High Fidelity Simulation of High Granularity Calorimeters with High Speed

AMALEA Annual Meeting

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17.12.2020

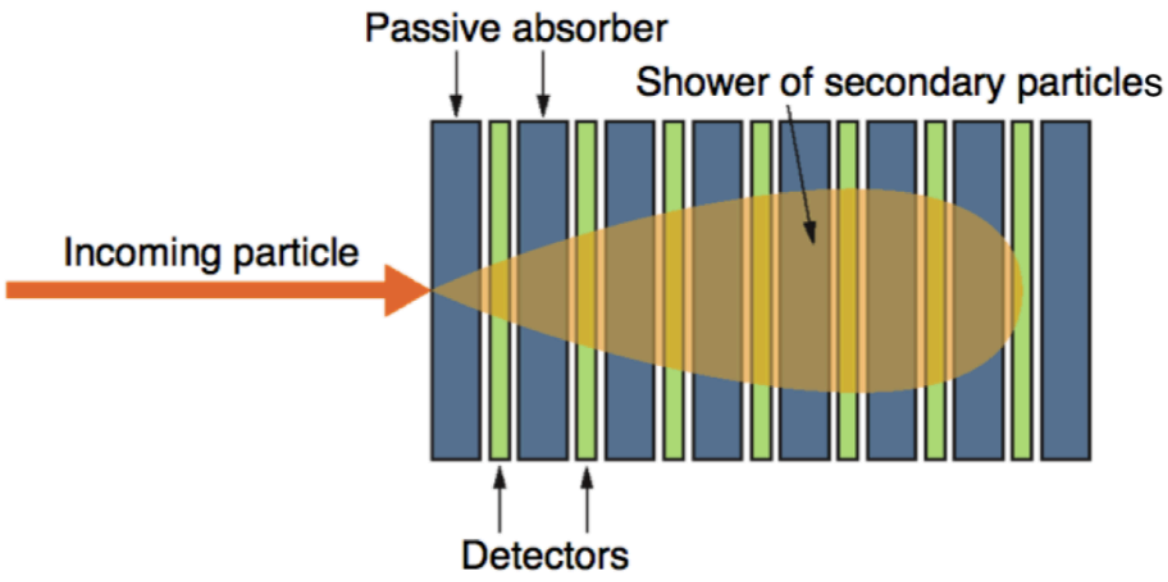
arxiv:2005.05334

HELMHOLTZ RESEARCH FOR GRAND CHALLENGES

CLUSTER OF EXCELLENCE QUANTUM UNIVERSE

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



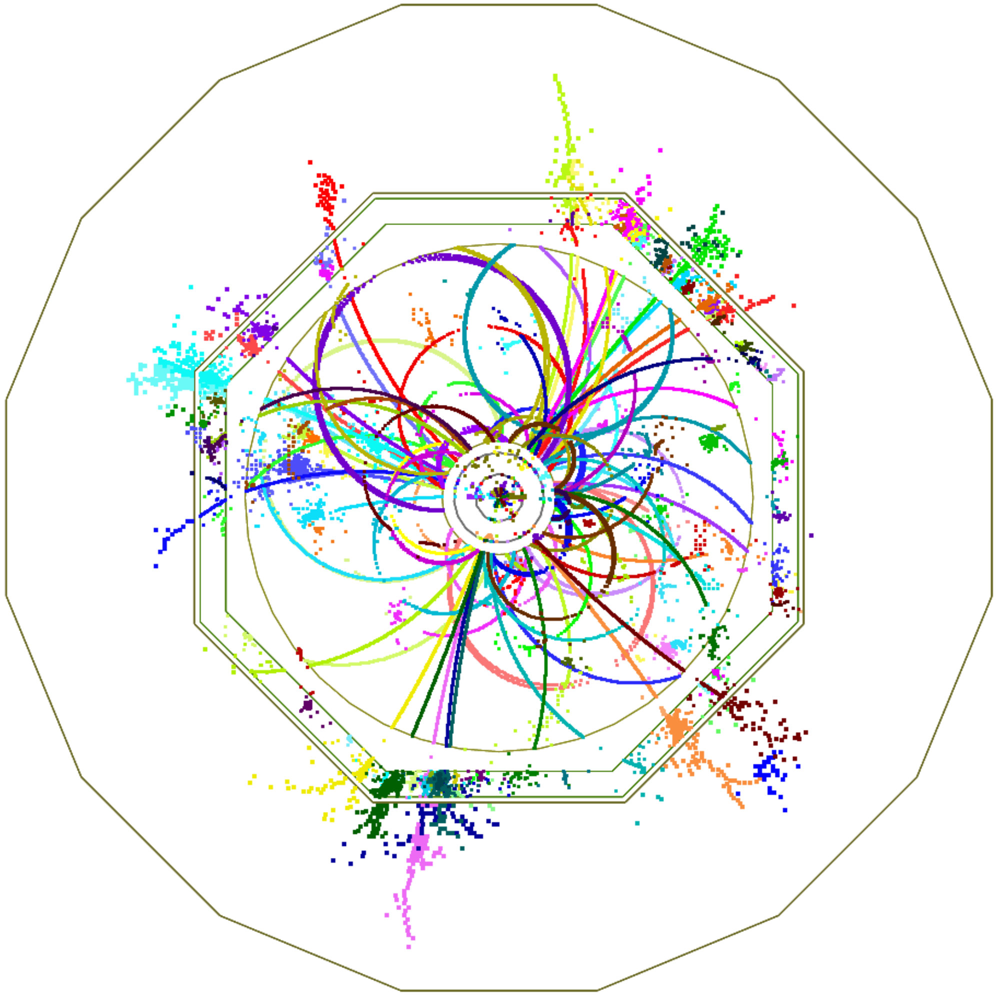
One type of EM calorimeter: sampling calorimeter

- 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

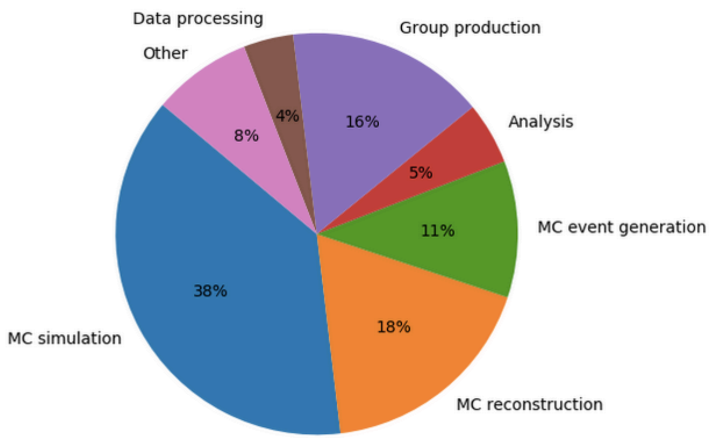


Figure from D.Costanzo, J.Catmore, LHCC meeting

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

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
CALOGAN	CPU	1	13.1
		10	5.11
		128	2.19
		1024	2.03
	GPU	1	14.5
		4	3.68
		128	0.021
		512	0.014
		1024	0.012

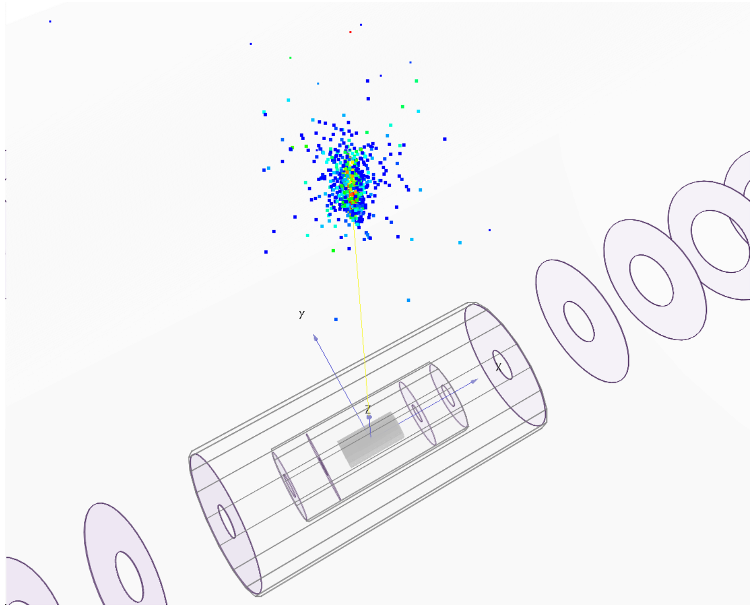
Goal:

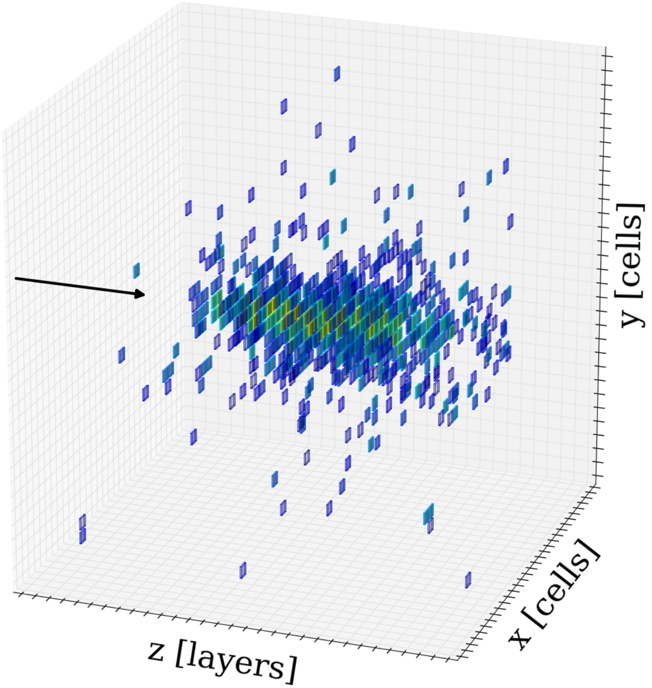
- Reproduce accurate shower simulations with a faster, powerful **generator**; based on state-of-the-art generative models
- **Enormous** amounts of **CPU time** could be potentially saved!

