility function
- Minimized using AD libraries (PyTorch, Tensorflow)

What

CRILIN: reference design

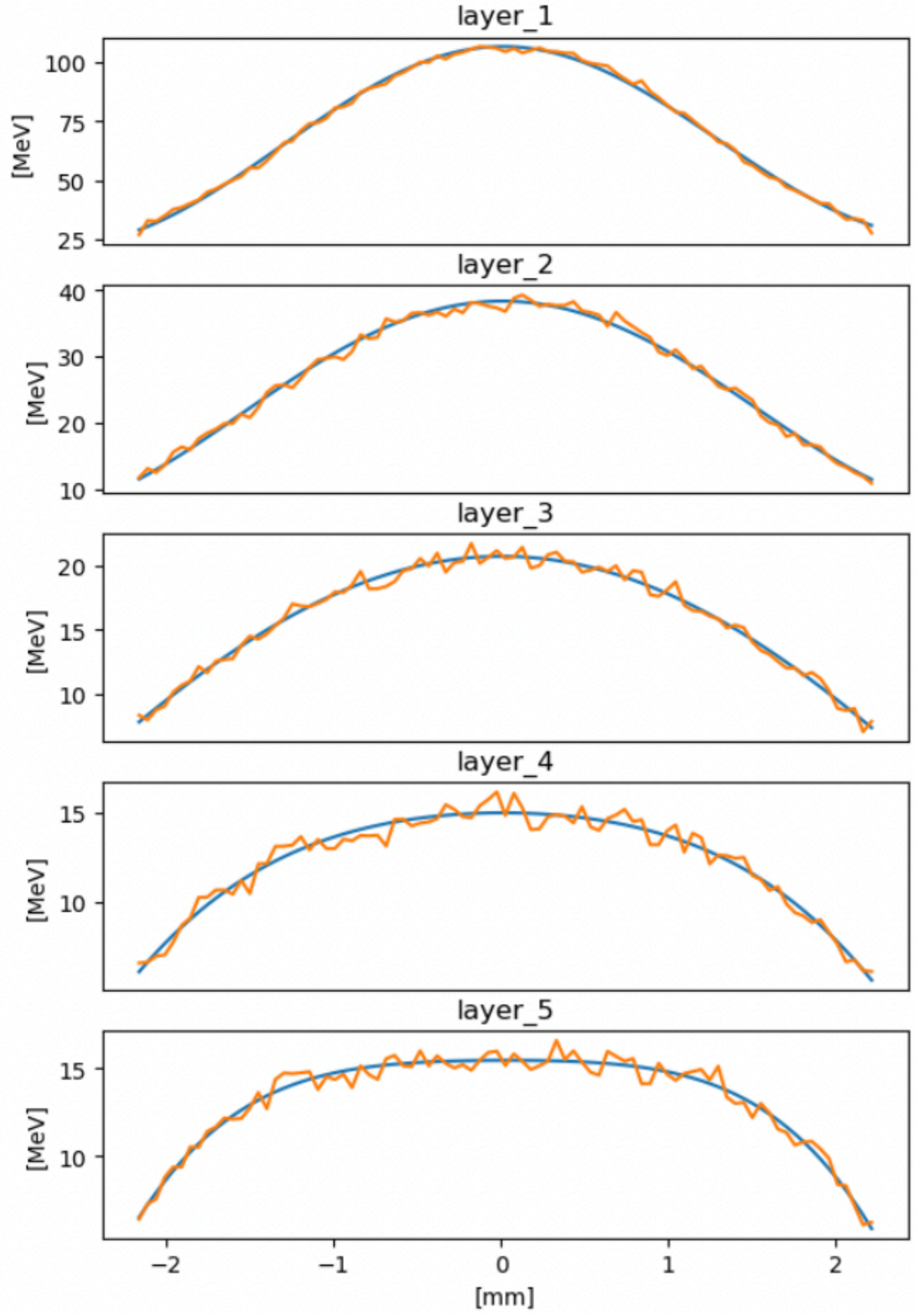
- Reference design chosen for our studies is CRILIN for the Electromagnetic Calorimeter (ECal)
- Array of $1x1x4.5cm^3$ PbF_2 voxels, arranged in a dodecahedron
- 5 layers per wedge
- Modular design, easy to modify and rearrange



Modules

BIB Generation

- Starting from a 1.5GeV simulation, BIB deposition in 5 ECal layers
- Cylindrical symmetry allows us to focus on a single layer
- Assuming uniformity in x-direction
- Initially polynomial fits layer-by-layer. Not ideal if we want to vary geometry

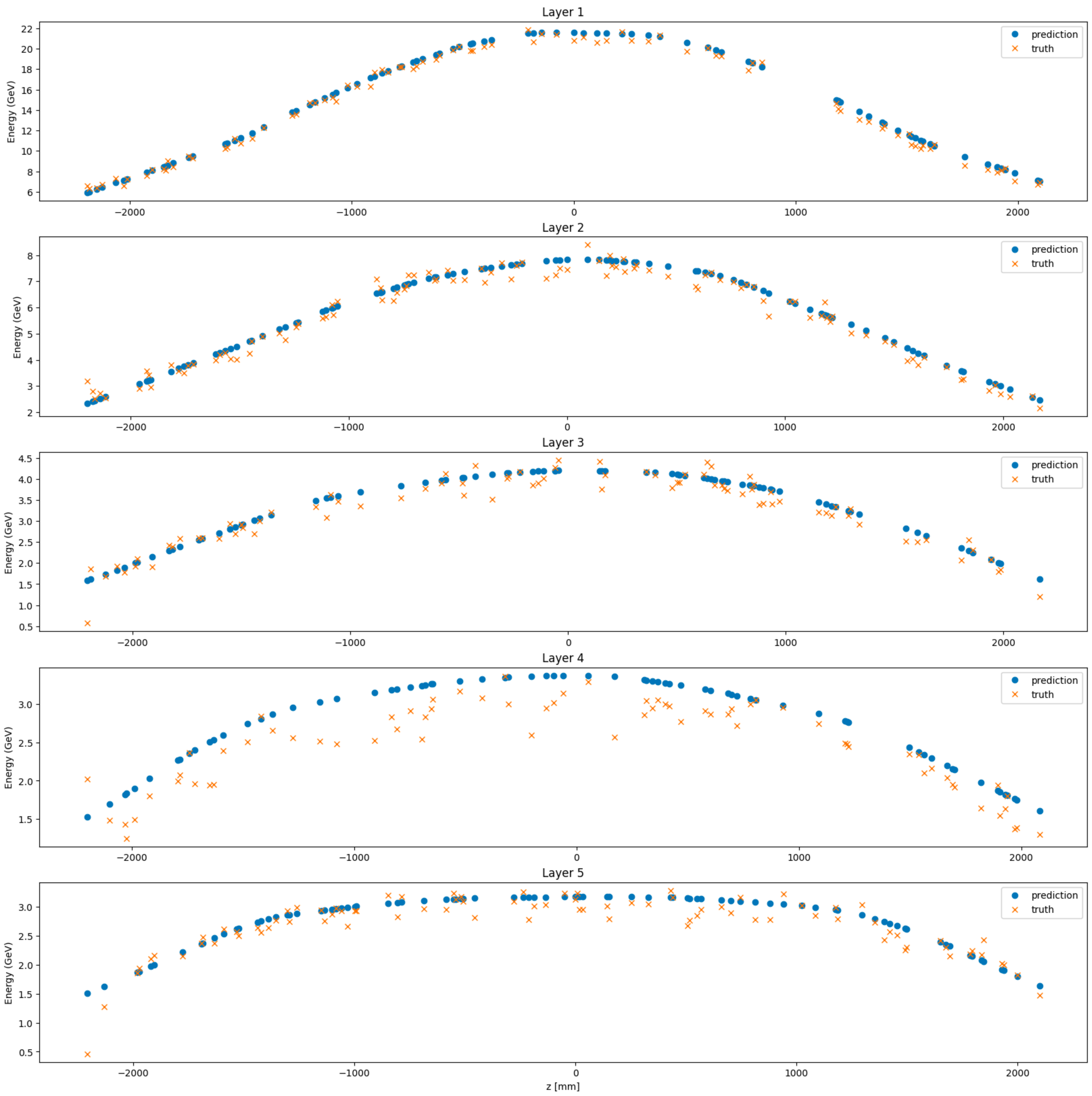


Modules

BIB Generation

- Set up a simple neural network (5 dense hidden layers) to generalize and allow for interpolation

