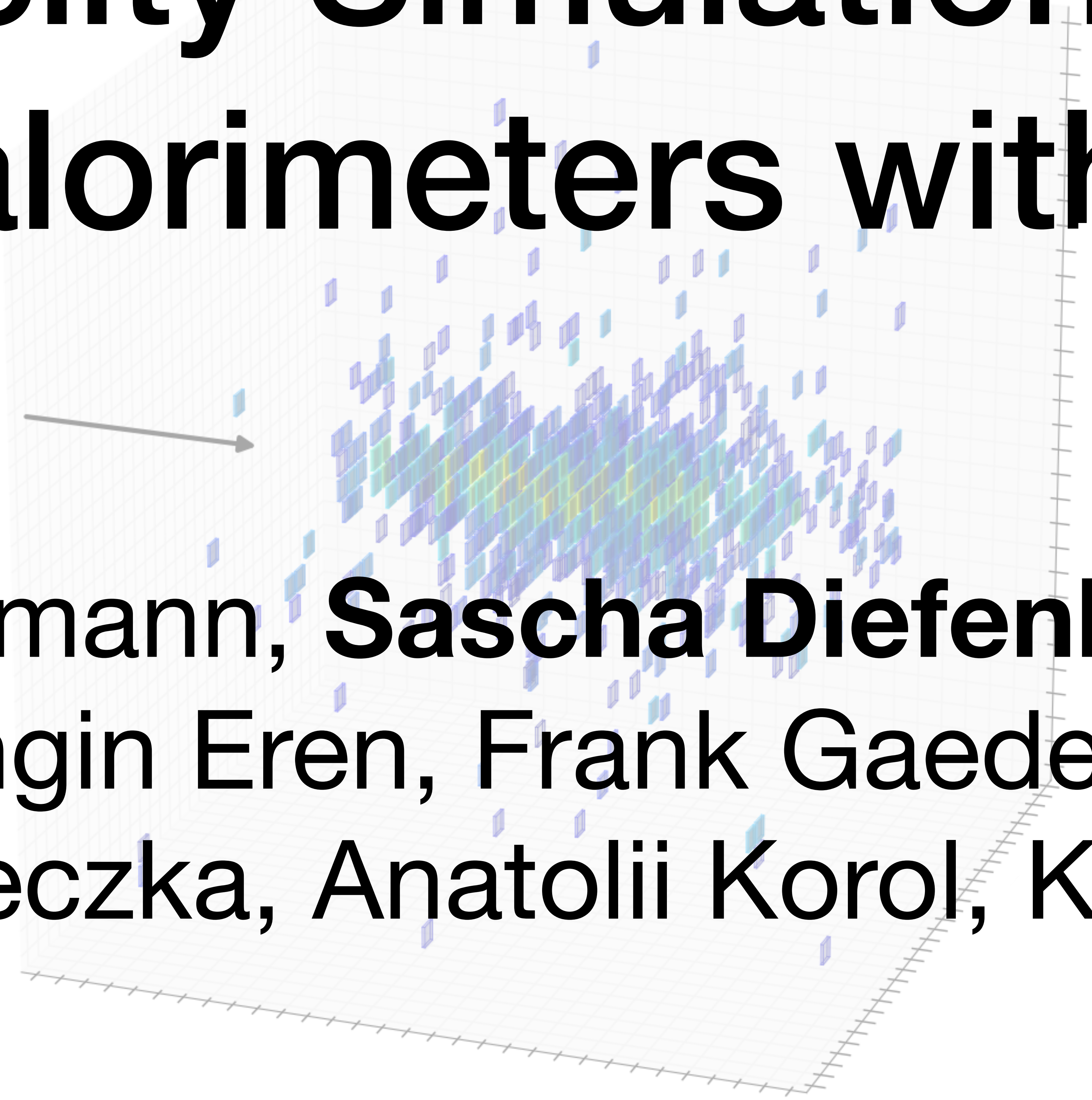
High Fidelity Simulation of High Granularity Calorimeters with High Speed



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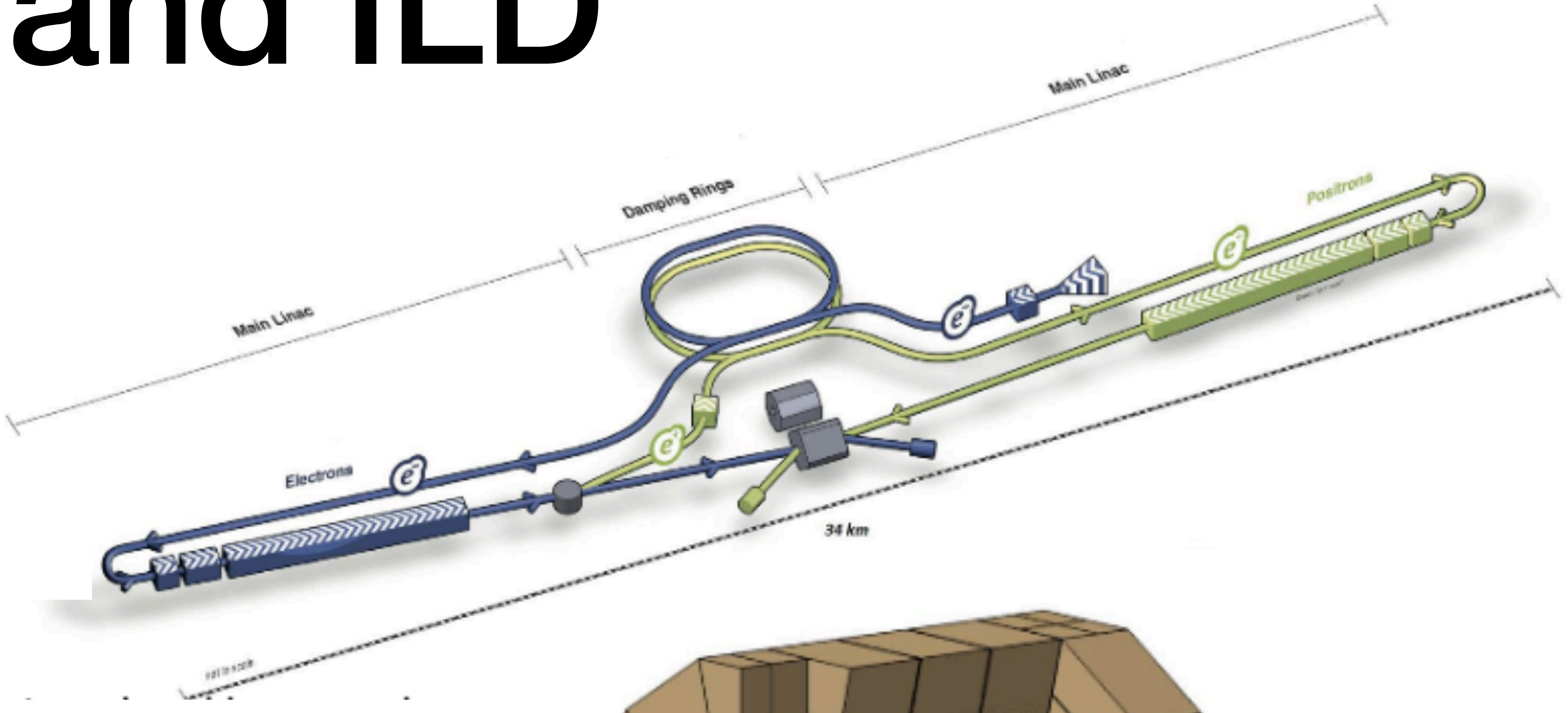
based on 2005.05334

