High Fidelity Simulation of High Granularity Calorimeters with High Speed

ACCLAIM Meeting
20.08.2021

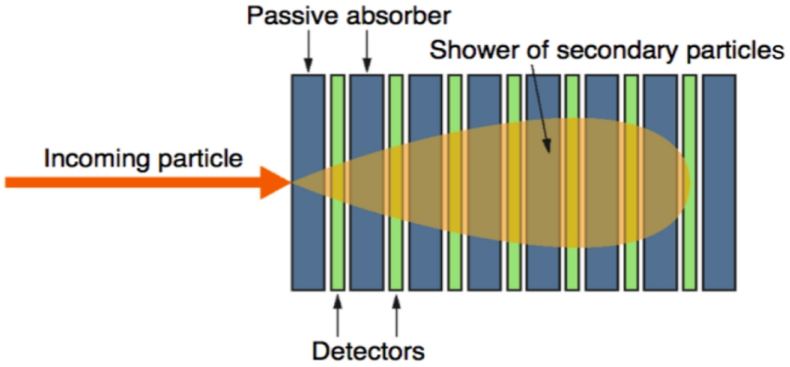
E. Buhmann, S. Diefenbacher, E. Eren, F. Gaede, D. Hundhausen, G. Kasieczka, W. Korcari, A. Korol, K. Krüger, P. McKeown and L. Rustige

HELMHOLTZ
RESEARCH FOR GRAND CHALLENGES

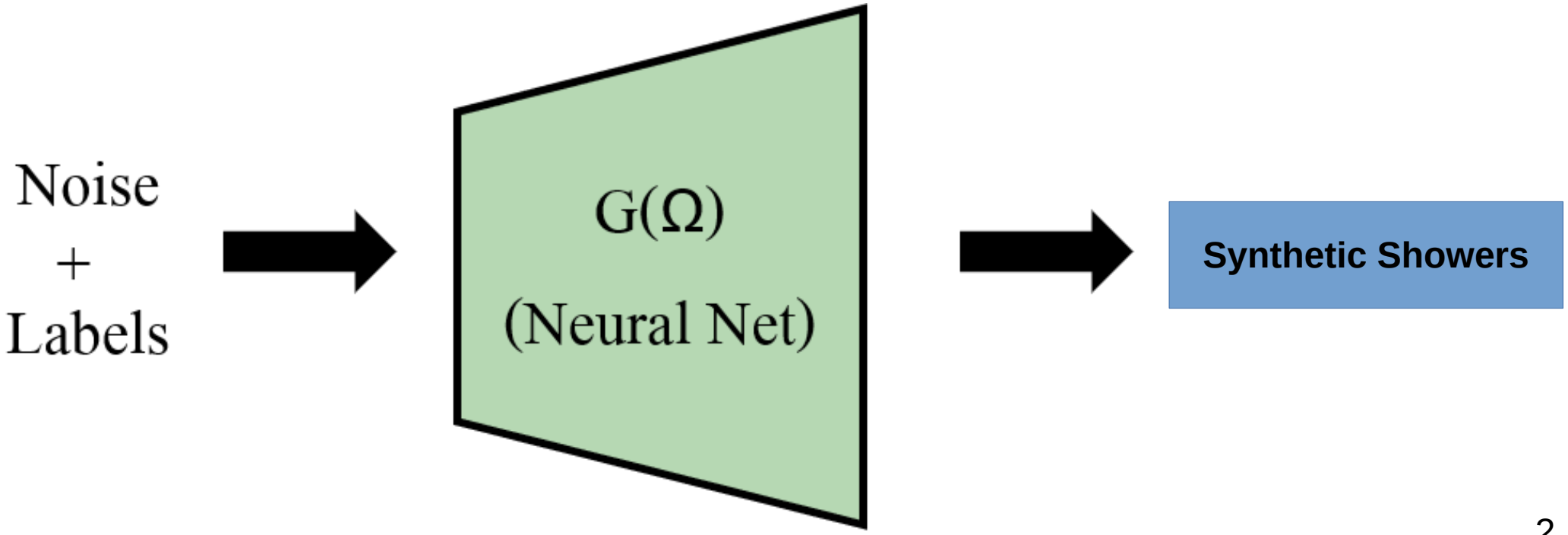
Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

CLUSTER OF EXCELLENCE
QUANTUM UNIVERSE

Deep Generative Models

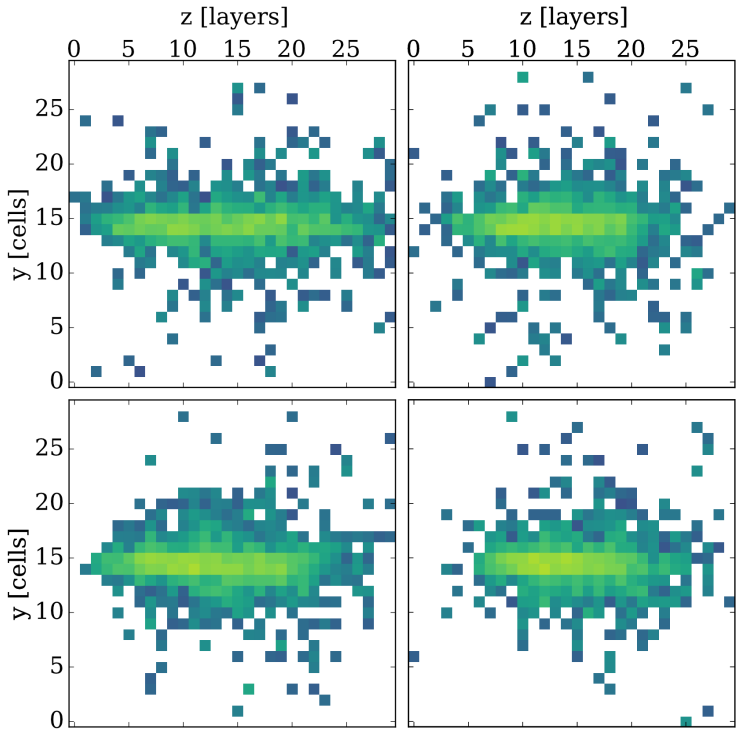


- Calorimeter simulation in HEP is CPU expensive!
- Promising solution for a **fast shower simulation**
  - Generate new samples by following the distribution of original data (i.e Geant4)
  - Map random noise to data
  - Conditioning