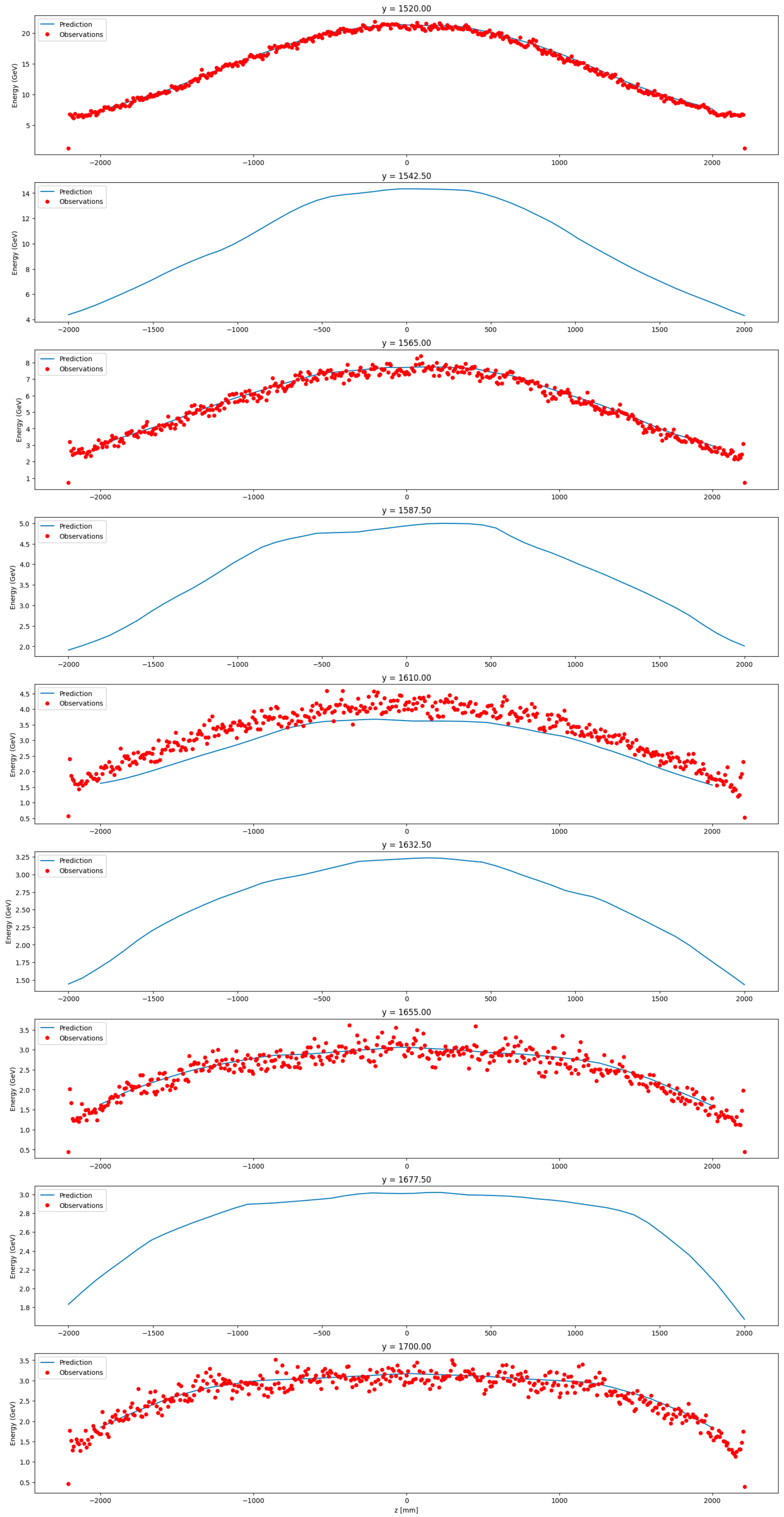
- Trained to predict an energy value for each cell z-centroid



Modules

BIB Generation

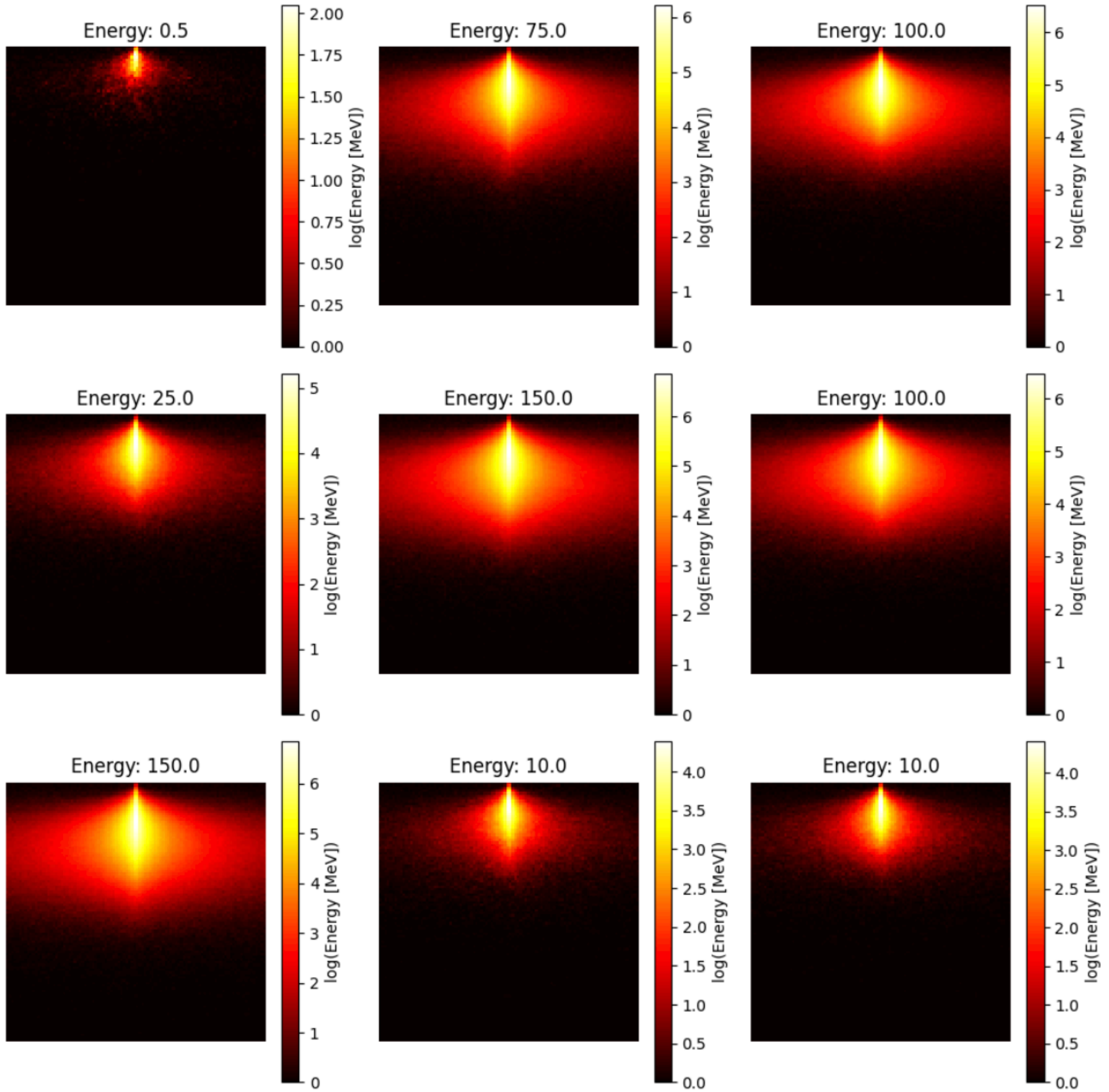
- Decent interpolation between simulated layers
- Visualization in question has been trained on all layers but the central one
- Energy density per cell left as normalization factor



