Generative Models For High Granularity Calorimeters

Machine Learning for Jets Workshop, New York University

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HELMHOLTZ RESEARCH FOR GRAND CHALLENGES

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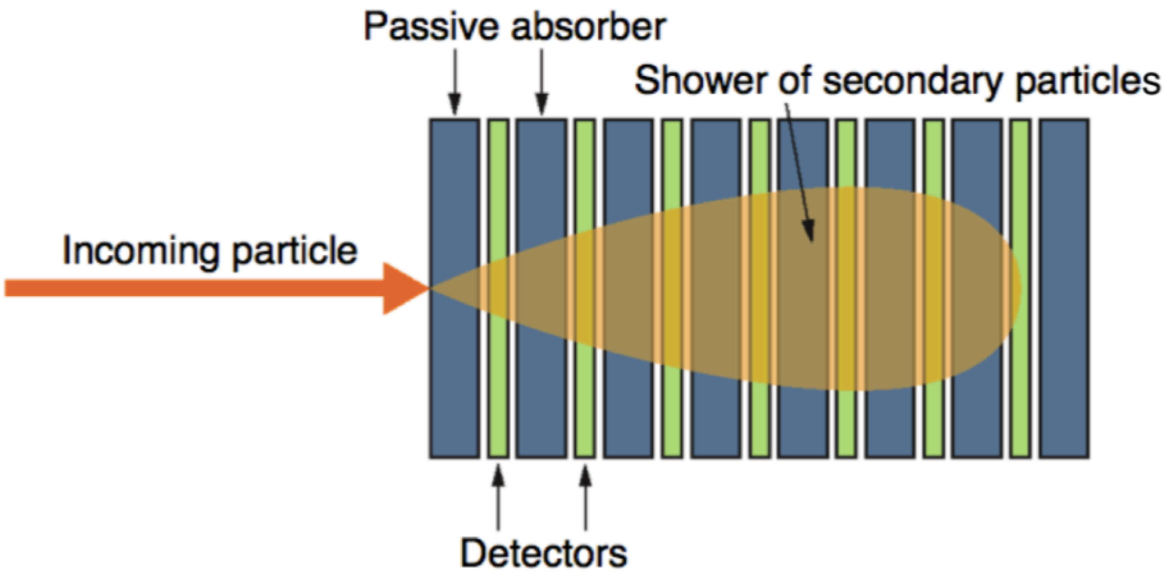
DESY.

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



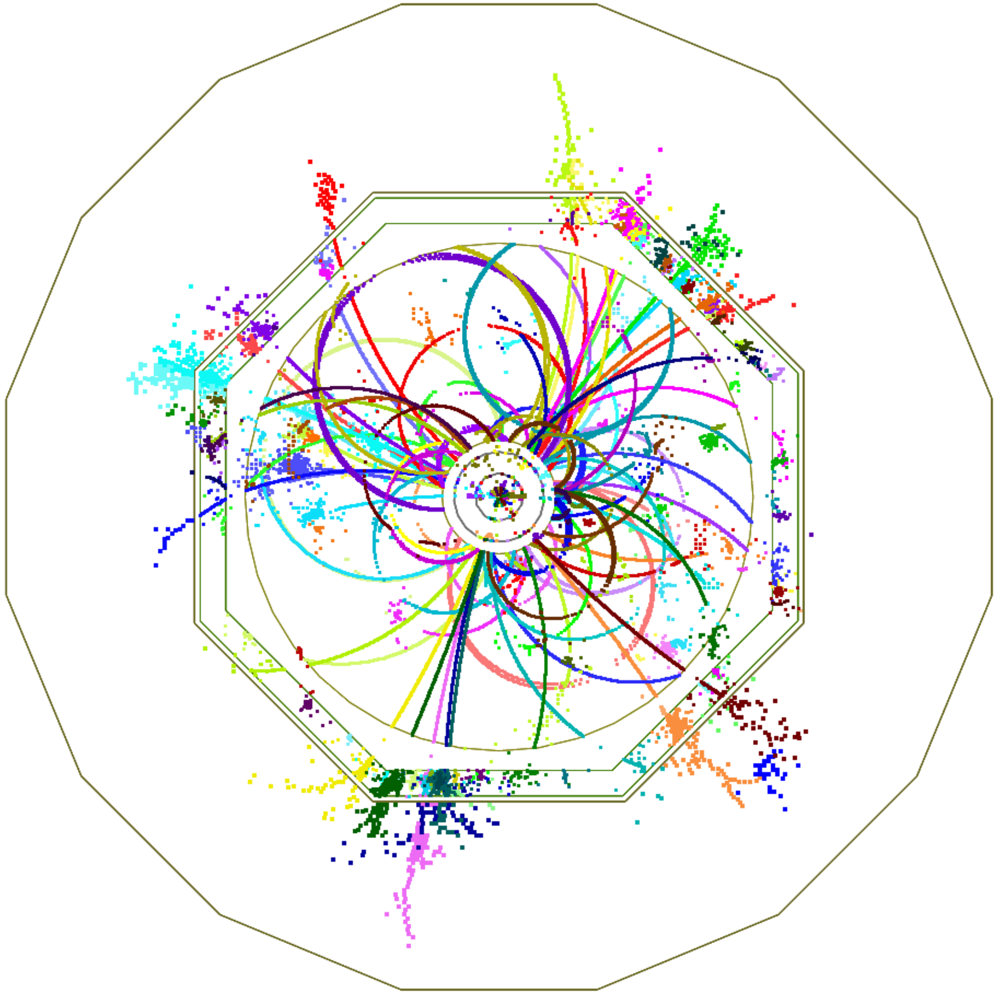
One type of EM calorimeter: sampling calorimeter

- 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

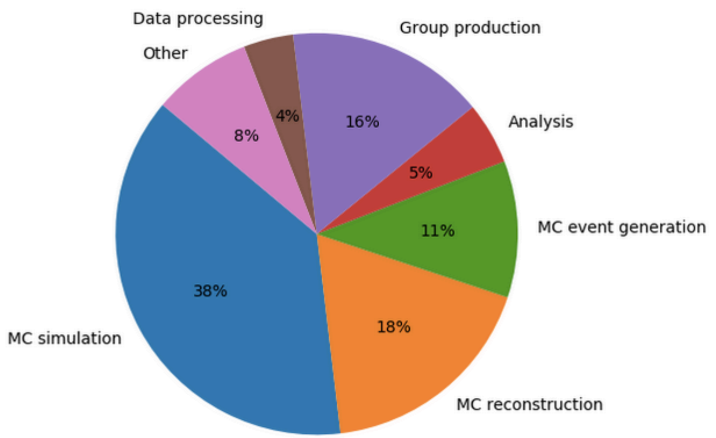


Figure from D.Costanzo, J.Catmore, LHCC meeting

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

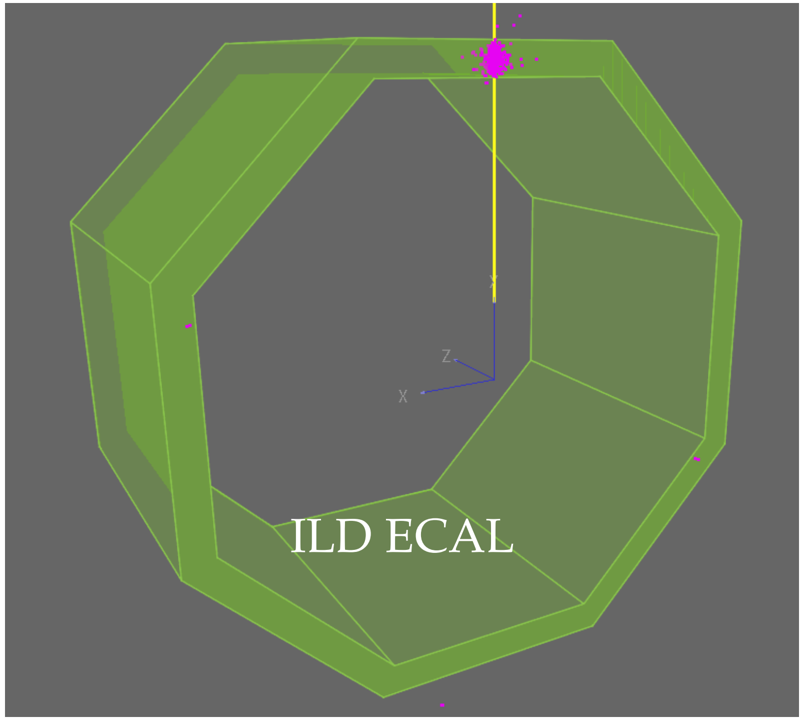
Goal:

- 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!