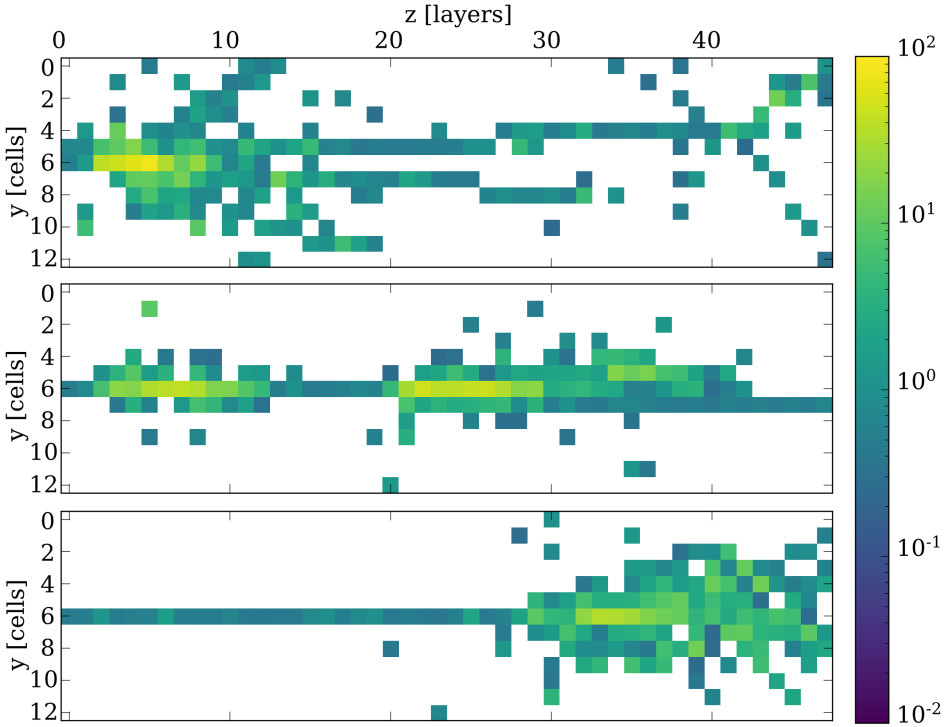
Hadron Showers

- 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 the active area (i.e shower core)
  - Started with GAN, WGAN, BIB-AE and alternatives



photon showers

vs.

