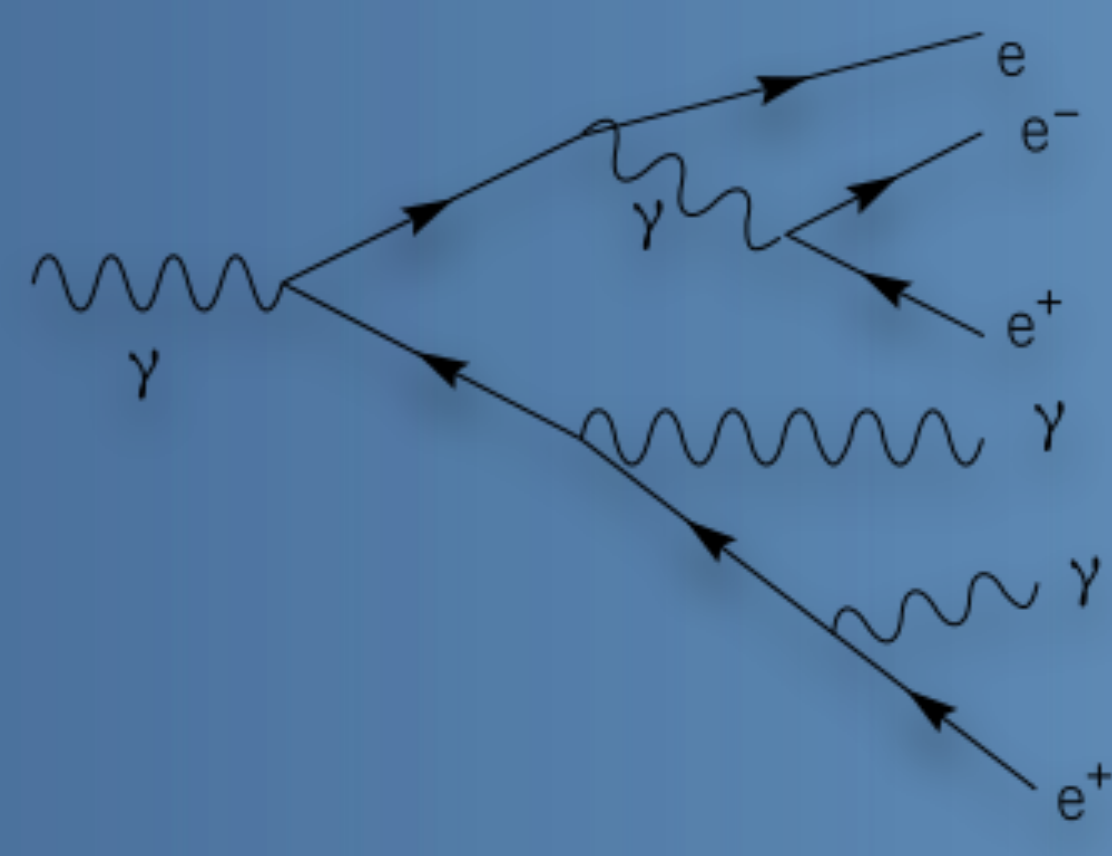


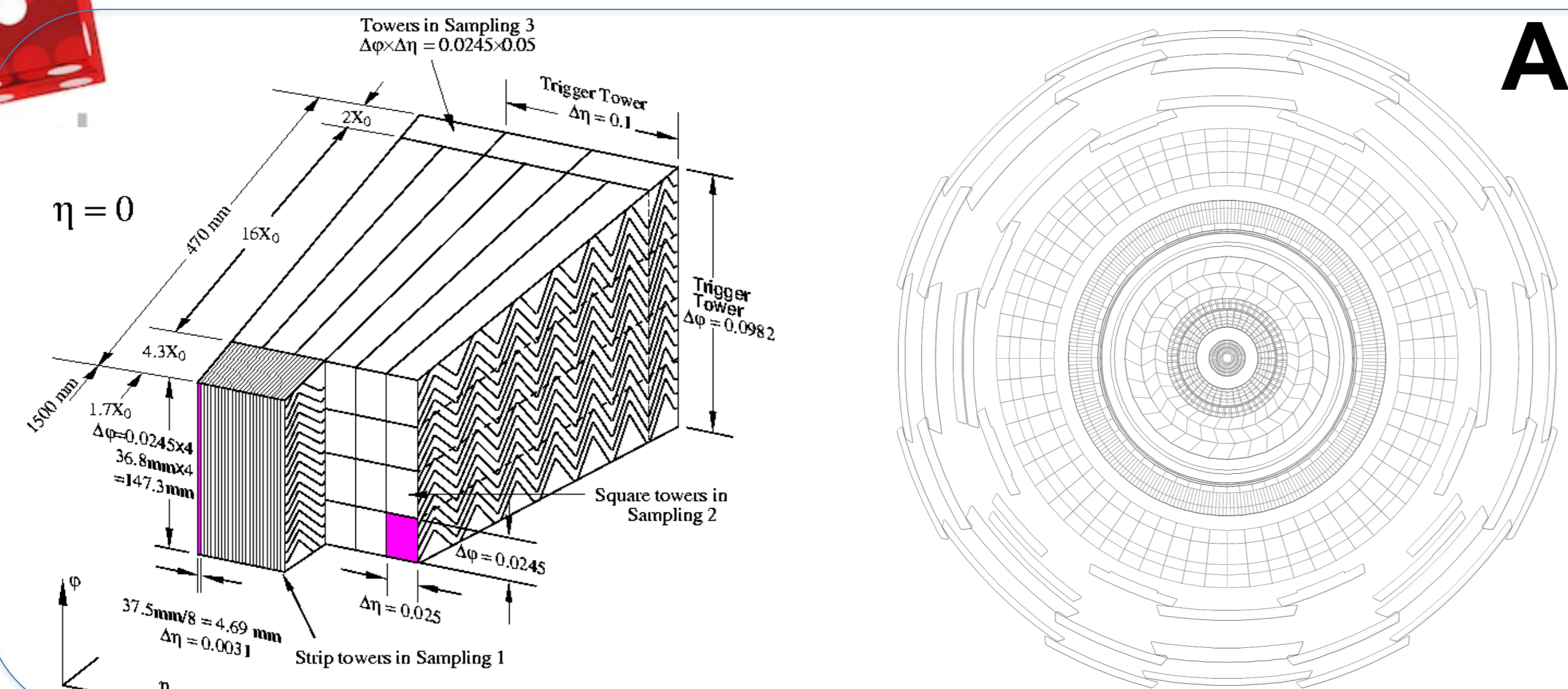
# Deep generative models for fast shower simulation in ATLAS



Current fast simulation methods fulfil need for large scale simulations at the cost of accuracy. Generative deep learning models that recently created photo-realistic natural images motivate the attempt to use lightning fast neural nets to generate physics simulations. GANs, VAEs are studied to produce EM showers.