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

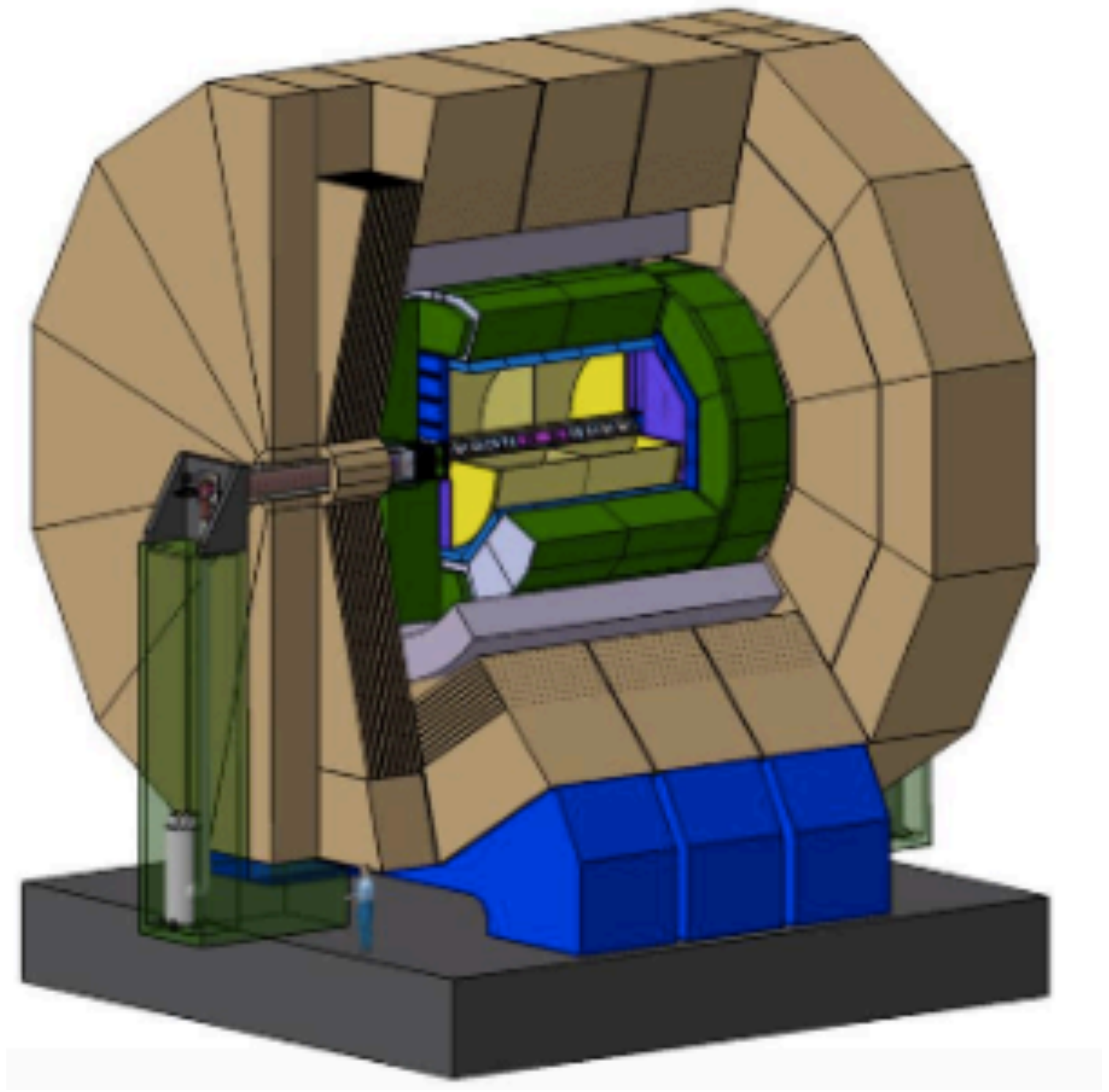
CLUSTER OF EXCELLENCE
QUANTUM UNIVERSE

ILC and ILD

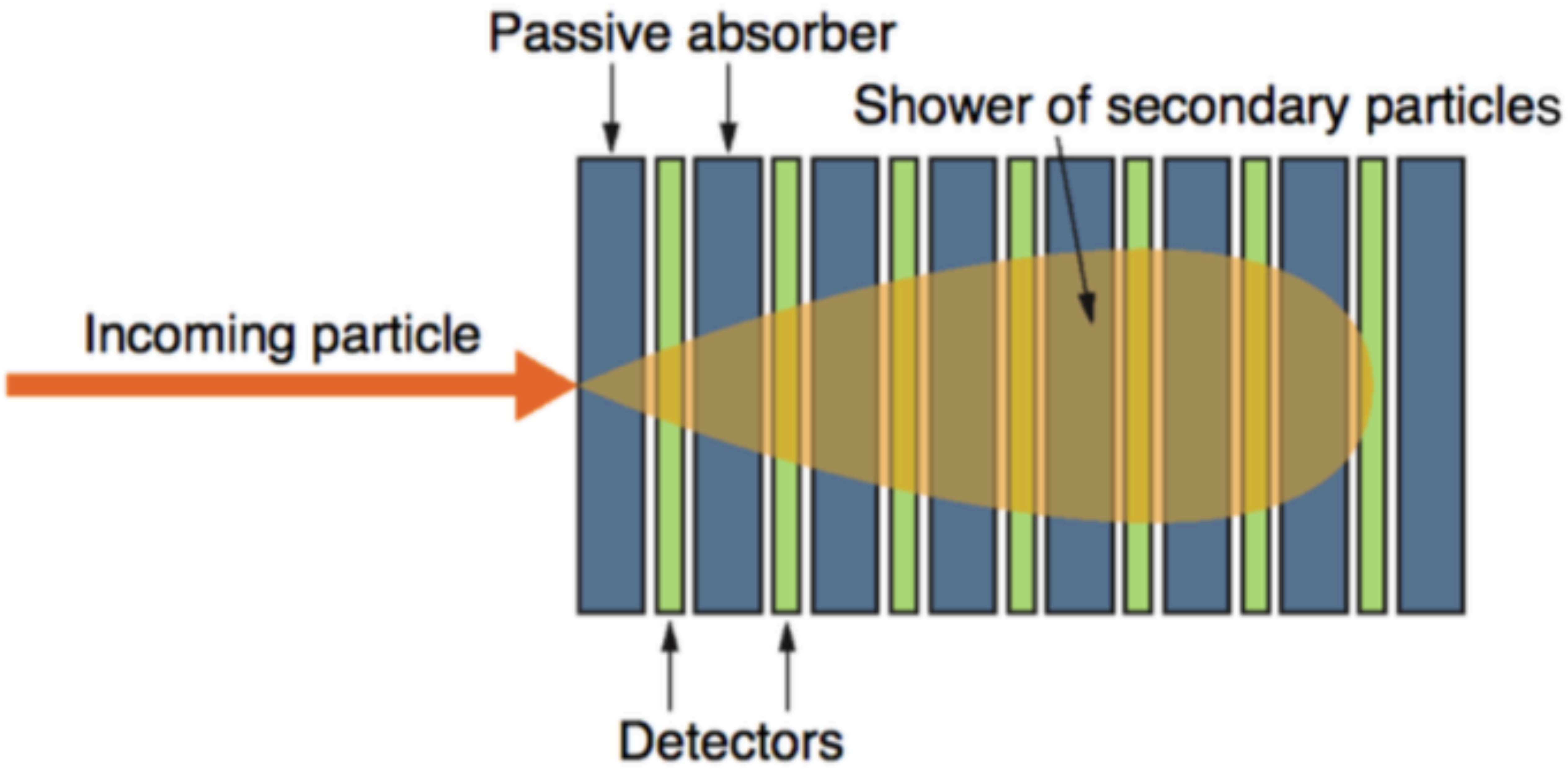
- International Linear Collider
  - Planned electron-positron collider
  - Initial 250 GeV center of mass energy
  - Designed for high luminosity



- International Large Detector
  - Proposed detector of the ILC
  - Features highly granular ECal and HCal



ILD ECal

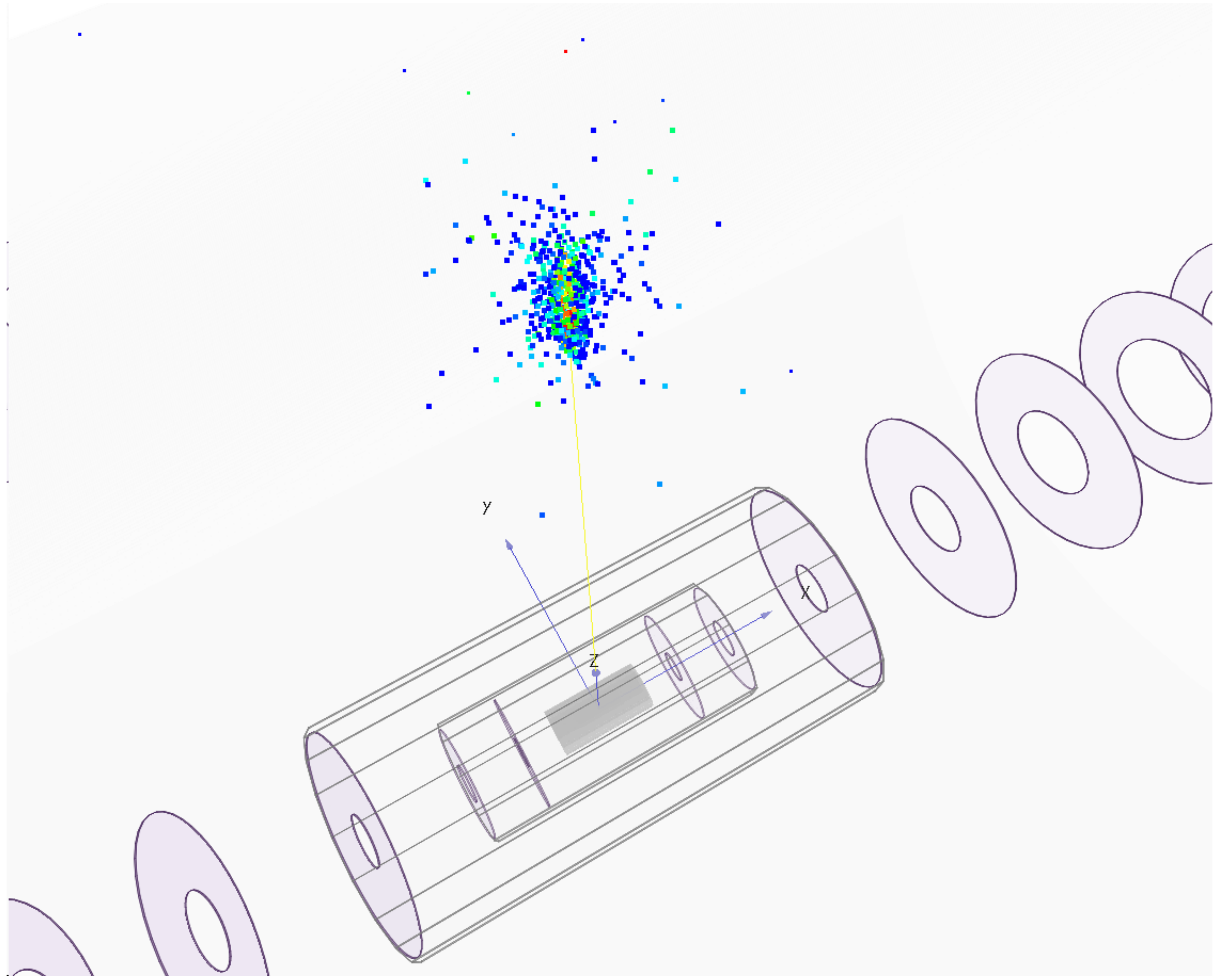


- Highly granular sampling calorimeter
  - Silicon, tungsten layers
  - Retains spacial information of shower
  - Only fraction of particle energy measured
  - 30 layers, 5mm x 5mm cells

Shower Simulation

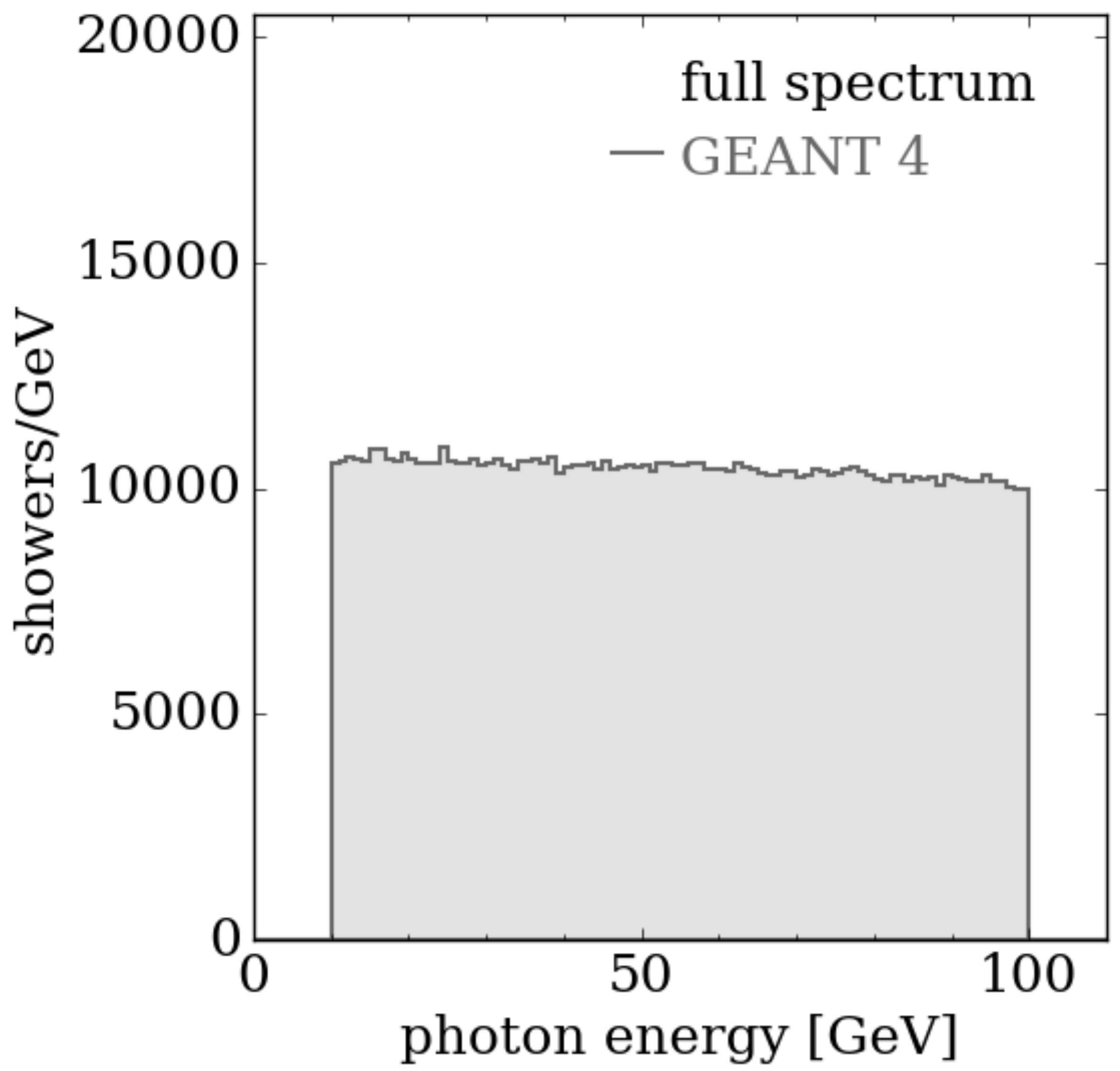
Simulator	Hardware	Batchsize	Time/shower*
GEANT4	CPU	N/A	4082 ± 170 ms