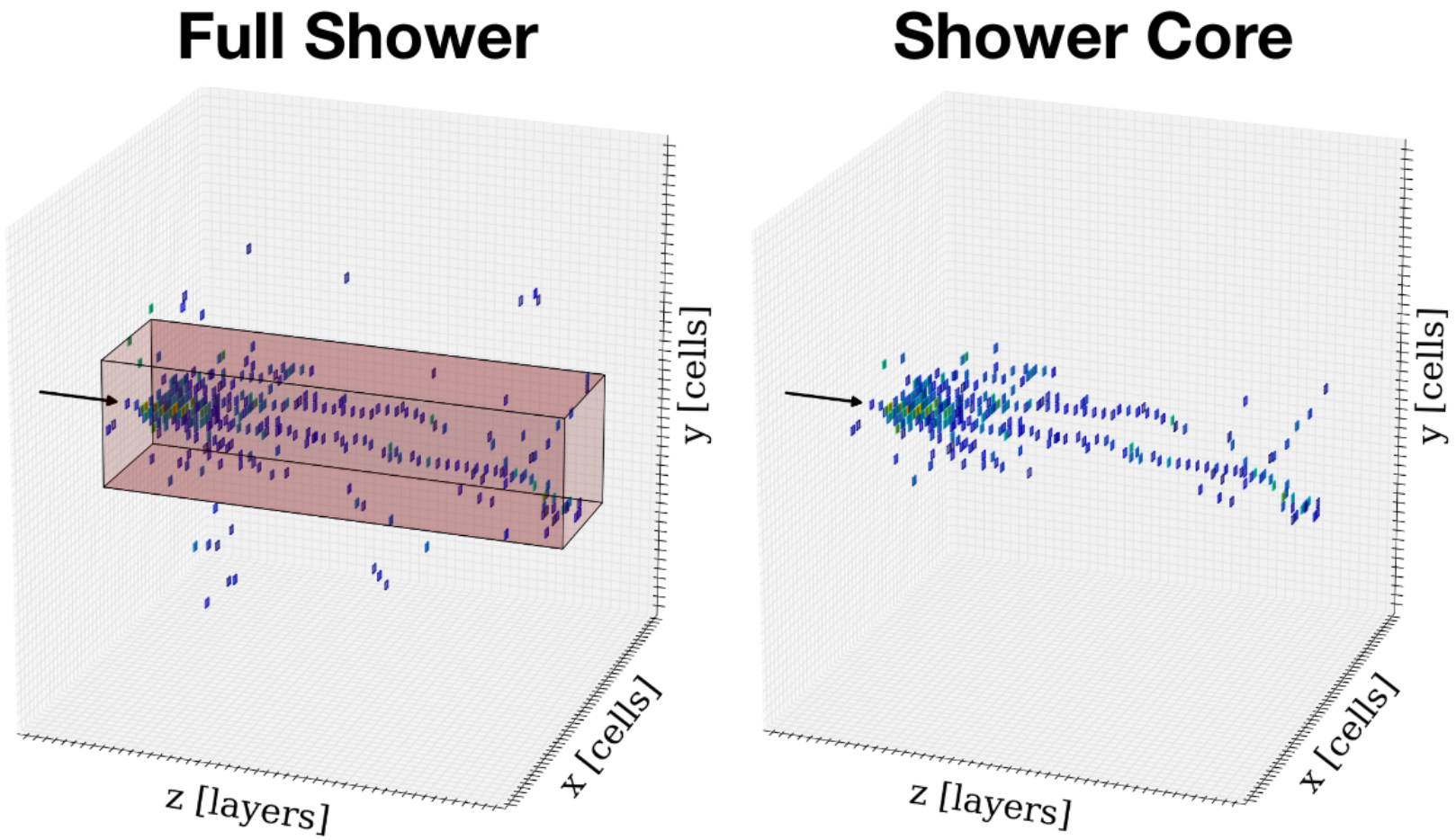


pion showers

Hadron Showers

Very preliminary

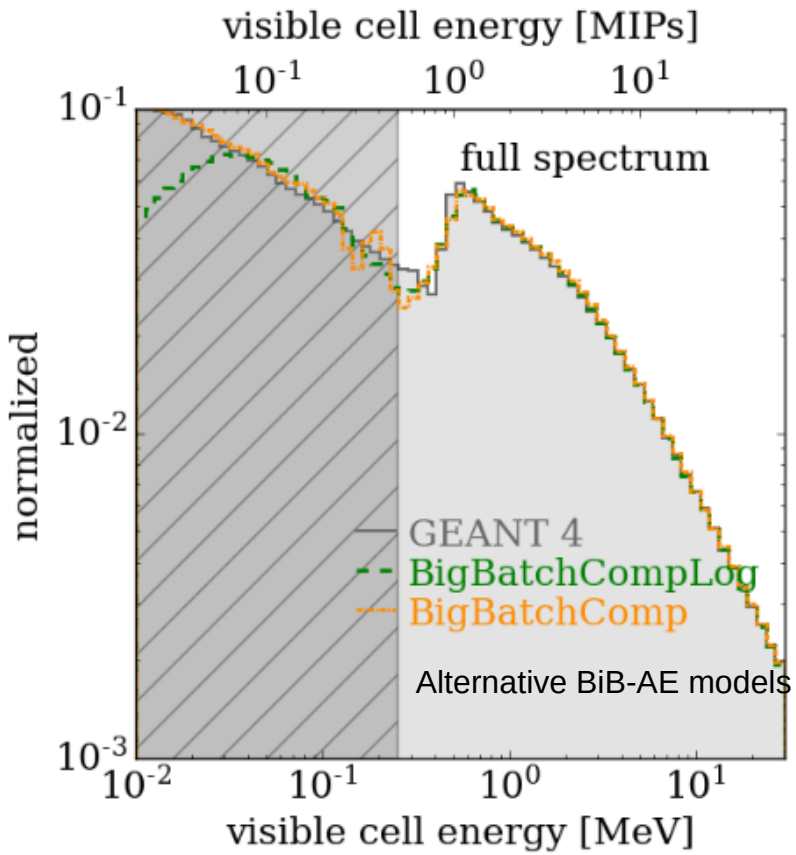
Now shower core (lateral) is extended to: 25x25

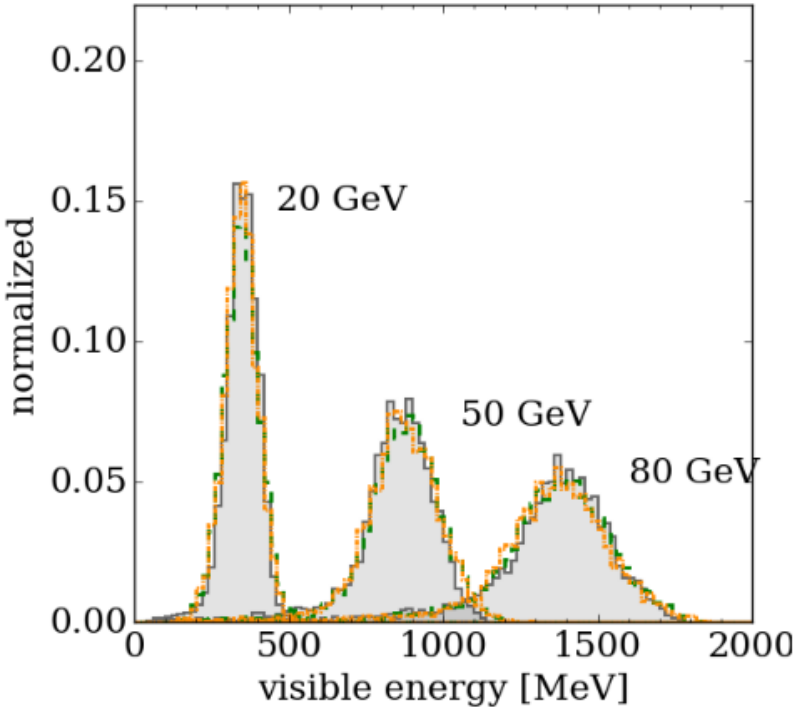


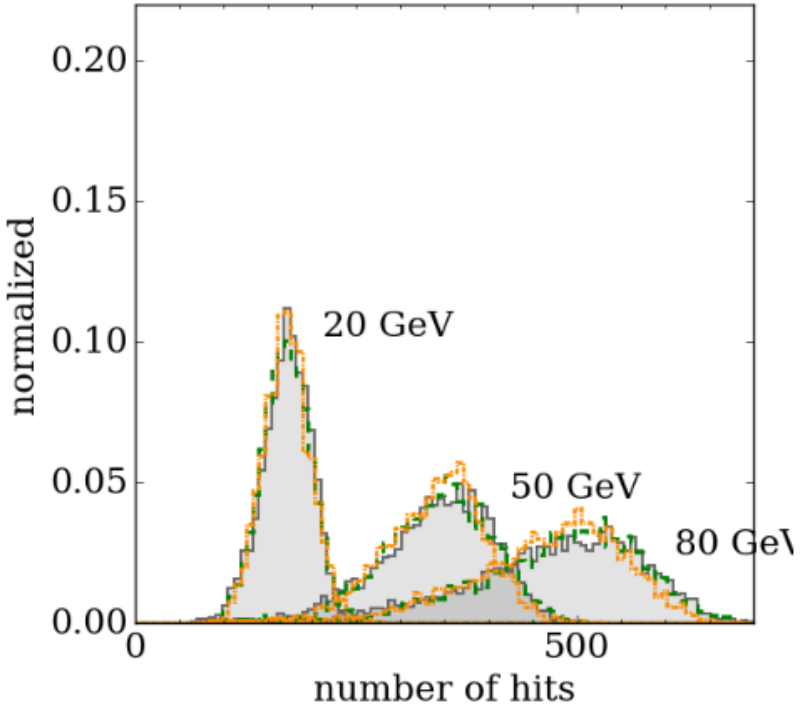
Hadron Showers

Very preliminary

Shower core (lateral) 25x25

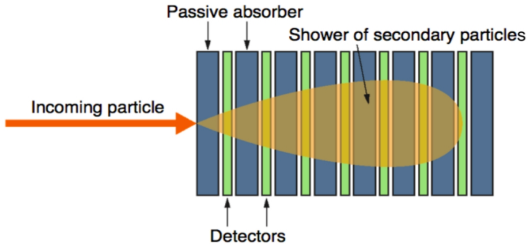






- Thanks to post-processing, MIP peak is correctly modeled in BIB-AE
- Energy-sum and number of hits are important physics quantities to get it right