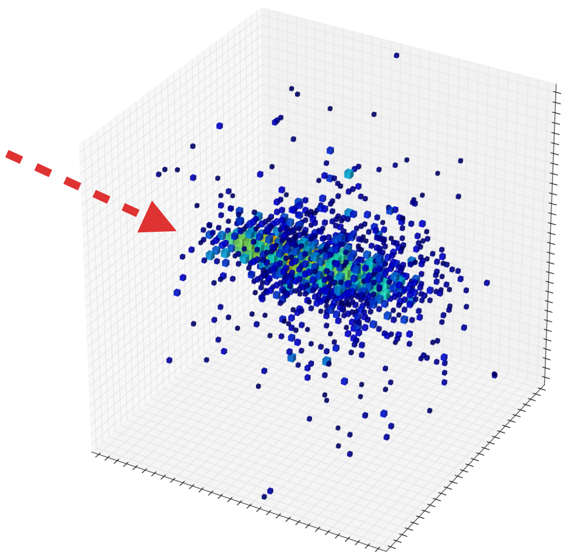
Training Data

Geant4 Simulation

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

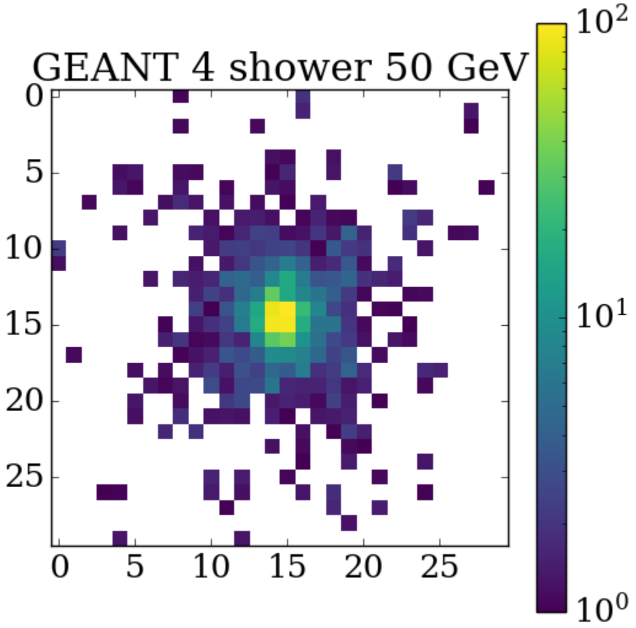


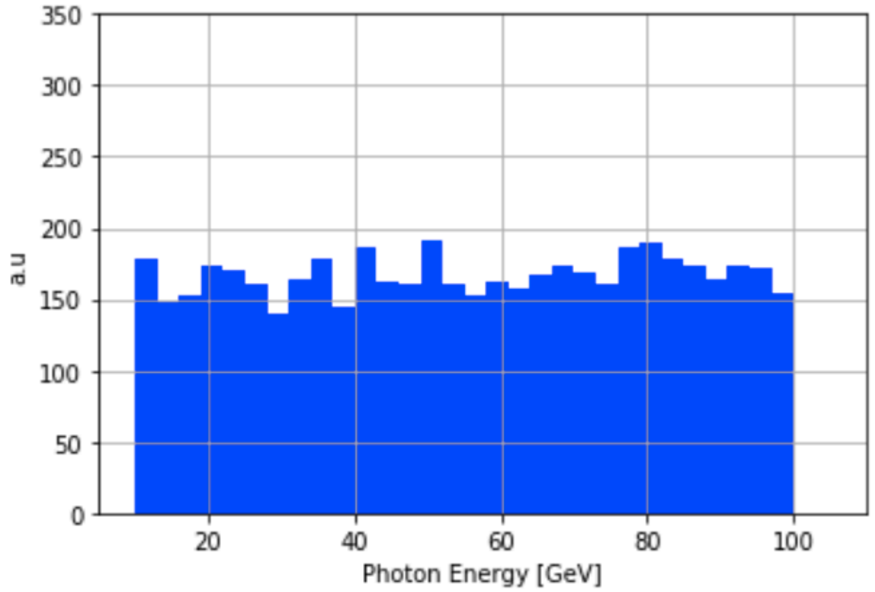
30x30x30 data (3D)



Project along z-axis

30x30 data (2D)

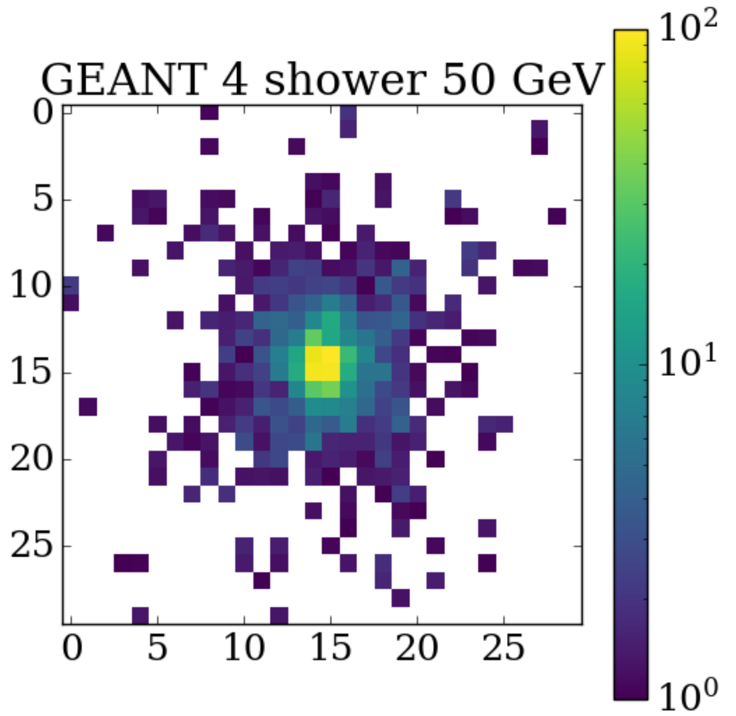


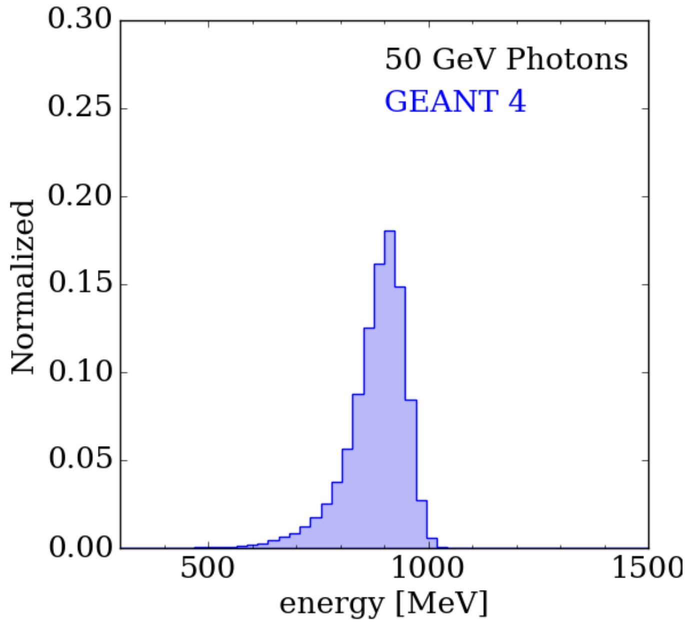


Challenges

Quality measures:

- Reproduce Geant4 showers
- <u>Shower shape variables </u>have to be examined, especially:
  - ◉ Number of hits (i.e occupancy)
  - ◉ 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 Model: Wasserstein GAN

Wasserstein GAN (Gradient-Penalty)

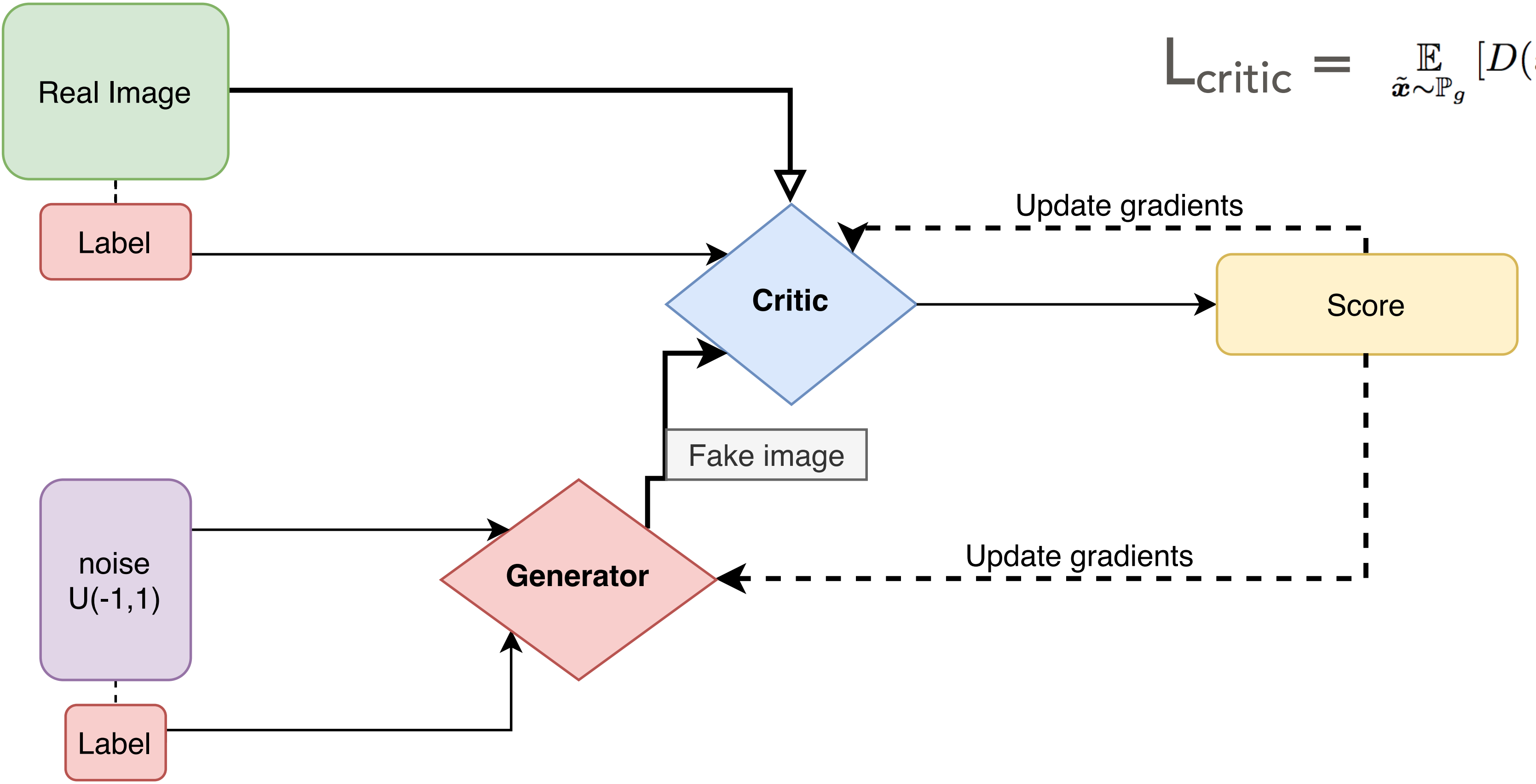
An alternative to traditional GAN training. Helps improve the stability of learning

- Label conditioning: Provide information on shower we are simulating (energy of incoming photons)
- Add loss term to the generator to reconstruct energy of generated showers.

$$\tilde{x} = g_\theta(z, y_{\text{label}})$$

$$L_{\text{gen}} = -\mathbb{E}[D(G(z))] + \kappa\left[y_{\text{label}} - a_{\theta'}(\tilde{x})\right]^2$$

$$L_{\text{critic}} = \underset{\tilde{\boldsymbol{x}}\sim\mathbb{P}_g}{\mathbb{E}}[D(\tilde{\boldsymbol{x}})] - \underset{\boldsymbol{x}\sim\mathbb{P}_r}{\mathbb{E}}[D(\boldsymbol{x})] + \lambda \underset{\hat{\boldsymbol{x}}\sim\mathbb{P}_{\hat{\boldsymbol{x}}}}{\mathbb{E}}\left[(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1)^2\right]$$



