

# High Fidelity Simulation of High Granularity Calorimeters with High Speed

ILD Analysis and Software Meeting

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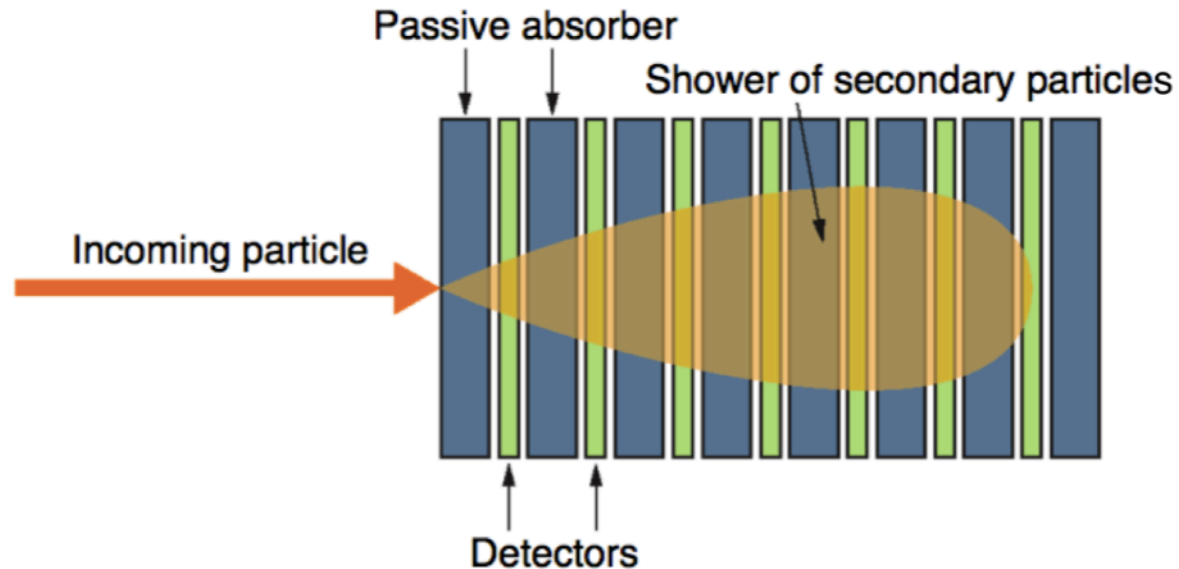
[arxiv:2005.05334](https://arxiv.org/abs/2005.05334)

HELMHOLTZ RESEARCH FOR GRAND CHALLENGES



# Calorimeters in a HEP Experiment

- Incoming particle initiates the showers and secondary particles are produced
- These secondary particles further produce other particles until the full energy is absorbed



## One type of EM calorimeter: sampling calorimeter

- Alternating layers of passive absorbers and active detectors
- Only **fraction** of particle energy is recorded (visible energy)

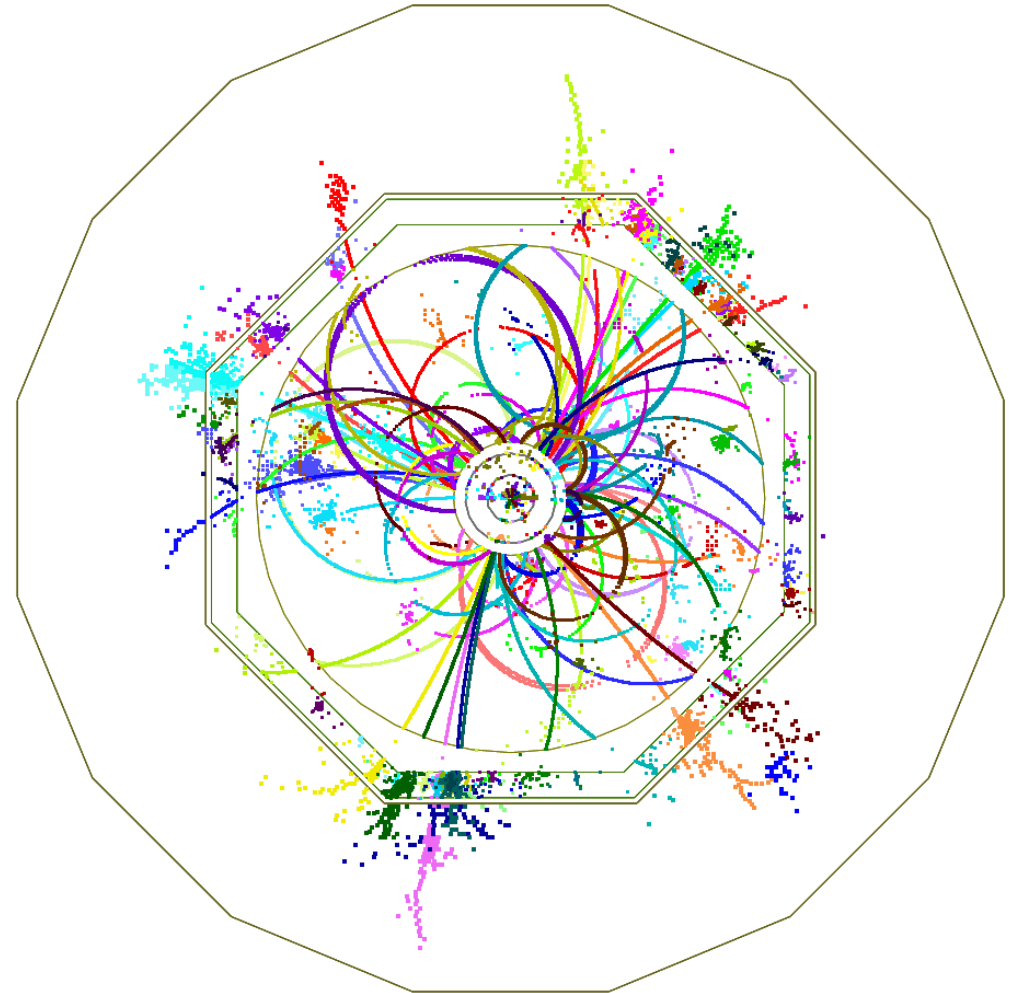
# High Granularity Calorimeter

## Very fine segmentation of channels

- Reconstruct all individual particle showers
- Optimised for Particle Flow Approach (PFA)
  - ✓ Improve overall precision

## Examples:

- ILD detector at ILC (Higgs Factory):
  - \* Si-W ECAL (5x5mm) + Scintillator-Steel HCAL (30x30mm)
- CMS High Granularity Calorimeter (HGCal)



# Shower Simulation

- Particle showers in the calorimeter are simulated by Geant4
  - ✓ First-principle **physics** based simulation
- Very CPU intensive, due to large number of interacting particles

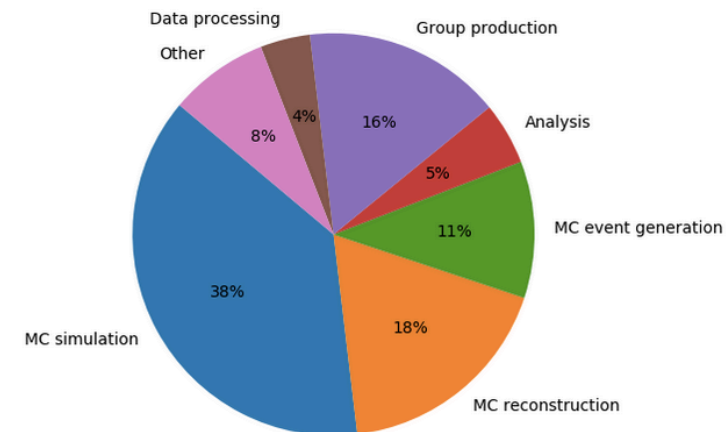


Figure from D.Costanzo, J.Catmore, LHC meeting

## Goal:

- Reproduce accurate shower simulations with a faster, powerful **generator**; based on state-of-the-art generative models
- **Enormous** amounts of **CPU time** could be potentially saved!