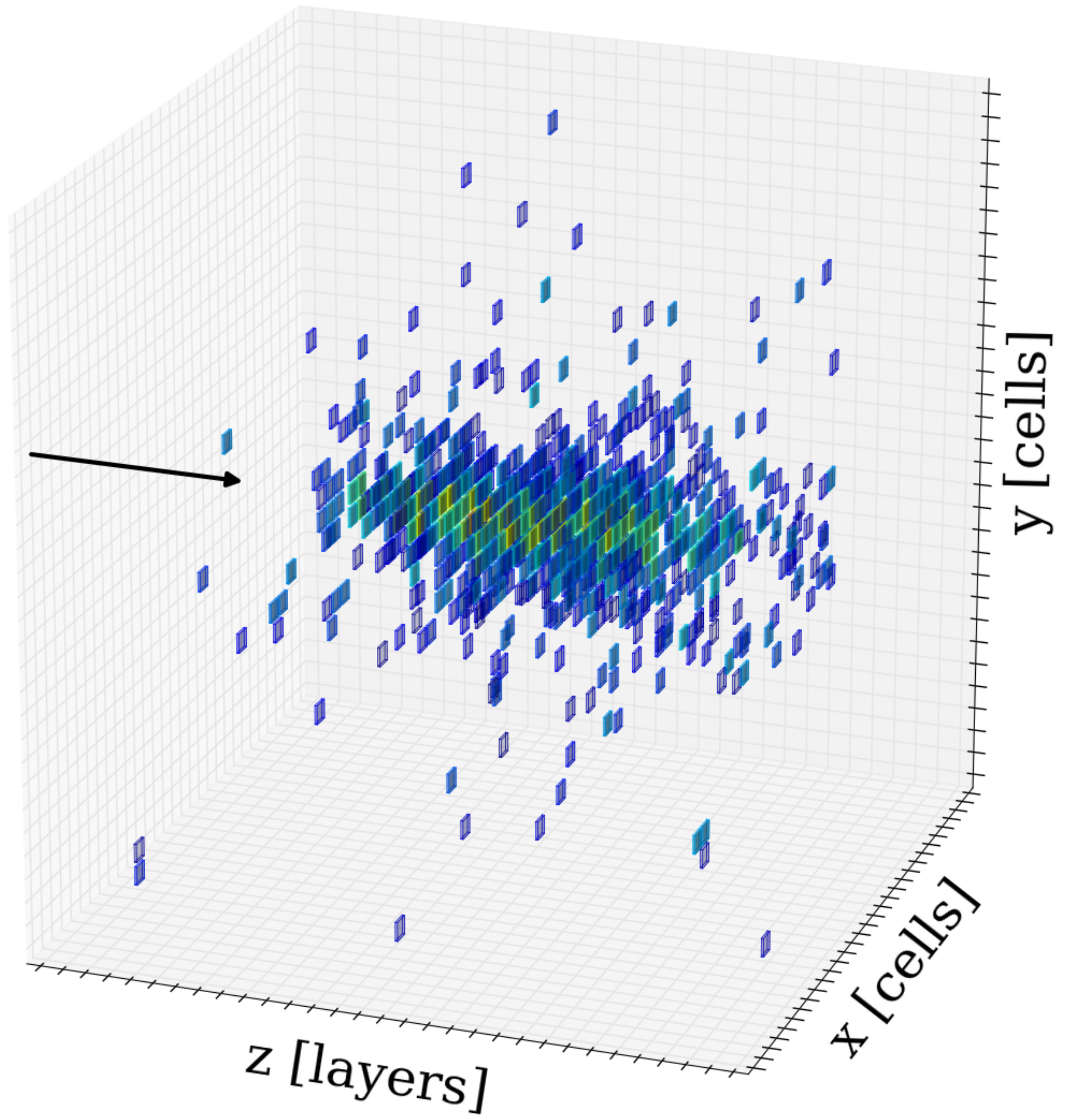
- Classically done using GEANT4
- First principle simulation modelling individual particle interactions
- Very computationally expensive
- Timing even more significant for higher luminosities
- Simulation can be sped up using generative models