Modules

Shower Generation

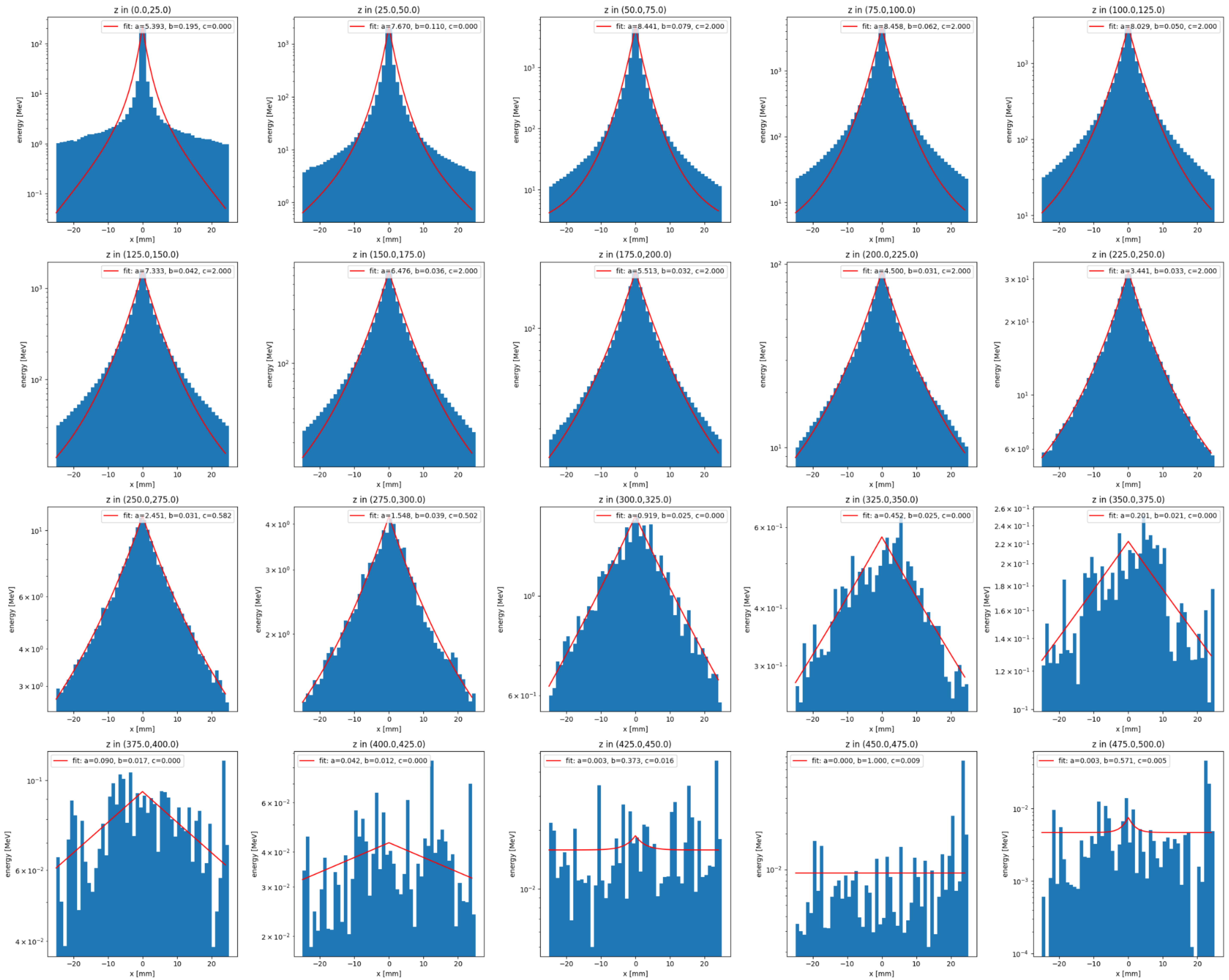
- For our signal chose to focus on monochromatic photons, 8 points in energy: [0.5, 10, 25, 50, 75, 100, 125, 150]GeV
- 1k events for each point generated with Geant4 in a block of PbF2
- Define ‘average event’ bootstrap average of 100 simulated showers
    - 500 average events per energy points
    - Area [-25,25]x[0,500]mm2



Modules

Shower Generation

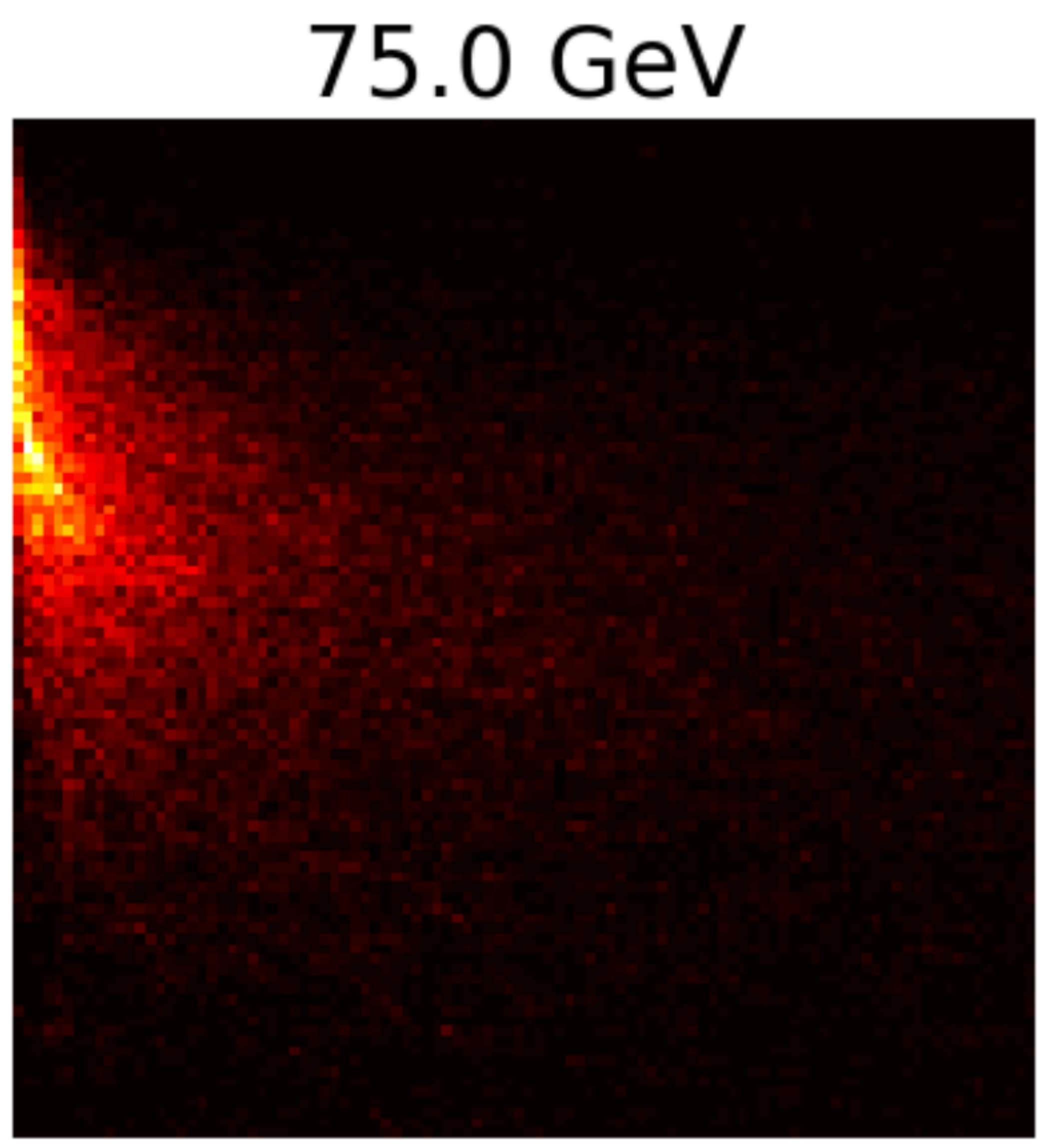
- Exploring different paths:
    - Fitting (x,y) component for each shower axis (z-) bin
    - In parallel testing a WGAN to produce new shower images