CALOGAN: Simulating 3D high energy particle showers in multilayer electromagnetic calorimeters with generative adversarial networks

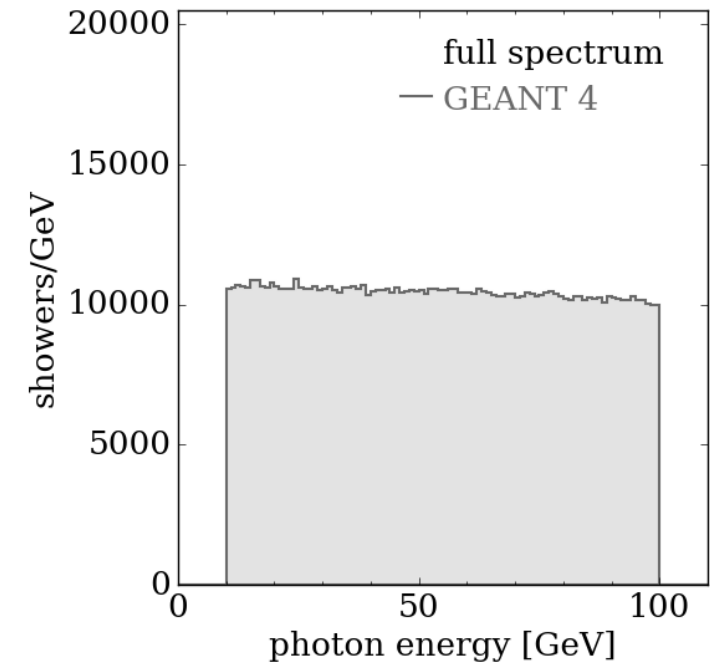
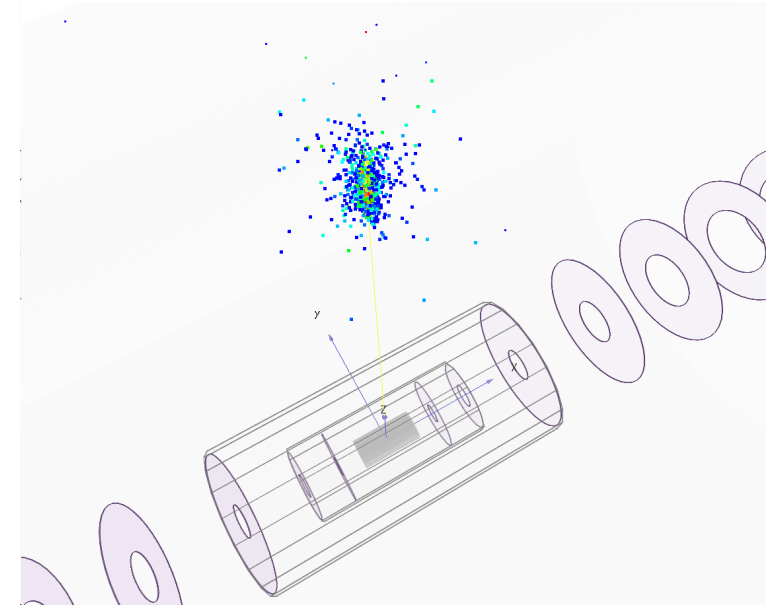
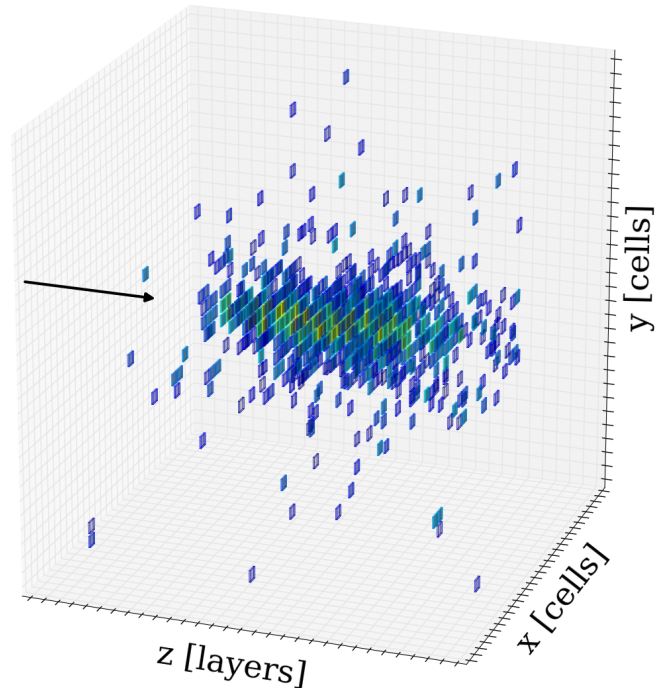
Michela Paganini, Luke de Oliveira, and Benjamin Nachman  
Phys. Rev. D **97**, 014021 – Published 30 January 2018

Simulator	Hardware	Batch size	ms/shower
GEANT4	CPU	N/A	1772
		1	13.1
		10	5.11
		128	2.19
		1024	2.03
CALOGAN	CPU	1	14.5
		4	3.68
		128	0.021
	GPU	512	0.014
		1024	0.012 ✓

# Training Data

## Geant4 Simulation

- Shooting photon perpendicular to the ILD-ECAL (Si-W)
  - Constant incident point
  - 950k photon showers
  - Photon energy: 10-100 GeV, continuous!
  - 30x30x30 pixels, centered on beam



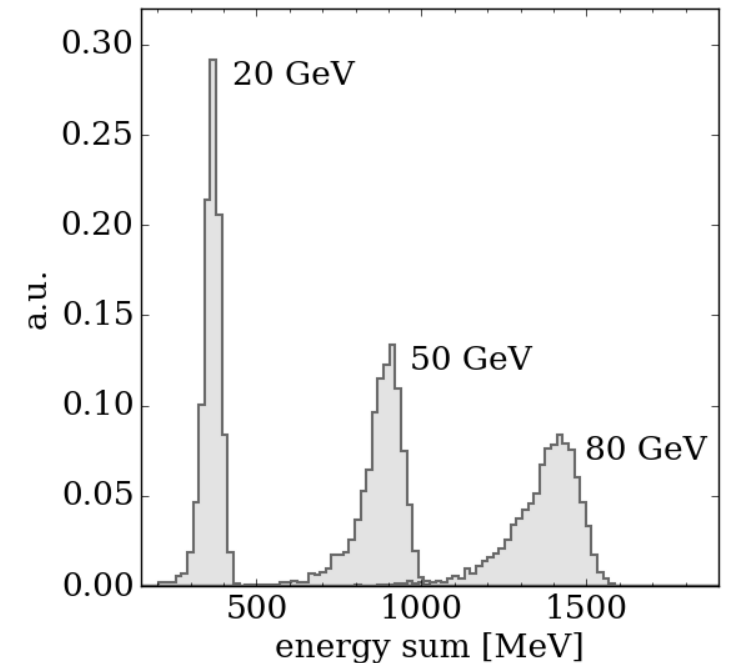
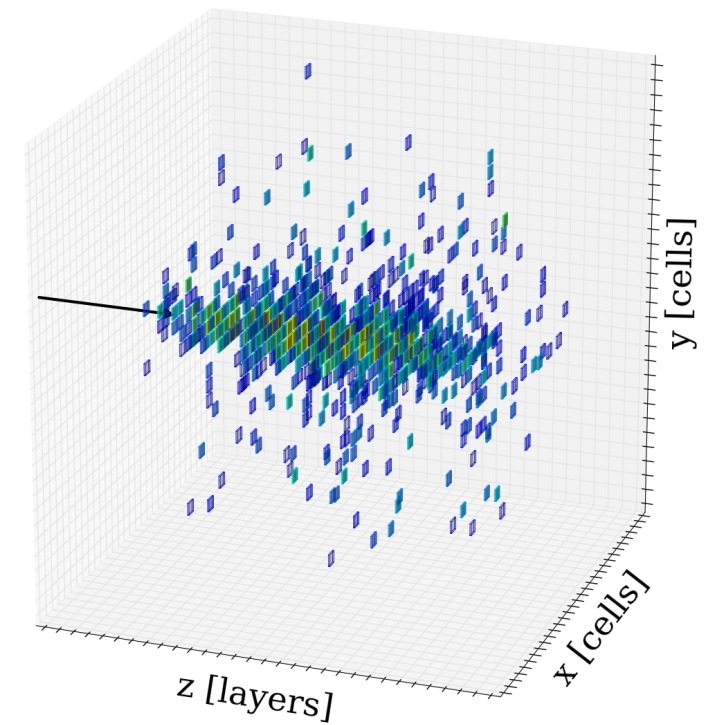
# Challenges

## Quality measures:

- Reproduce Geant4 showers
- Shower shape variables have to be examined, especially:
  - ◉ Number of hits
  - ◉ Radial & longitudinal profile
- Differential energy distributions: shape & accuracy

## Energy conditioning

- Condition generator / decoder on incoming particle's energy
  - ◉ Not same as visible (or reconstructed) energy!