* average time for 10-100 GeV showers

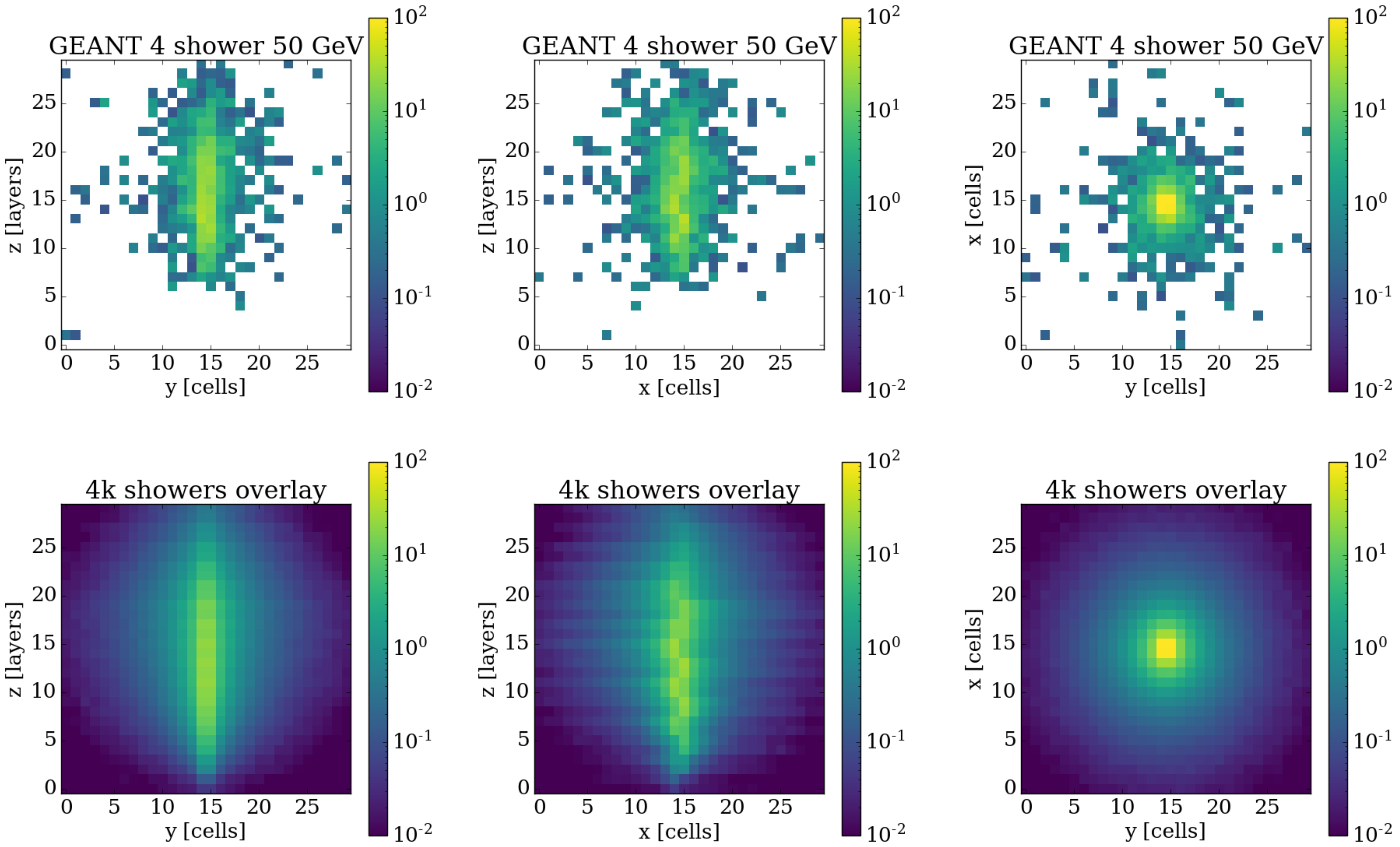
Training Dataset

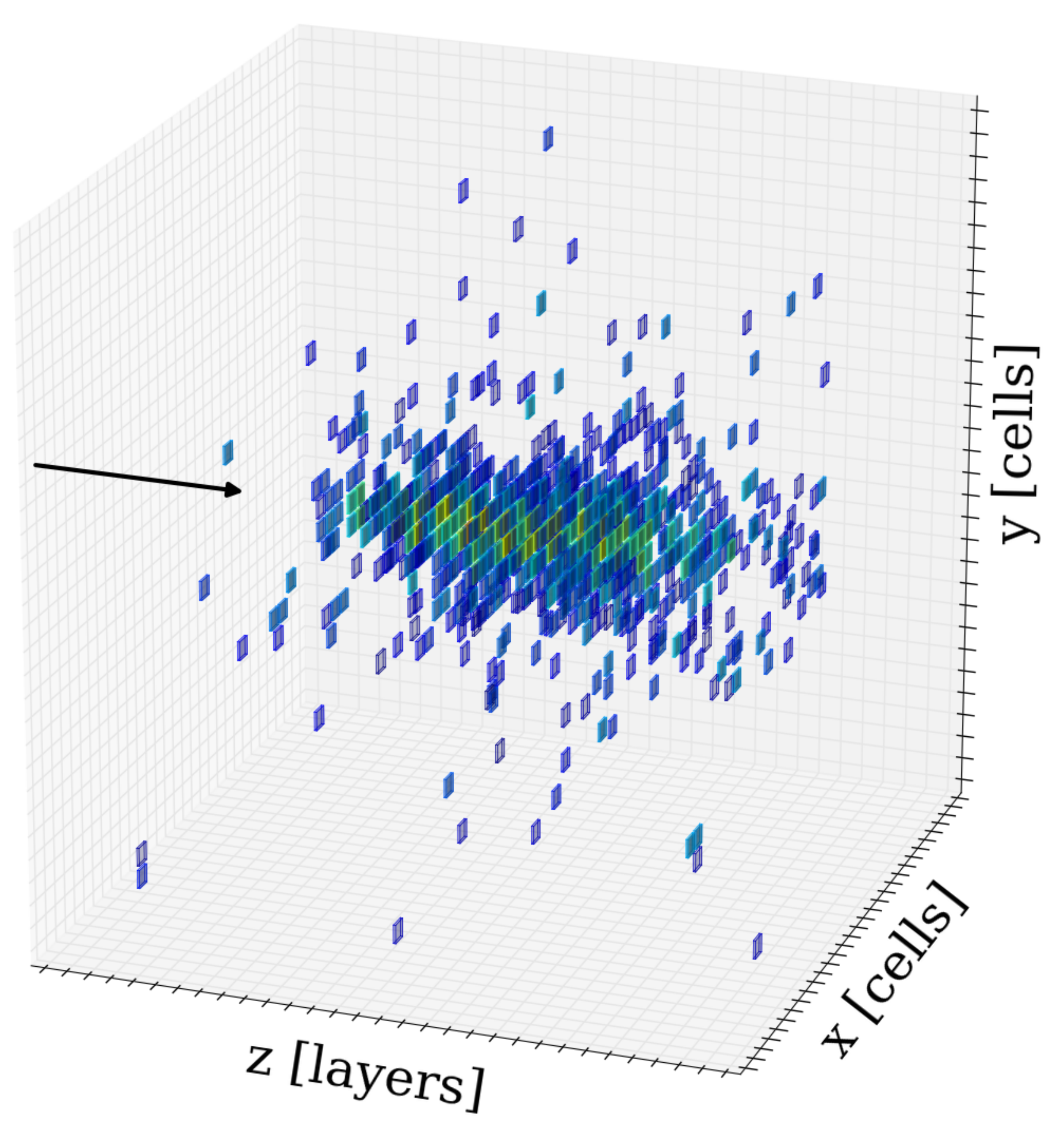




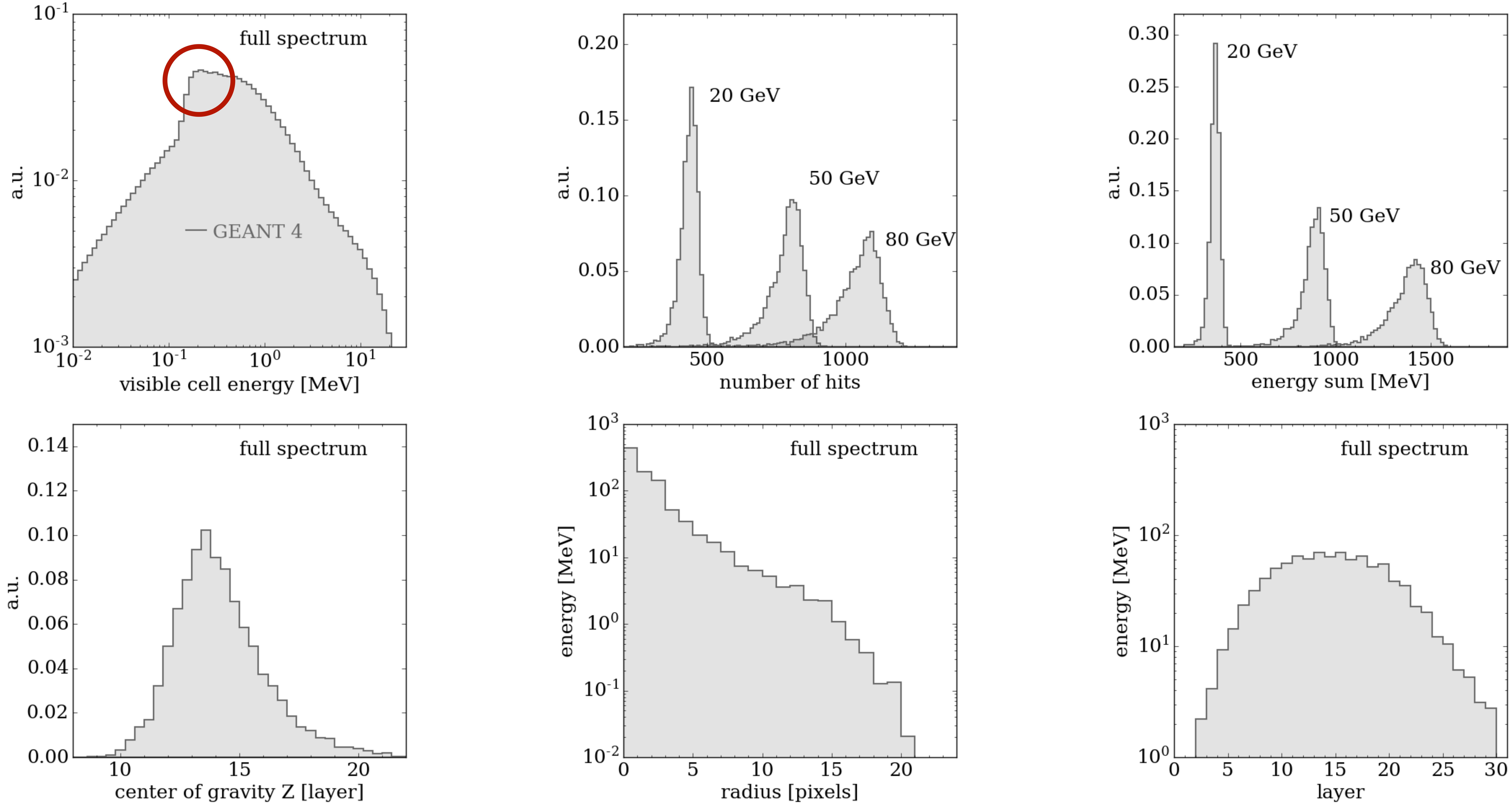
- 950k photon showers
- Continuous incident energy from 10 GeV to 100 GeV
- Constant incident point and angle
- Each shower 30x30x30 image

Training Dataset



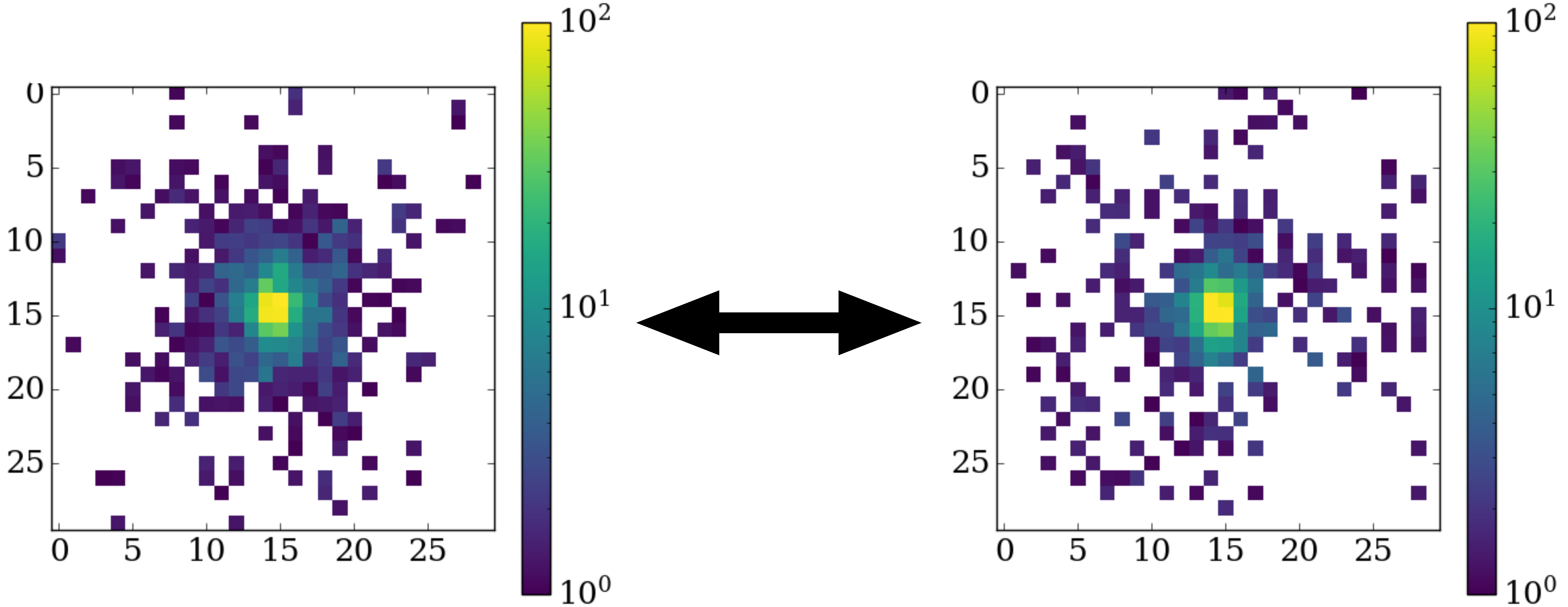


Training Dataset



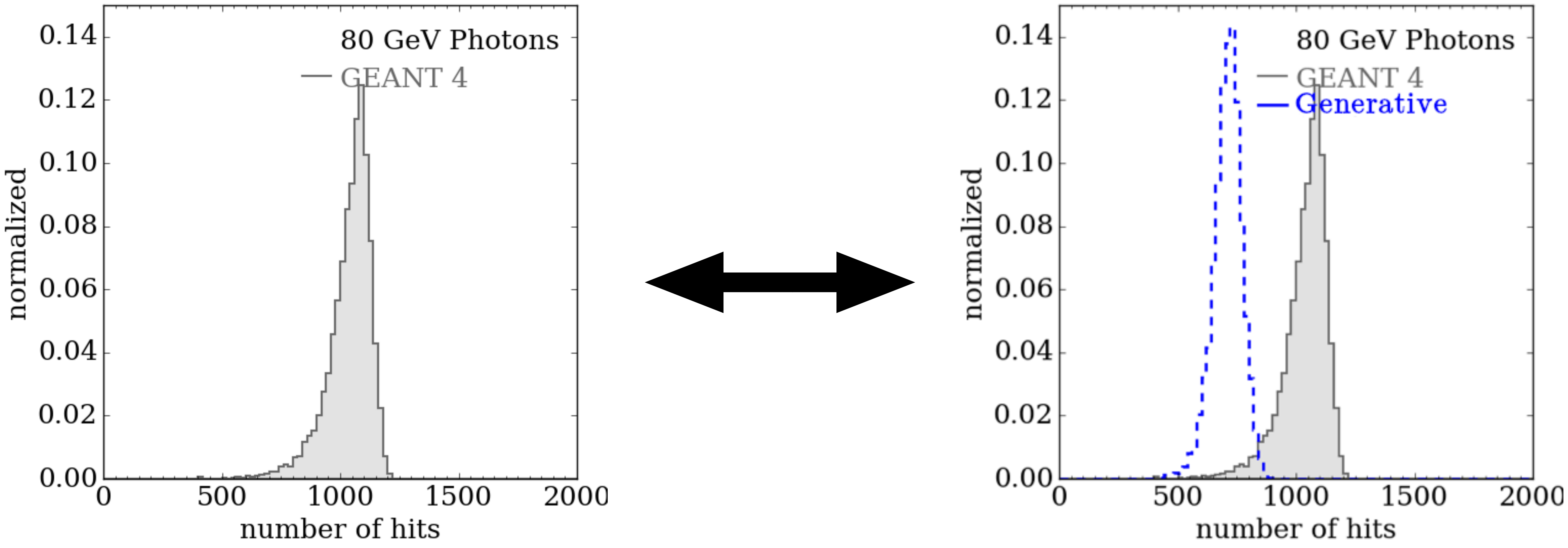
Difficulties

- Loss function (optimisation objective)
    - Intuitive for classification tasks with labels
    - Complex issue for generative models:
    - How to measure EM-shower-ness?