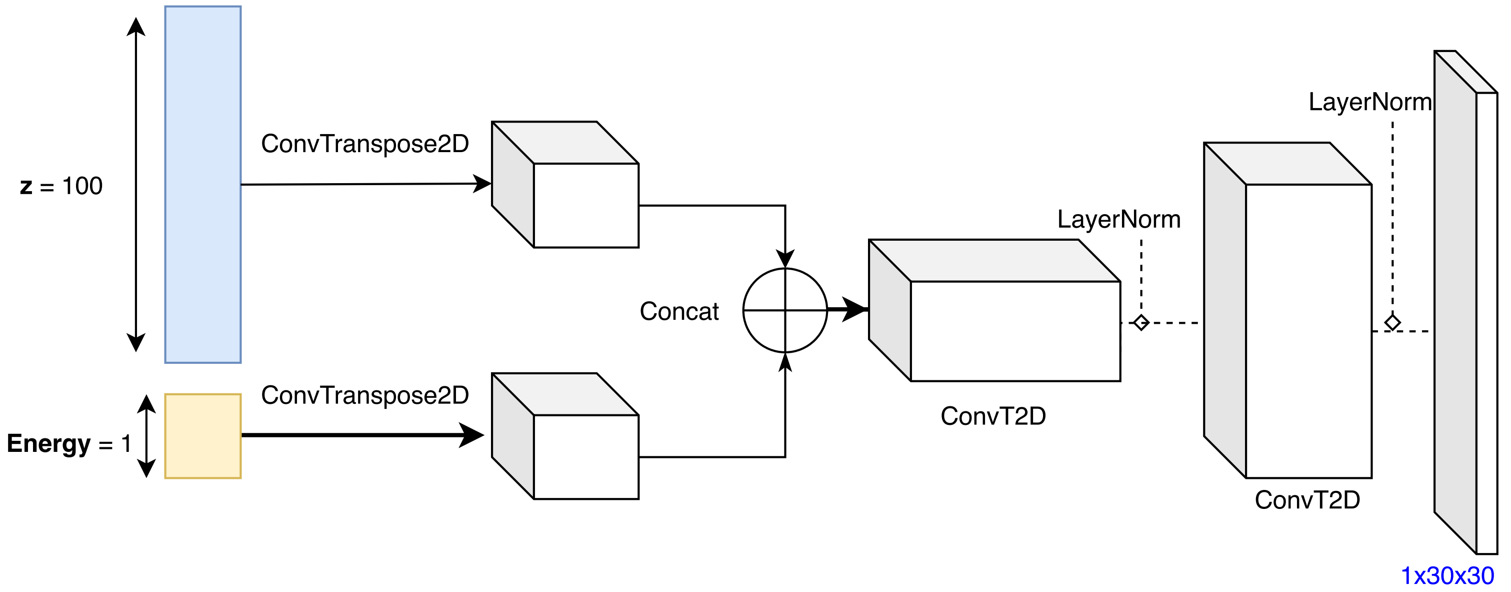
- Erdmann, *et al*. Precise Simulation of Electromagnetic Calorimeter Showers Using a Wasserstein Generative Adversarial Network: ***arXiv:1807.01954***

- Erdmann, *et al*. Generating and Refining Particle Detector Simulations Using the Wasserstein Distance in Adversarial Networks: ***arXiv:1802.03325***

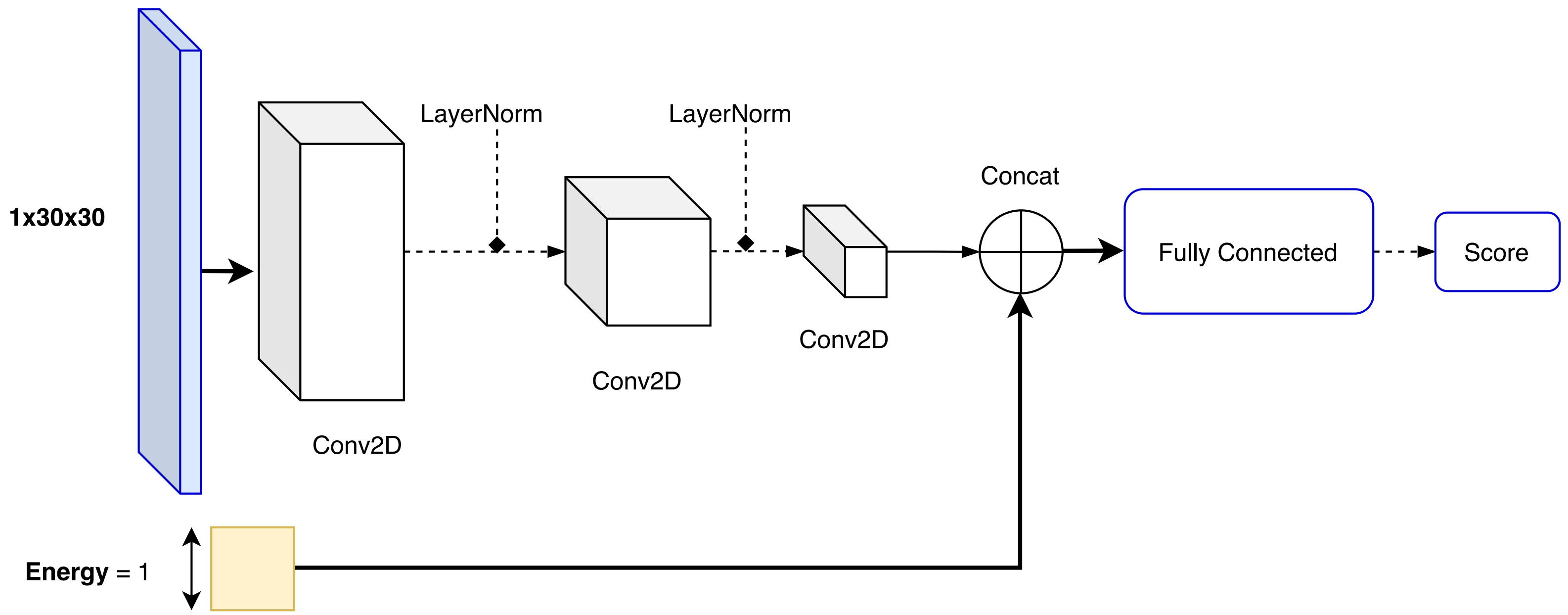
Wasserstein GAN (2D Data)

Architecture

Generator



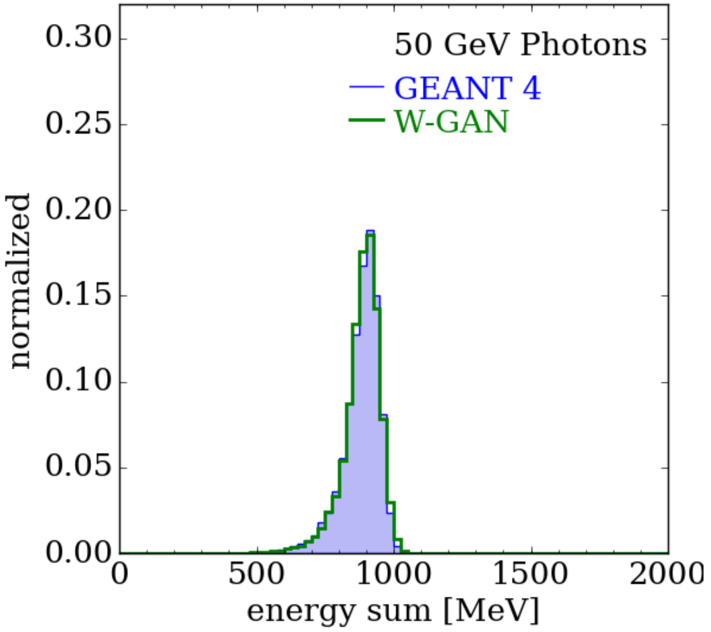
Critic

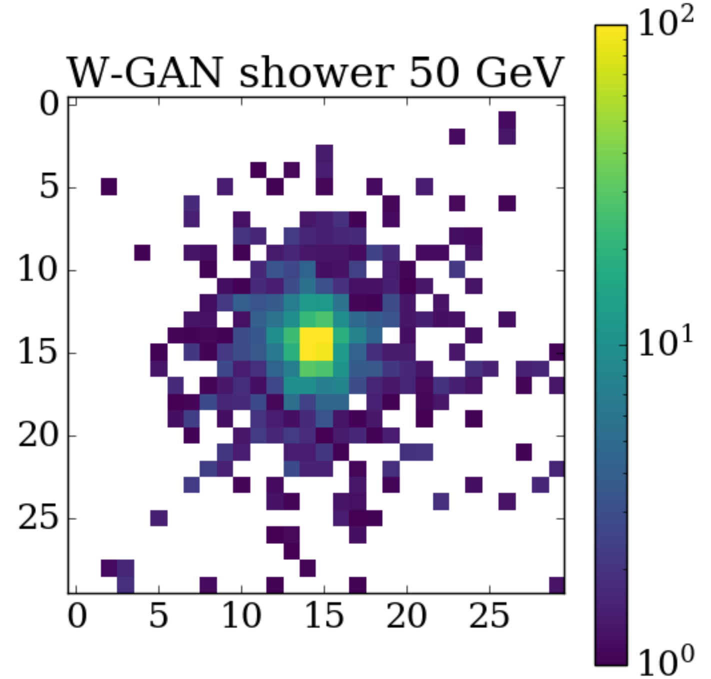


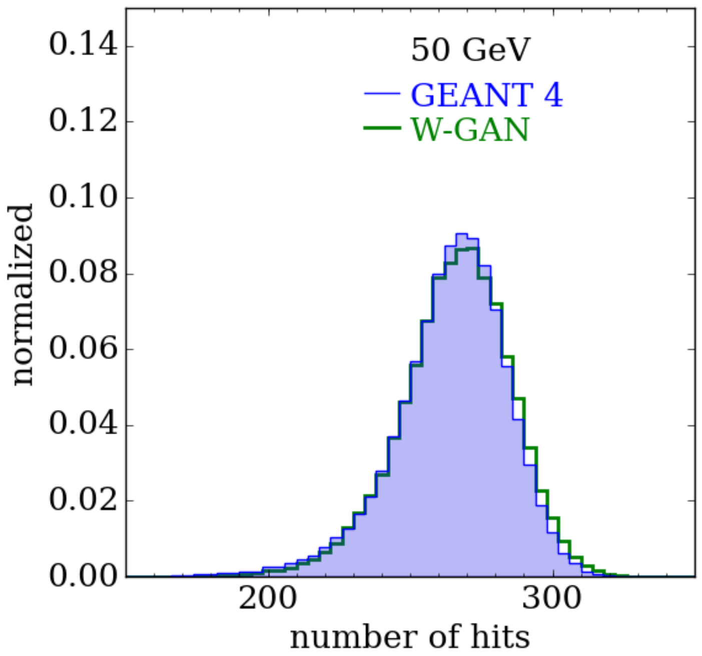
WGAN-GP (2D Data)

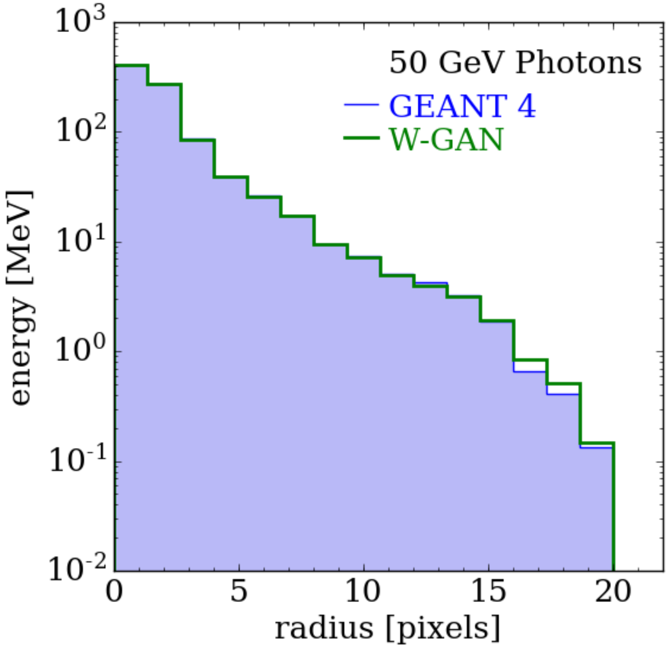
Trained <u>only on</u> 50 GeV

- (No energy-conditioning)
- Very good agreement with G4!