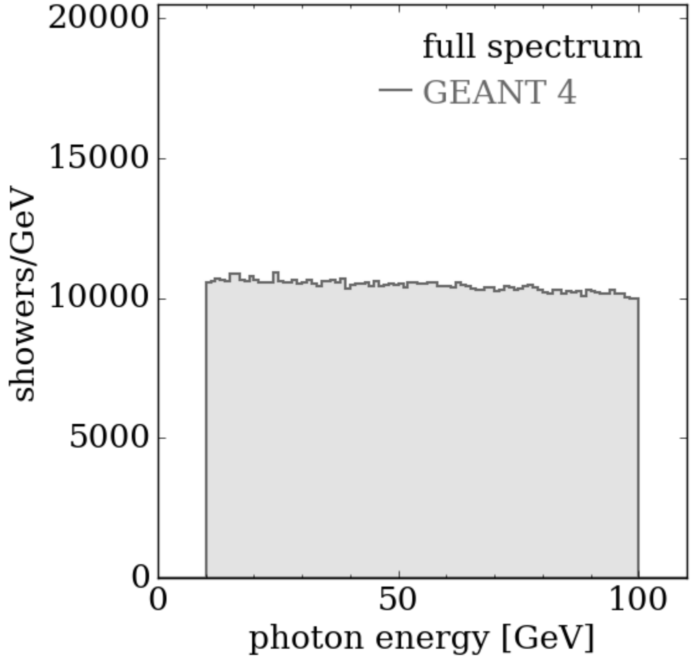
Training Data

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





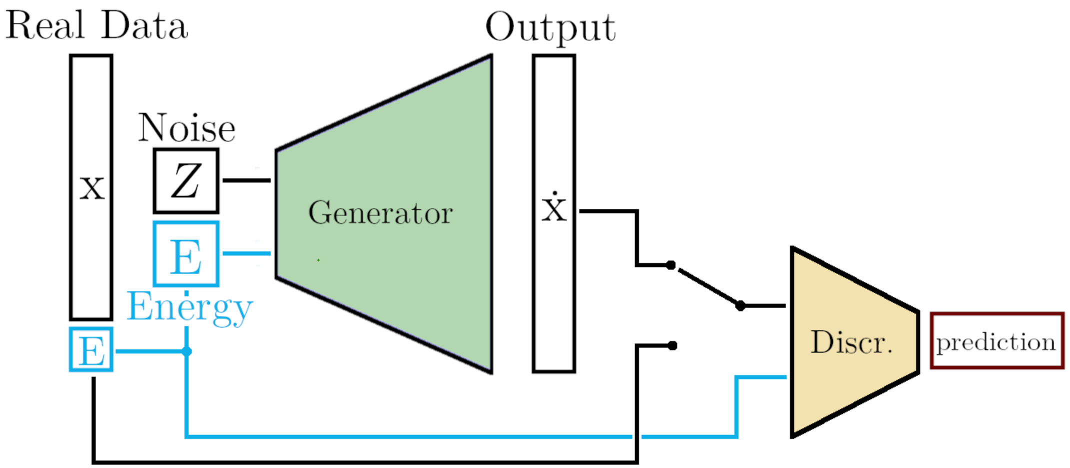


Generative Models

GAN and WGAN

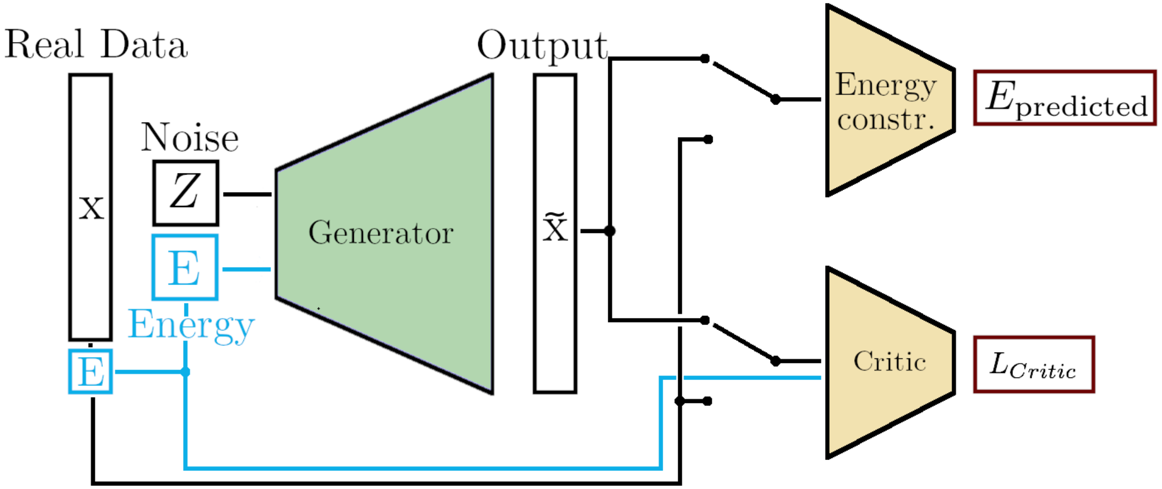
Generative Adversarial Network (GAN)

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



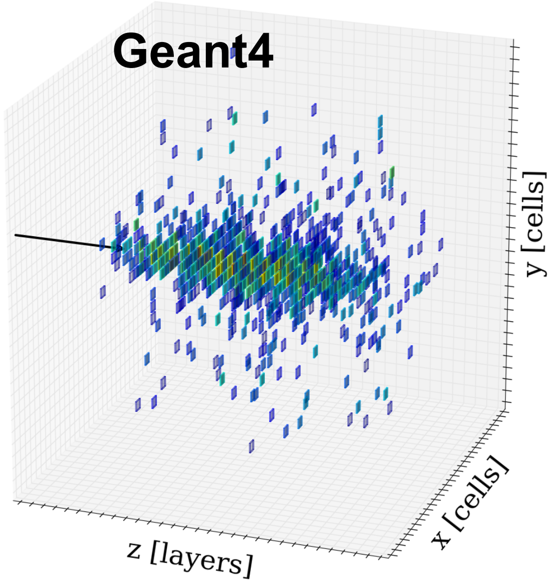
Wasserstein GAN (WGAN)

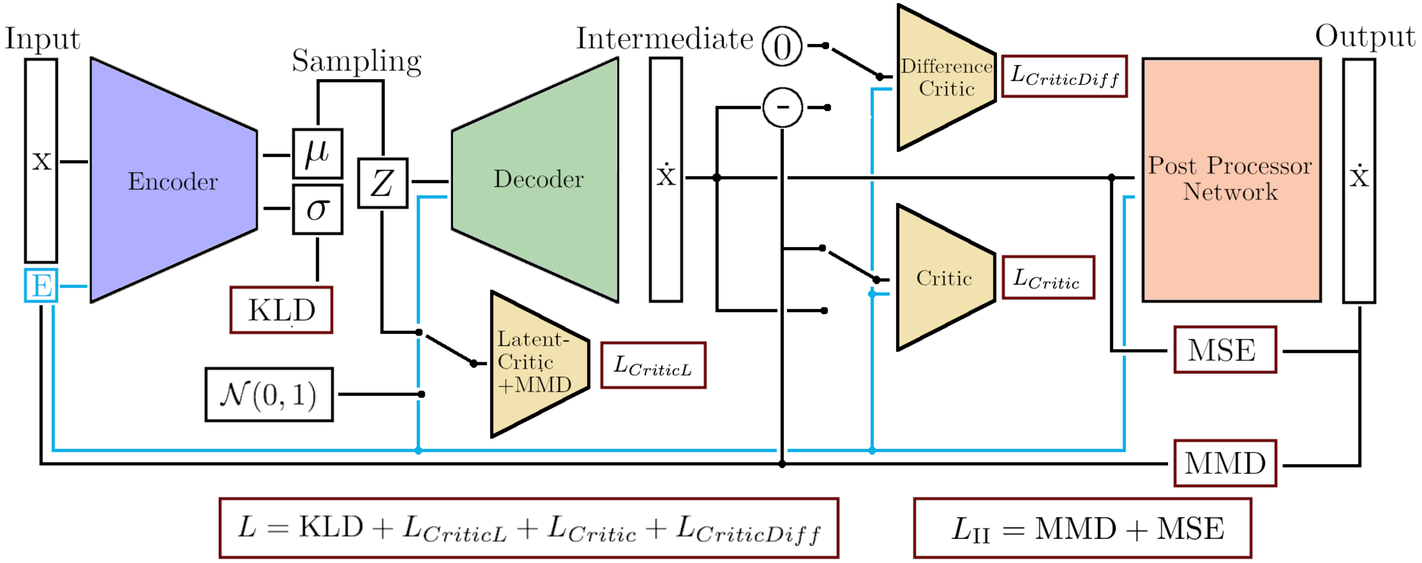
- Alternative to classical GAN training
  - ➡ Helps improve the stability of the training
  - ➡ Use Wasserstein-1 distance as a loss function
  - ➡ Critic network does regression (i.e. gives a score)
- Second network to constrain the energy