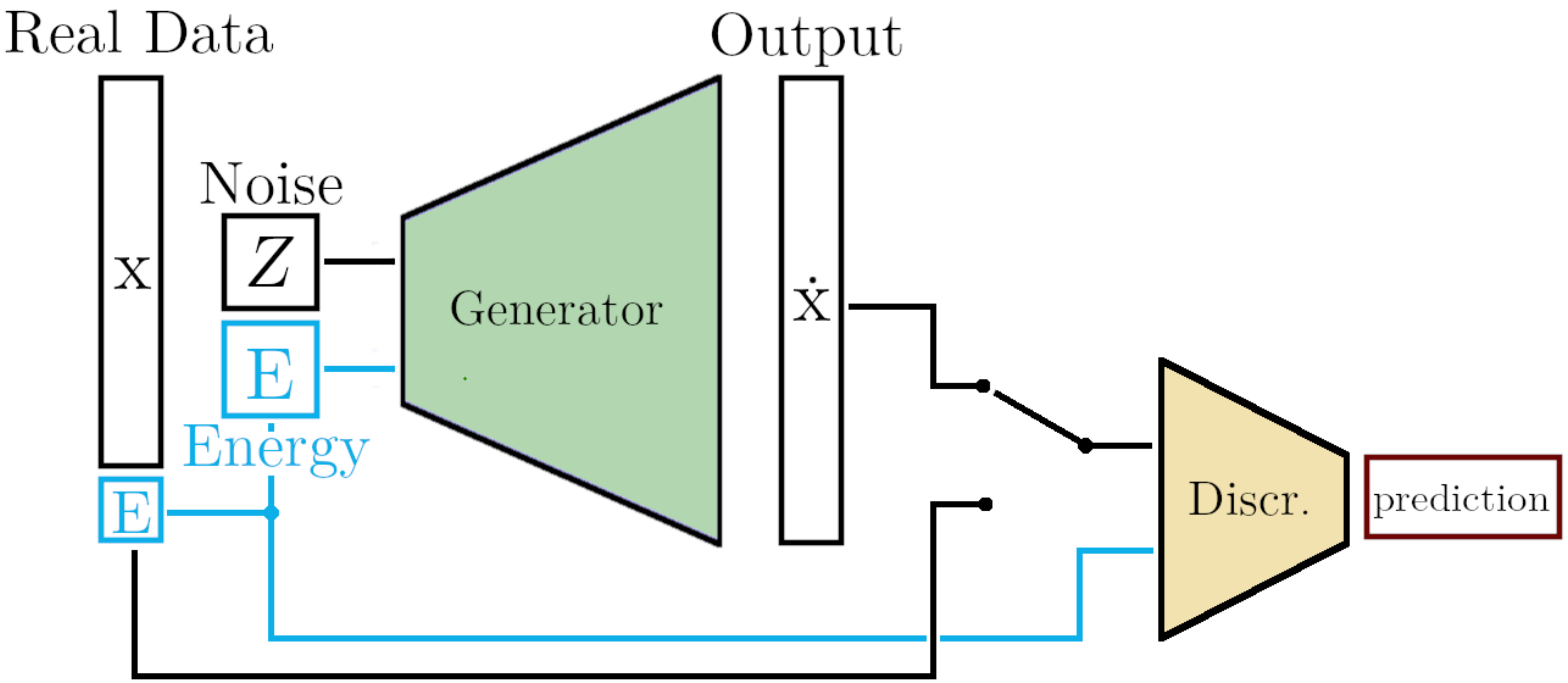


Difficulties

- Global features
  - Insufficient to produce well looking individual showers
  - Also needs to reproduce global distributions
  - E.g. number of active pixels/hits



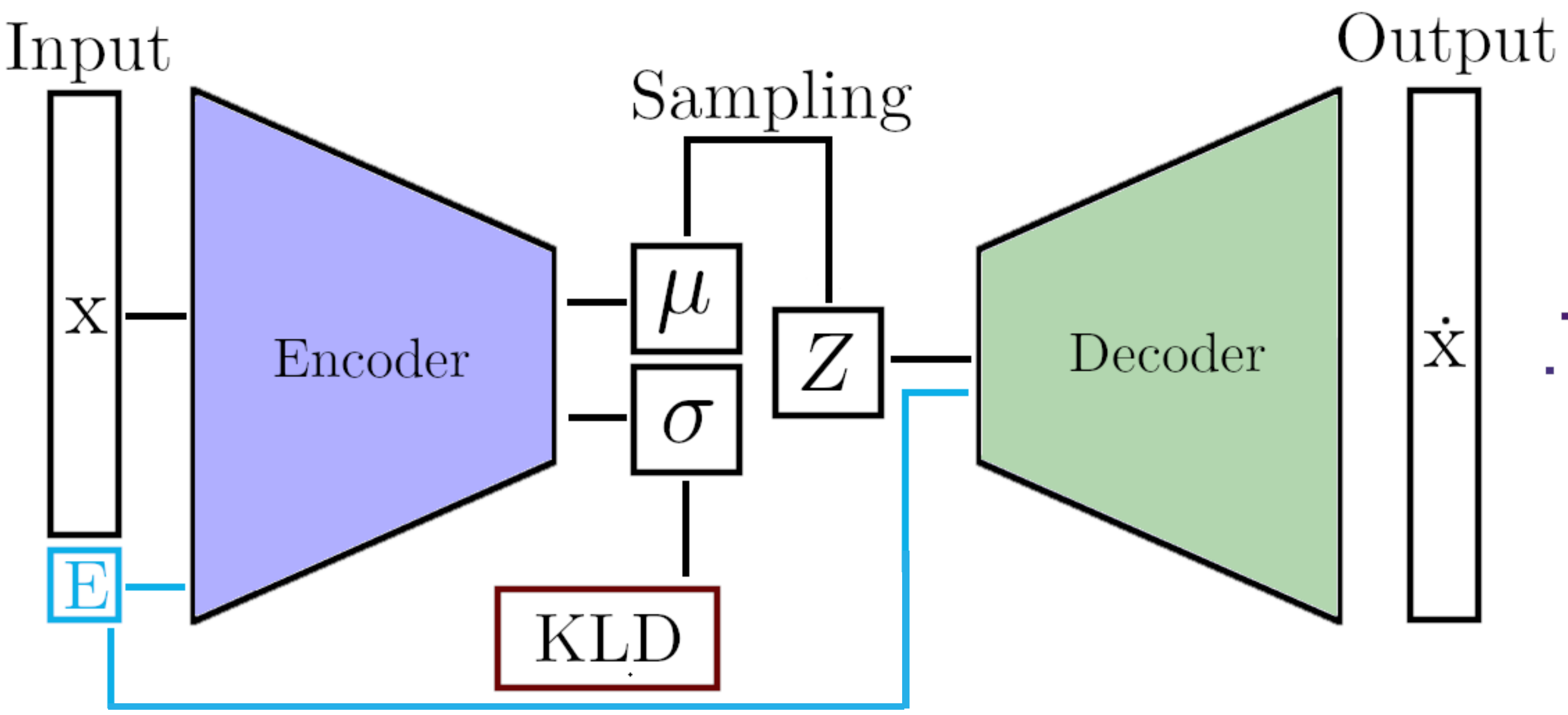
GAN

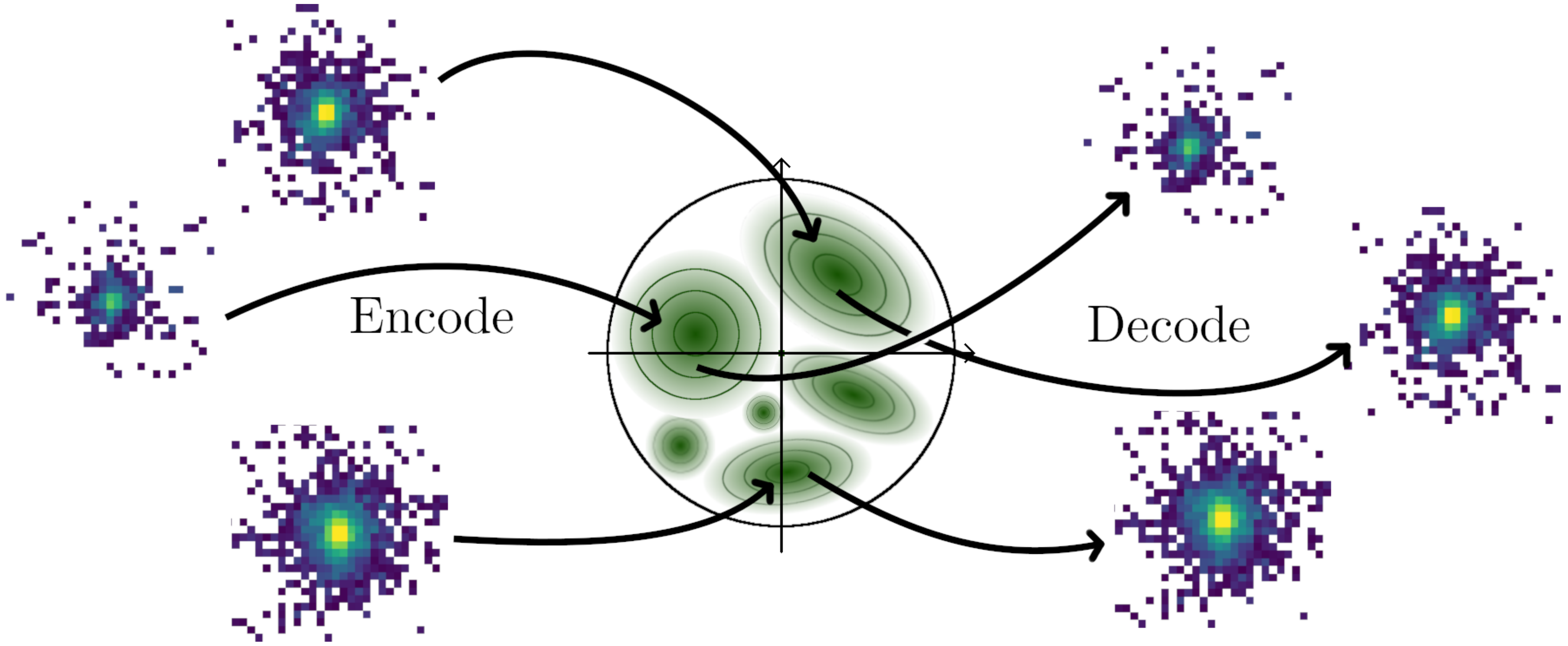


$$L = \mathrm{BCE}(p(\mathrm{real}), 1) + \mathrm{BCE}(p(\mathrm{fake}), 0)$$

- Generative Adversarial Network
  - Generator generates new fake images from noise
  - Uses second network output as loss function