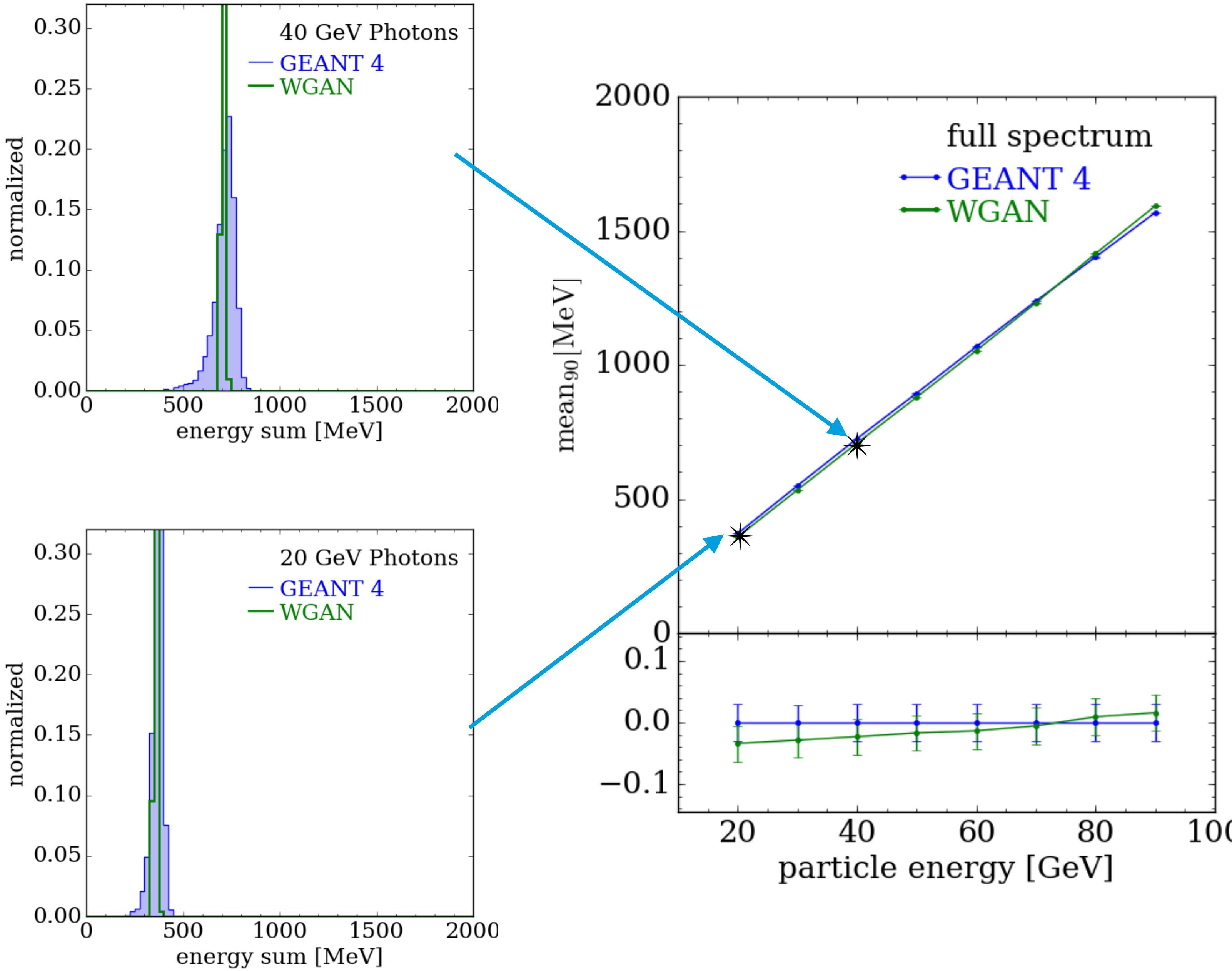




WGAN-GP (2D Data)

Trained on full spectrum

- Great linearity
- Energy shape broken



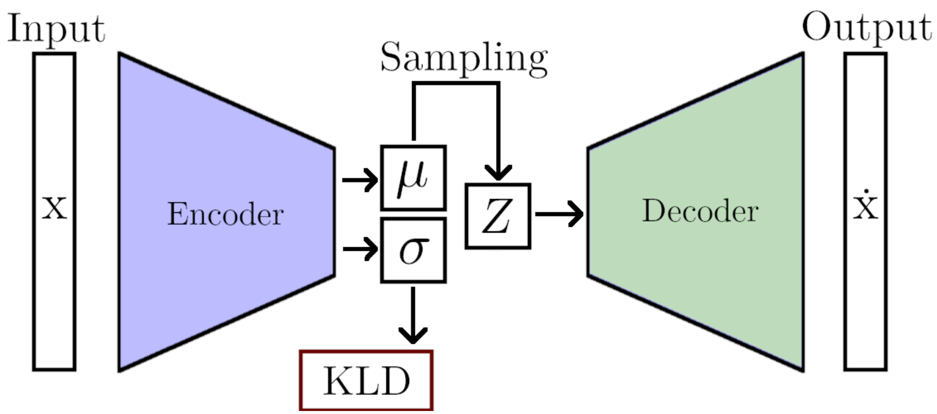
Generative Model:
BIB-AE

BIB-AE

CS-paper: arXiv:1912.00830

Variational Autoencoder

- MSE for reconstruction
- KLD for individual latent distr. shape

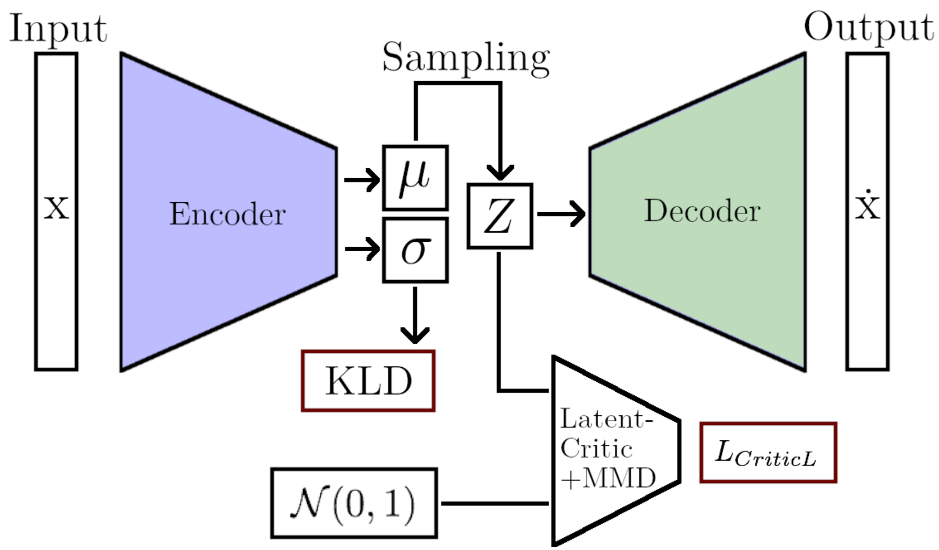


BIB-AE

CS-paper: arXiv:1912.00830

Variational Autoencoder

- MSE for reconstruction
- KLD for individual latent distr. shape
- Latent critic for global latent distr. shape



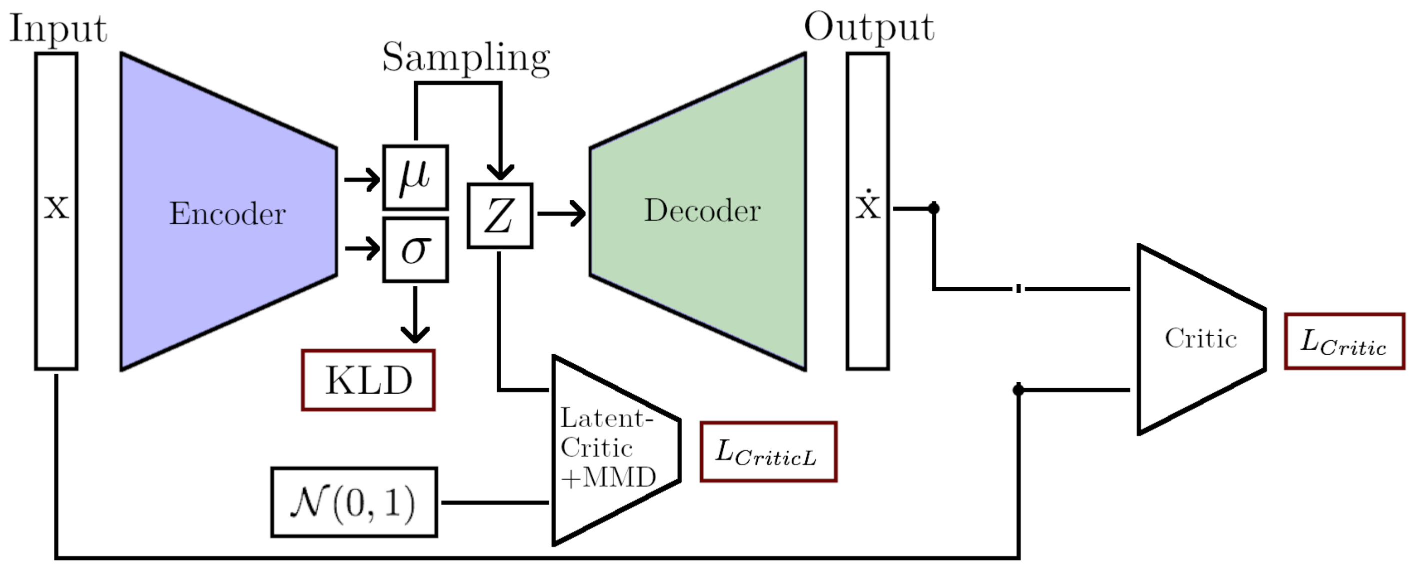
BIB-AE

CS-paper: arXiv:1912.00830

Variational Autoencoder

- ~~MSE for reconstruction~~
- KLD for individual latent distr. shape
- Latent critic for global latent distr. shape
- MSE problematic for sparse images