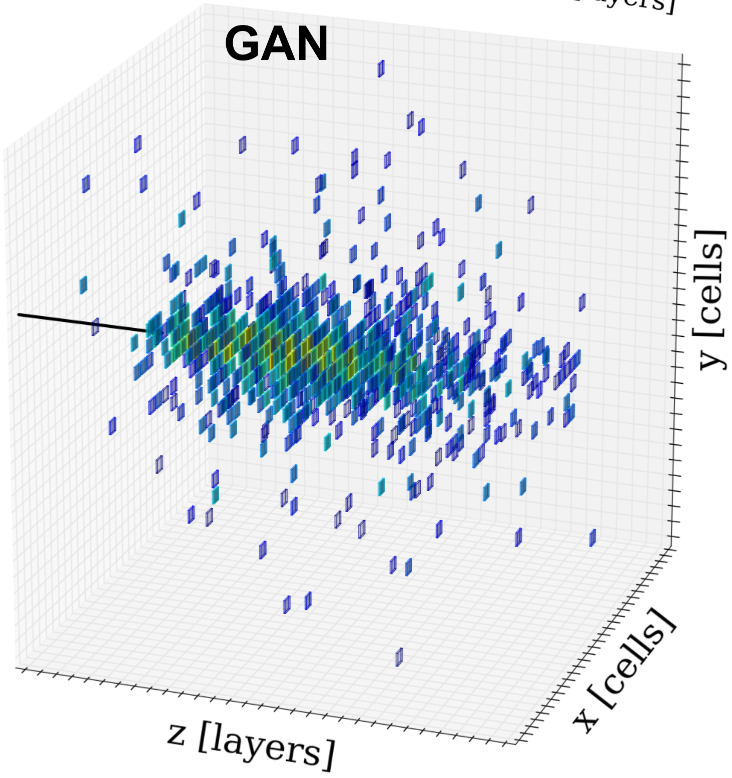


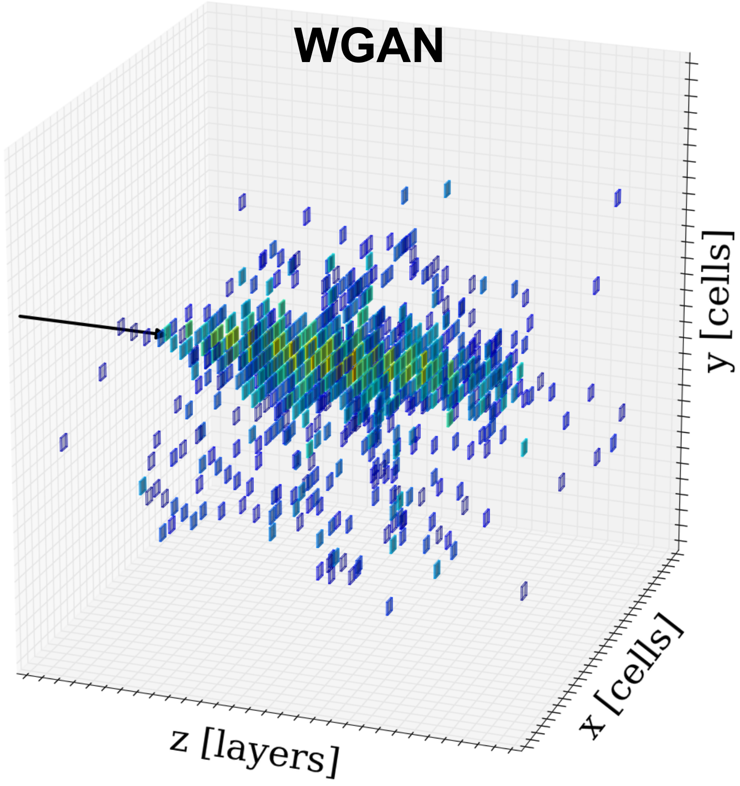
Results

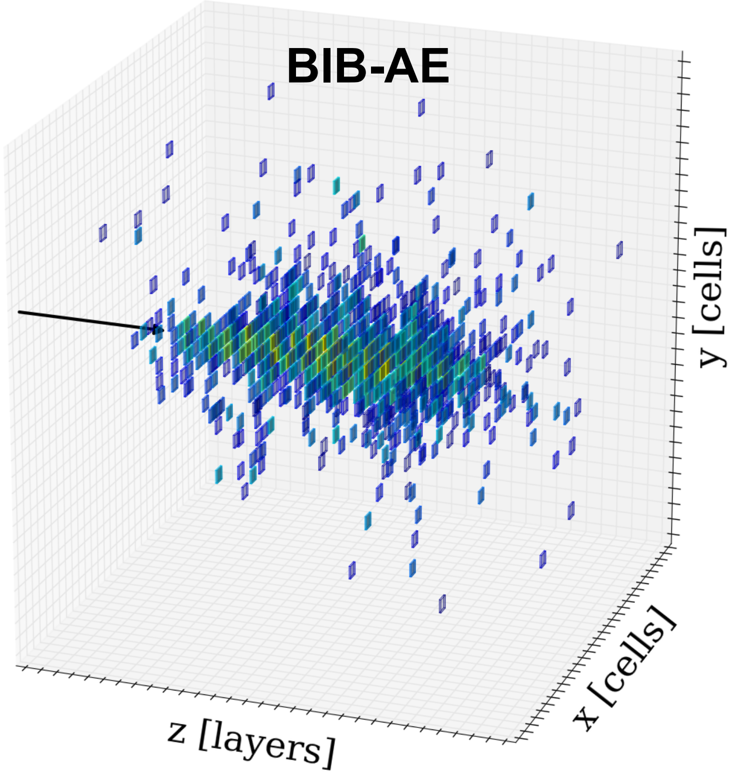
looks realistic???



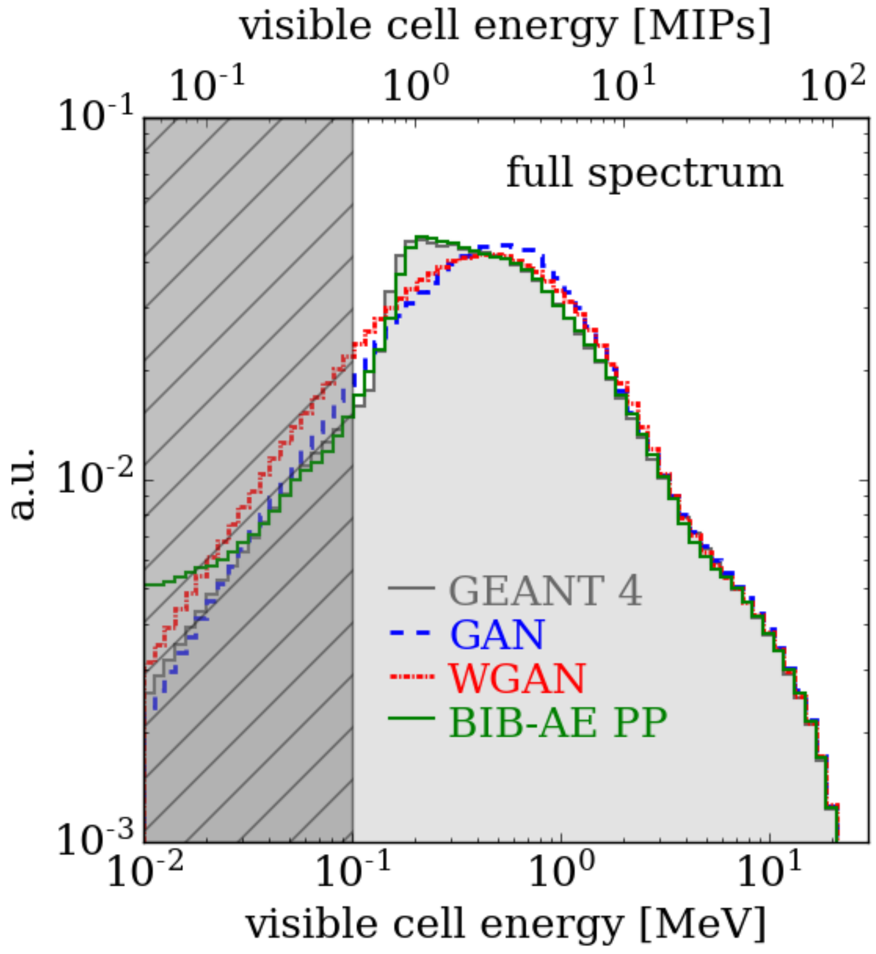


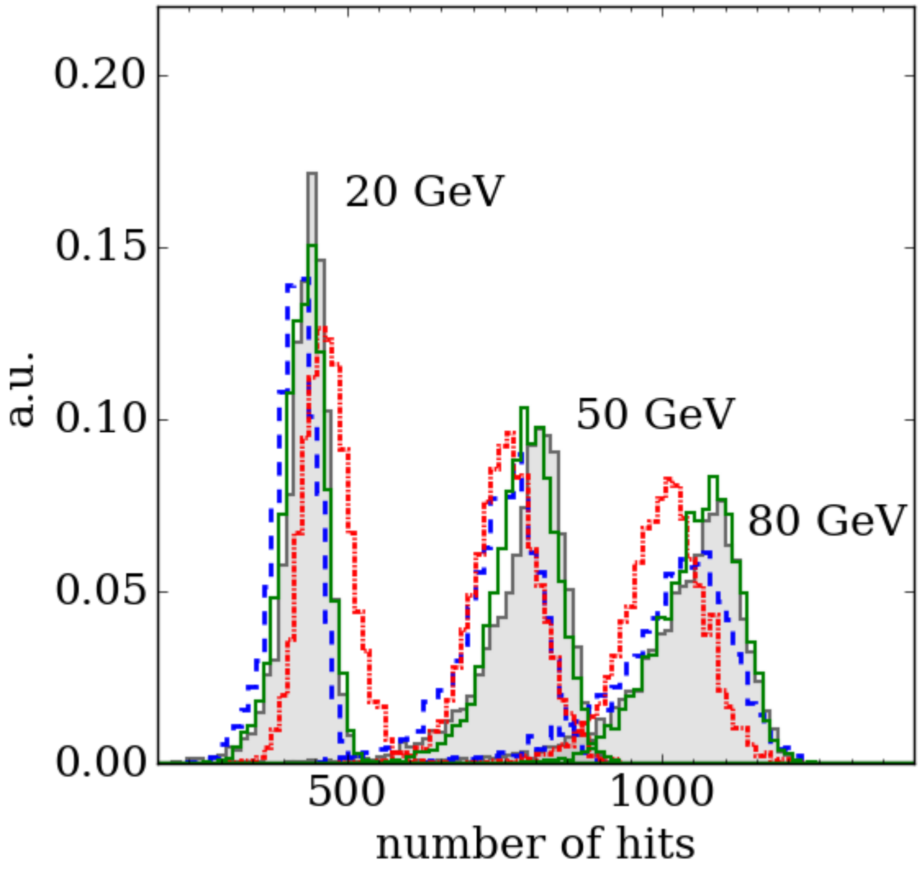






Results: Cell energy and Number of hits





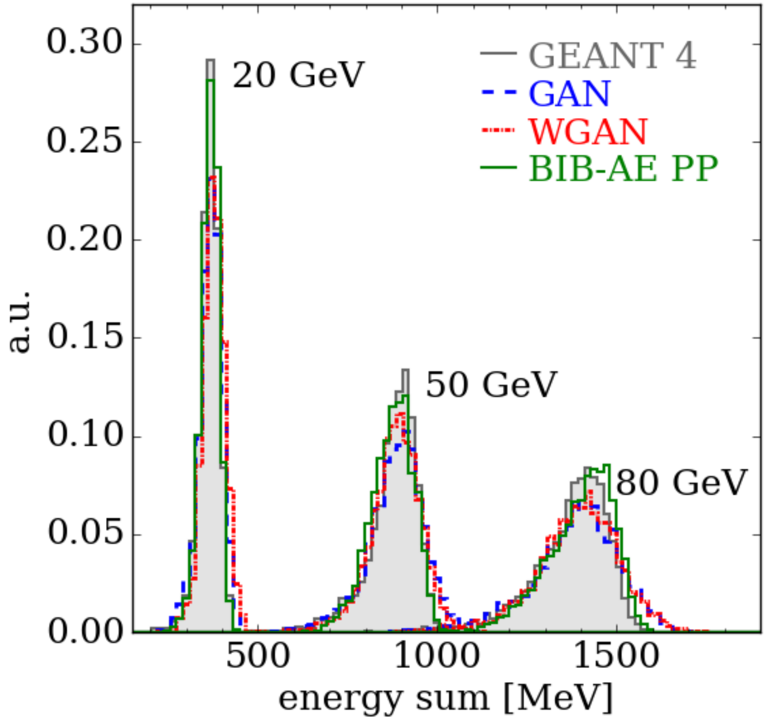
- Both GAN and WGAN fail to capture MIP bump around 0.2 MeV