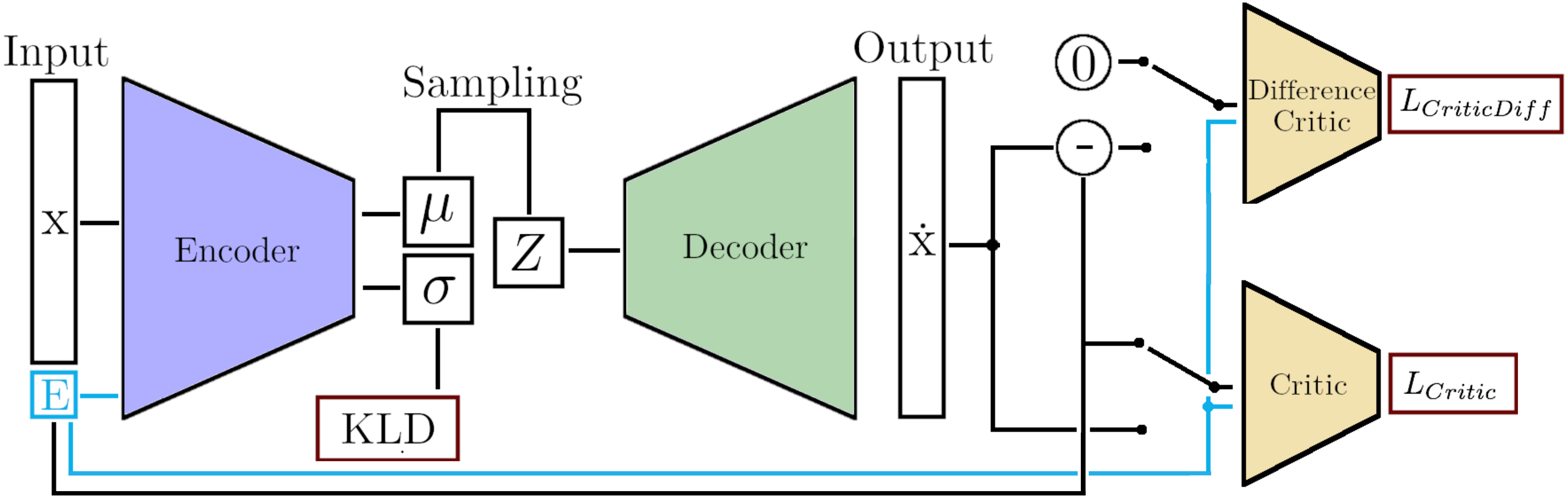
VAE





- Variational AutoEncoder
  - Encodes images into Gaussian latent space
    - Loss: KLD encourages $\mu=0$, $\sigma=1$ for individual Gaussians
  - Decodes images from latent space information
    - Loss: pixel-wise difference between input and output

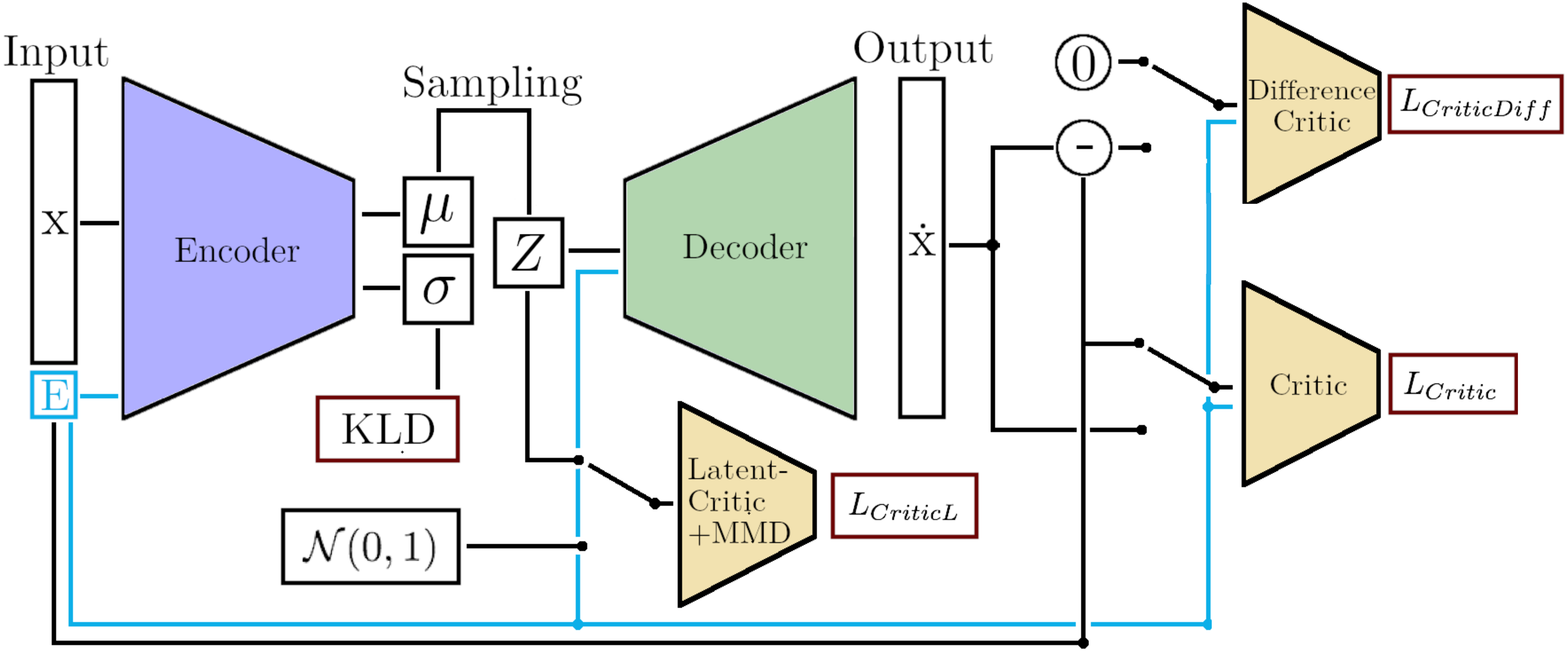
BIB-AE



- Bounded Information Bottleneck AutoEncoder
  - Expanded VAE structure
  - Adversarial critic networks instead of pixel-wise difference
  - Better shower quality

Slava Voloshynovskiy et al.:
Information bottleneck through variational glasses: 1912.00830

BIB-AE



$$L = \text{KLD} + L_{CriticL} + L_{Critic} + L_{CriticDiff}$$

- Additional critic for more regualized latent space

BIB-AE Post Processor

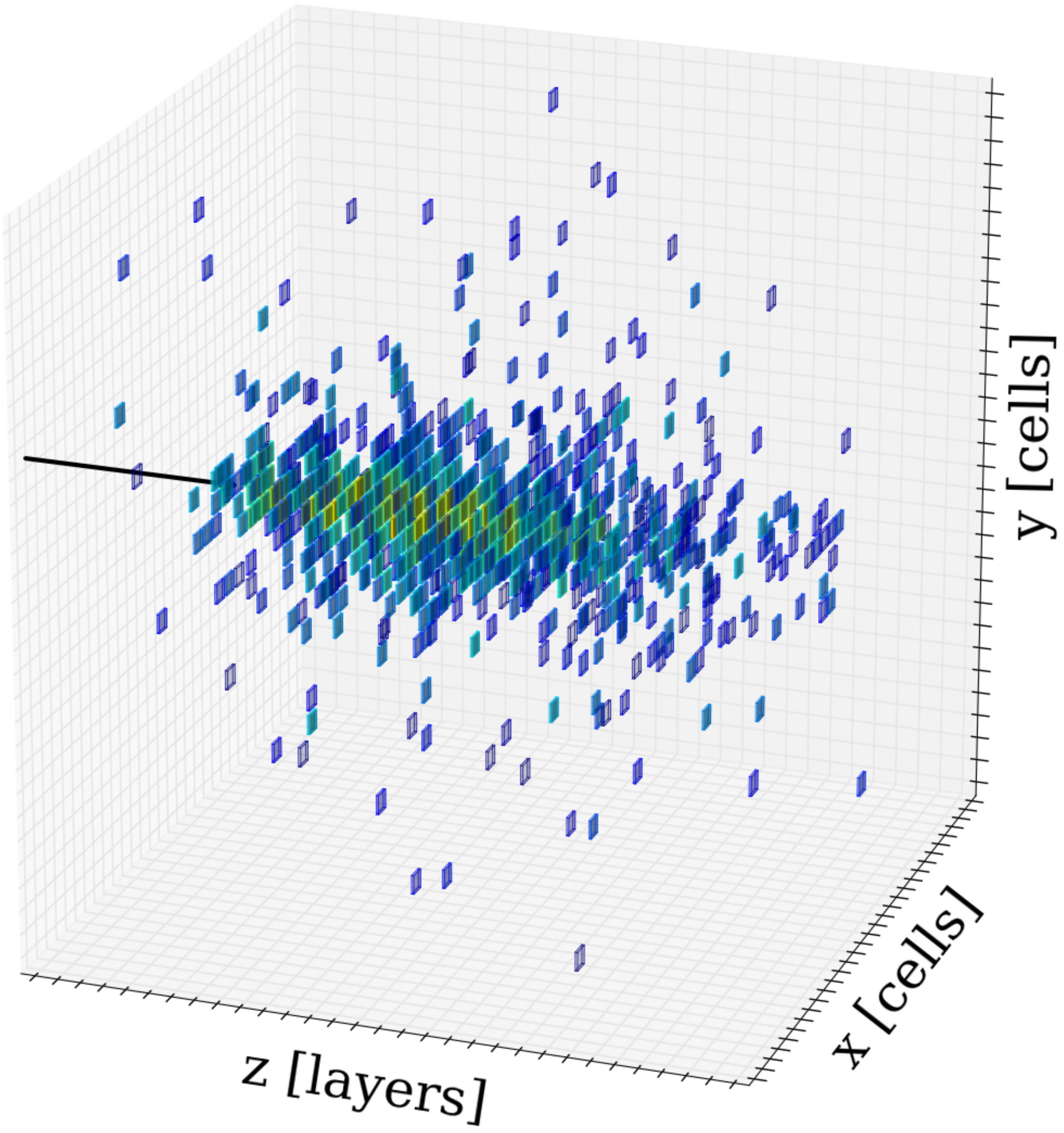
$$L = \text{KLD} + L_{CriticL} + L_{Critic} + L_{CriticDiff}$$