➡ Critic network



BIB-AE

CS-paper: arXiv:1912.00830

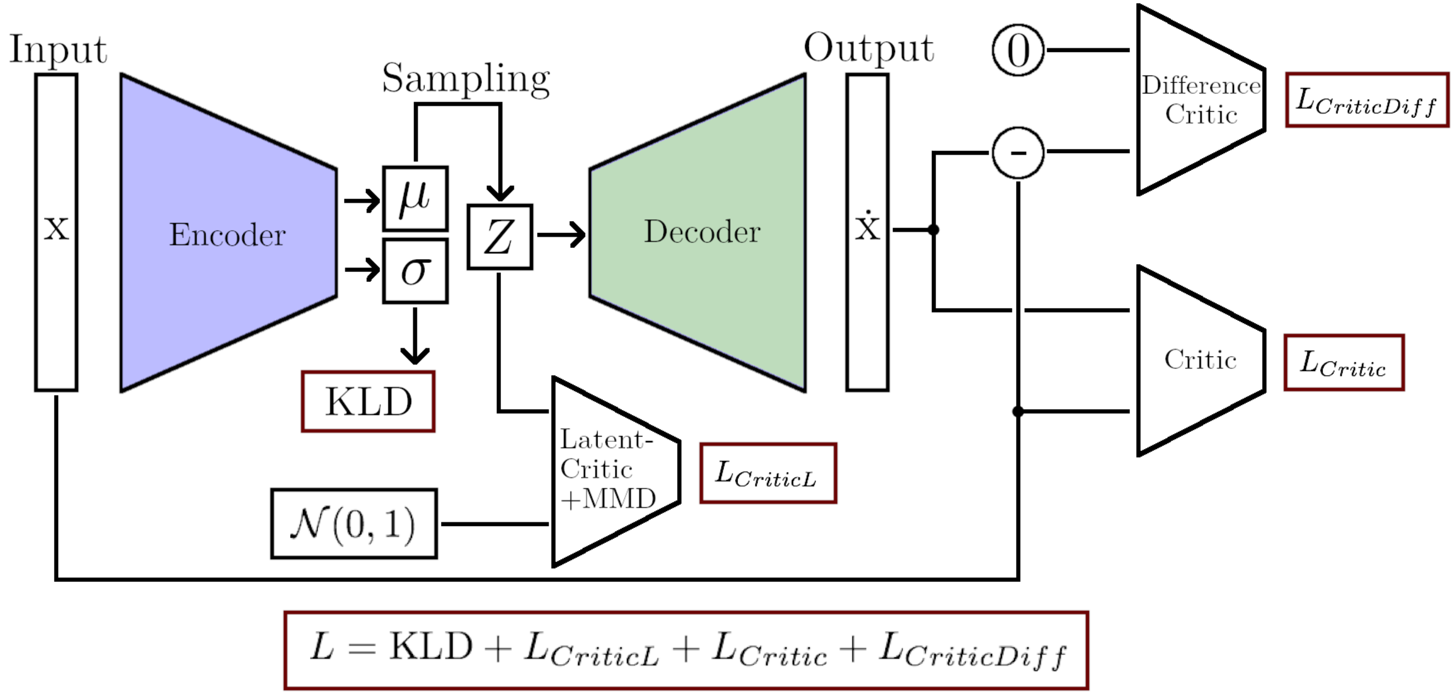
Bounded Information Bottleneck Autoencoder

- ~~MSE for reconstruction~~
- KLD for individual latent distr. shape
- Latent critic for global latent distr. shape
- MSE problematic for sparse images

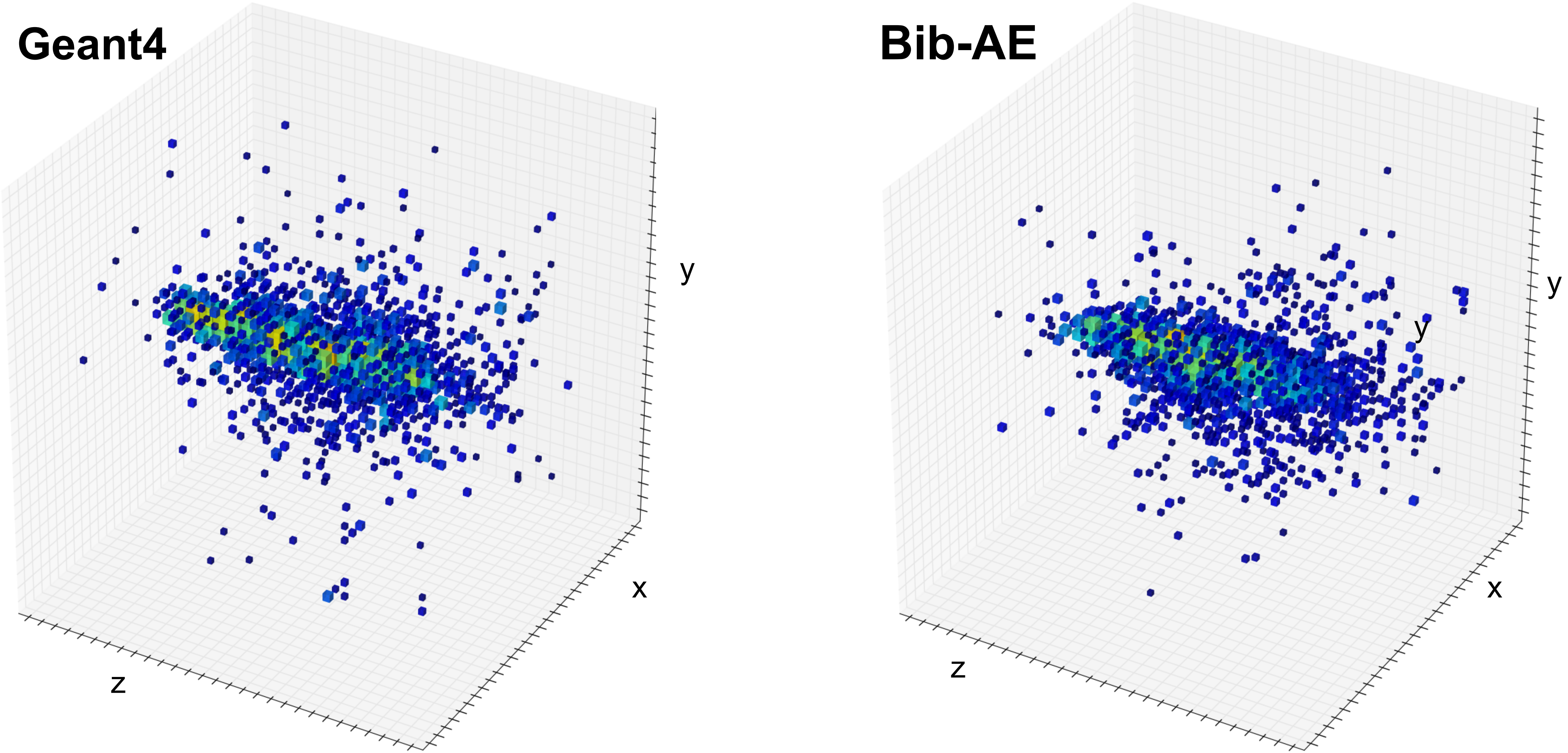
➡ Critic network

- Information in Latent space needs reconstruction

➡ Difference Critic



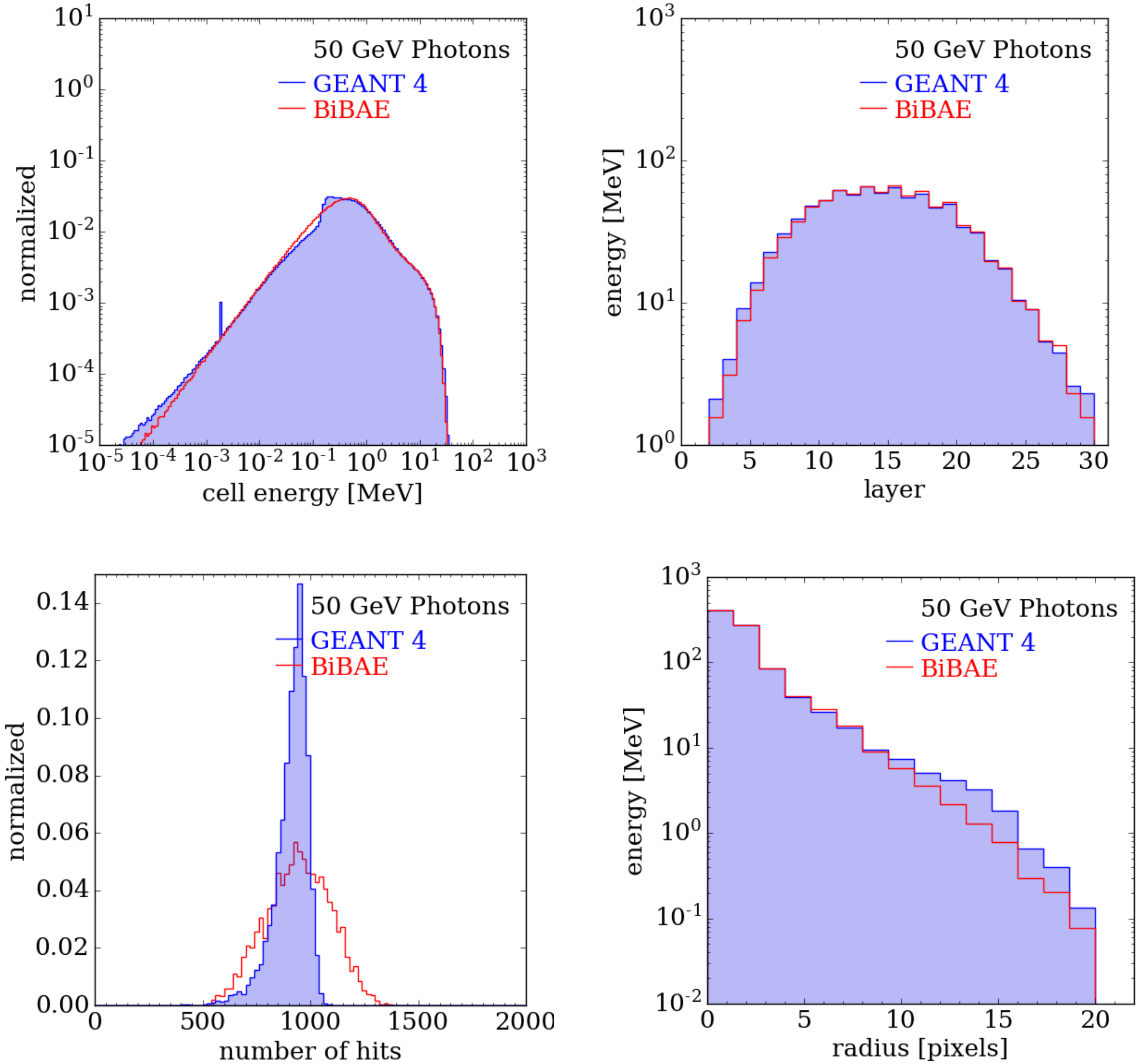
Bib-AE (3D Data)



Bib-AE (3D Data)