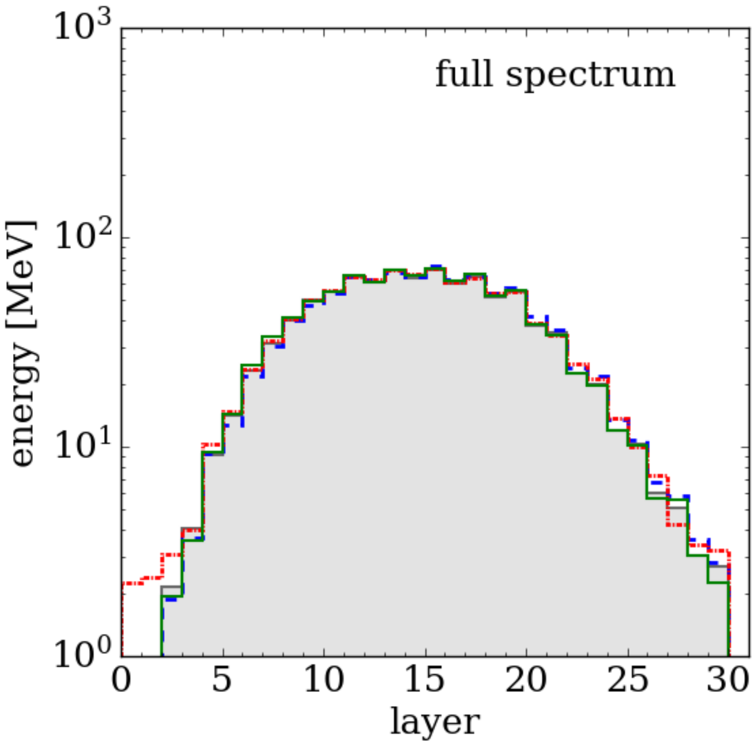
✓ BiB-AE is able to produce this feature thanks to Post-Processing network

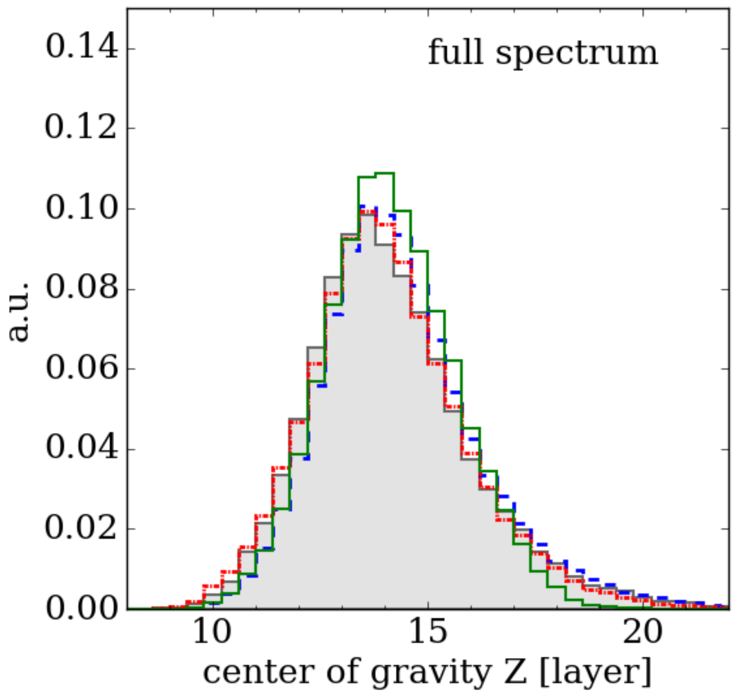
- GAN and WGAN slightly underestimate the total number of hits

✓ 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.

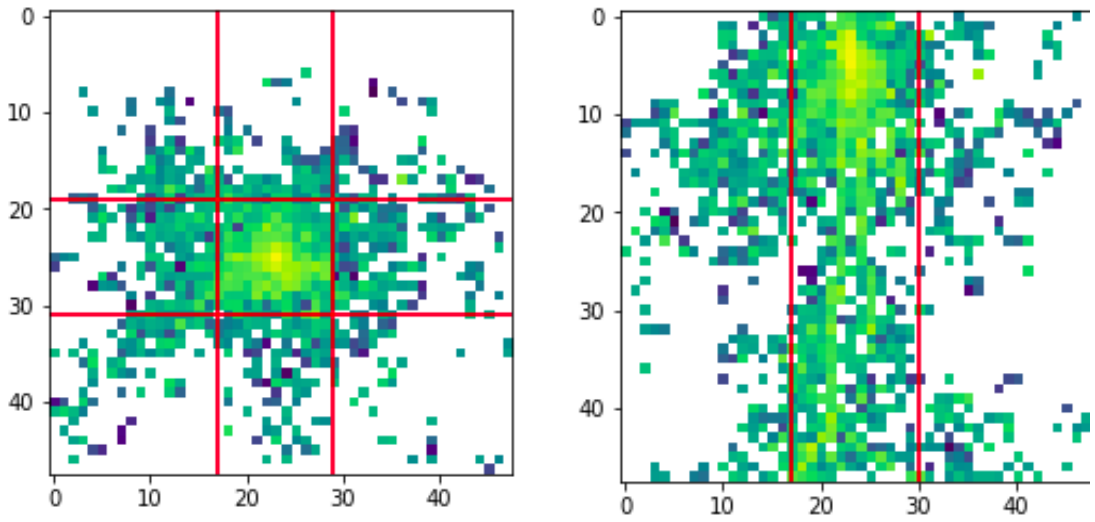
- slight deviations for the WGAN appear around the edges

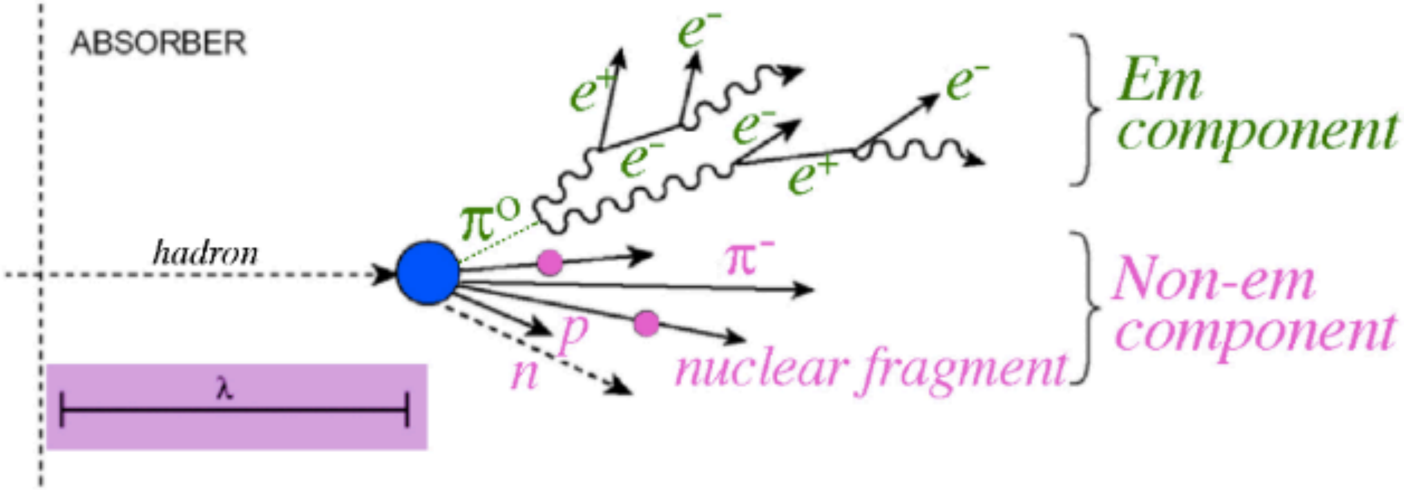
- Deviations for BiB-AE
  - ✓ Explainable via latent space encoding

Hadron Showers

a bit tricky…

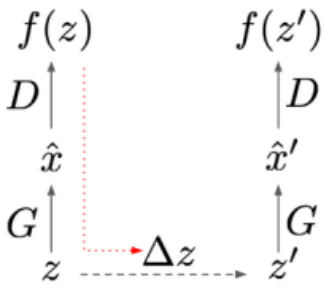
- After success with GAN based simulation for electromagnetic showers, we started to address hadronic (pion) showers
- Much more complex shower structure
- Currently training with a smaller 3D image containing only the shower core
- Started with GAN, WGAN, BIB-AE and alternatives





A new WGAN

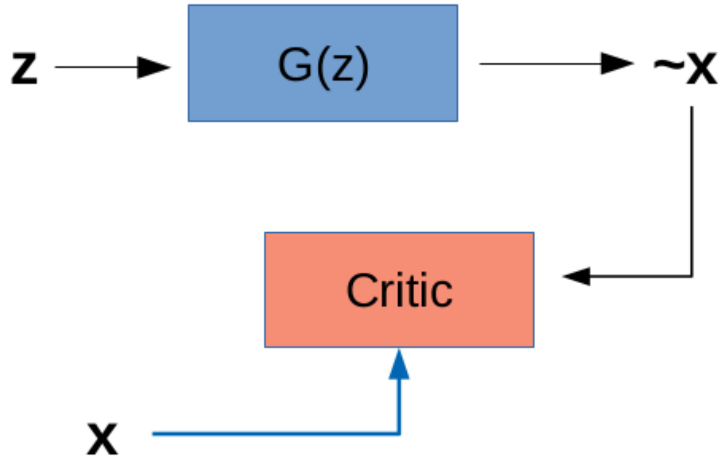
- Trained on 40 GeV showers. Approx half a million
- Shower is 48x13x13
- Architectures
  - very similar to WGAN in our “getting high paper”
  - Latent Optimized WGAN, inspired by DeepMind

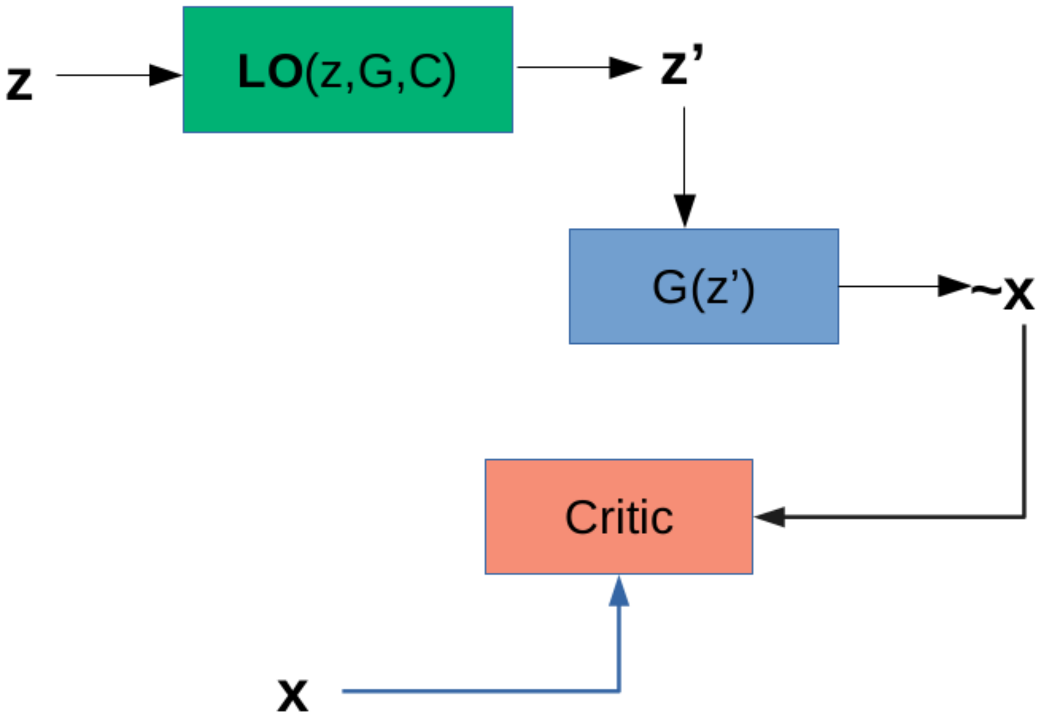


arXiv: 1912.00953

Figure 3: (**a**) Schematic of LOGAN. We first compute a forward pass through G and D with a sampled latent z. Then, we use gradients from the generator loss (dashed red arrow) to compute an improved latent, z'. After we use this optimised latent code in a second forward pass, we compute gradients of the discriminator back through the latent optimisation into the model parameters θ_D, θ_G. We use these gradients to update the model. (**b**) Truncation curves illustrate the FID/IS trade-off