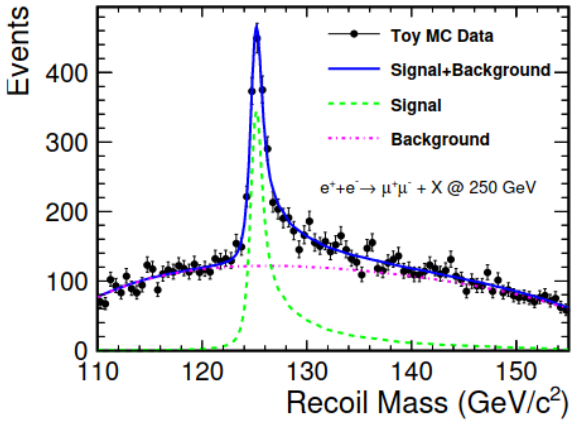
Pion Generation and Reconstruction

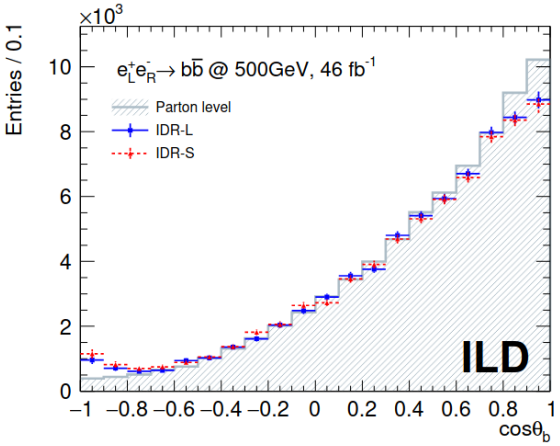


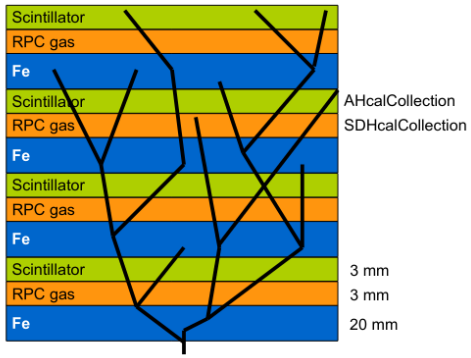
Geant4

Calibration & Digitization

Particle Flow Reconstruction







Pion Generation and Reconstruction

Geant4

Calibration & Digitization

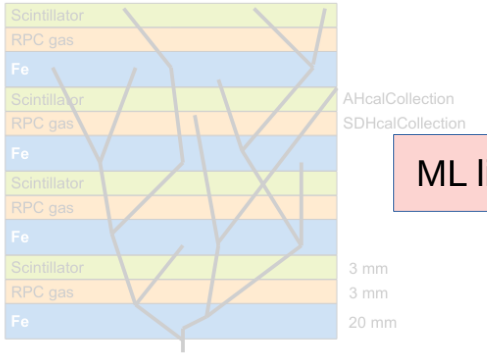
Particle Flow Reconstruction

??

Noise
+
Labels

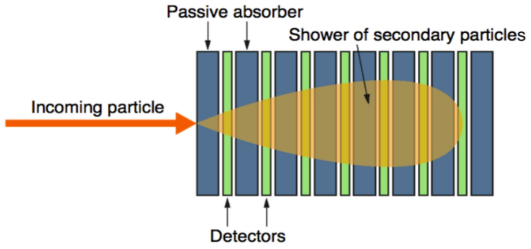
G(Ω)
(Neural Net)

+



ML libraries and software env.

Pion Generation and Reconstruction



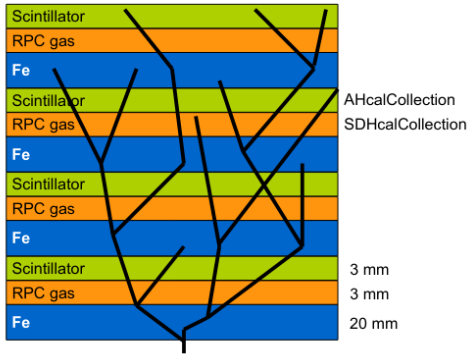
Geant4

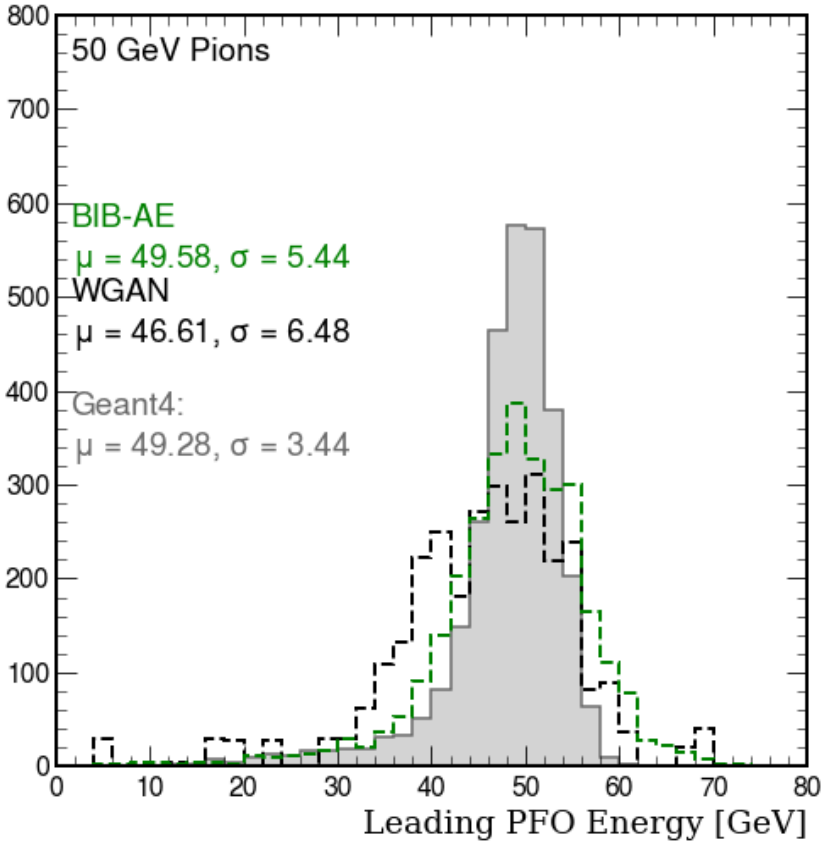
Calibration & Digitization

Particle Flow Reconstruction

Noise + Labels

G(Ω) (Neural Net)