$$L_{\text{II}} = \text{MMD} + \text{MSE}$$

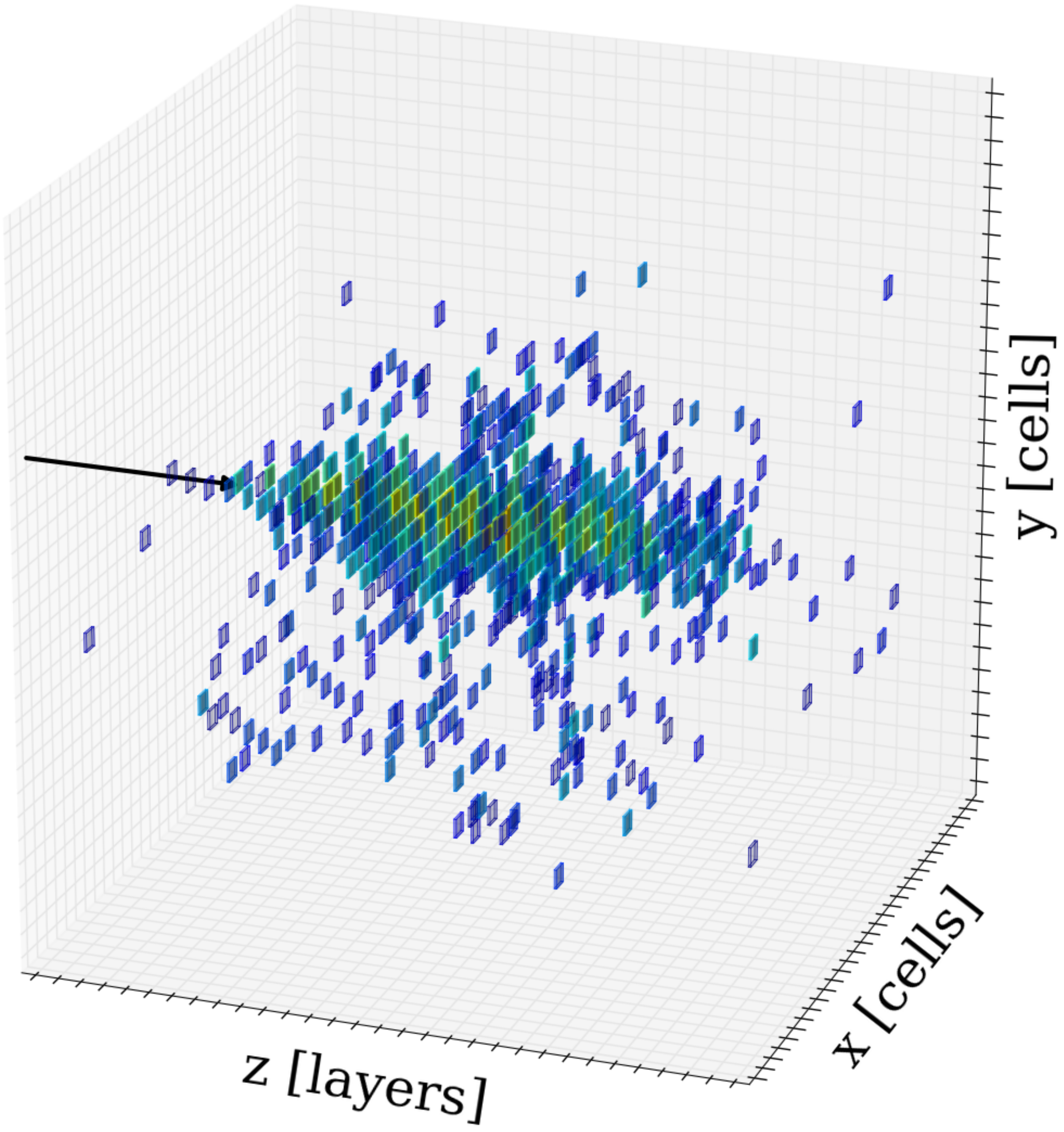
- Final Post Processor Network for fine tuning