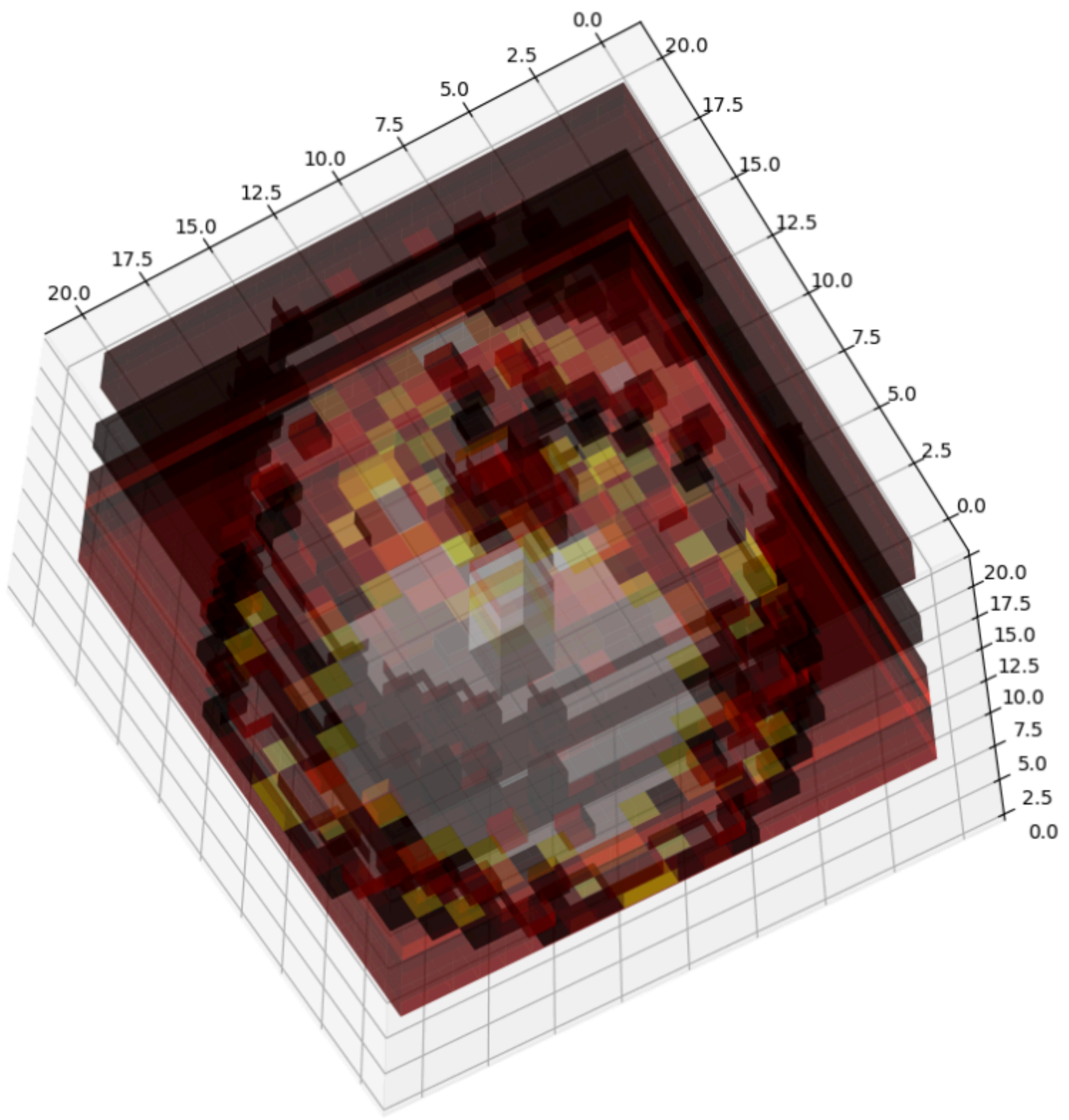


Modules

Shower Generation

- 2D distribution generalized to 3D shape
- Evaluated on a grid with custom dimensions (n_x, n_y, n_z)
- BIB needs to be overlayed on the same grid