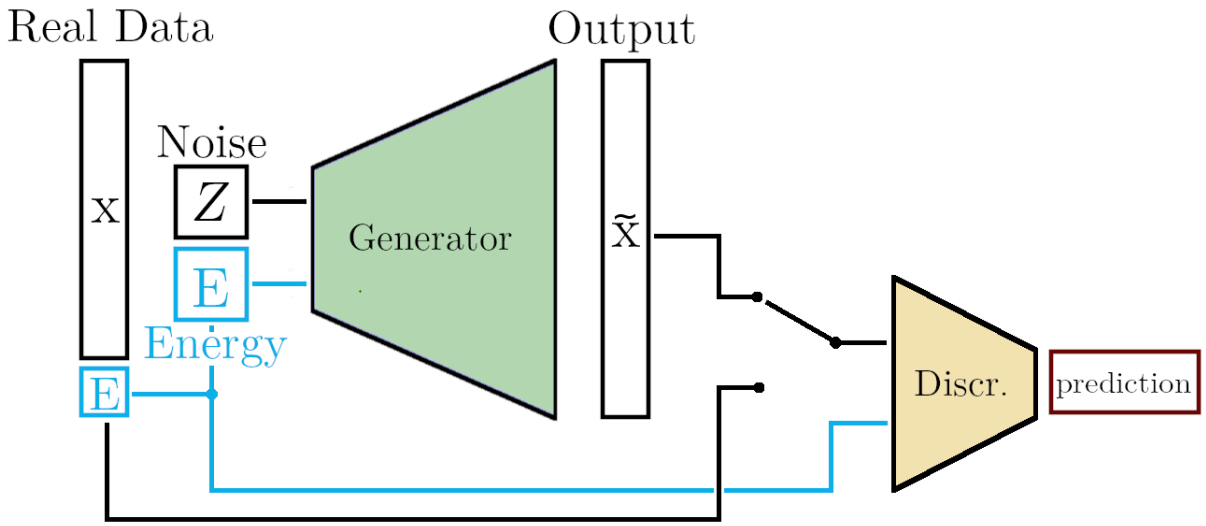
- First attempts to integrate generative ML models into the reconstruction workflow
- Soon: Reconstruction based fidelity score for shower generation and automation

Thank you

Recap: Generative Adversarial Neural Networks (GANs)

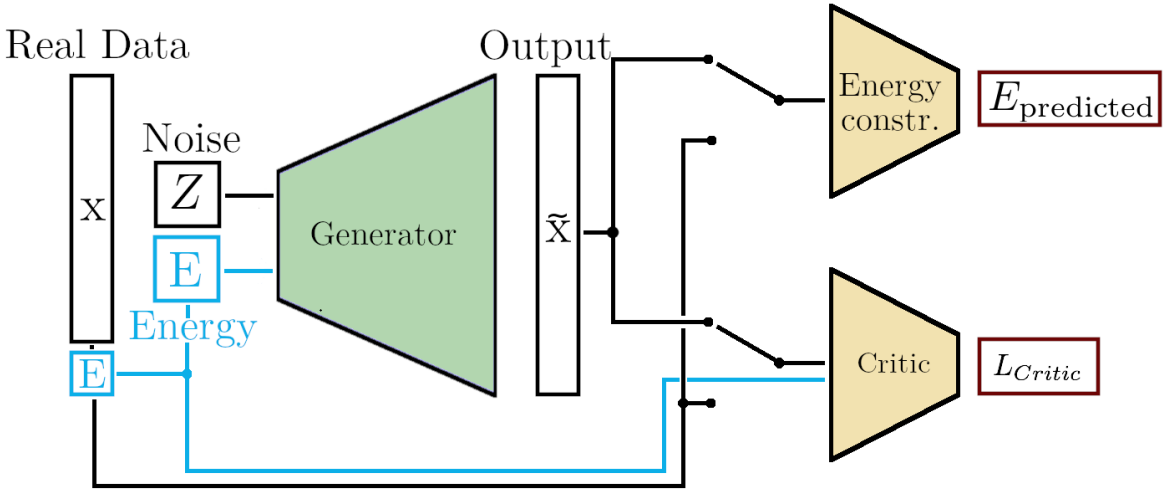
Vanilla-GAN

- First generative architecture used for simulating showers
- Discriminator tries to differentiate: Fake or Real ?
- Generator tries to fool the distriminator
- Apply mini-batch discrimination (for pion showers)



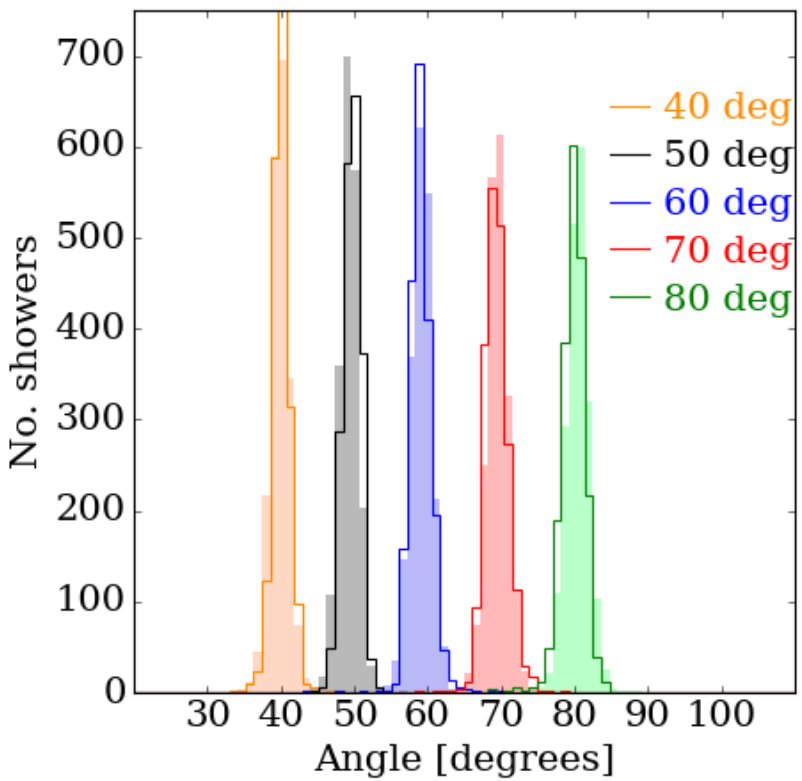
WGAN

- Alternative to classical GAN training:
  Helps improve the stability of the training
  Use Wasserstein-1 distance as a loss with gradient penalty
- Second network to constrain energy
- Latent optimization method (LO) is employed (pion showers)