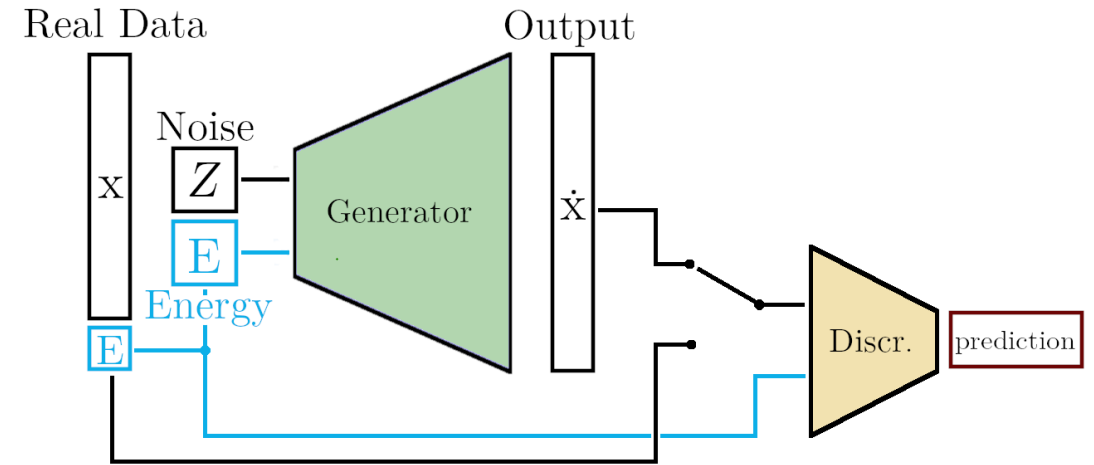


# Generative Models

## GAN and WGAN

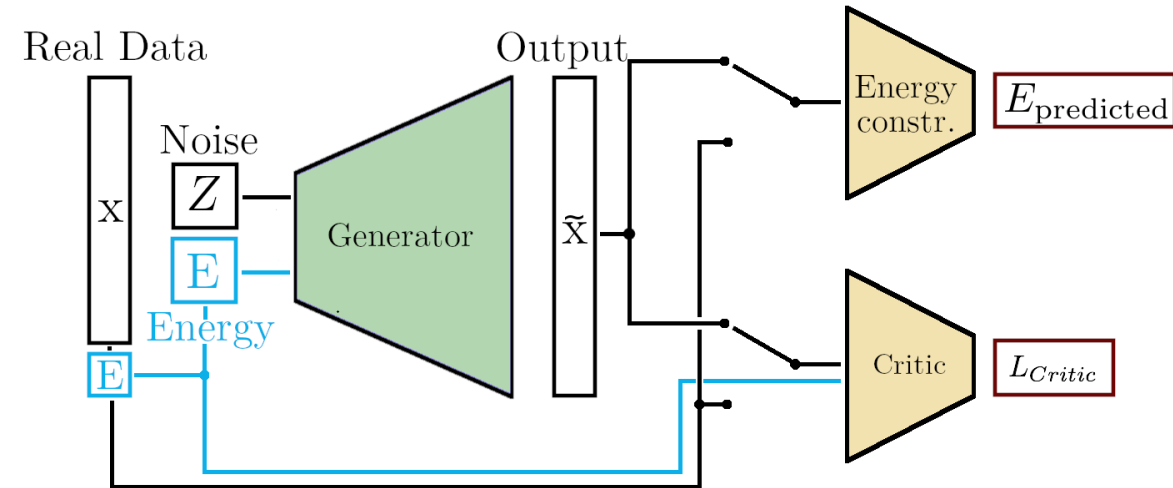
### Generative Adversarial Network (GAN)

- Generator generates new fake images from noise
- Discriminator tries to differentiate: Fake or Real ?
  - ➔ Binary classification

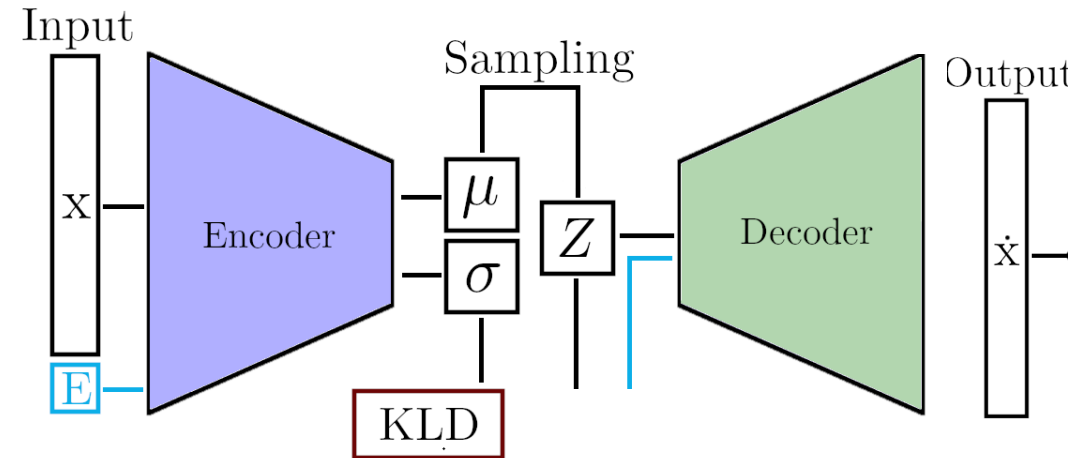


### Wasserstein GAN (WGAN)

- Alternative to classical GAN training
  - ➔ Helps improve the stability of the training
  - ➔ Use Wasserstein-1 distance as a loss function
  - ➔ Critic network does regression (i.e. gives a score)
- Second network to constrain the energy

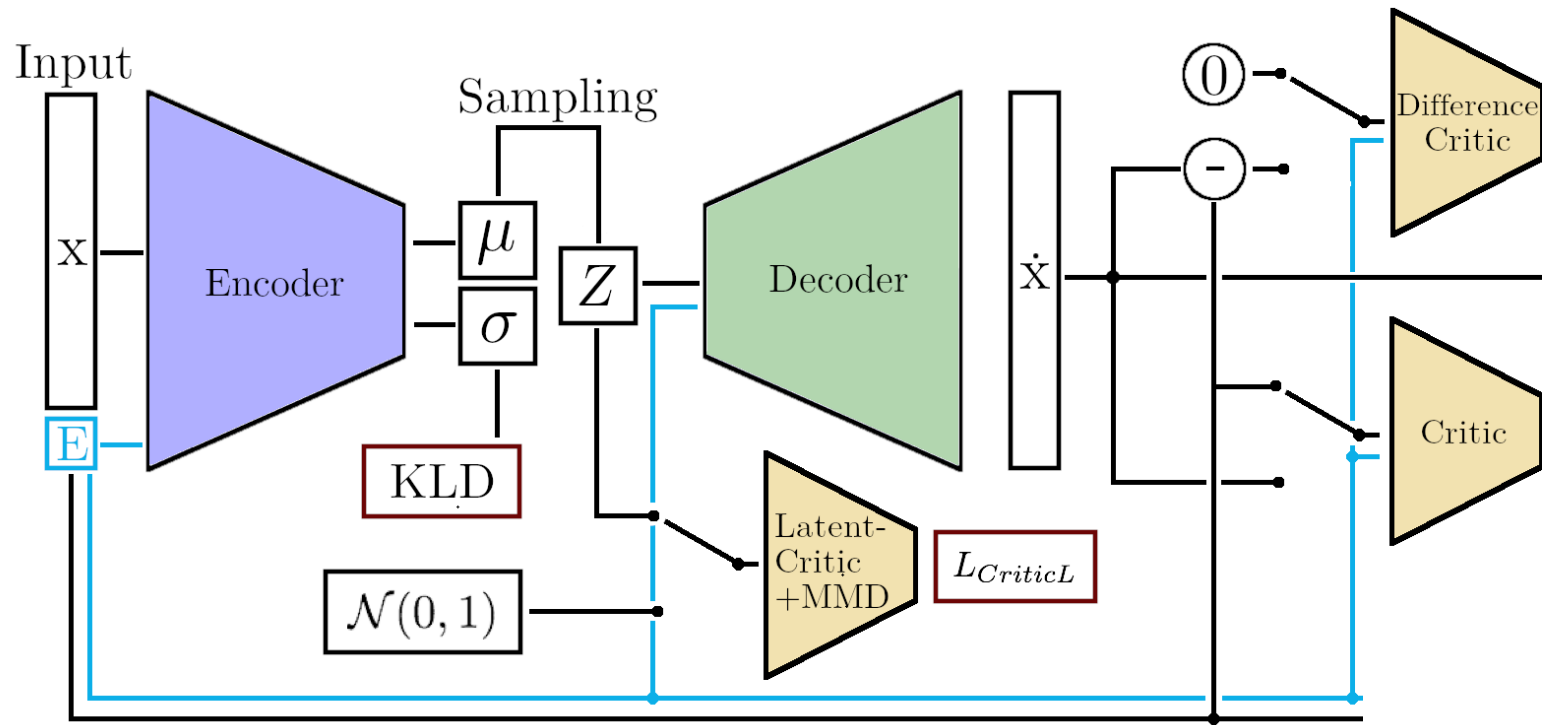


# Variational Autoencoders (VAE)



- Encodes images to Gaussian latent space
- Reconstructs images from latent space information
  - \* Loss function: Pixel wise difference between input and output
  - \* KLD loss to regularise the latent space