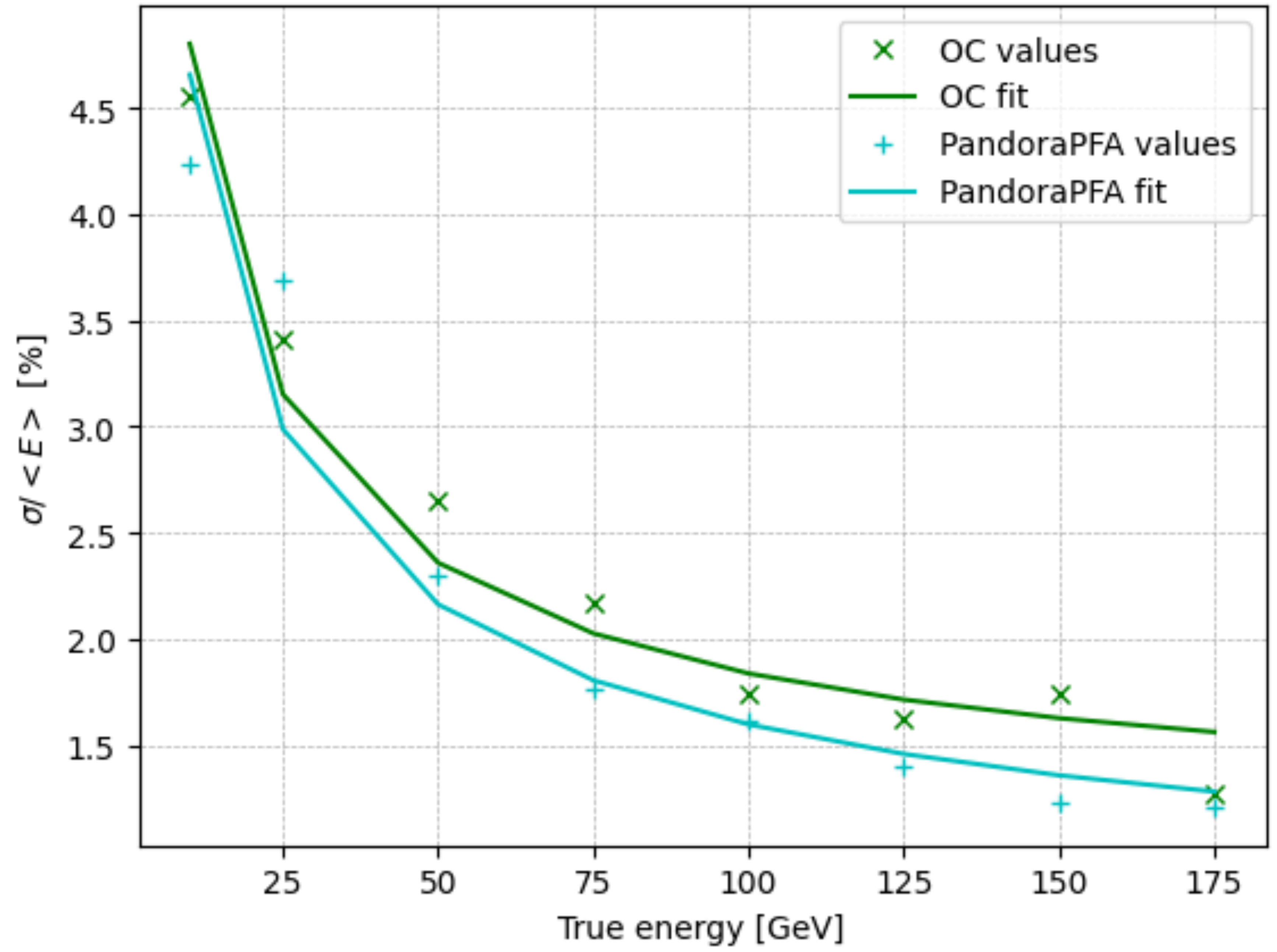


Photon Reconstruction

Where we left

https://arxiv.org/abs/2204.01681

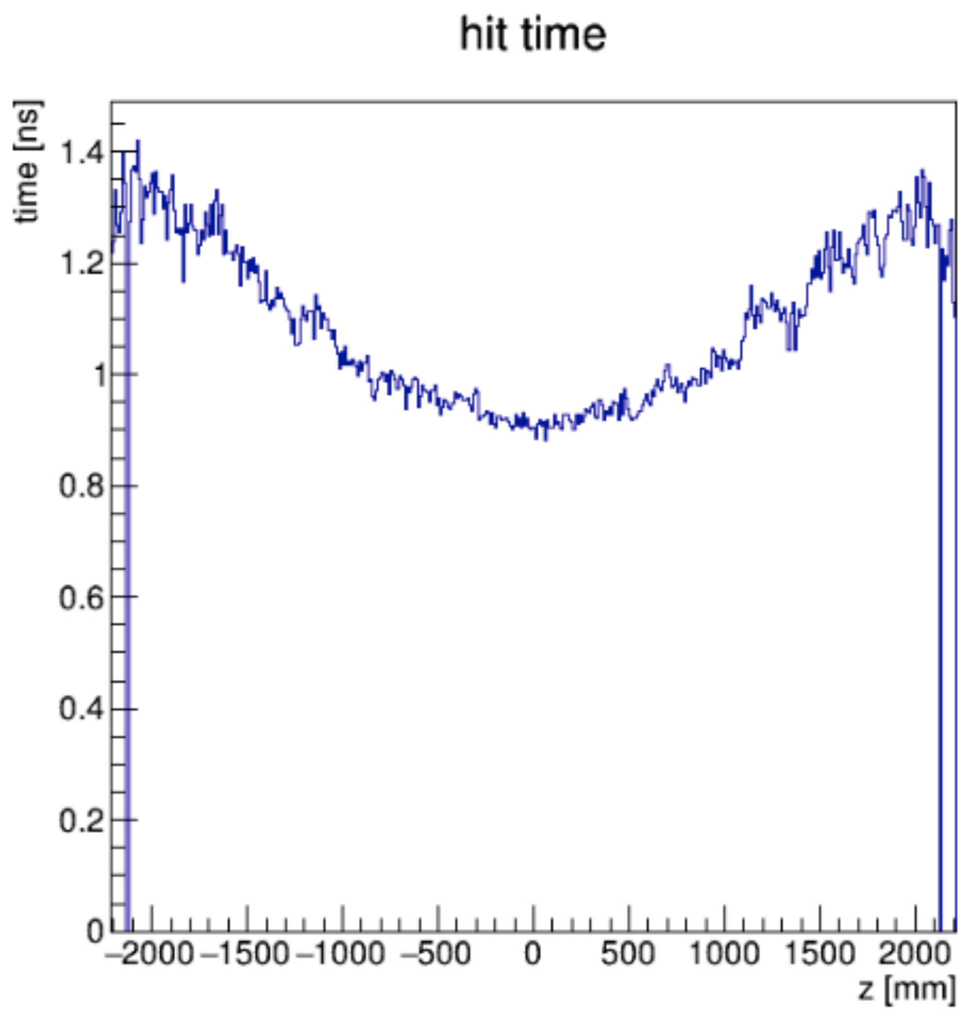
- Employed DeepJetCore for object reconstruction:
  - Essentially a Graph Neural Network performing clustering
  - Signal photon vs BIB discrimination
  - Trained on 10k photons uniformly distributed in [10, 175]GeV
  - Tested on 8 fixed energy points
  - Reconstruct photon energy given cell coordinates (x,y,z) and total deposit