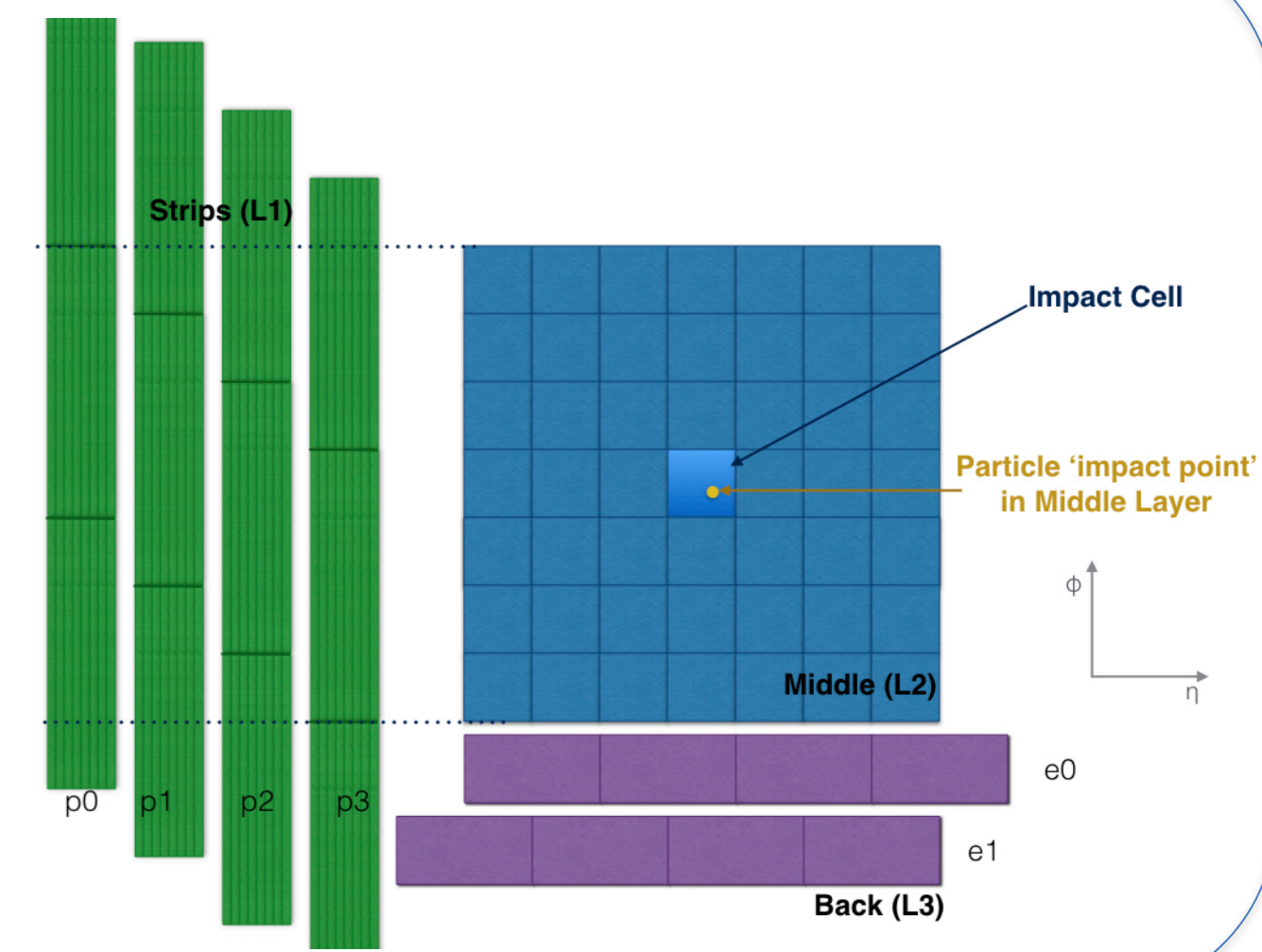


## Atlas EM Calorimeter

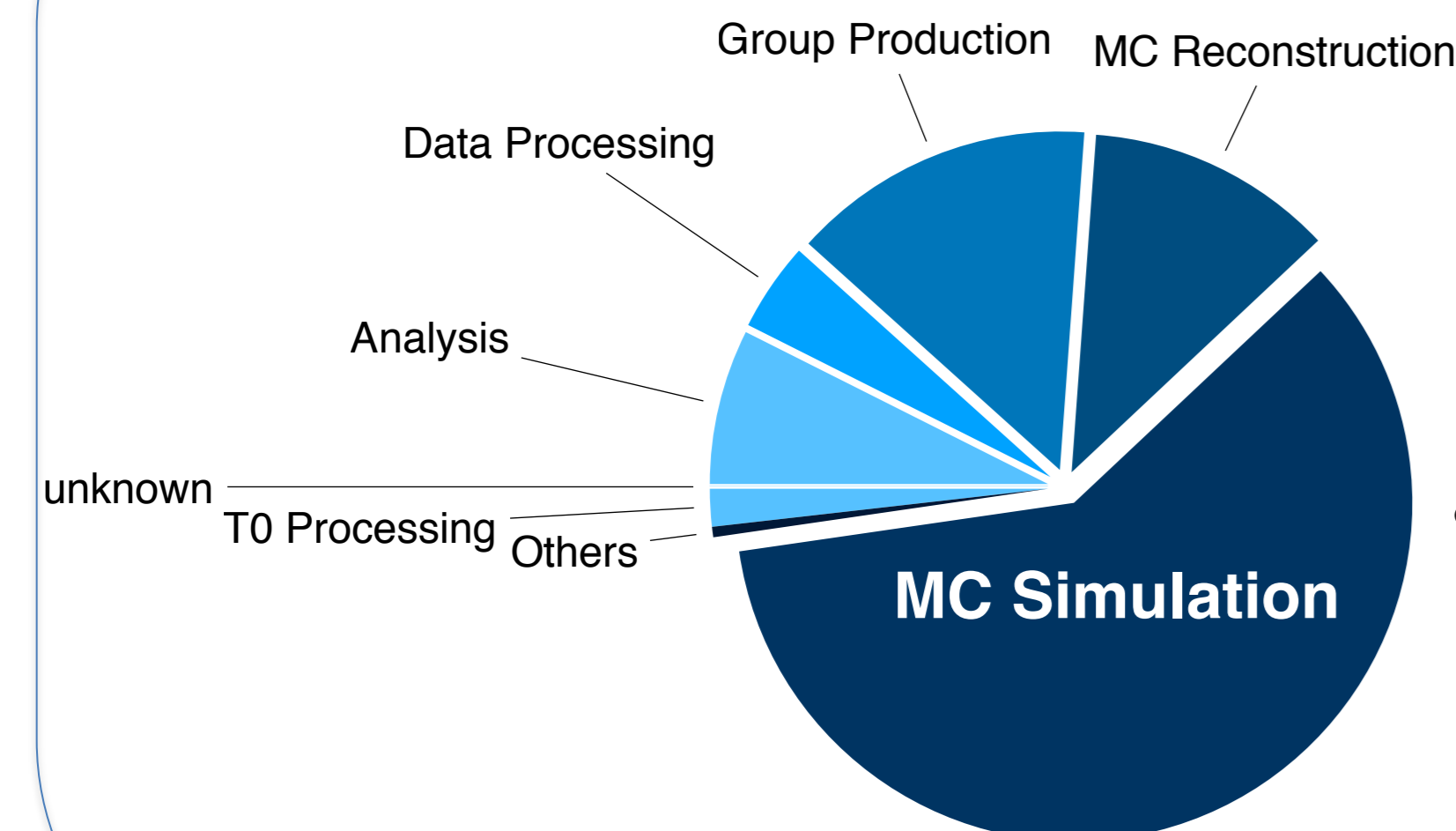