Our classical WGAN

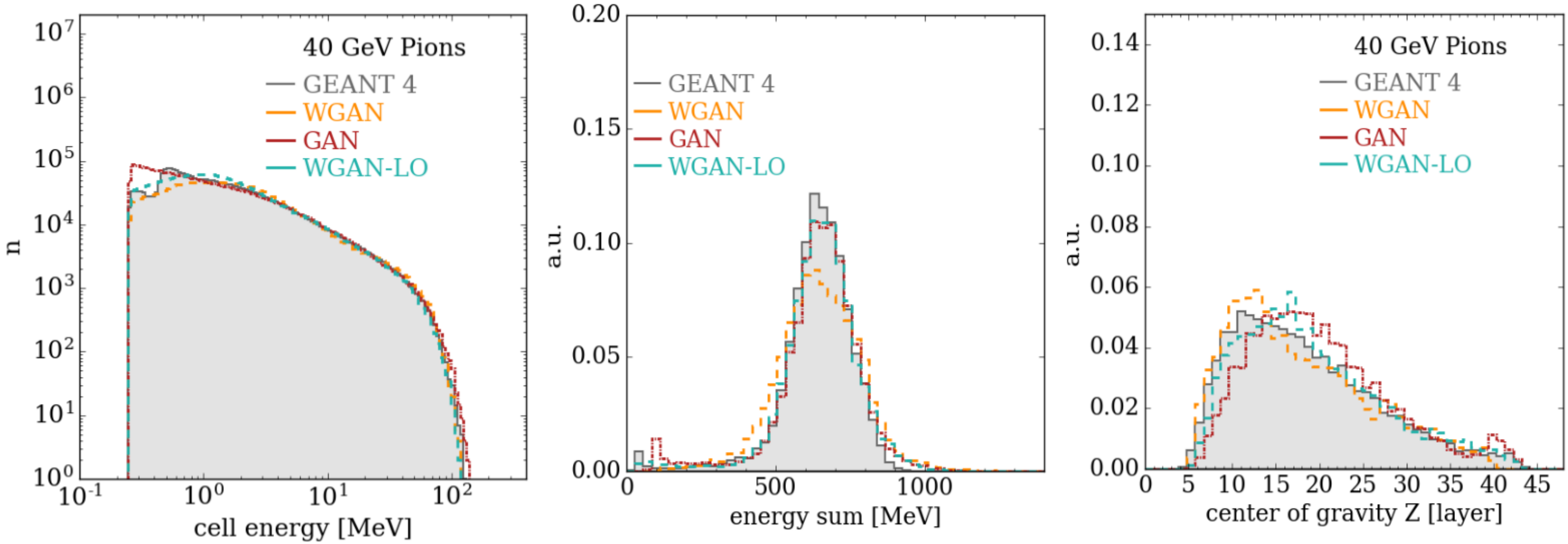




WGAN update

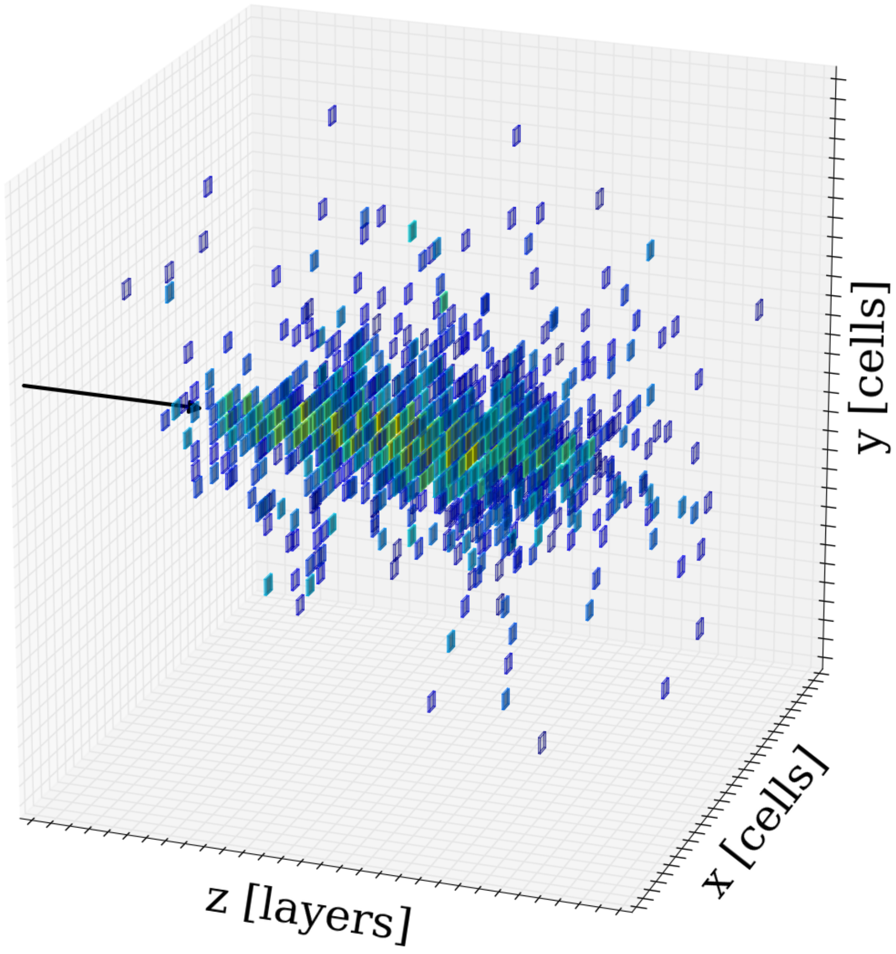
WORK IN PROGRESS

- Trained on 40 GeV showers. Approx half a million
- Shower is 48x13x13



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
  - ◉ CMS HGCal
  - ◉ integrate into existing tools / frameworks



Paper: [arxiv:2005.05334] (submitted to journal, soon to be published)