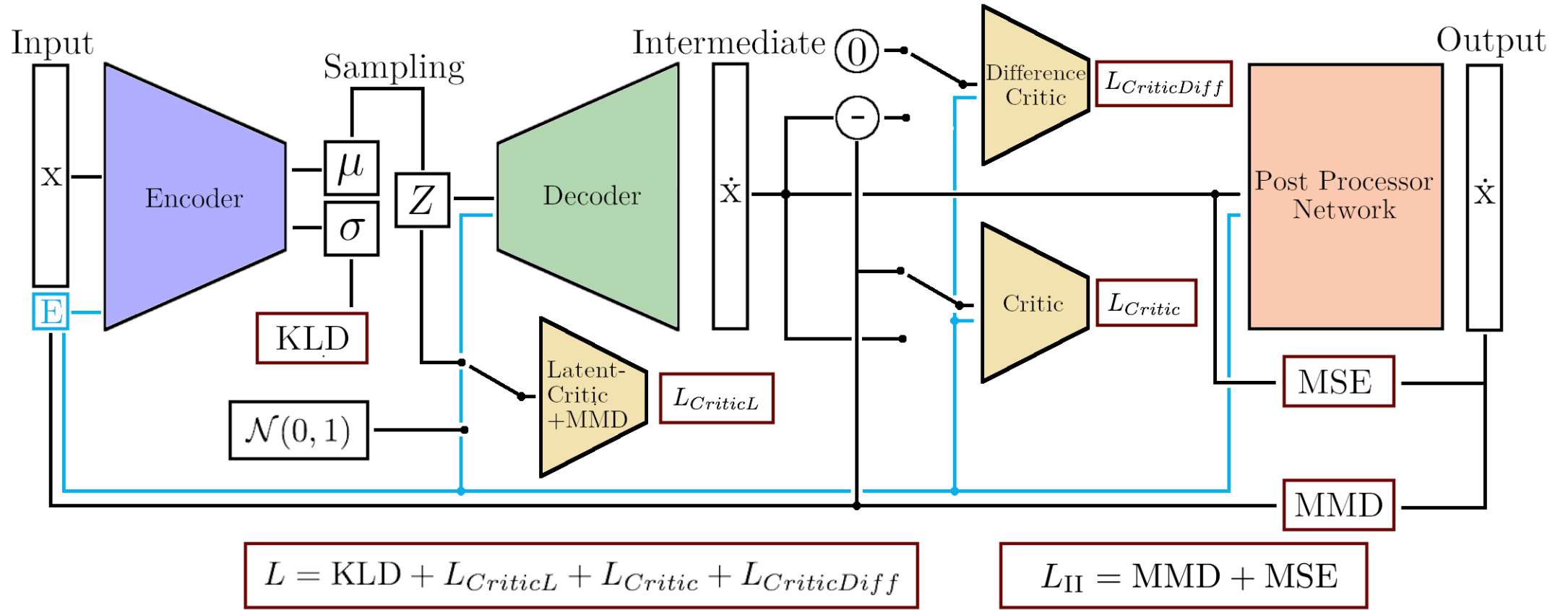




$$L = \text{KLD} + L_{\text{Critic}L} + L_{\text{Critic}} + L_{\text{CriticDiff}}$$

## Bounded Information Bottleneck AutoEncoder (BiB-AE)

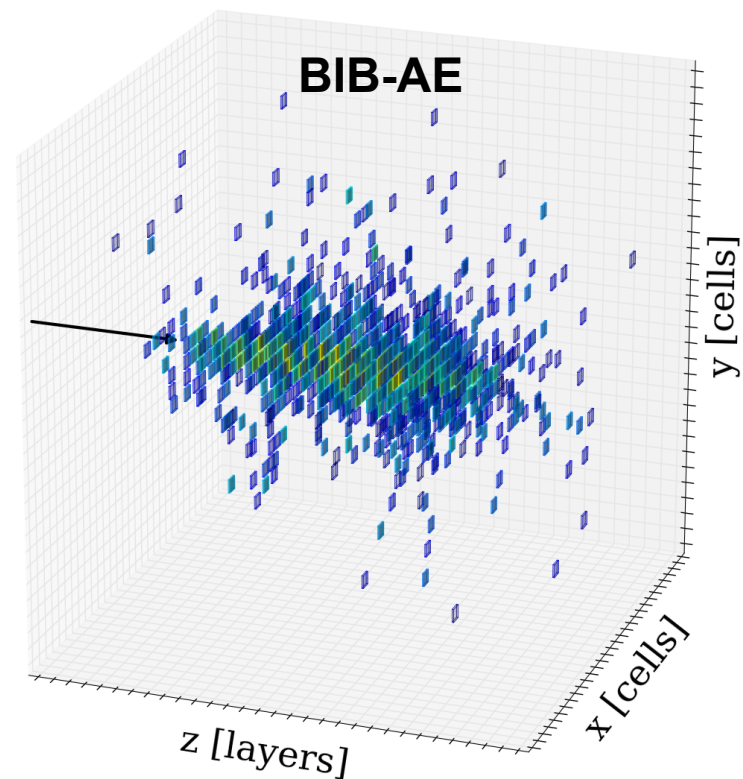
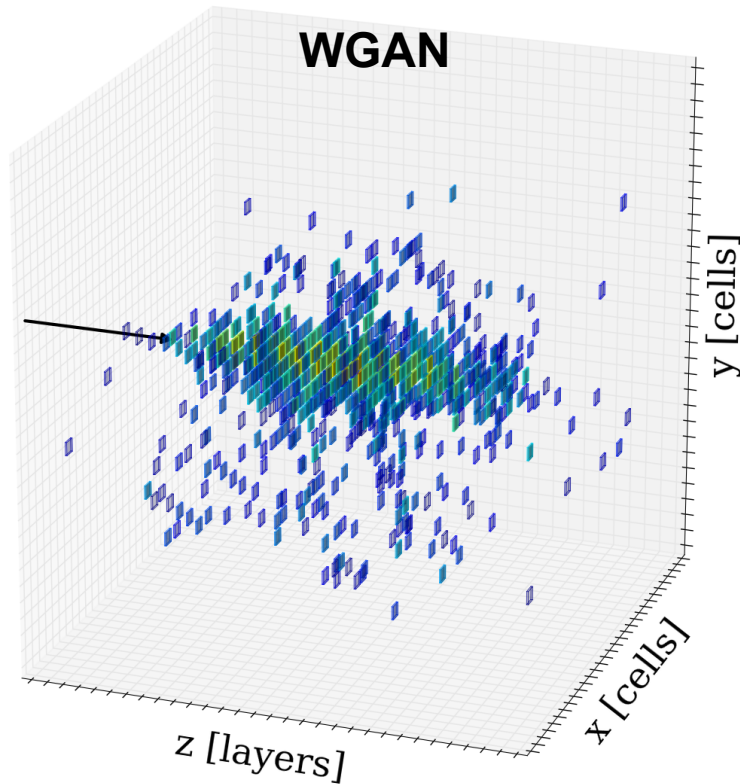
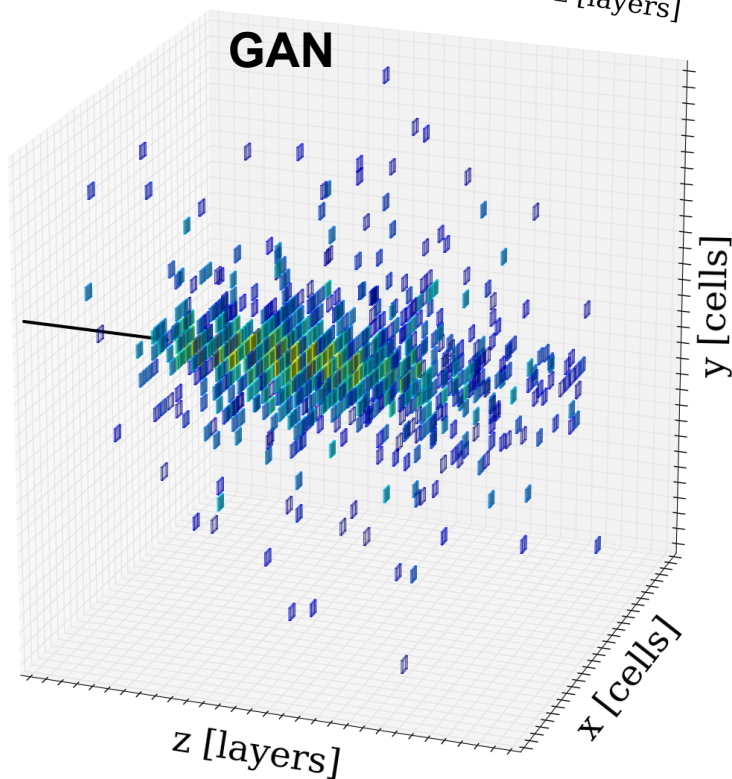
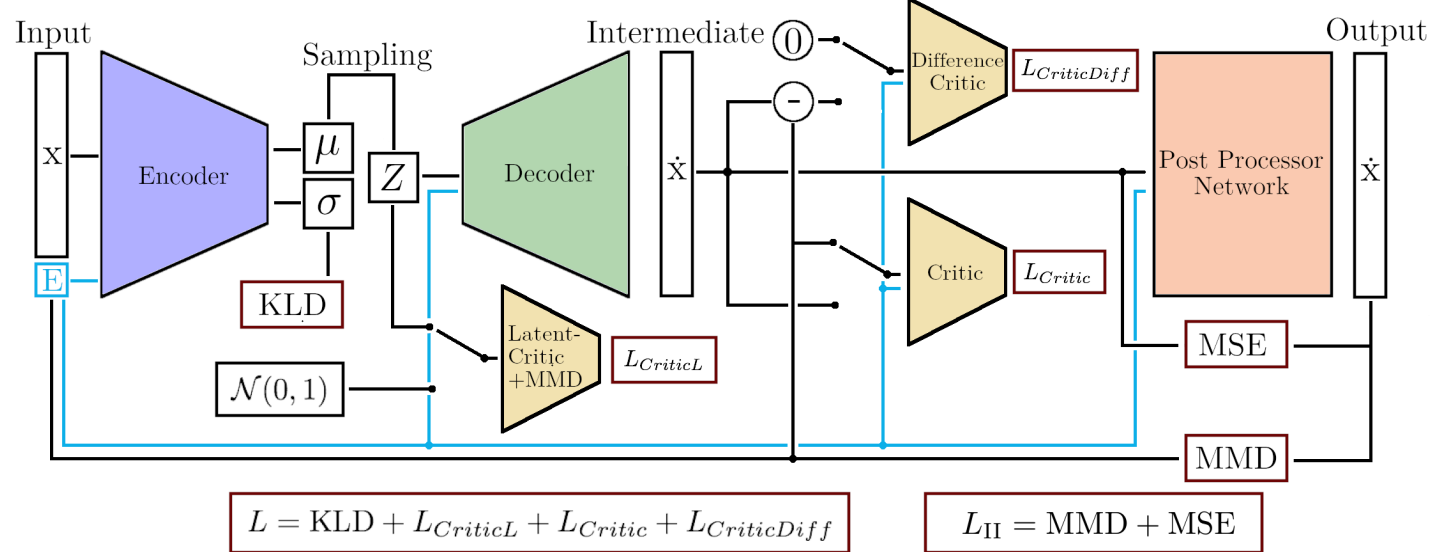
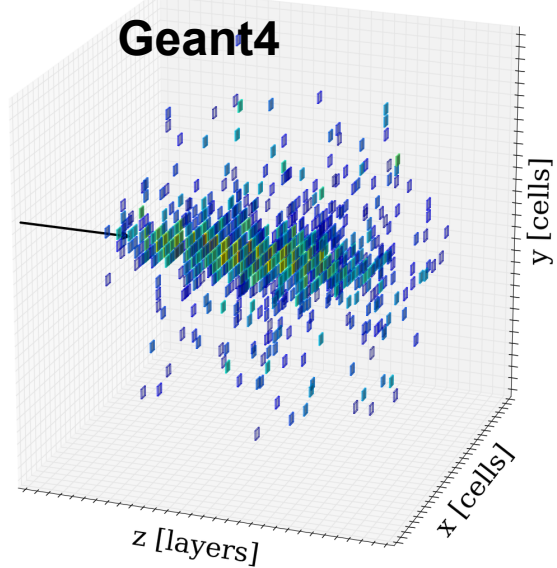
- It expands VAE structure
- Additional critics for
  - Latent space regularisation
  - Reconstruction
- Inspired by CS paper