### Alignment Configurations :

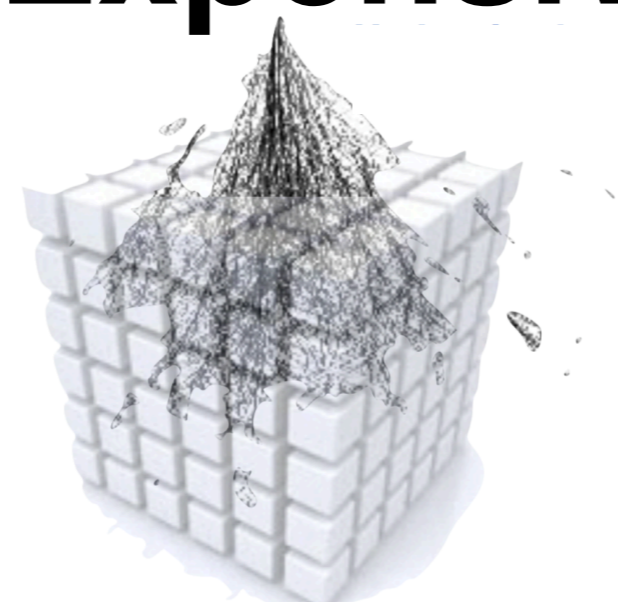
- 2- periodic in  $\eta$
- 4-periodic in  $\phi$