Backup

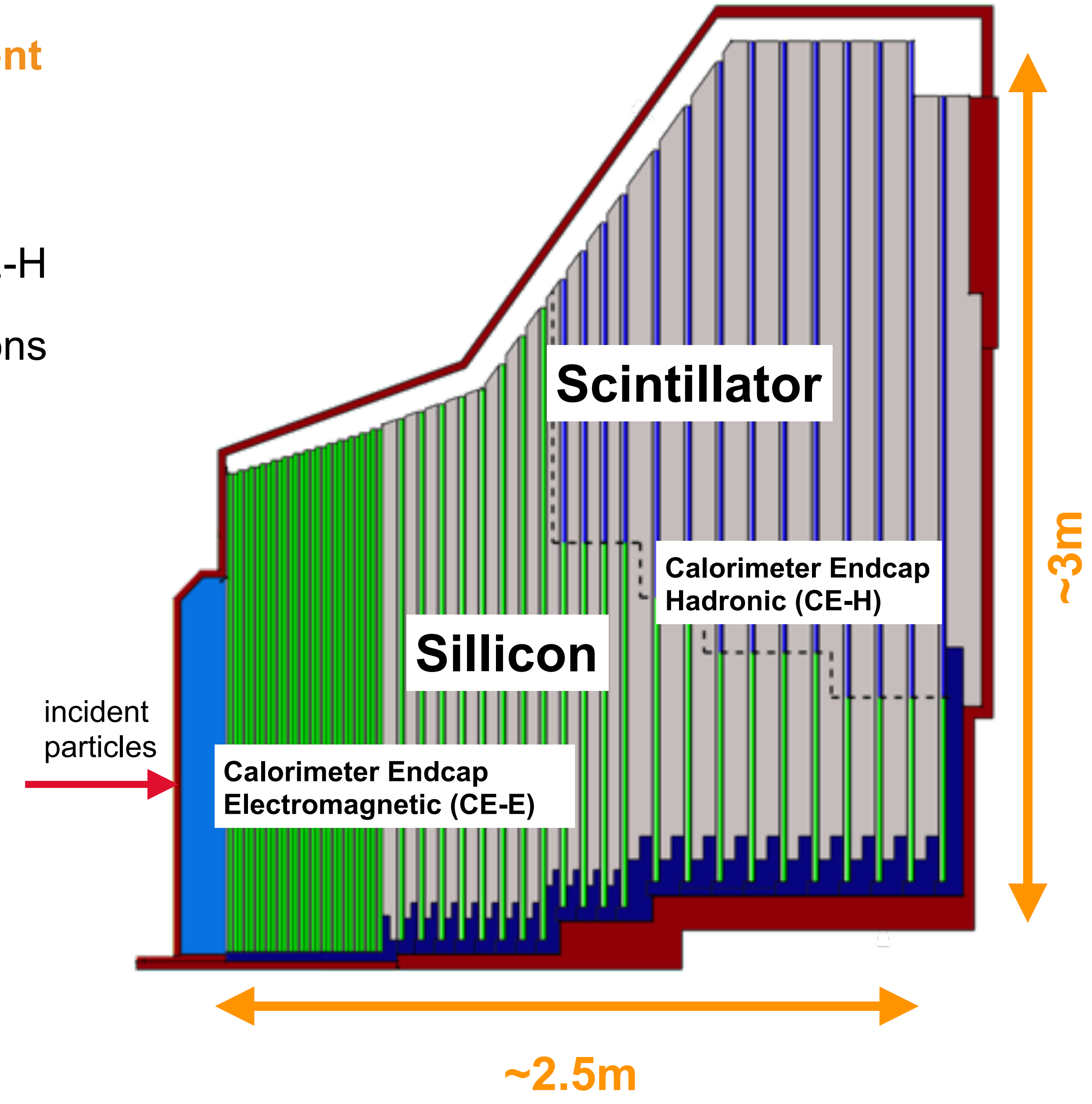
New Challenge: CMS HGCal

Planned High Granular Calorimeter for CMS Experiment

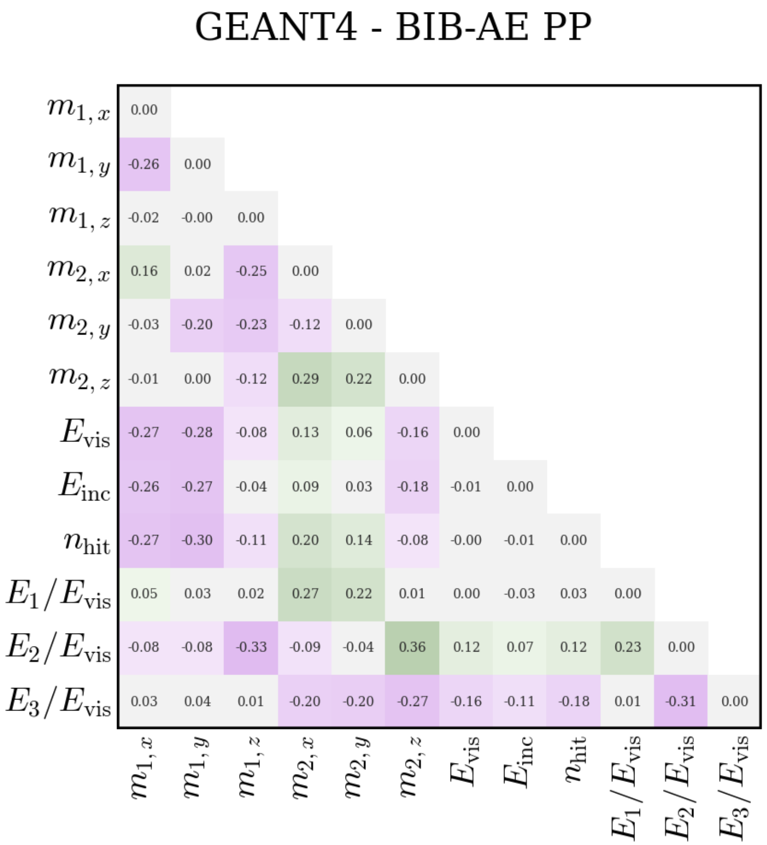
- HGCAL is a **sampling** calorimeter
- Silicon sensors in CE-E and high radiation regions of CE-H
- Scintillating tiles with SiPM readout in low-radiation regions of CE-H
- 3D imaging calorimeter with timing capabilities

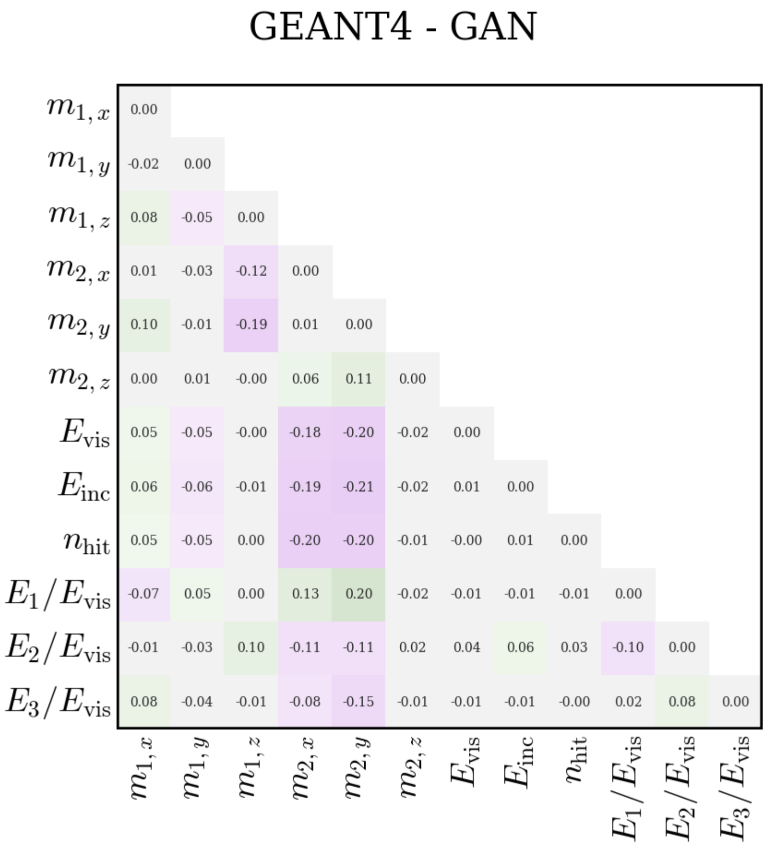
Application of generative networks to CMS HGCal has started in our group with **close collaboration** with experts in the field

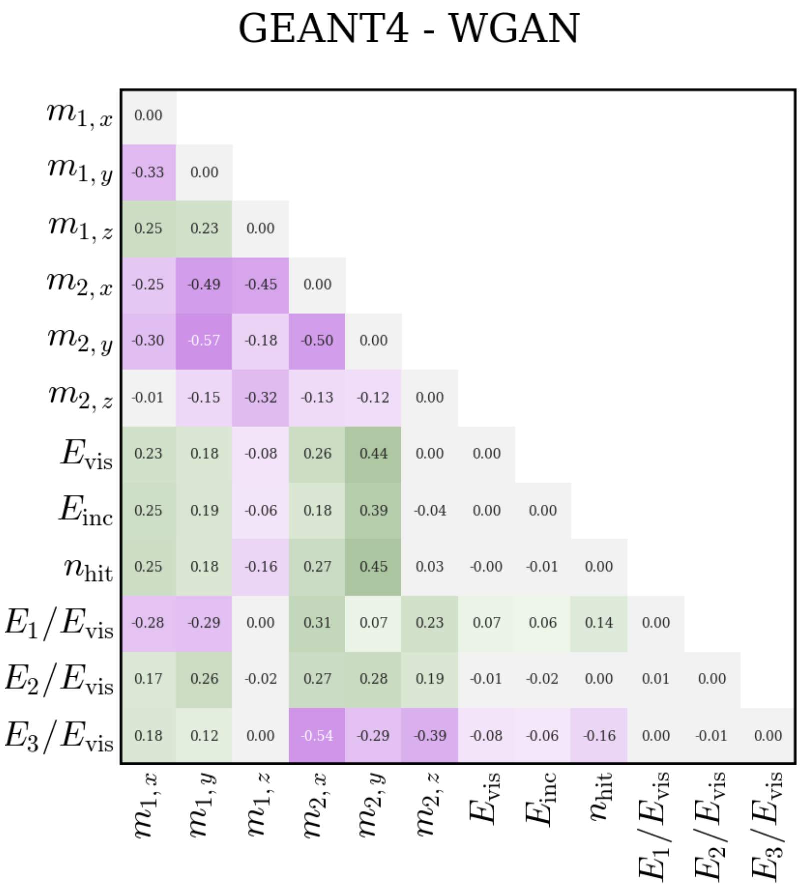
Stay tuned for our preliminary results!!



Correlations





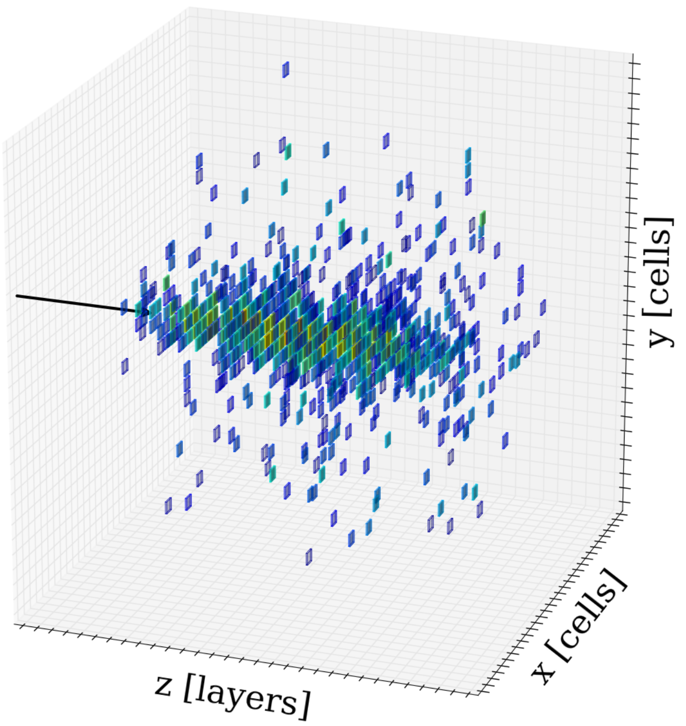


✓ Correlations between individual shower properties present in GEANT4 are correctly reproduced by our generative models

Challenges

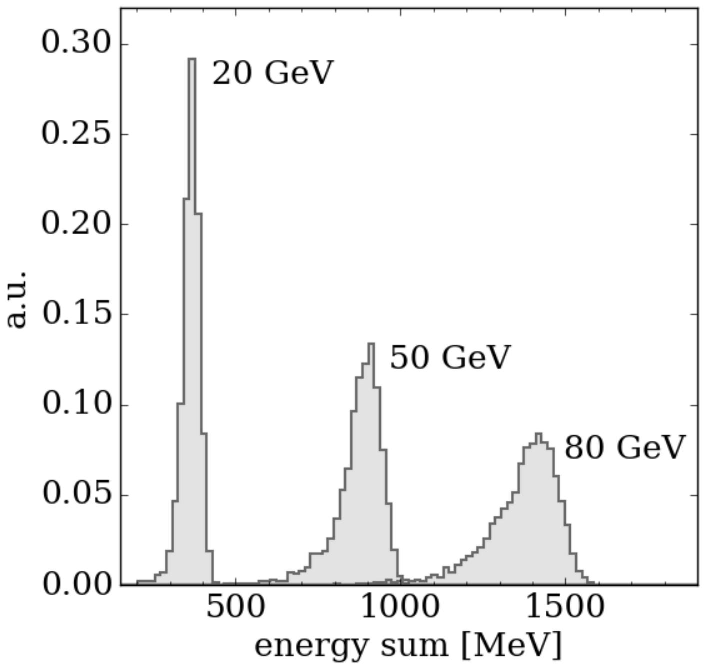
Quality measures:

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



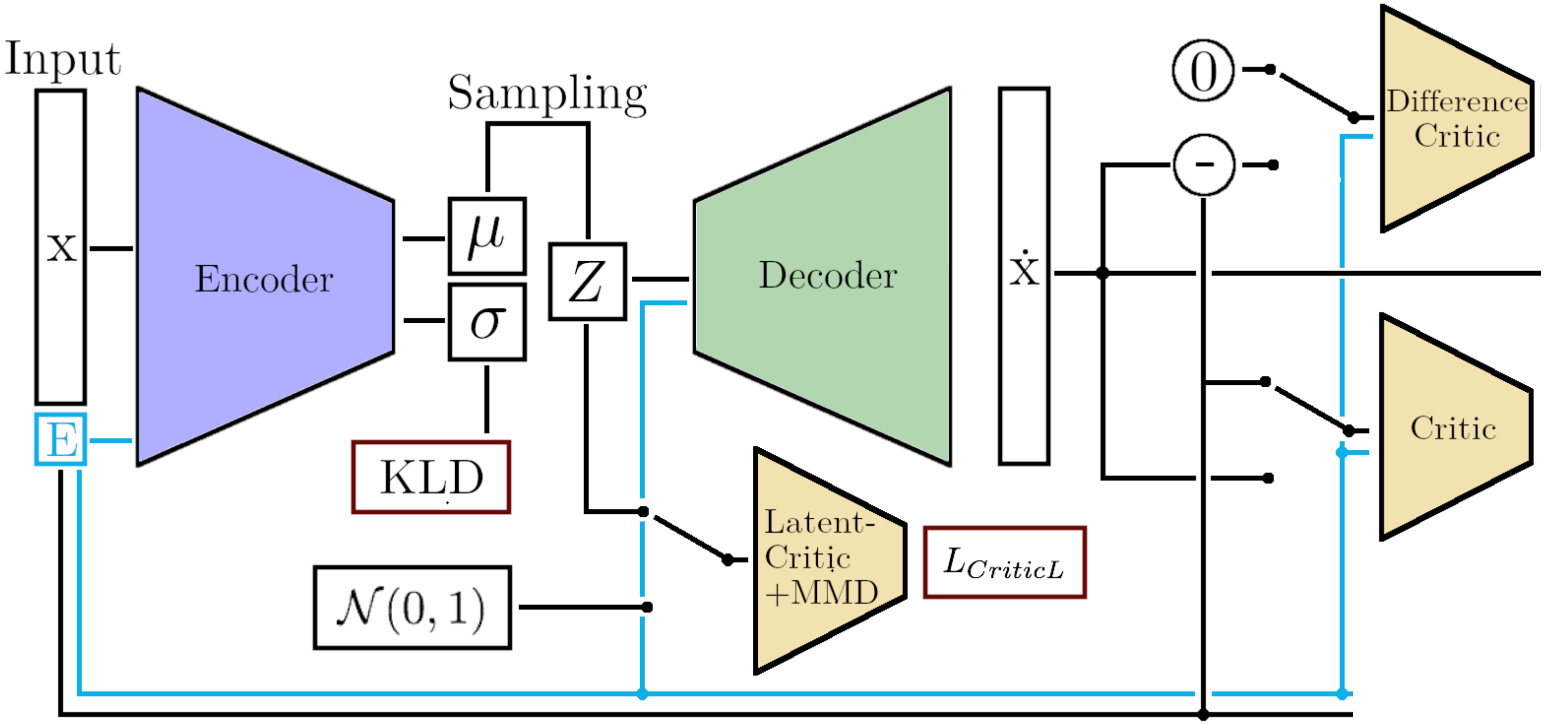
Energy conditioning

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



BiB-AE

arXiv:1912.00830

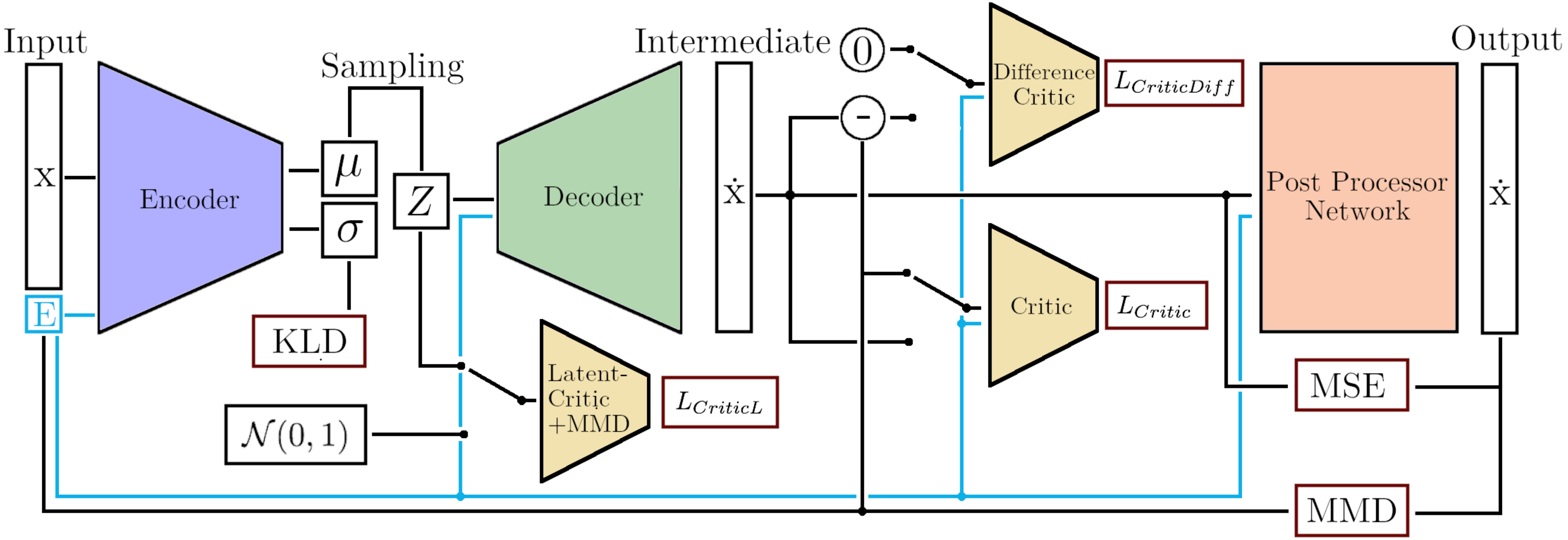


$$L = \mathrm{KLD} + L_{CriticL} + L_{Critic} + L_{CriticDiff}$$

Bounded Information Bottleneck AutoEncoder (BiB-AE)

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

BiB-AE

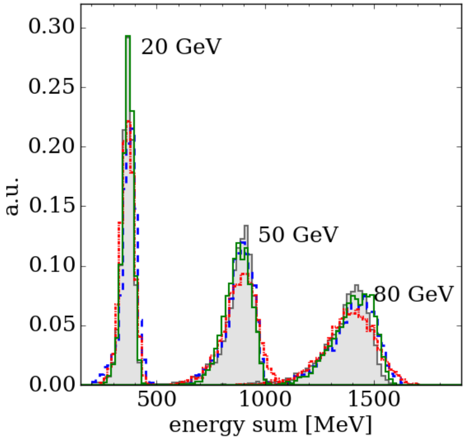


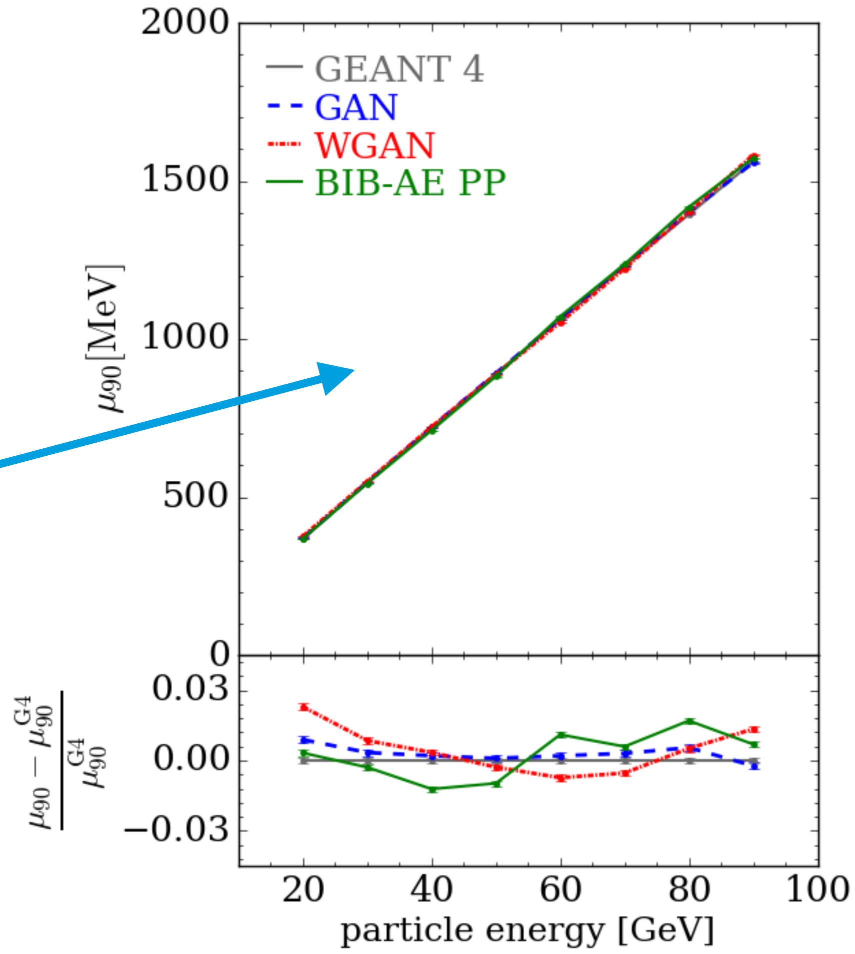
$L = \mathrm{KLD} + L_{CriticL} + L_{Critic} + L_{CriticDiff}$

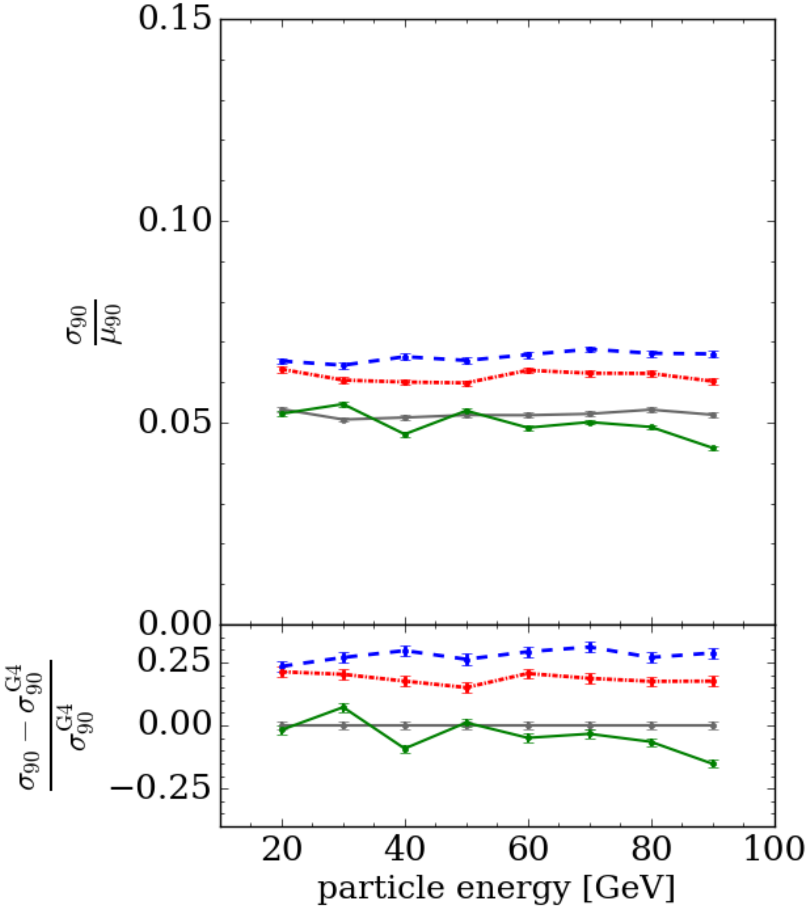
$L_{\mathrm{II}} = \mathrm{MMD} + \mathrm{MSE}$

Post Processor Network for final cell-energy tuning!!