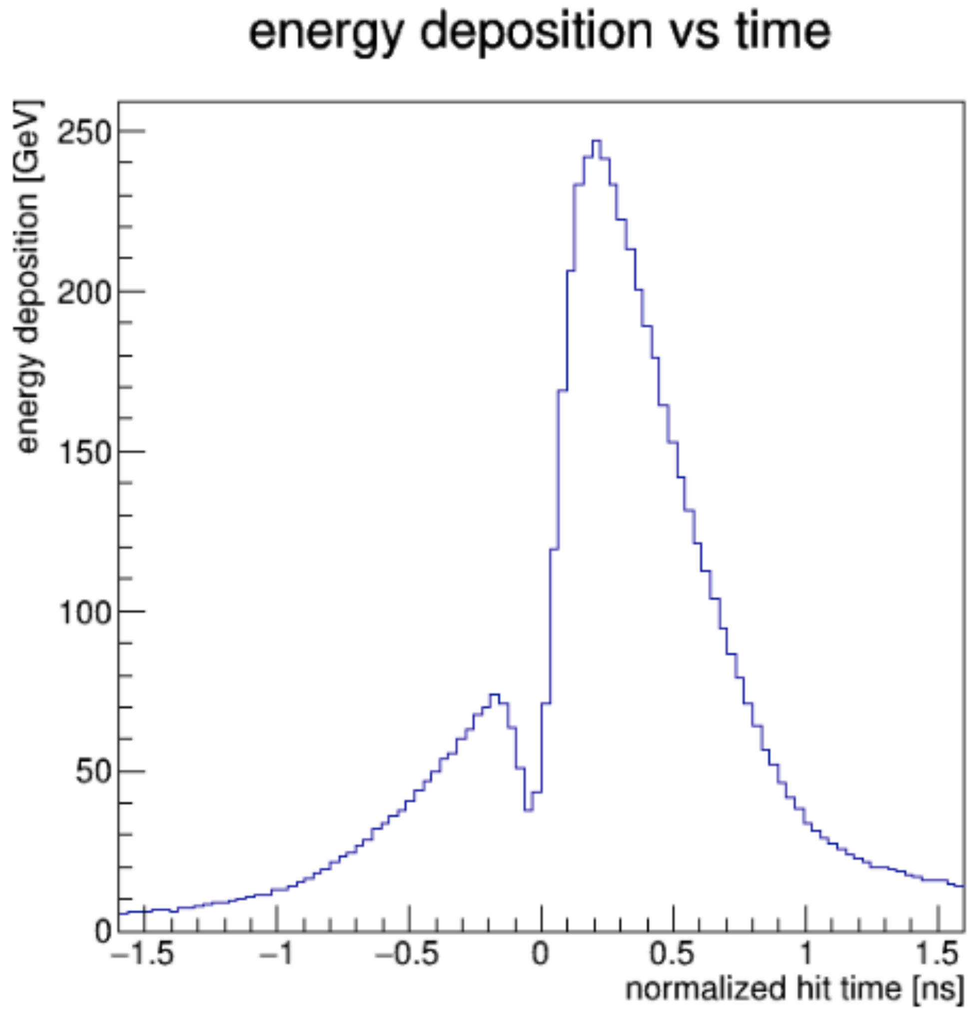


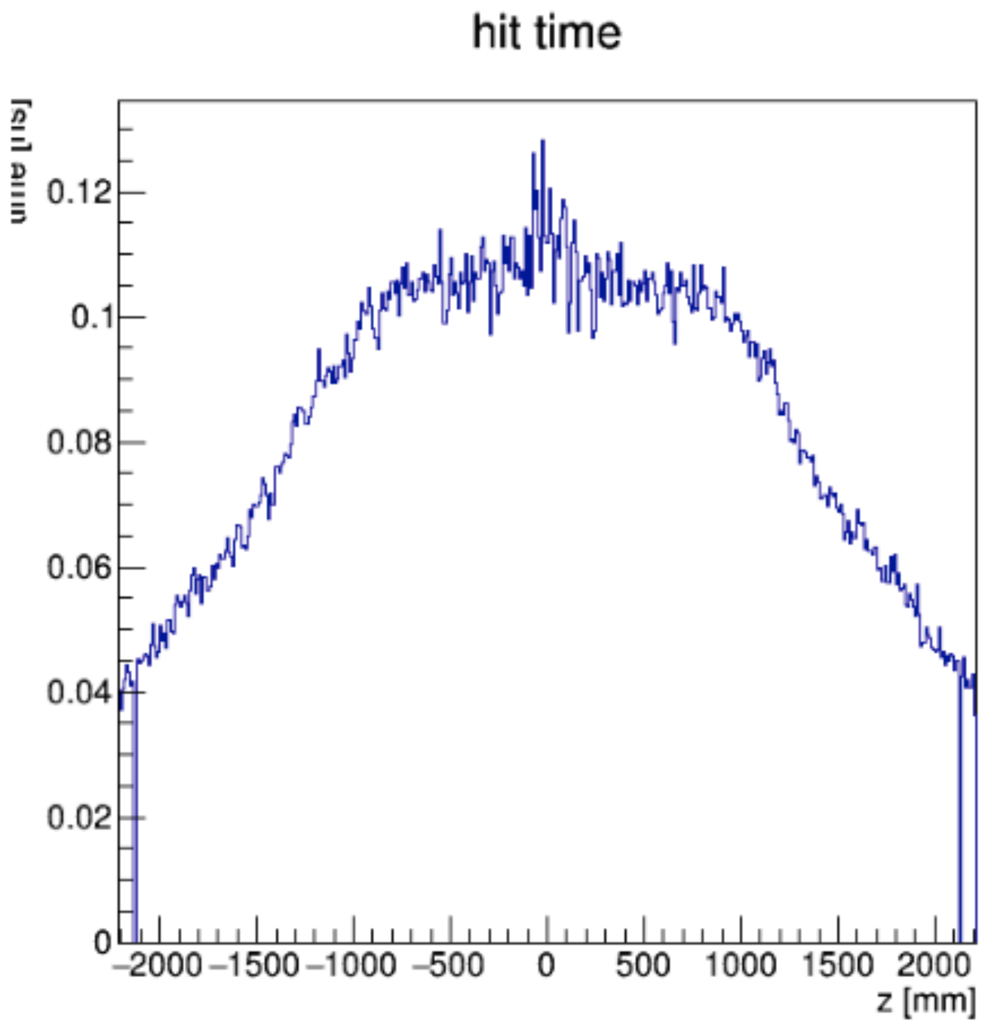
Photon Reconstruction

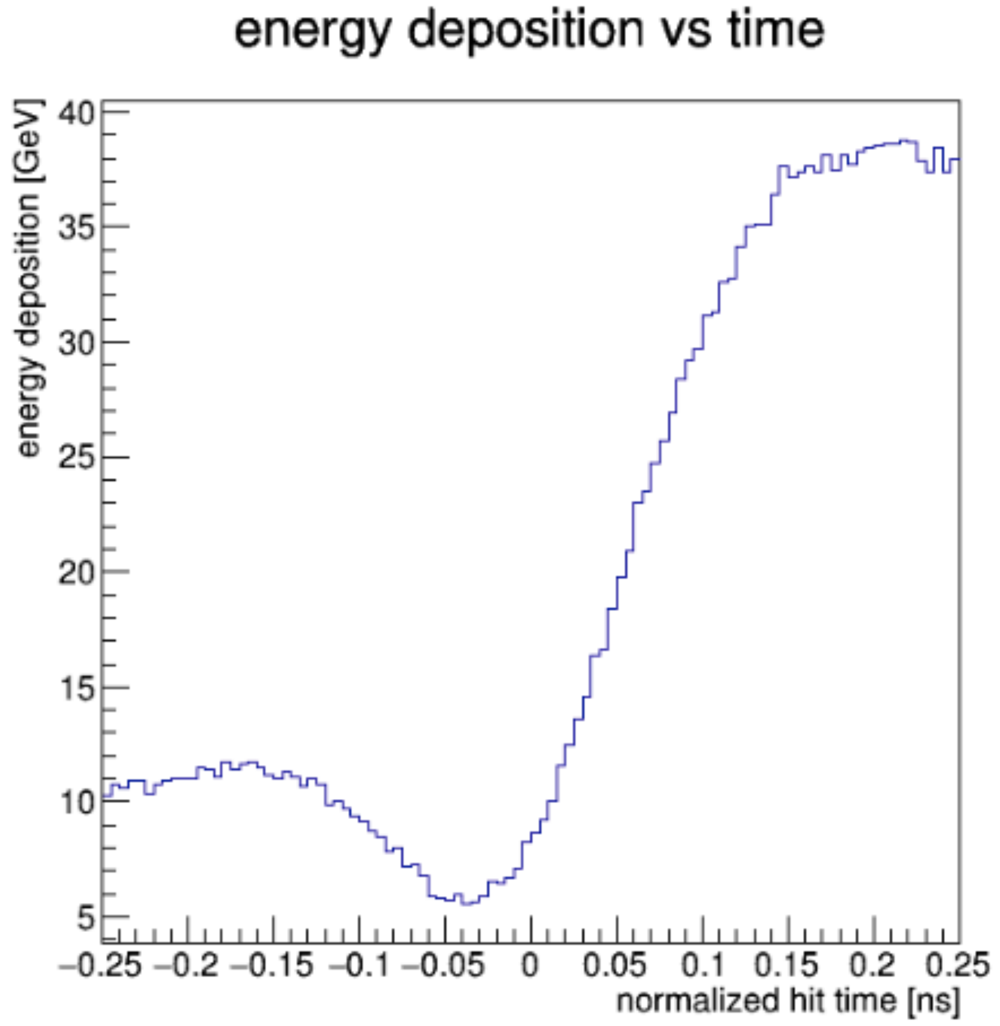
Adding time variables

- Result obtained with overlay of full BIB and shower dataset, without time information
- Introduce time into the game
  - First by implementing the time window [-250,250]ps in the overlay
- Train 2 models
  - With cut and (t,x,y,z) inputs
  - With cut and only (x,y,z) inputs