Best results so far

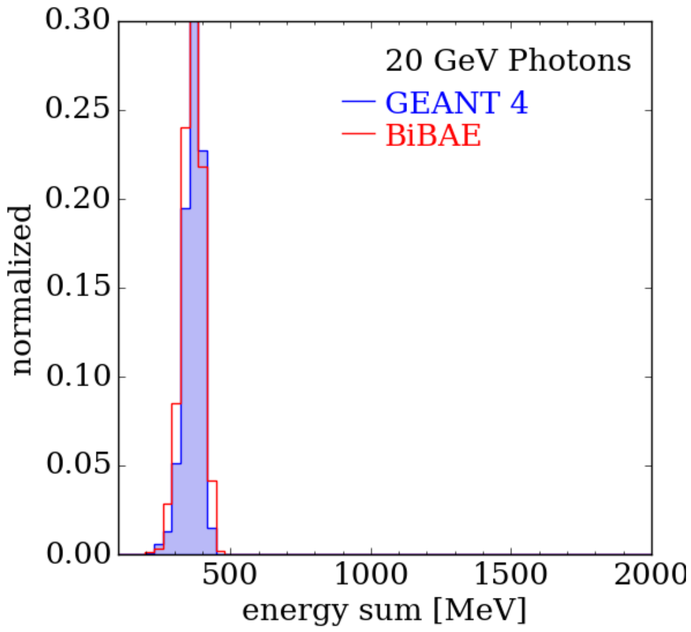
- Overall good agreement with G4!
  - Except for Sparcity and lower cell energies

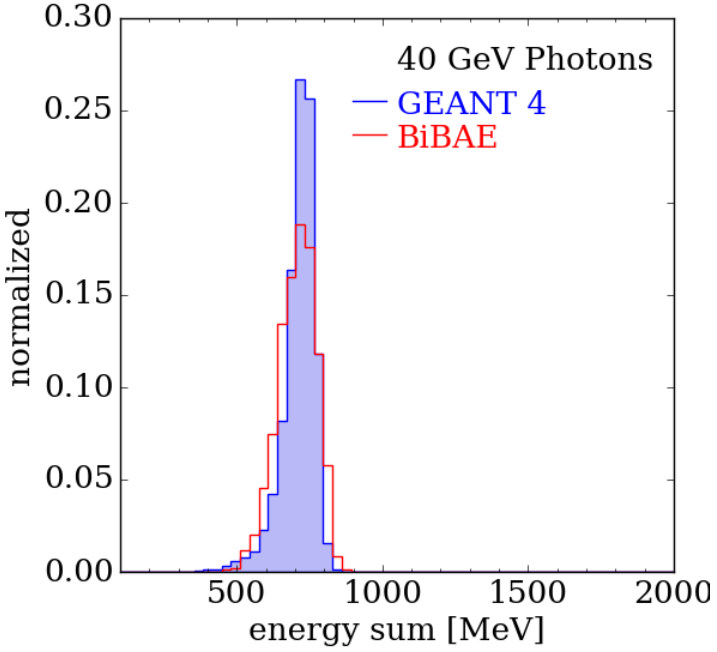


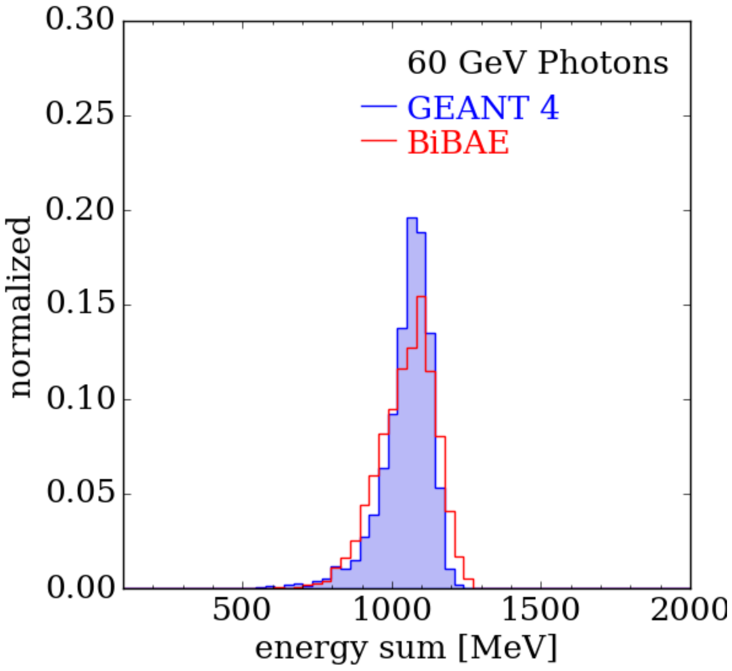
Bib-AE (3D Data)

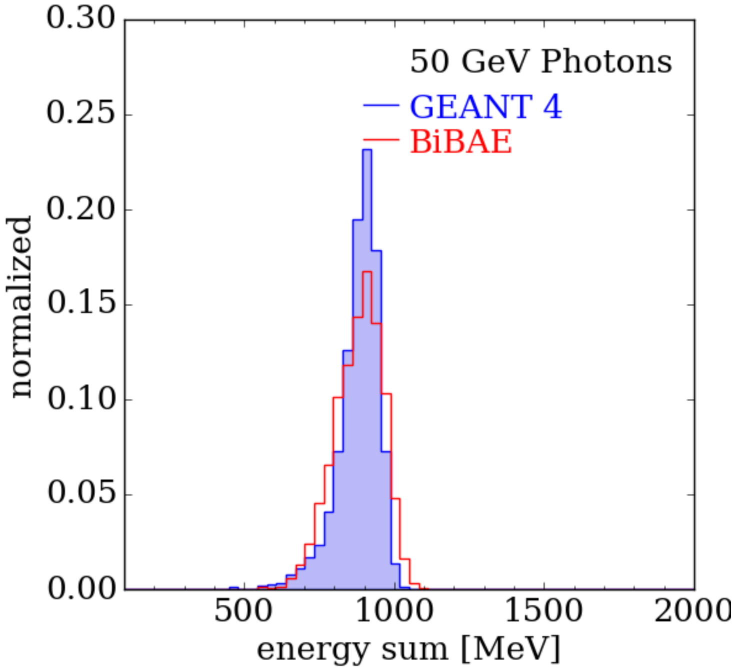
Energy conditioning

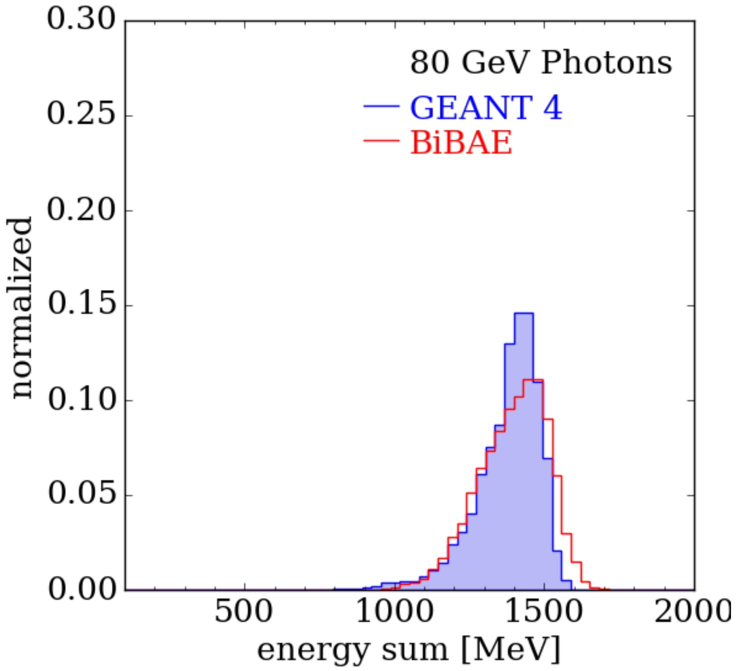
- Tested on different energies: Working ✔









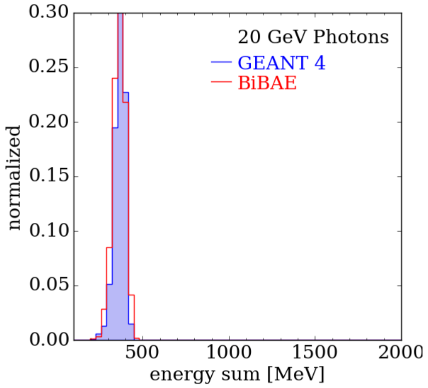


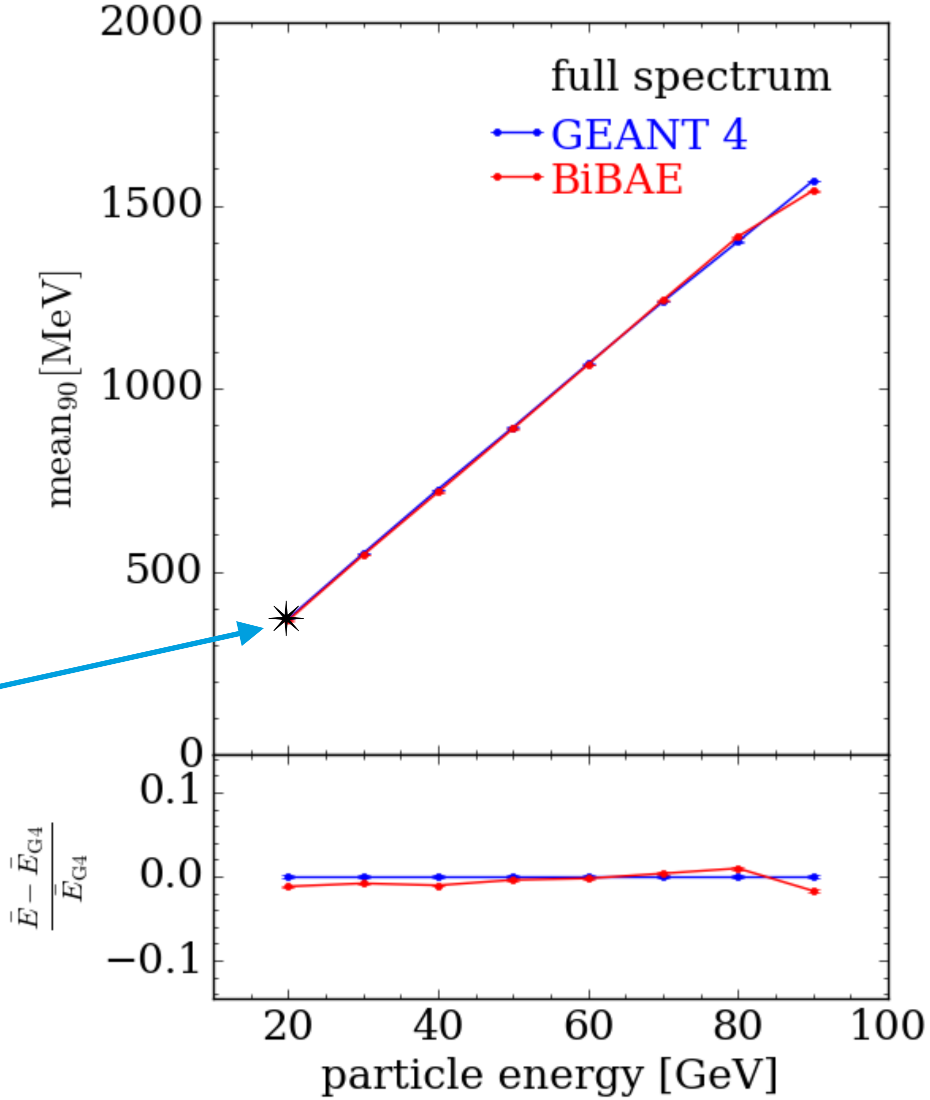
Bib-AE (3D Data)