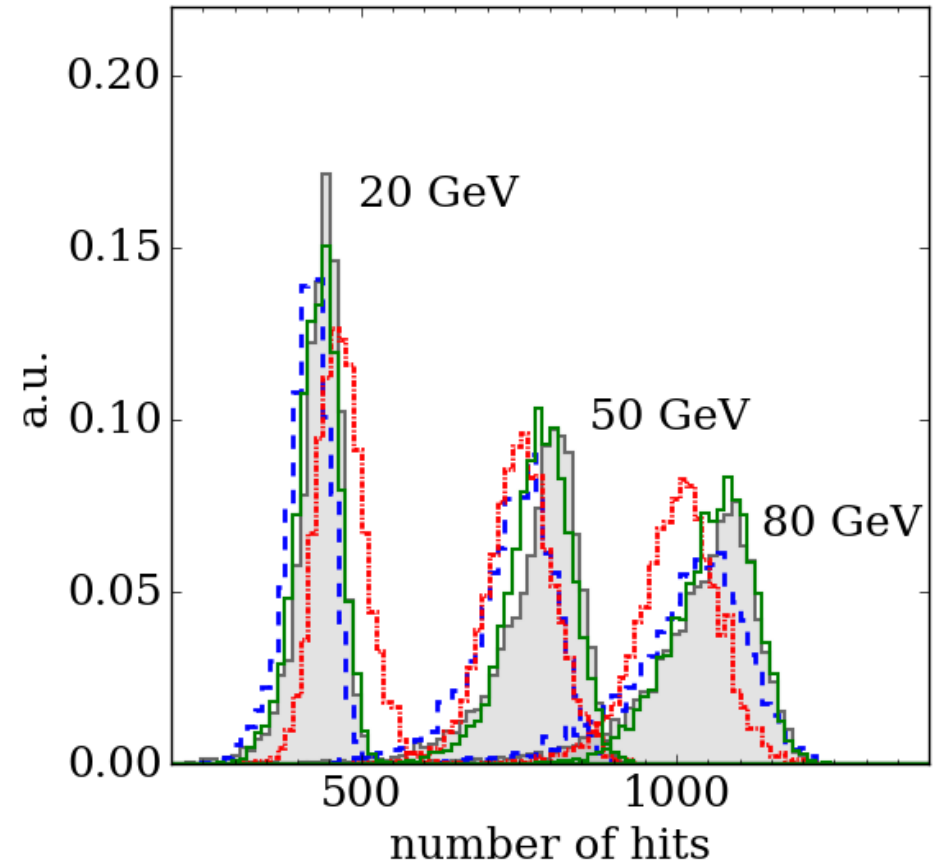
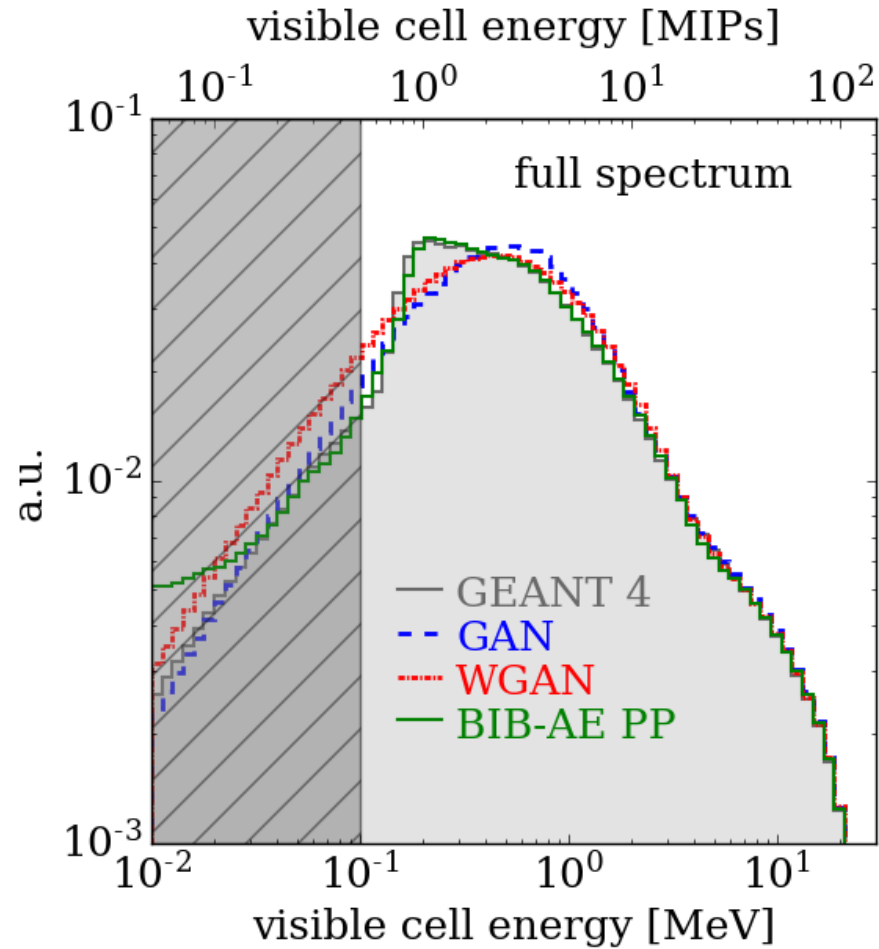
Post Processor Network for final cell-energy tuning!!

# Results

looks realistic???