Results: Linearity and Width



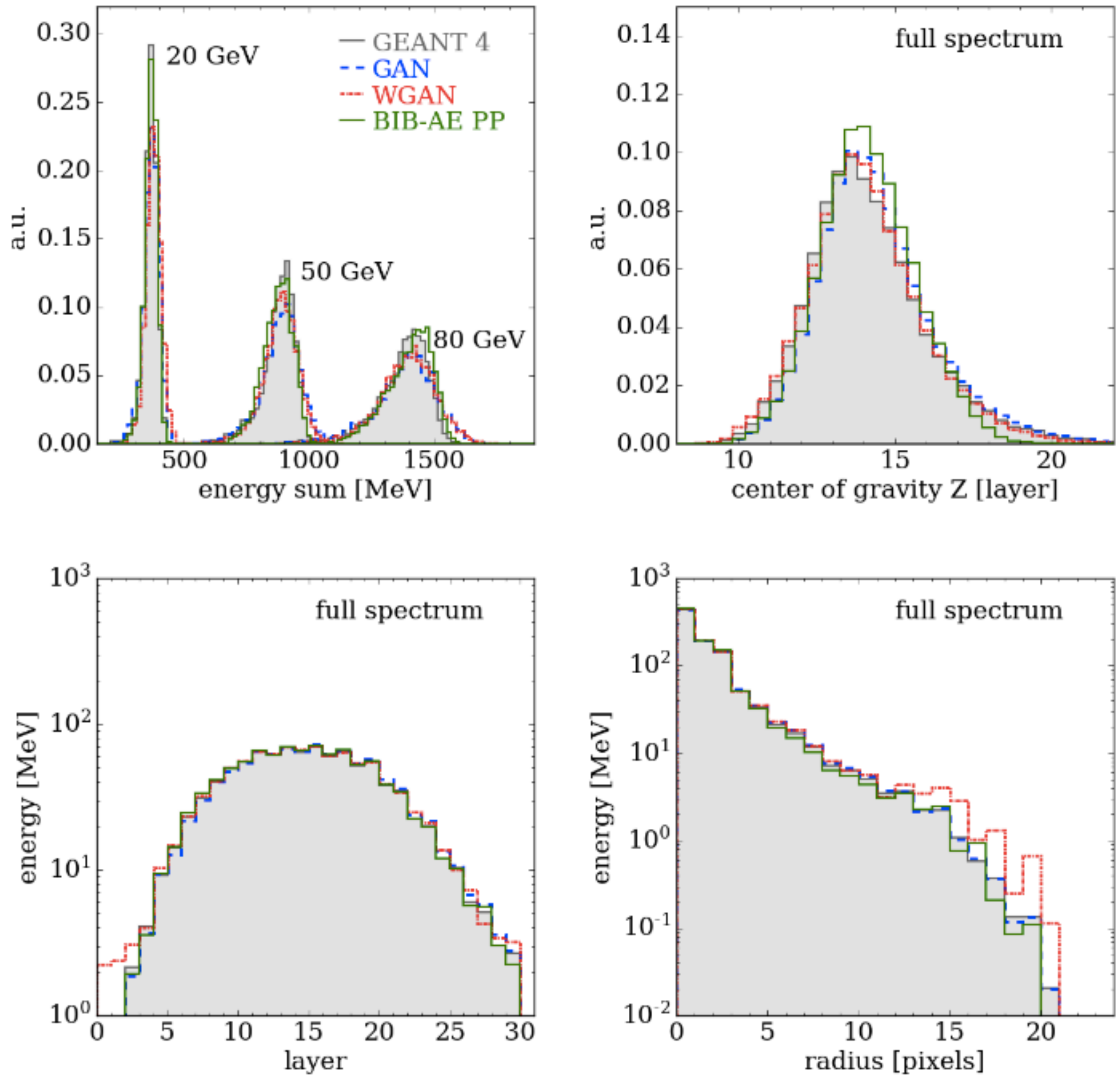




✓ Overall good modelled by all generative models. Deviations up to few percent

◉ Overestimated by GAN and WGAN

Distributions…



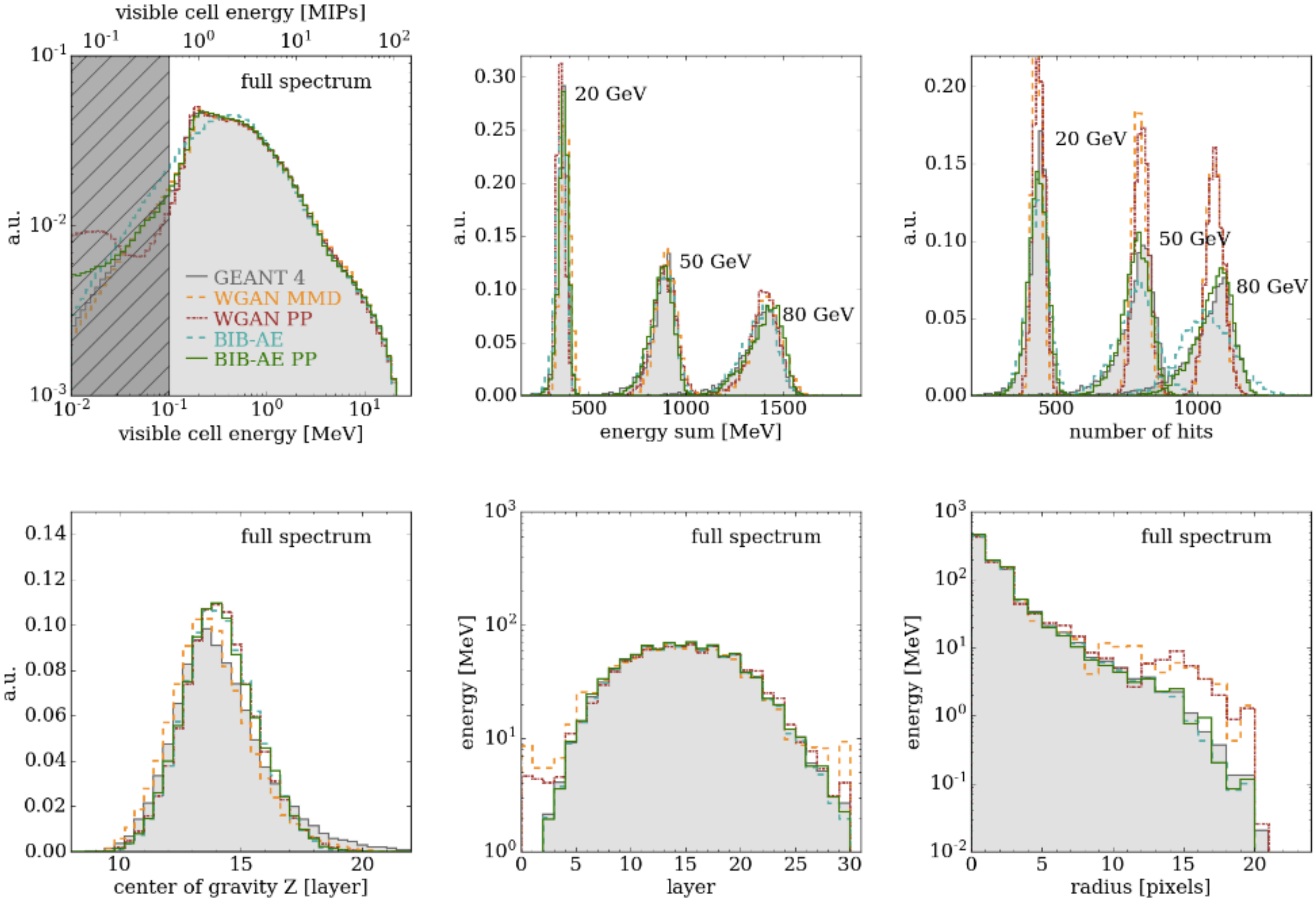
Computation Time

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	**x23**	63.14 ± 0.34 ms	**x65**
		10	59.53 ± 0.45 ms	**x24**	56.65 ± 0.33 ms	**x72**
		100	58.31 ± 0.93 ms	**x25**	58.11 ± 0.13 ms	**x70**
		1000	57.99 ± 0.97 ms	**x25**	57.99 ± 0.18 ms	**x70**
BIB-AE	CPU	1	426.60 ± 3.27 ms	**x3**	426.32 ± 3.62 ms	**x10**
		10	422.60 ± 0.26 ms	**x3**	424.71 ± 3.53 ms	**x10**
		100	419.64 ± 0.07 ms	**x3**	418.04 ± 0.20 ms	**x10**
WGAN	GPU	1	3.24 ± 0.01 ms	**x446**	3.25 ± 0.01 ms	**x1256**
		10	6.13 ± 0.02 ms	**x236**	6.13 ± 0.02 ms	**x666**
		100	5.43 ± 0.01 ms	**x266**	5.43 ± 0.01 ms	**x752**
		1000	5.43 ± 0.01 ms	**x266**	5.43 ± 0.01 ms	**x752**
BIB-AE	GPU	1	3.14 ± 0.01 ms	**x838**	3.19 ± 0.01 ms	**x1279**
		10	1.56 ± 0.01 ms	**x1287**	1.57 ± 0.01 ms	**x2600**
		100	1.42 ± 0.01 ms	**x1366**	1.42 ± 0.01 ms	**x2874**

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**

WGAN + PP



visible cell energy [MIPs]
full spectrum
GEANT 4
WGAN MMD
WGAN PP
BIB-AE
BIB-AE PP
a.u.
visible cell energy [MeV]
20 GeV
50 GeV
80 GeV
energy sum [MeV]
number of hits
center of gravity Z [layer]
energy [MeV]
layer
radius [pixels]