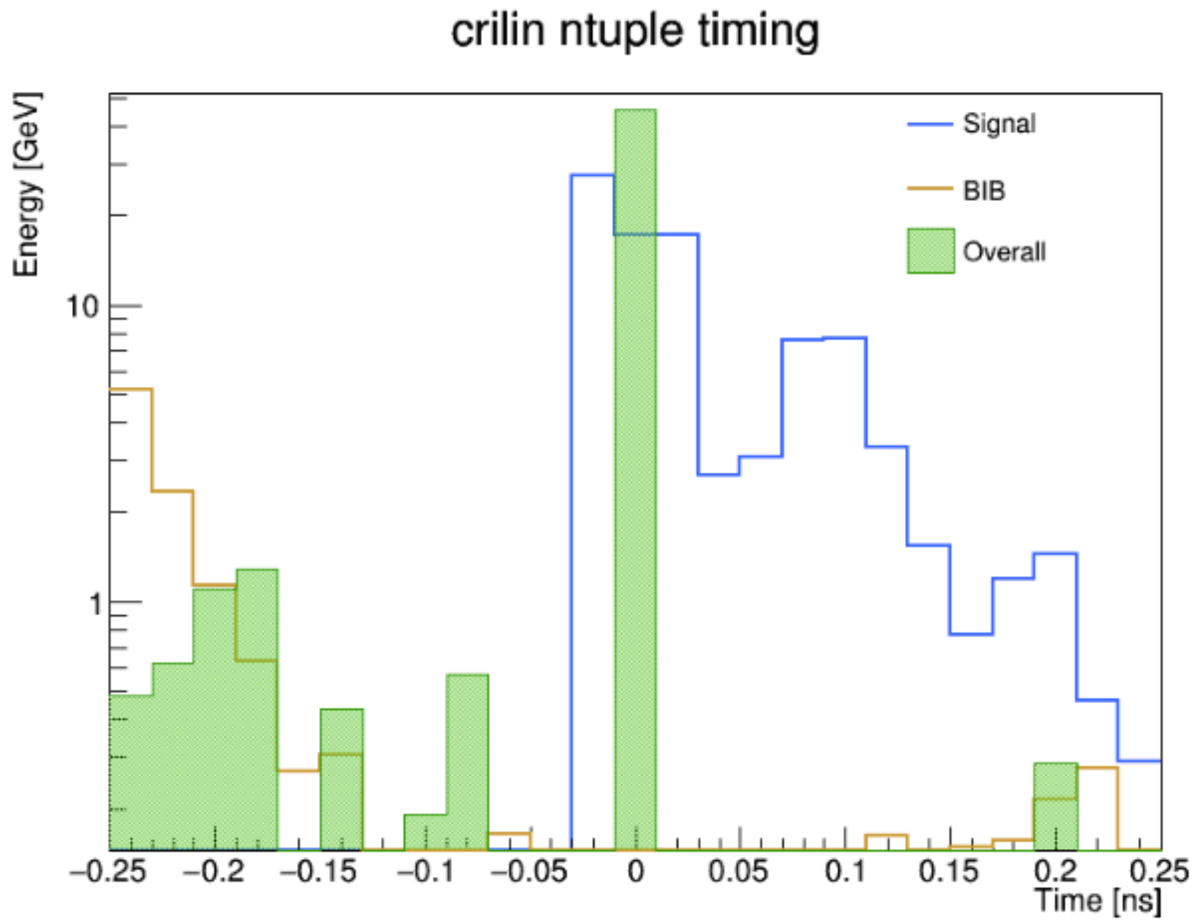


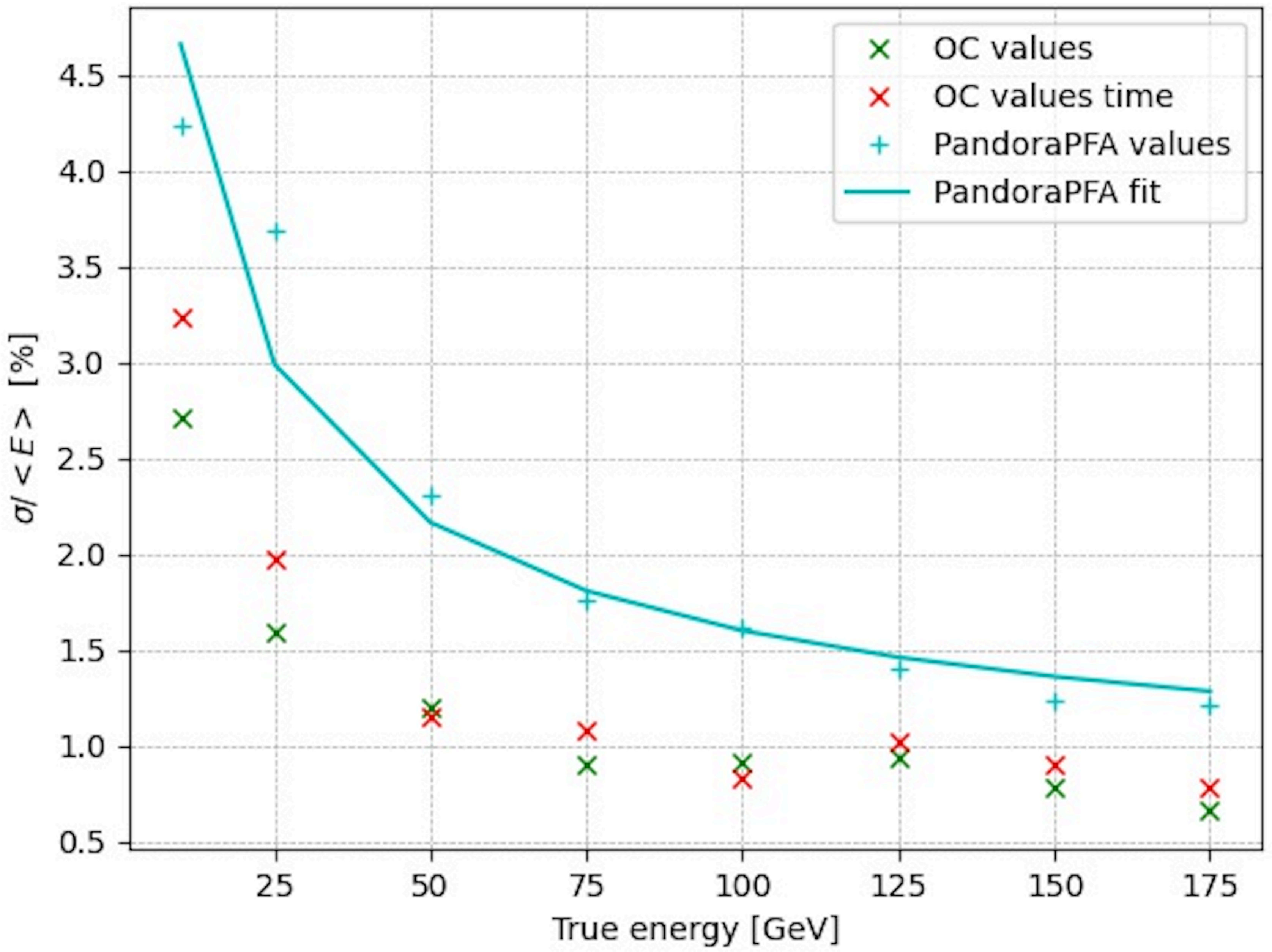


Photon Reconstruction

Introducing time

- Significant performance improvement
- Time variable seems to introduce noise
    - However might be due to some bug in the overlay of time variable





Towards full pipeline

Toy steps

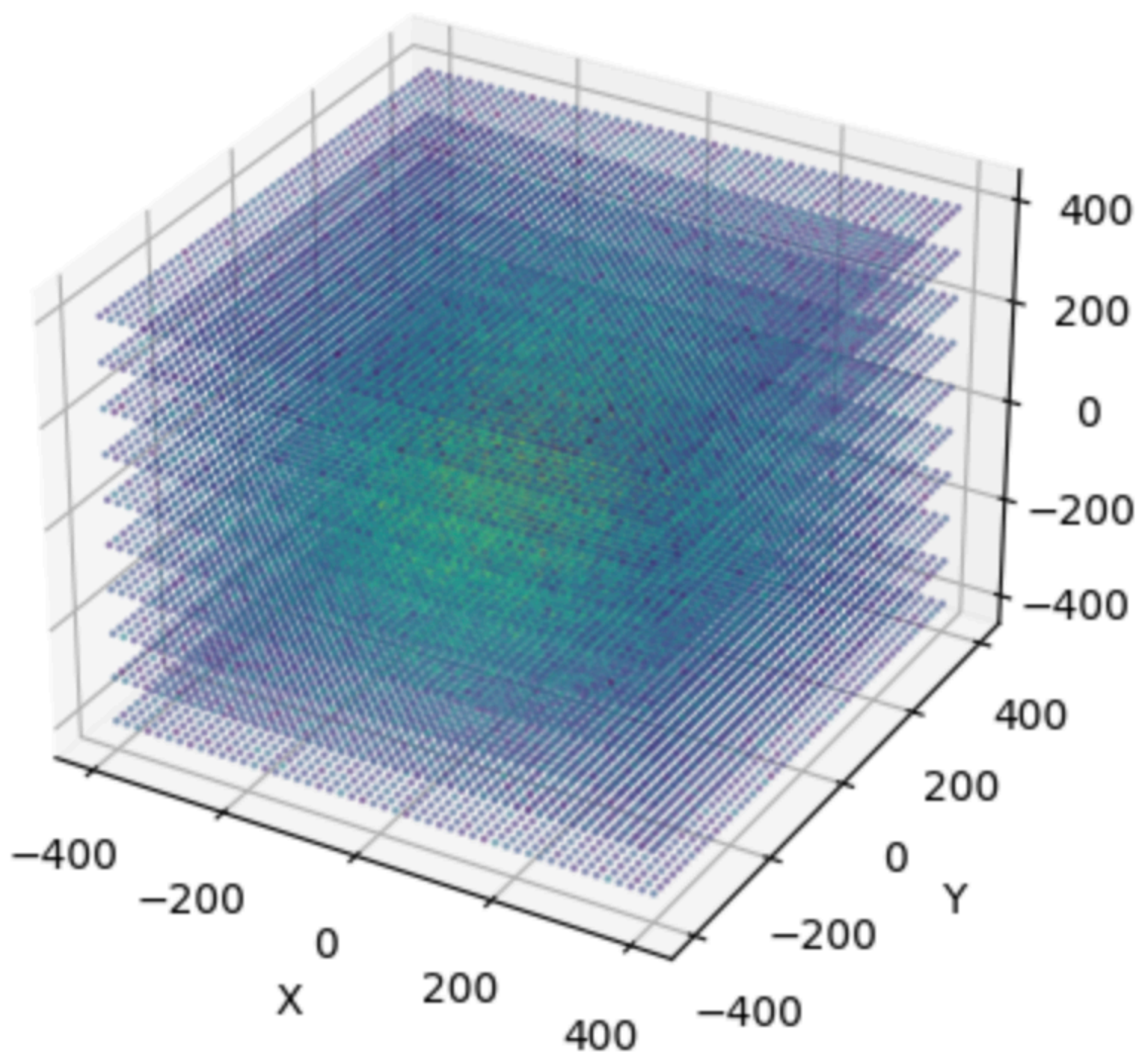
- Idea: represent Crilin detector as a 3D grid of voxels, and optimizing the spacing (Δx,Δy,Δz) between them.

- Started to work on a toy model:

  - **Defining the geometry**: simple 3D grid with custom # voxels

  - **Evaluating a function on the grid**: 3D gaussian with $\sigma_x \neq \sigma_y \neq \sigma_z$ + random noise

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




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

Muon Collider

Towards setting up a pipeline

- **Reconstruction**: Use maximum-likelihood estimators to infer the gaussian parameters $\hat{\mu}, \hat{\sigma}$
- **Evaluating loss:** MSE for gaussian parameters + regularizer to prevent spacing to collapse towards degeneracy

$$\sum_{i=x,y,z} (\hat{\mu}_i - \mu_i)^2 + (\hat{\sigma}_i - \sigma_i)^2 + \frac{1}{\Delta x_i^2}$$