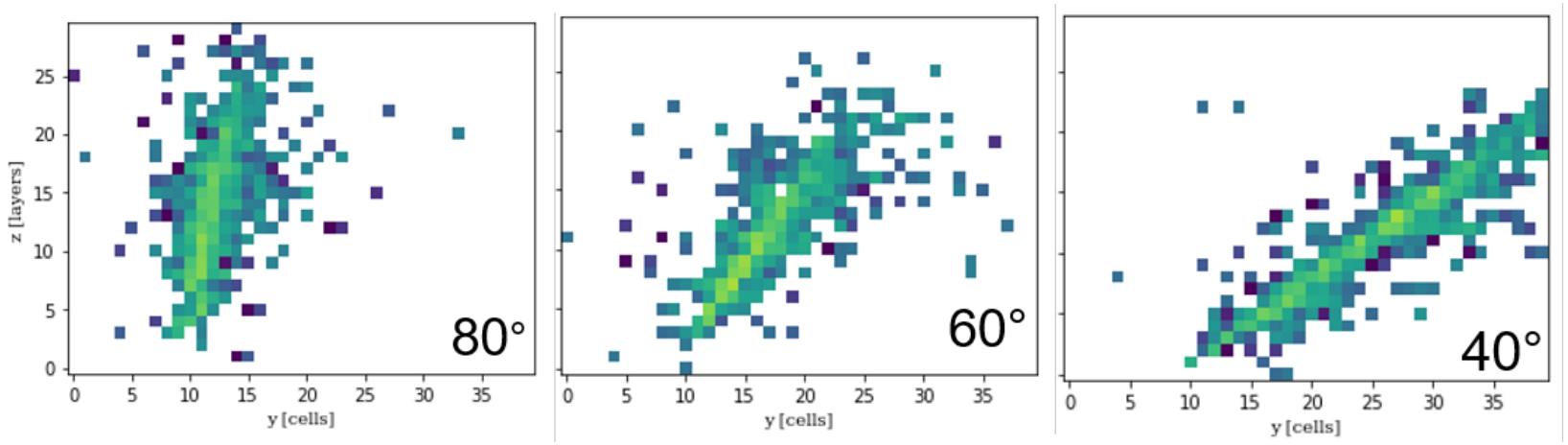


Photon showers with an angle

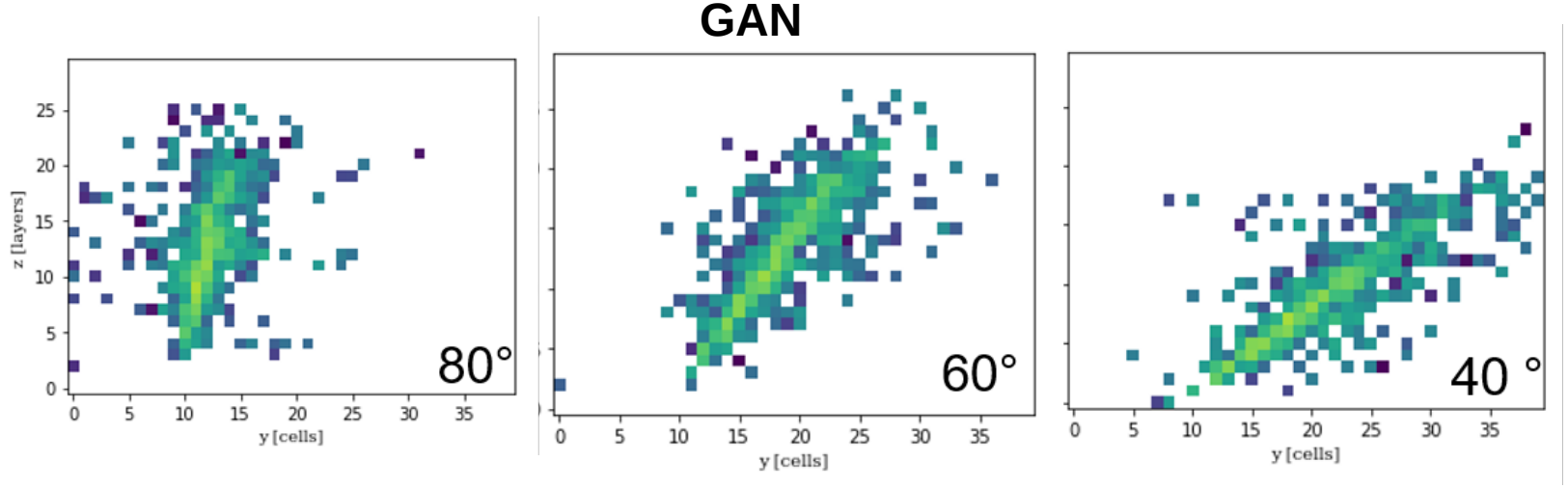
Very preliminary



Geant4



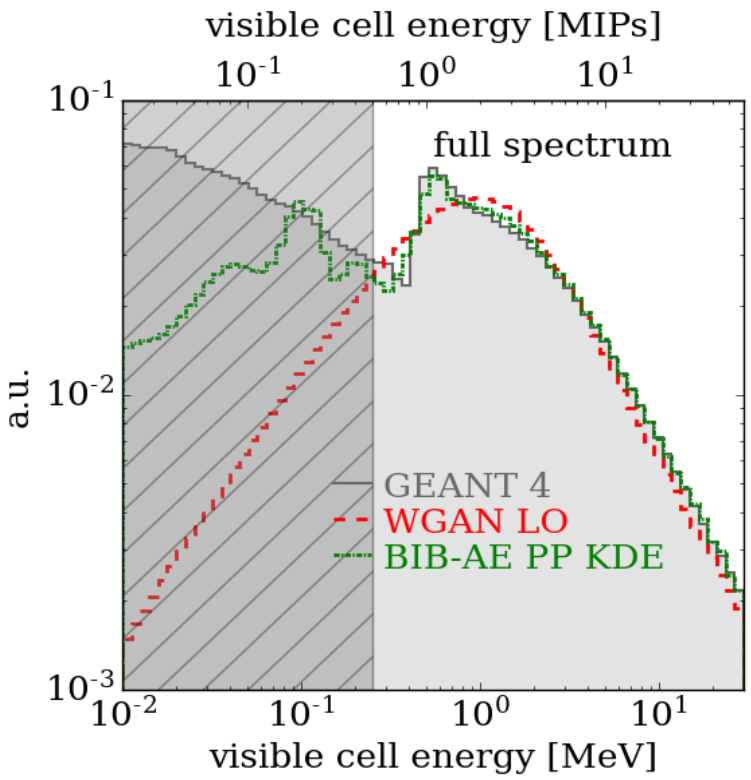
GAN

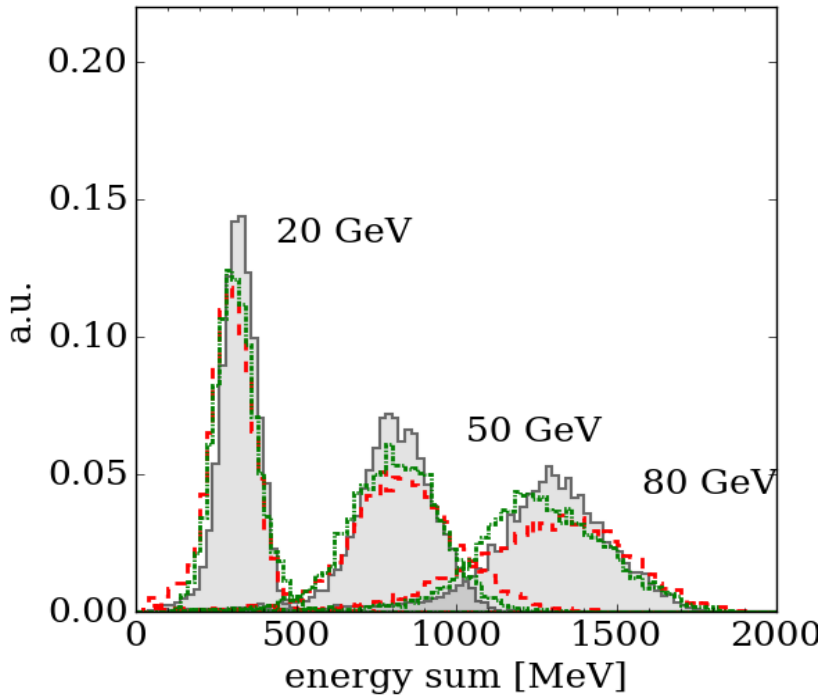


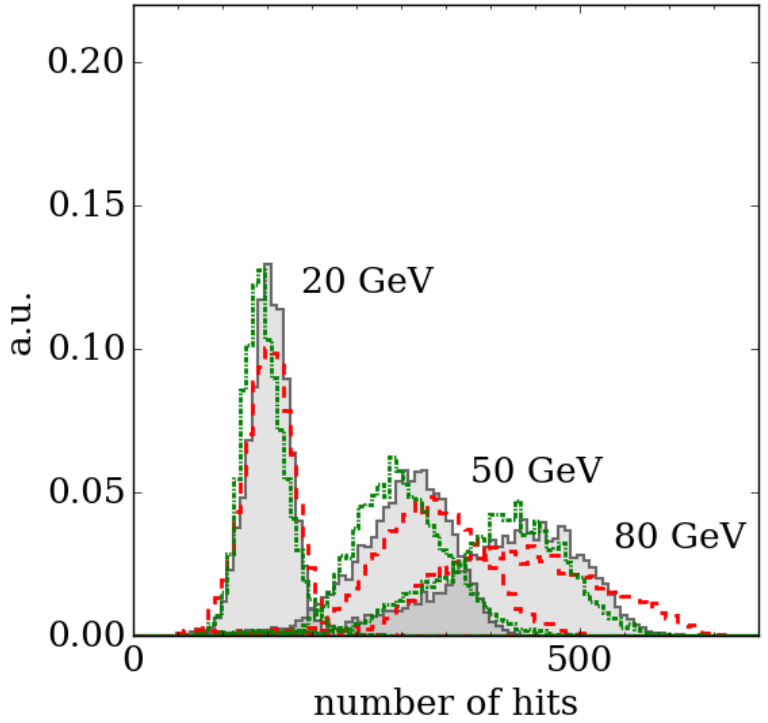