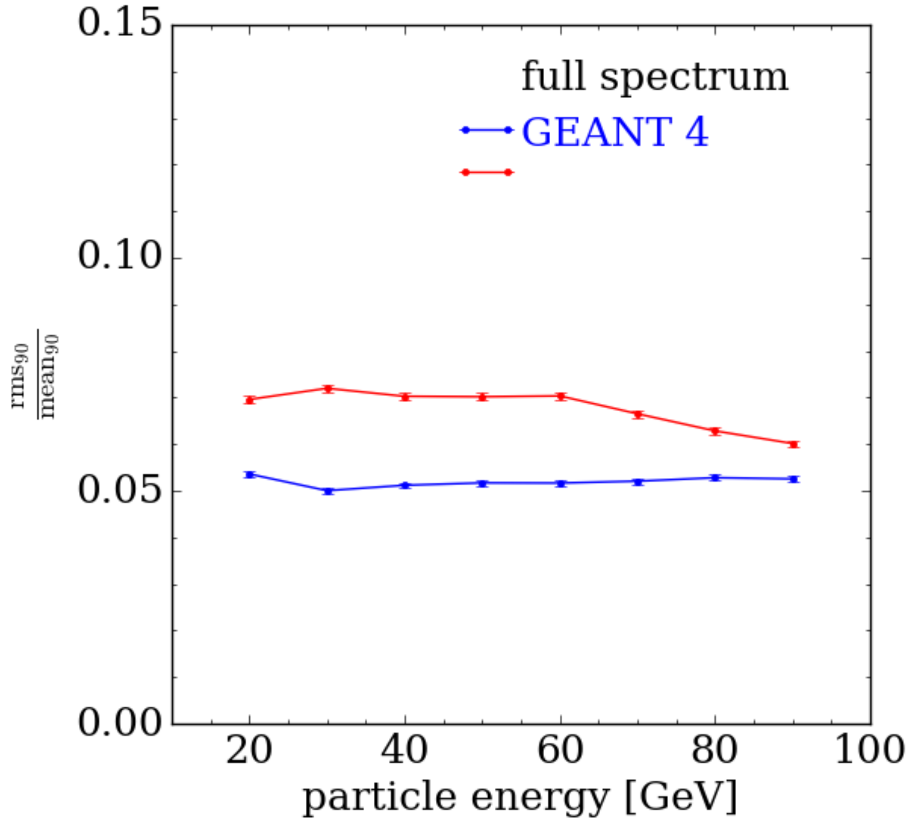
Linearity & Resolution

Trained full spectrum

- Great linearity

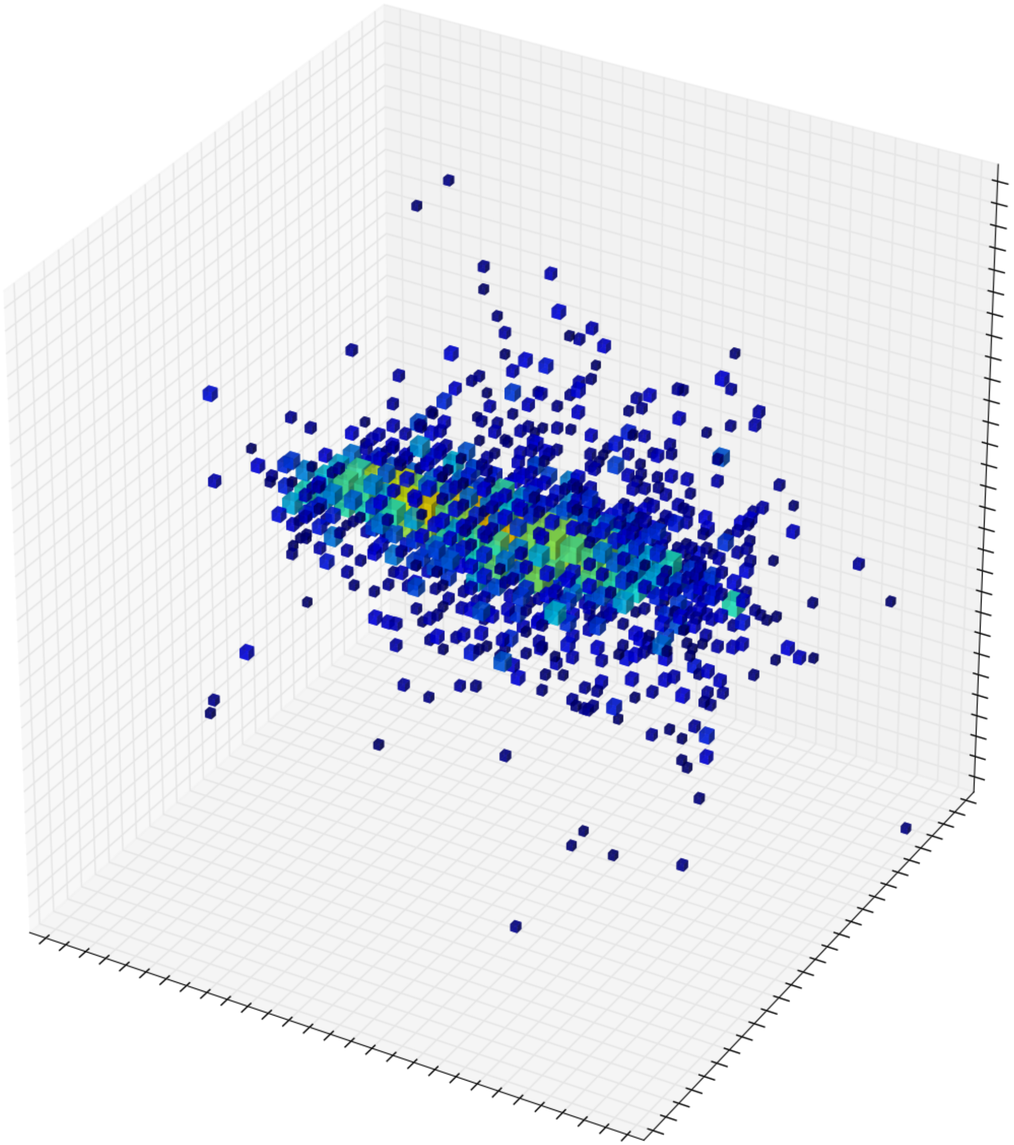






Conclusion

- High granularity calorimeters will play key role for future experiments
- Application of generative models to high resolution EM Shower Simulation
- Architectures:
  - WGAN (2D)
  - Bib-AE (3D) (**New!**)
- Goals:
  - Shower shapes
  - Energy distribution
  - Conditioning



Thank you

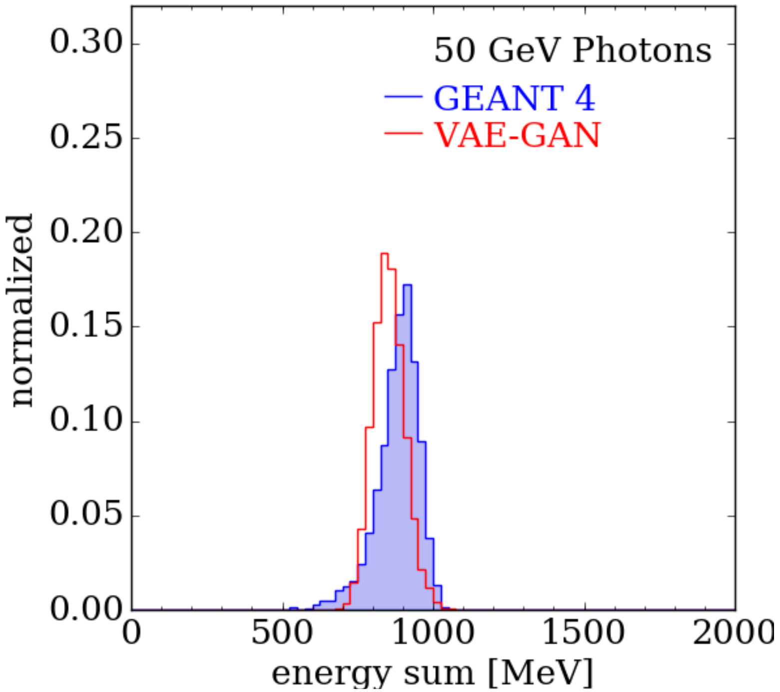
Backup Slides

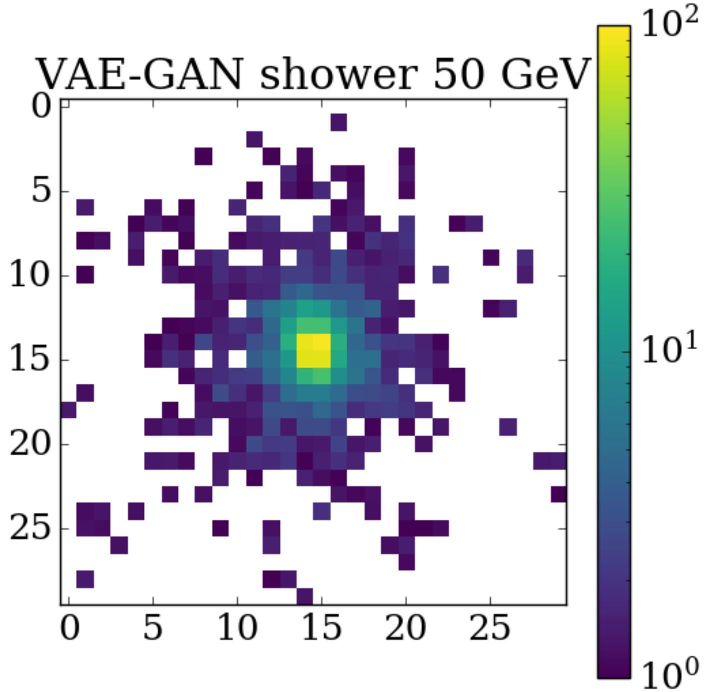
VAE-GAN (2D Data)