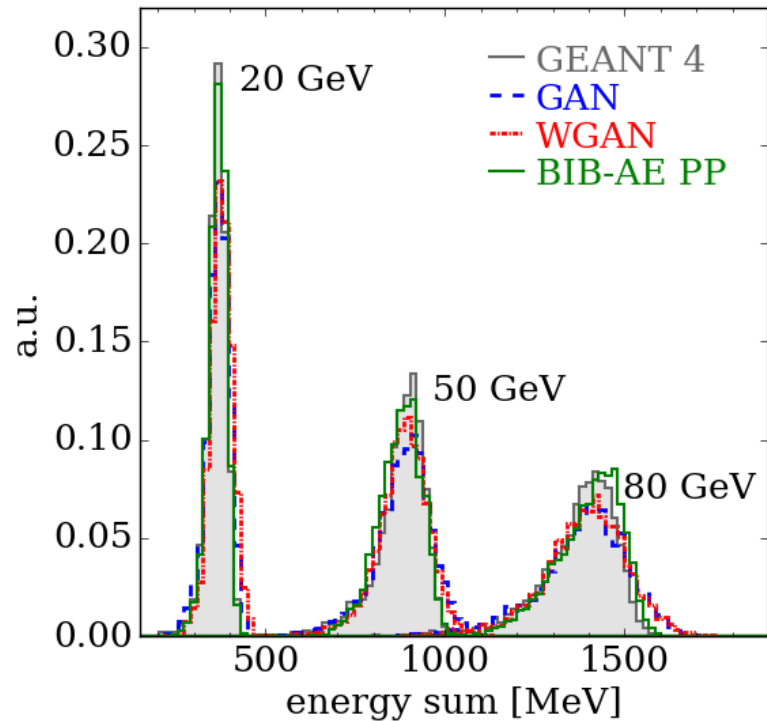
# Results: Cell energy and Number of hits



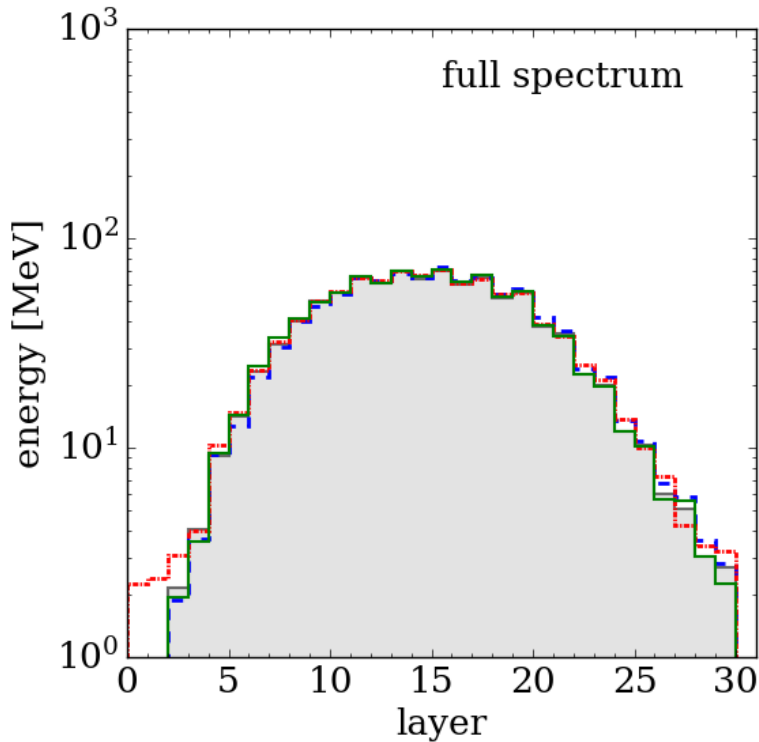
- Both GAN and WGAN fail to capture MIP bump around 0.2 MeV
- ✓ BiB-AE is able to produce this feature thanks to Post-Processing network

- GAN and WGAN slightly underestimate the total number of hits
- ✓ BiB-AE reproduces the shape and width

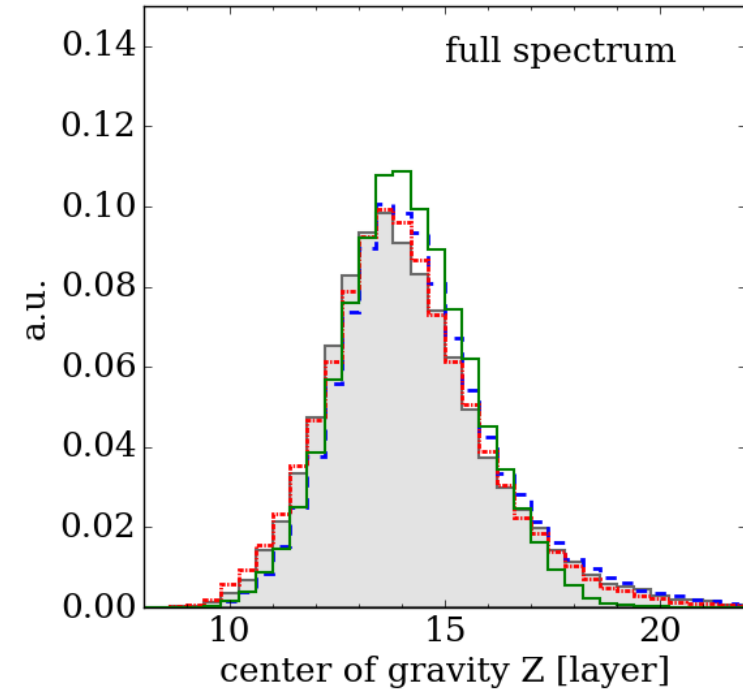
# Results: Other important distributions



- ✓ the shape, center and width of the peak are well reproduced for all models

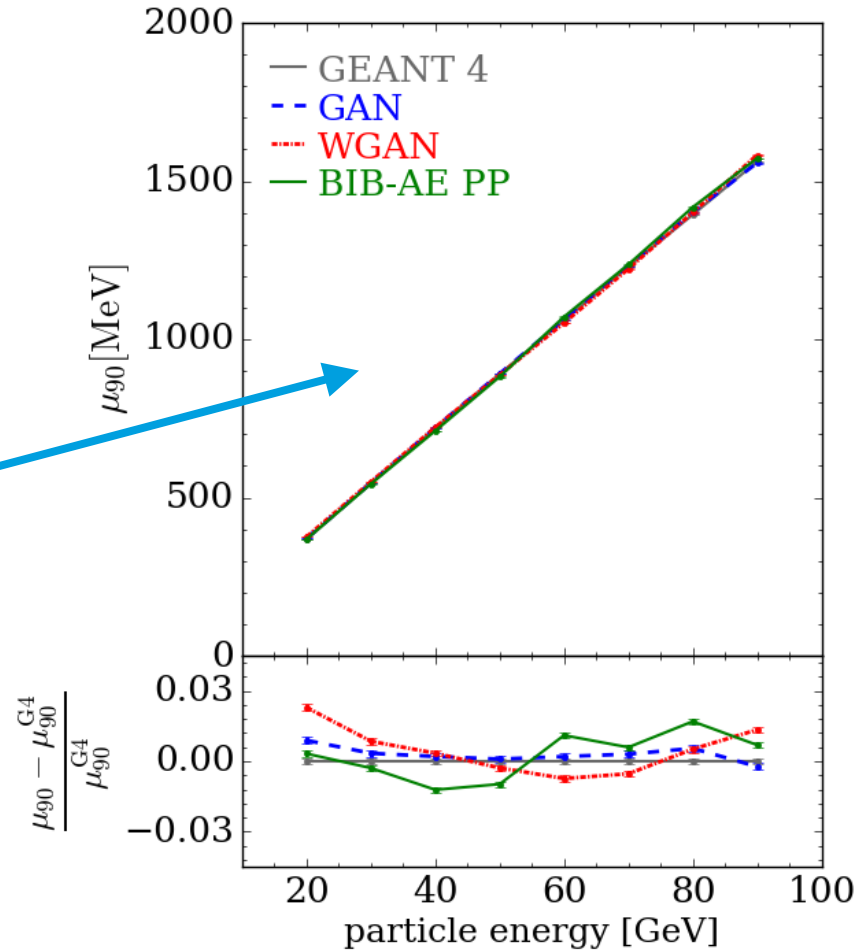
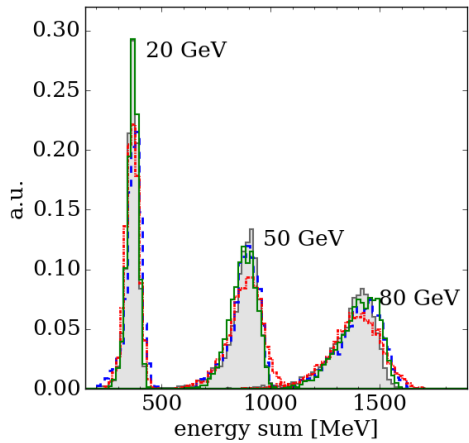


- ✓ reproduce the bulk of the distributions very well.
  - slight deviations for the WGAN appear around the edges