Results

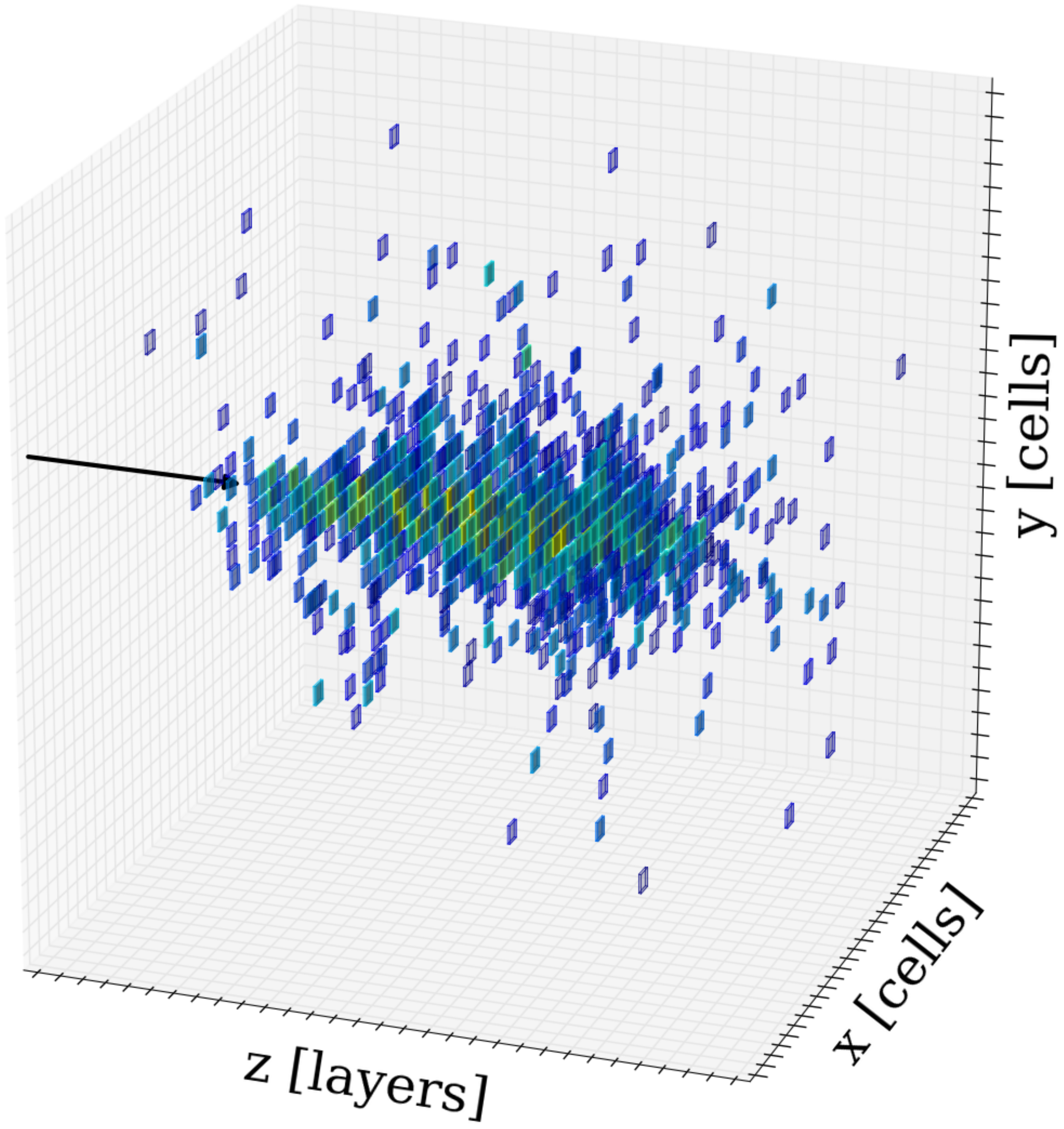
GAN



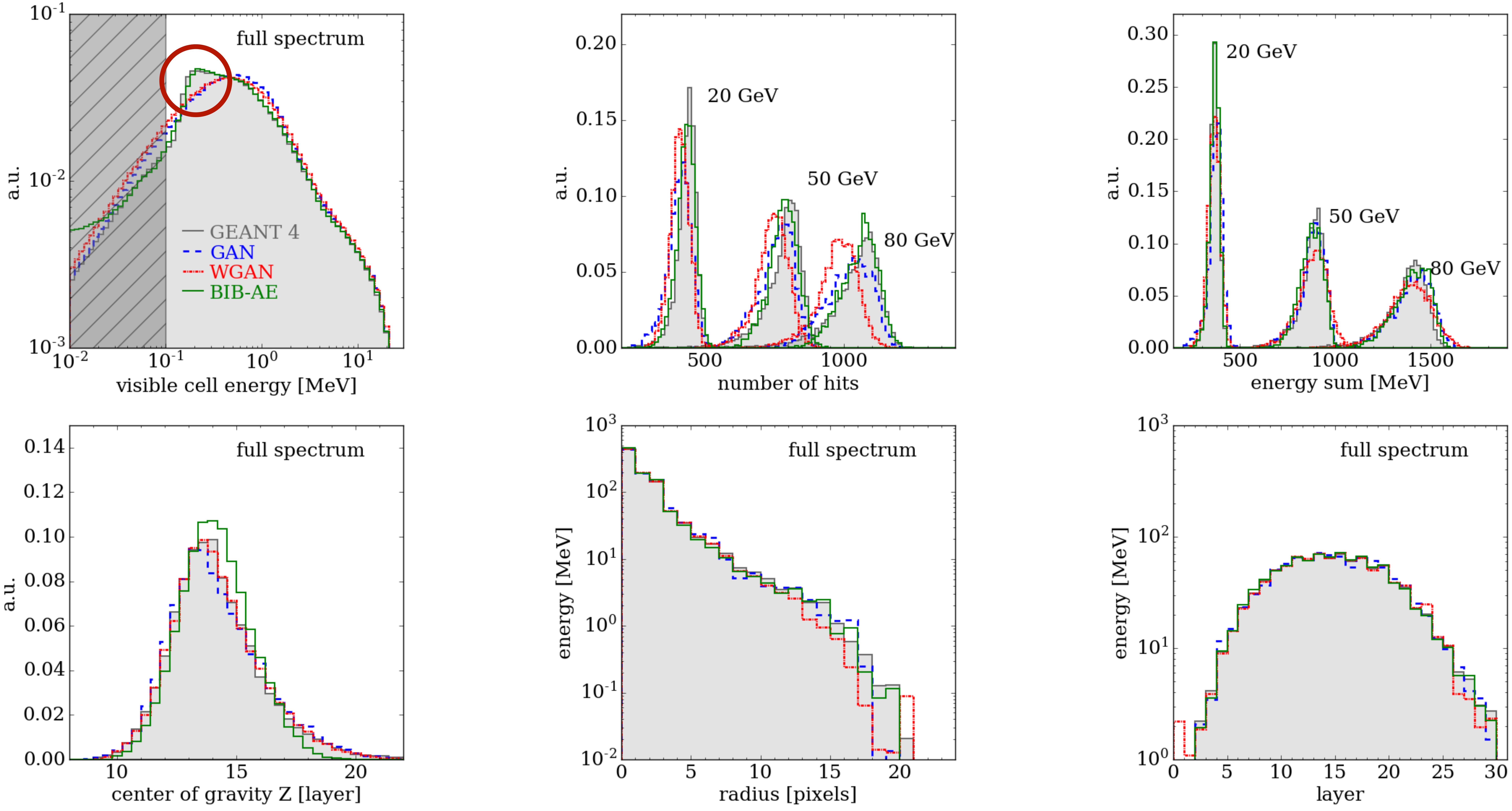
WGAN



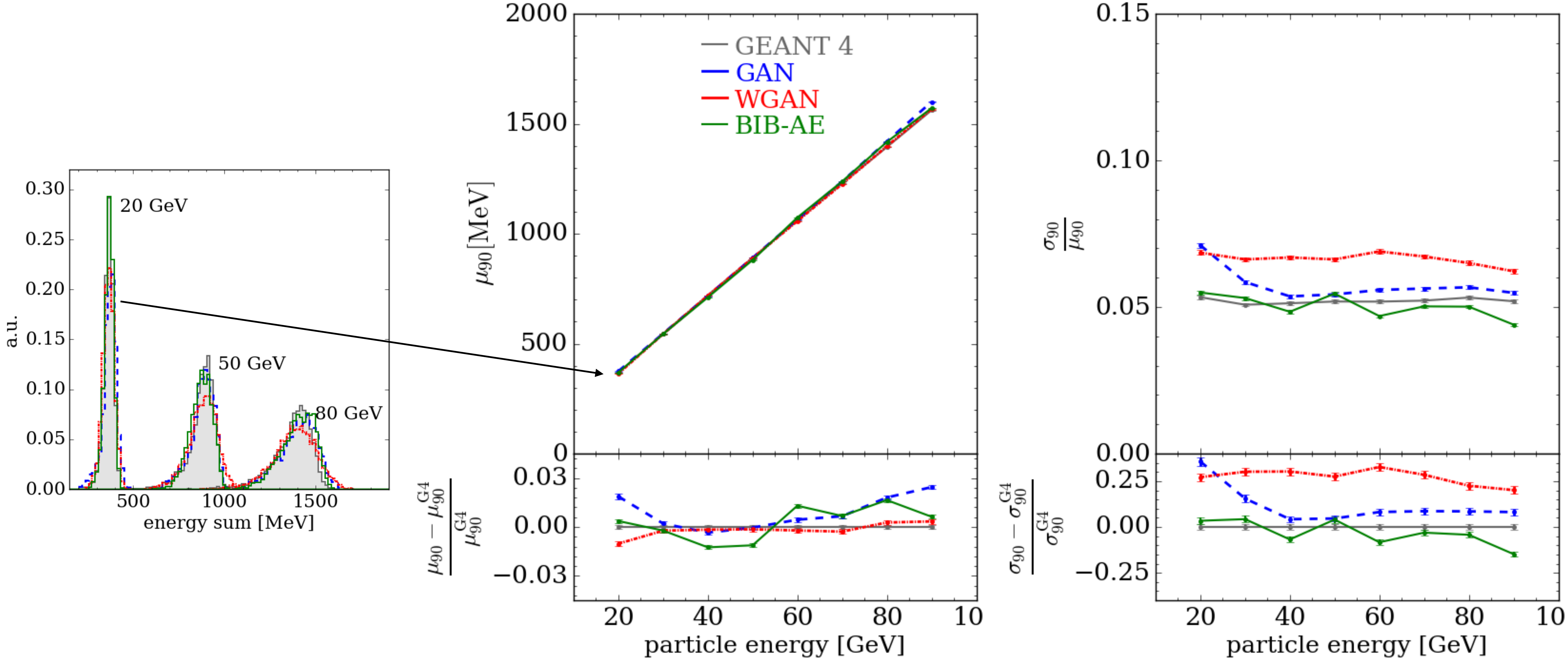
BIB-AE



Differential Distributions



Linearity and Resolution*



* actually not the ECAL resolution as not correction for sampling fraction variation performed

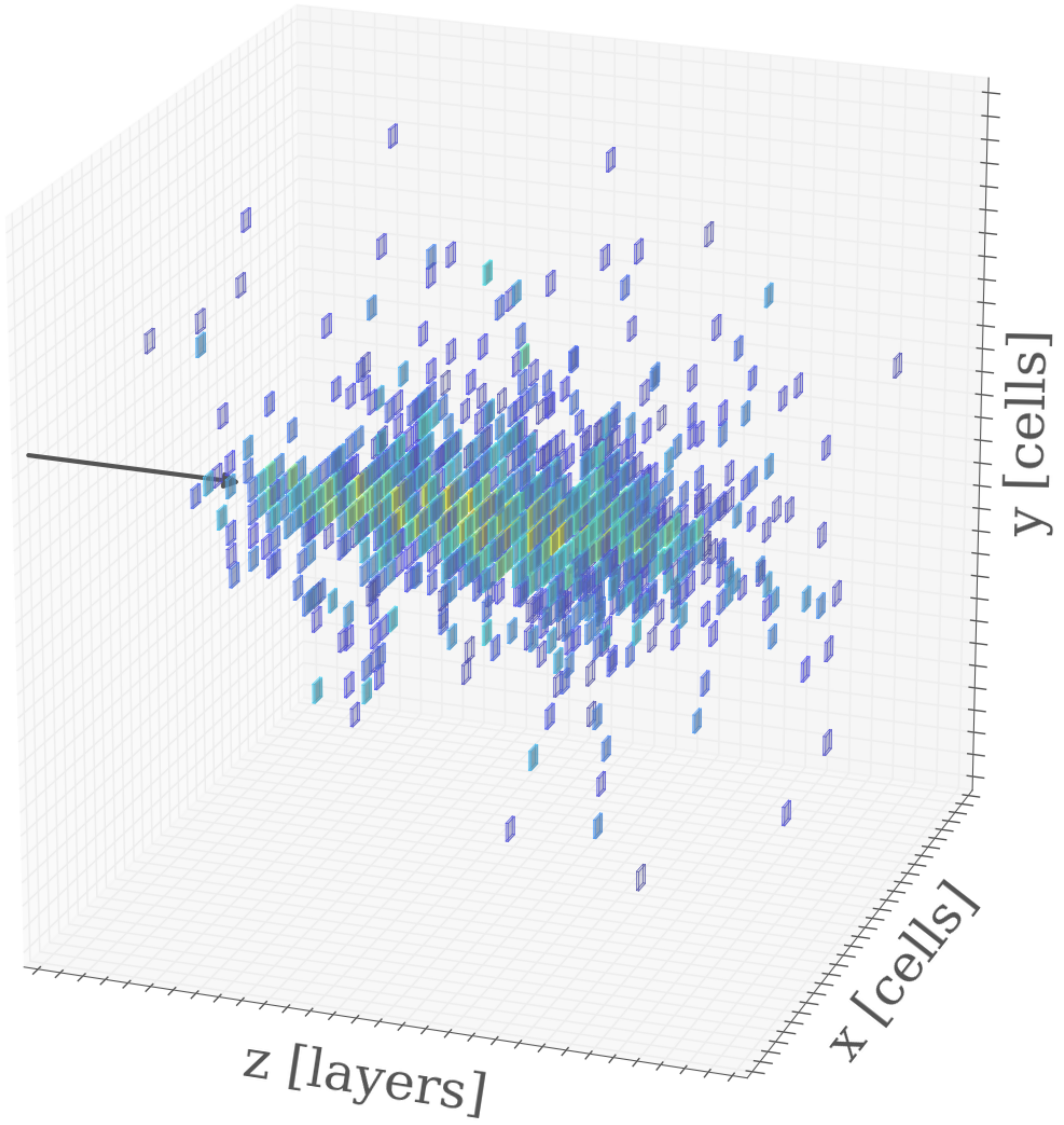
Computation Time

- For 10-100 GeV showers:
  - 3 Orders of magnitude speedup compared to GEANT4

Simulator	Hardware	Batchsize	Time/shower	Speedup
GEANT4	CPU	N/A	4082 ± 170 ms	-
BIB-AE	CPU	1	426.3 ± 3.6 ms	x10
BIB-AE	GPU V100	1	3.19 ± 0.01 ms	x1279
BIB-AE	GPU V100	100	1.42 ± 0.01 ms	x2874

Conclusion

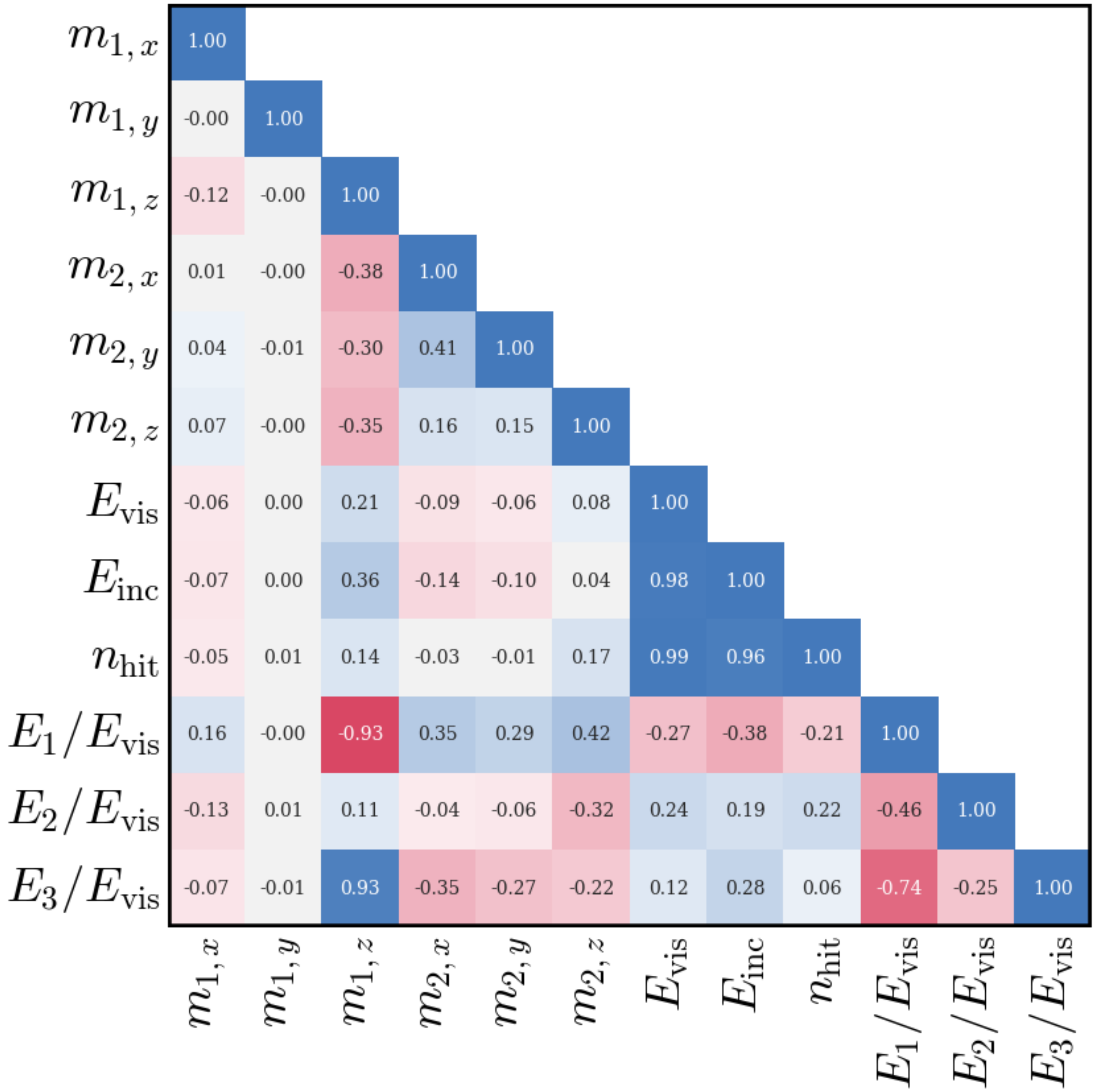
- Exciting new architecture for fast calorimeter simulations
  - Able to model GEANT4 distributions very closely
  - Provides orders of magnitude speedup
- Future plans:
  - Varied incident position/angle
  - Hadronic showers



Thank you

Correlations

GEANT4



GEANT4 - BIB-AE