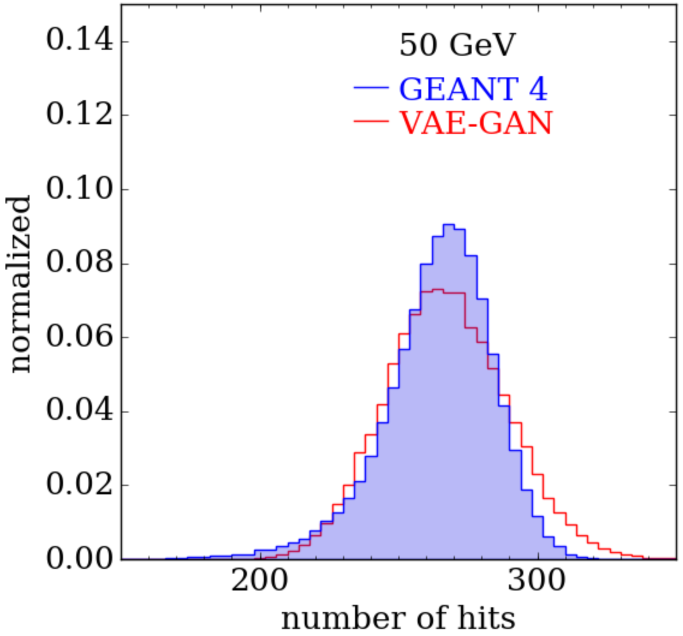
Best results so far

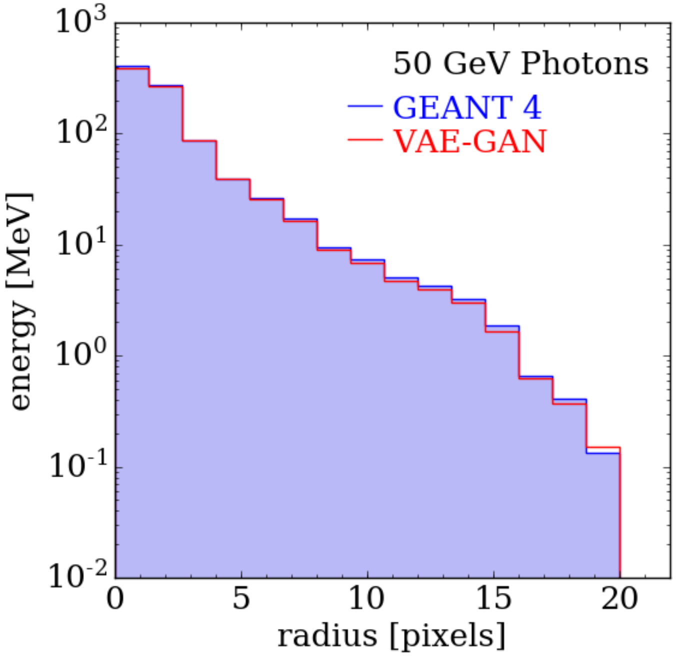
Overall good agreement :

- energy shape and sparsity are not optimal
- Radial energy is in a very good agreement



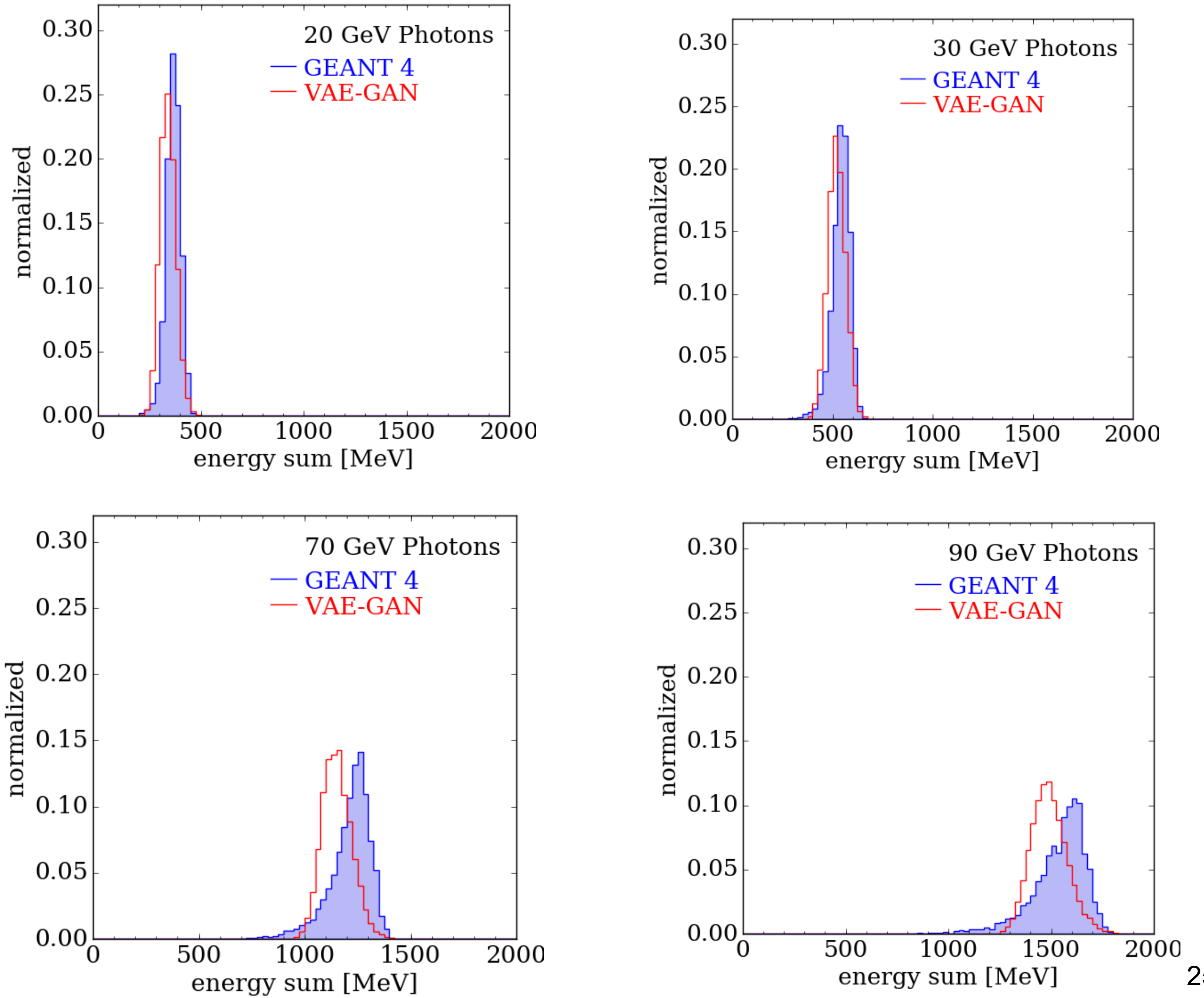






VAE-GAN (2D Data)

energy conditioning



energy conditioning looks promising!!

Challenges

NVIDIA paper : arXiv:1710.10196

Distance between eyes ?

Length of a nose ?

VAE-GAN

combination of GAN and VAE

Similarity measures via MSE Loss:

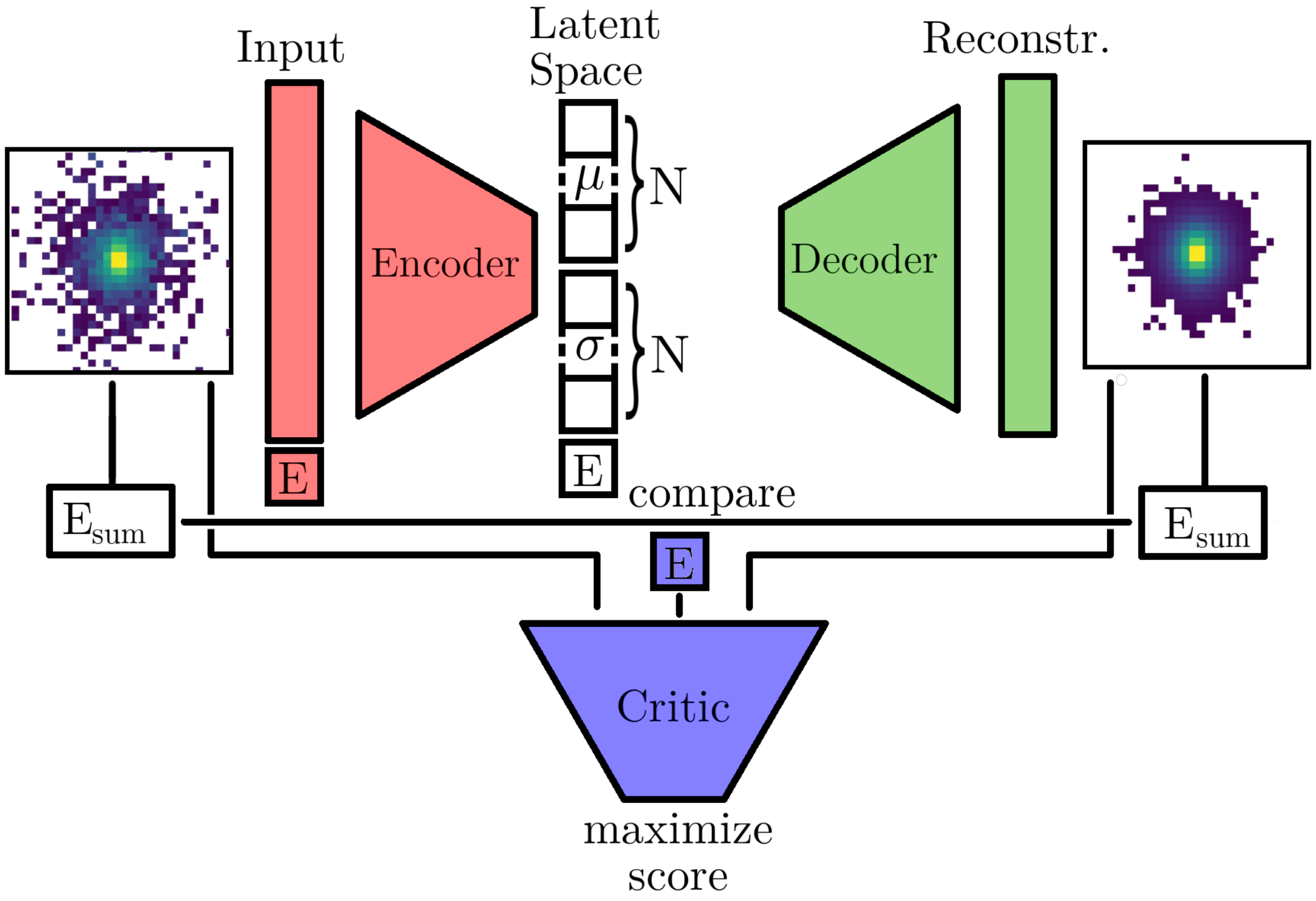
- Is a simple element-wise metric
- Might not be suitable for image data.

Instead of MSE Loss in the VAE:

- Use adversarial network

Adversarial critic :

- Wasserstein critic!
- Does not perform reconstruction
- No information in latent space



Original paper, Larsen et al.
arXiv:1512.09300