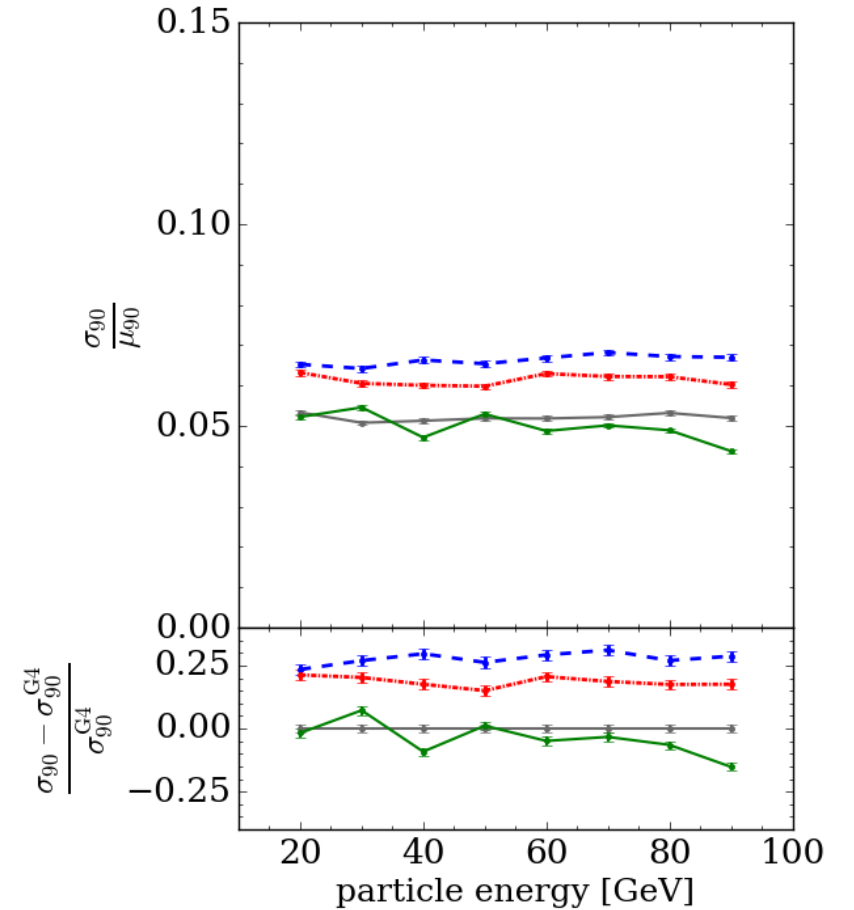


- Deviations for BiB-AE
  - ✓ Explainable via latent space encoding

# Results: Linearity and Width



✓ Overall good modelled by all generative models. Deviations up to few percent



⊙ Overestimated by GAN and WGAN

# Computation Time

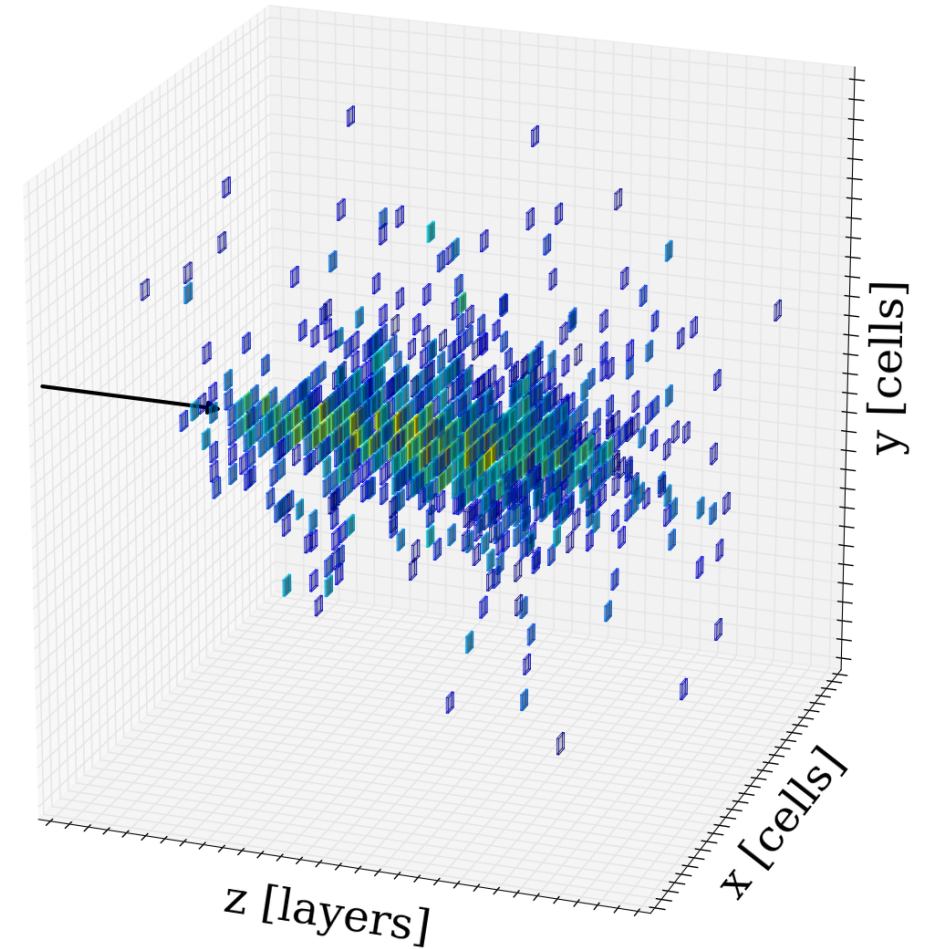
Simulator	Hardware	Batch Size	15 GeV	Speed-up	10-100 GeV Flat	Speed-up
GEANT4	CPU	N/A	1445.05 ± 19.34 ms	-	4081.53 ± 169.92 ms	-
WGAN	CPU	1	64.34 ± 0.58 ms	<b>x23</b>	63.14 ± 0.34 ms	<b>x65</b>
		10	59.53 ± 0.45 ms	<b>x24</b>	56.65 ± 0.33 ms	<b>x72</b>
		100	58.31 ± 0.93 ms	<b>x25</b>	58.11 ± 0.13 ms	<b>x70</b>
		1000	57.99 ± 0.97 ms	<b>x25</b>	57.99 ± 0.18 ms	<b>x70</b>
BIB-AE	CPU	1	426.60 ± 3.27 ms	<b>x3</b>	426.32 ± 3.62 ms	<b>x10</b>
		10	422.60 ± 0.26 ms	<b>x3</b>	424.71 ± 3.53 ms	<b>x10</b>
		100	419.64 ± 0.07 ms	<b>x3</b>	418.04 ± 0.20 ms	<b>x10</b>
WGAN	GPU	1	3.24 ± 0.01 ms	<b>x446</b>	3.25 ± 0.01 ms	<b>x1256</b>
		10	6.13 ± 0.02 ms	<b>x236</b>	6.13 ± 0.02 ms	<b>x666</b>
		100	5.43 ± 0.01 ms	<b>x266</b>	5.43 ± 0.01 ms	<b>x752</b>
		1000	5.43 ± 0.01 ms	<b>x266</b>	5.43 ± 0.01 ms	<b>x752</b>
BIB-AE	GPU	1	3.14 ± 0.01 ms	<b>x838</b>	3.19 ± 0.01 ms	<b>x1279</b>
		10	1.56 ± 0.01 ms	<b>x1287</b>	1.57 ± 0.01 ms	<b>x2600</b>
		100	1.42 ± 0.01 ms	<b>x1366</b>	1.42 ± 0.01 ms	<b>x2874</b>

For 10-100 GeV showers, Bib-AE and WGAN

- 3 orders of magnitude speed-up on **GPU**
- 2 orders of magnitude speed-up on **CPU**

# Conclusion

- ▶ Application of generative models to high resolution EM shower simulation
  - ✓ Modelling of MIP peak and high fidelity
  - ✓ Speedup: 3 orders of magnitude
- ▶ Architectures:
  - GAN
  - WGAN
  - BIB-AE (**New!**)
- ▶ Future Plans:
  - condition on incident position/angle
  - hadronic showers
  - integrate into existing tools / frameworks



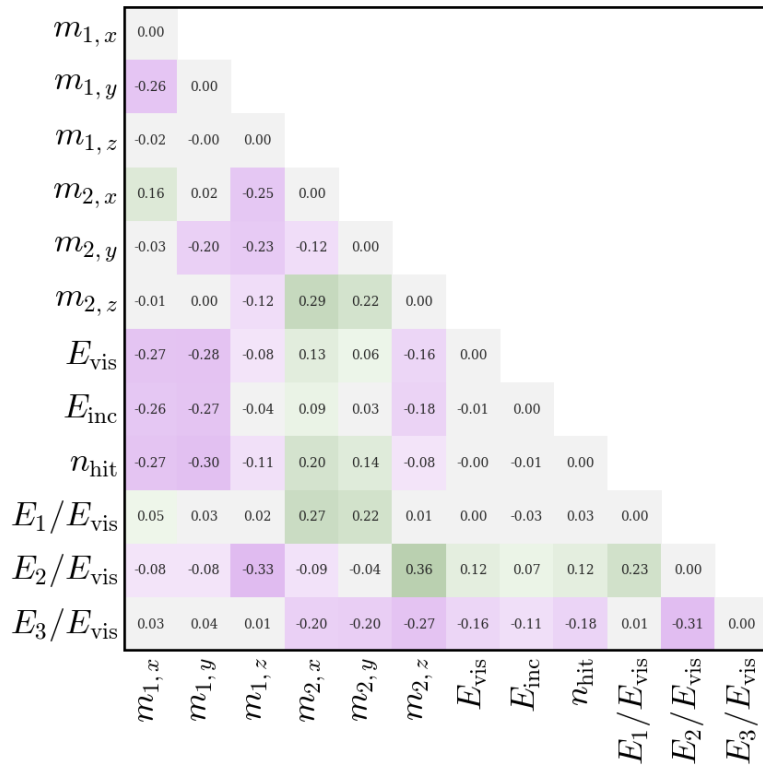
Paper: [\[arxiv:2005.05334\]](https://arxiv.org/abs/2005.05334) (submitted to journal, soon to be published )