With the help of angular constraining network, GAN seems to **guided** to generate better showers

Hadron Showers

very preliminary



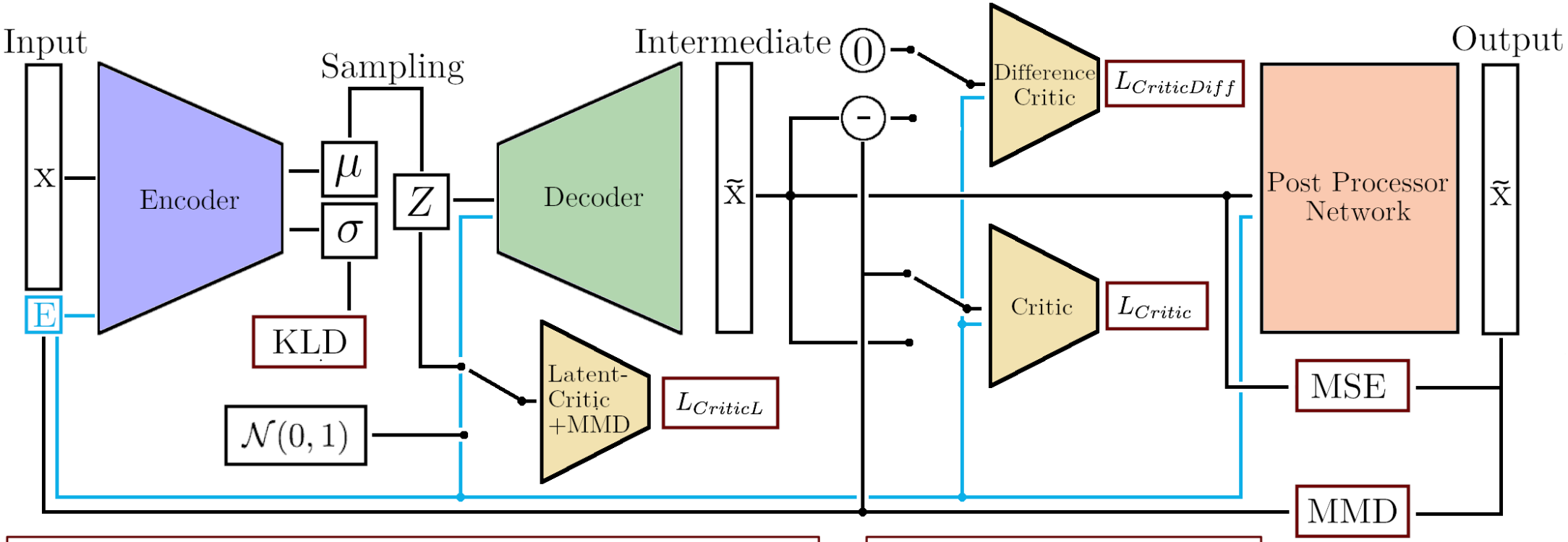




- Thanks to post-processing, MIP peak is correctly modeled in BIB-AE

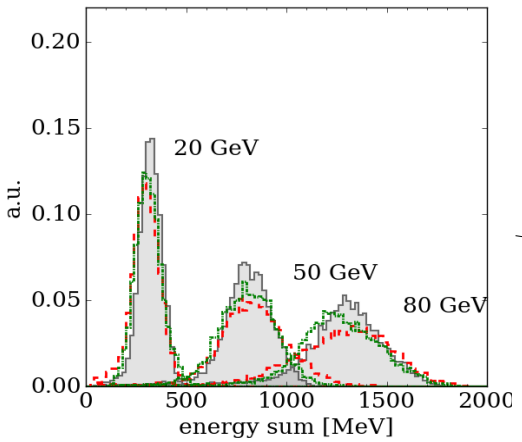
Bounded-Information Bottleneck Autoencodes (BIB-AE)