- **Minimization** of loss and identification of ideal parameters

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Initial spacing:  [1.0   1.0   1.0]
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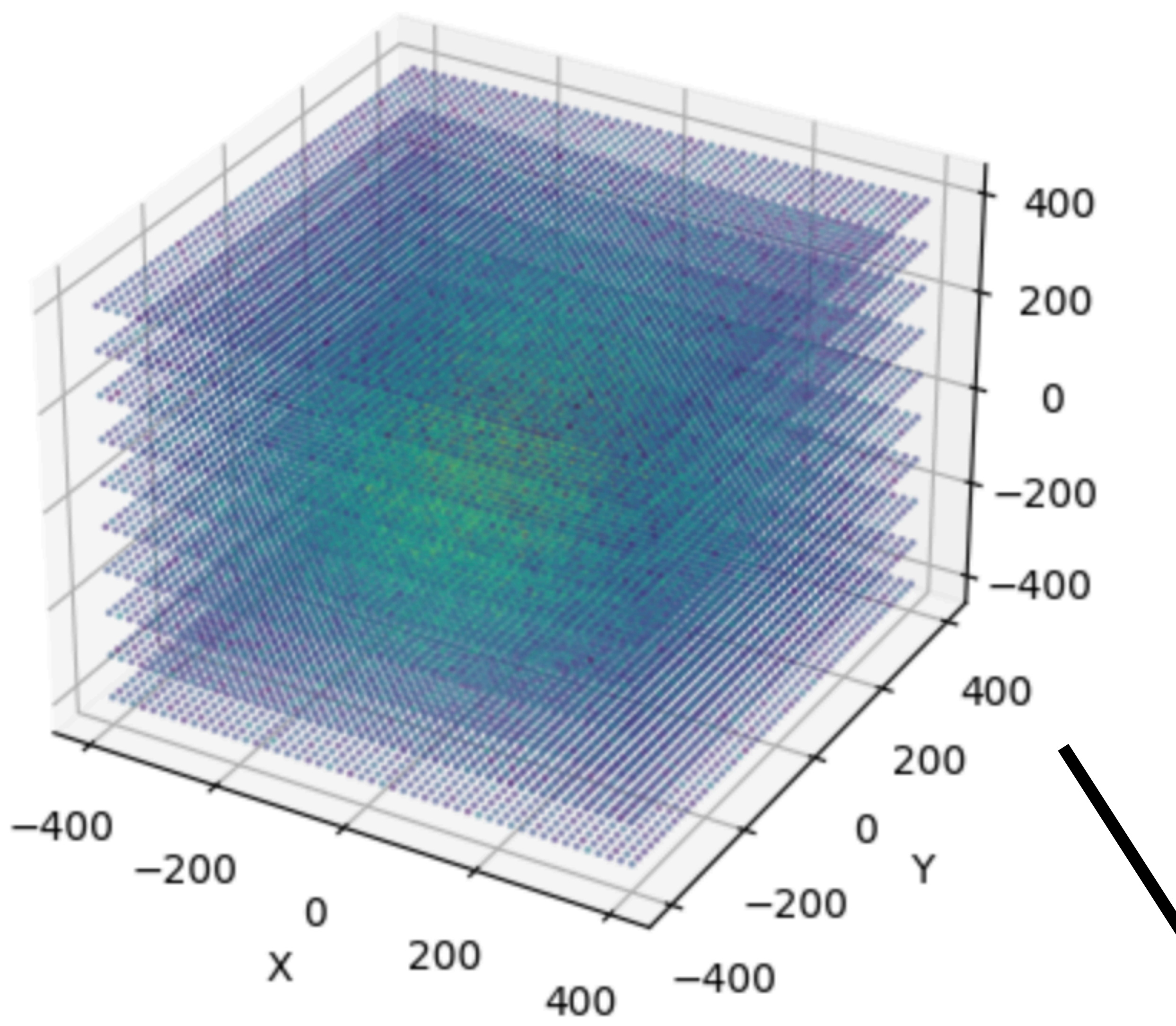
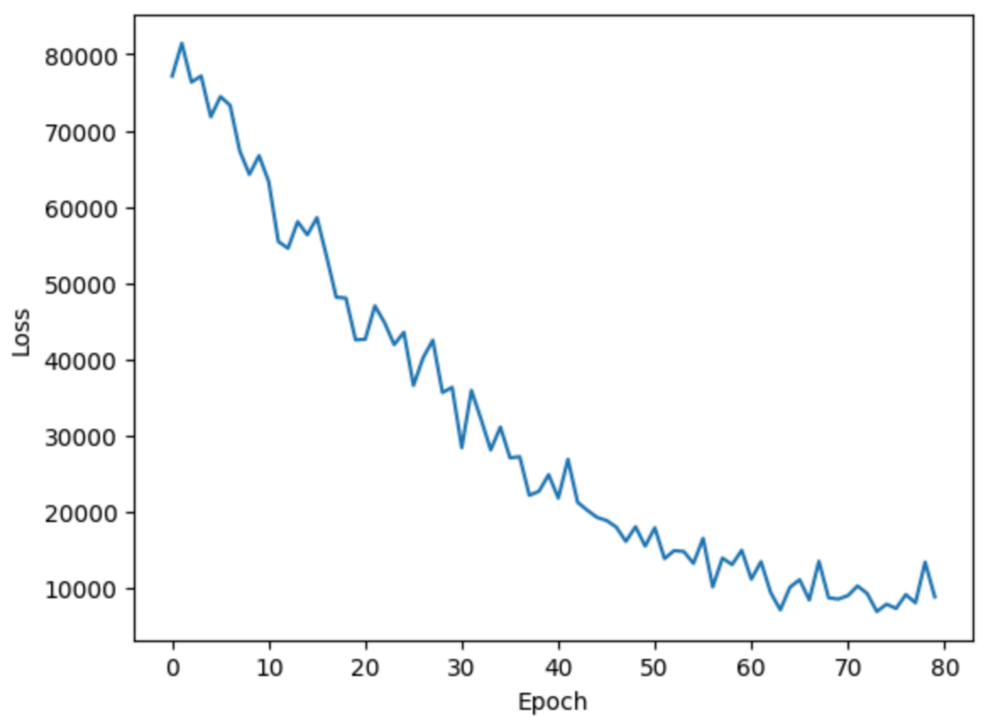
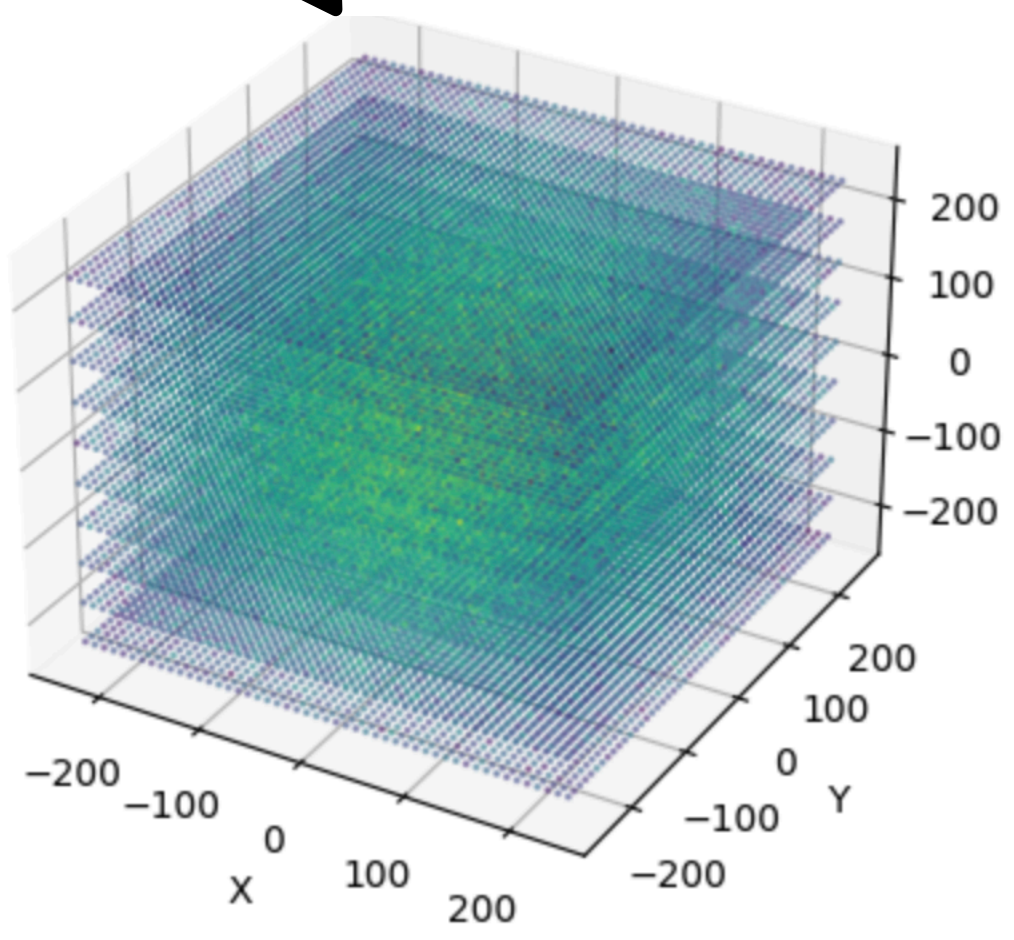


100 epochs
Lr = 0.001






```
Final spacing:  [0.47563136 0.5433373  0.44885612]
```

Summary and further steps

- Simplifying the Object Reconstruction to regress a signal fraction per voxel
    - Less computationally demanding, enough for our simplified problem with single photons
- Generate a signal+BIB dataset with different voxel sizes to train the reconstruction including those parameters (parametric ML)
- Connect all modules and run the full pipeline

Thank you!