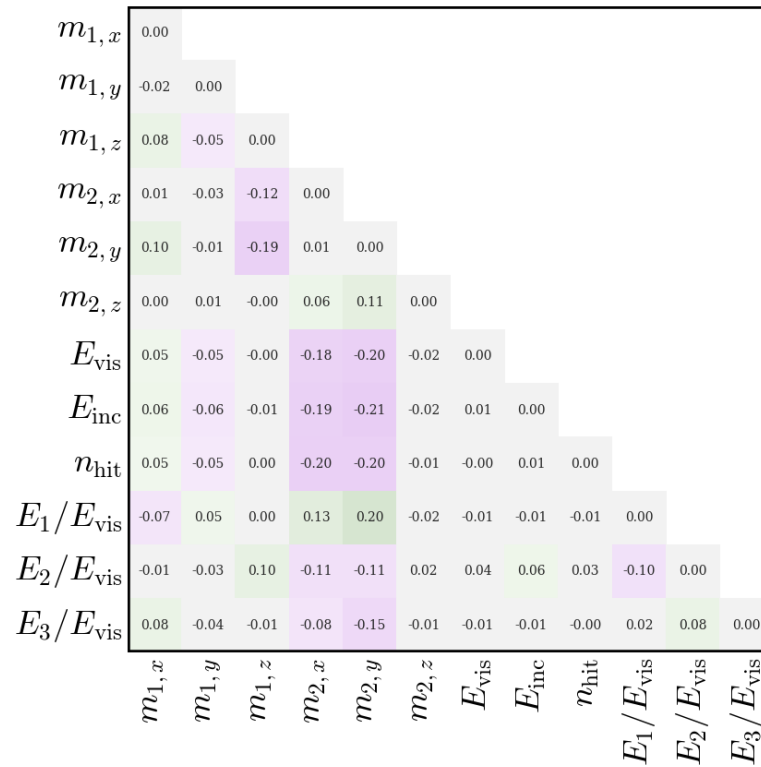
# Backup

# Correlations

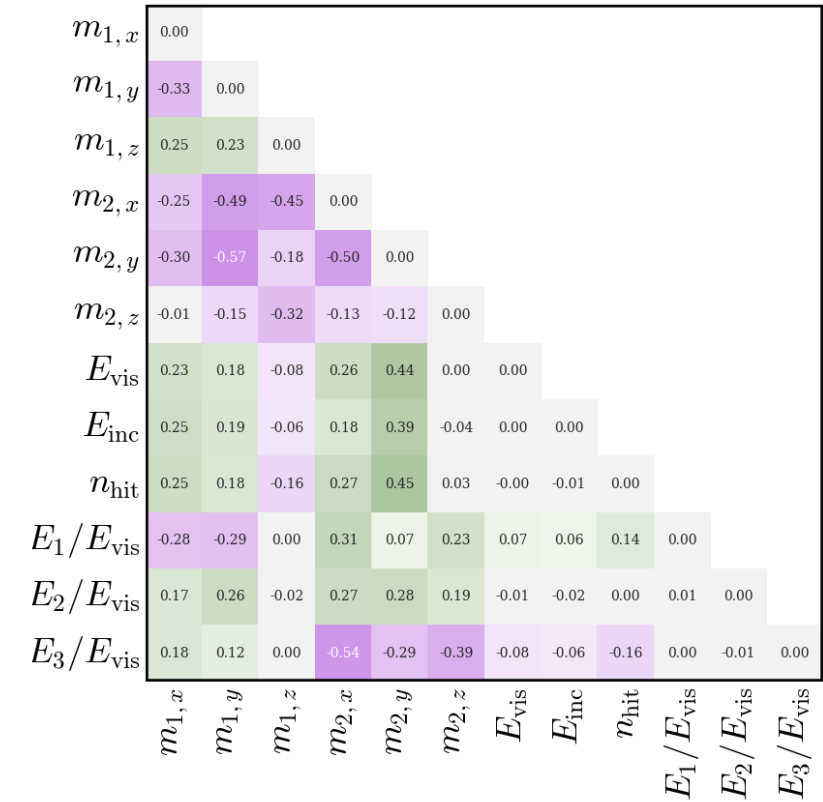
GEANT4 - BIB-AE PP



GEANT4 - GAN

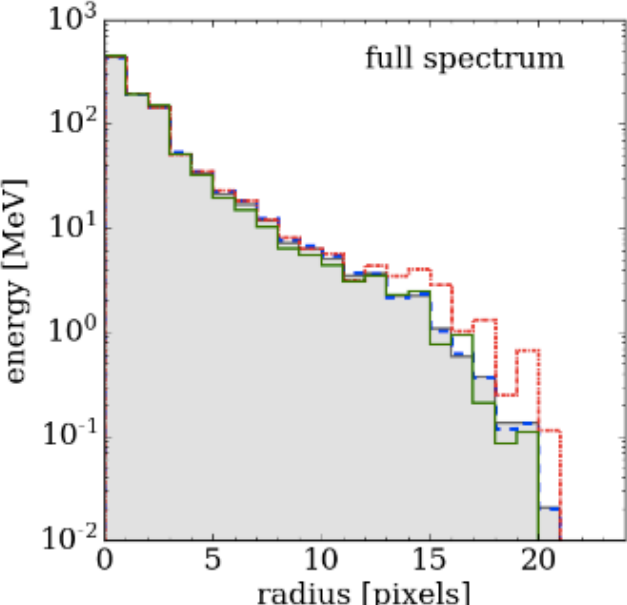
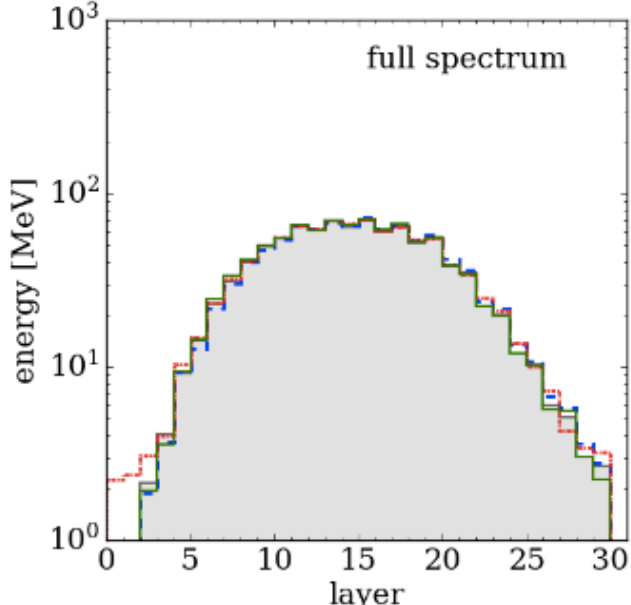
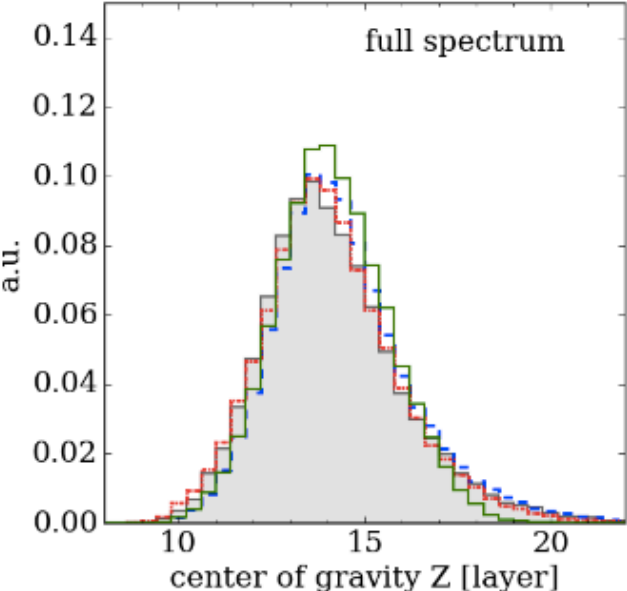
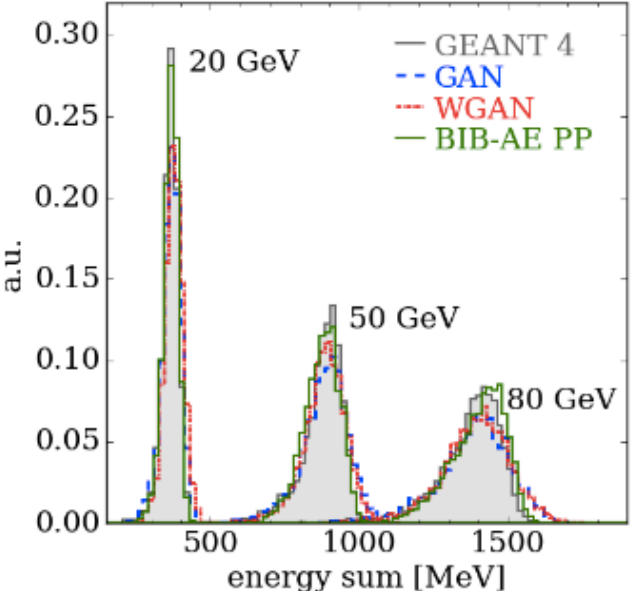


GEANT4 - WGAN



✓ Correlations between individual shower properties present in GEANT4 are correctly reproduced by our generative models

# Distributions...



# WGAN + PP