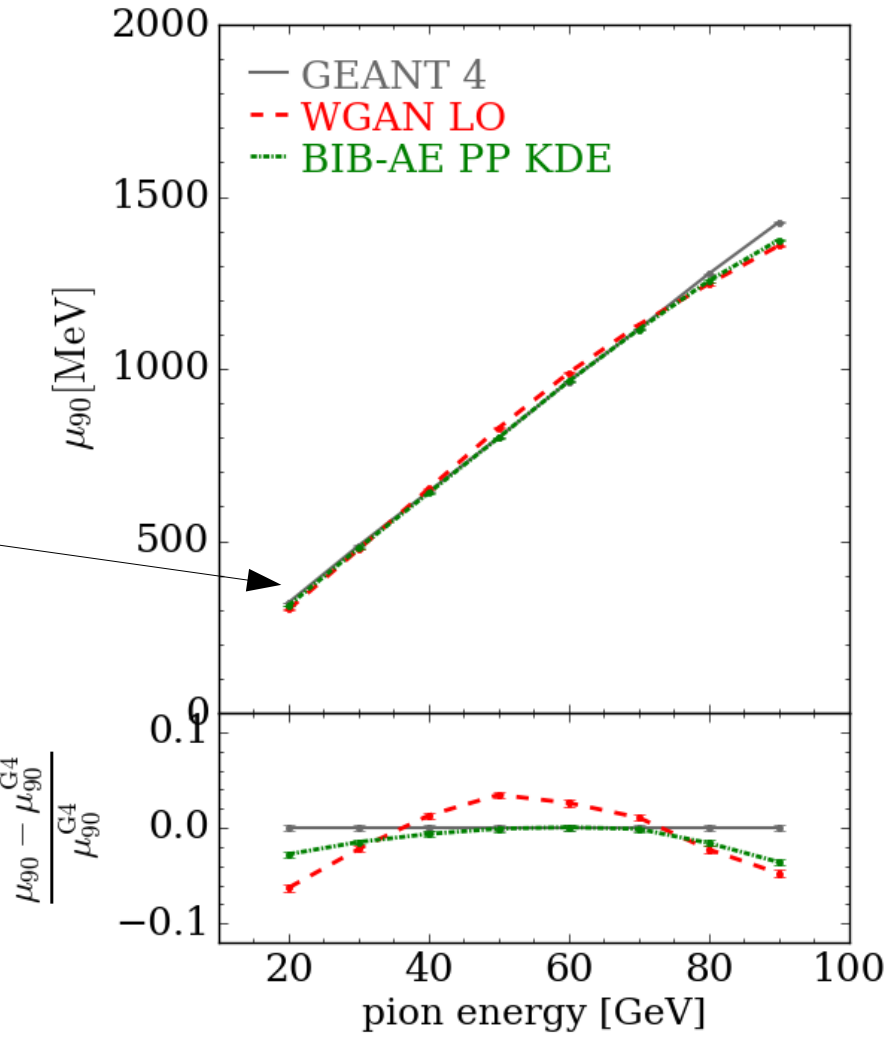
- Unifies features of GANs and Autoencoders (arXiv:1912.00830)
- WGAN-like critics evaluate the quality of reconstructed images
- Latent regularization is improved by an additional critic and a Maximum Mean Discrepancy (MMD) term
- Additional Post-Processor network, trained in a second step, is used to improved per-pixel energies
- Sampling from encoded latent space via multi-dimensional Kernel Density Estimation (KDE) (for pions)

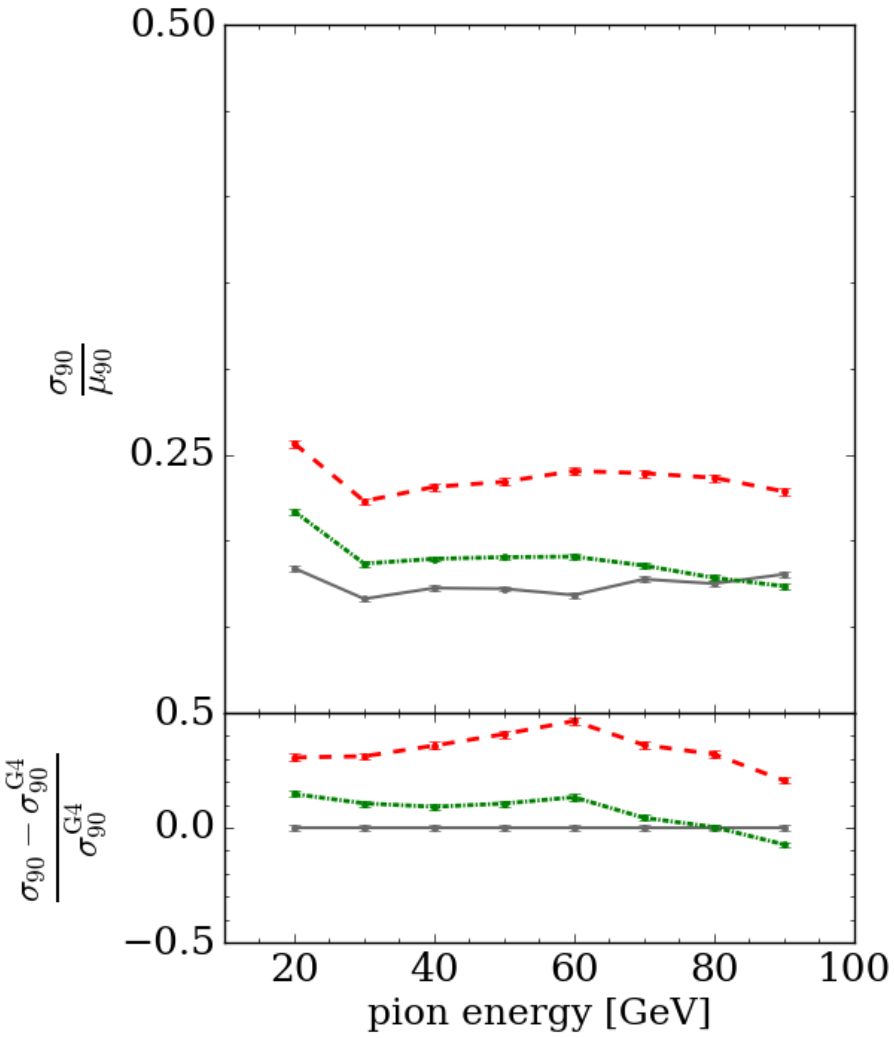


Hadron Showers

very preliminary







- Reasonable agreement with Geant4
- WGAN overestimates resolution