## Showers Computationally Expensive

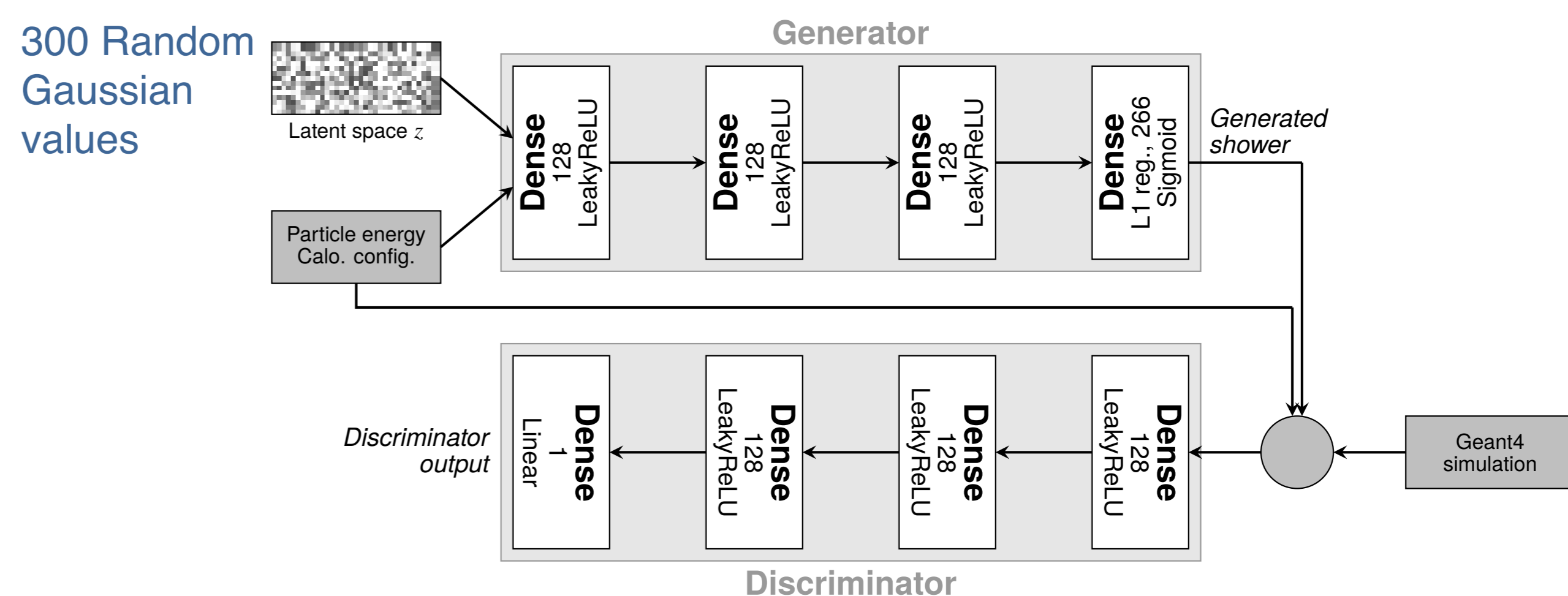


- Cascade quantum simulations are expensive for Geant4
- Only final shower image is recorded



## (W) Generative Adversarial Networks

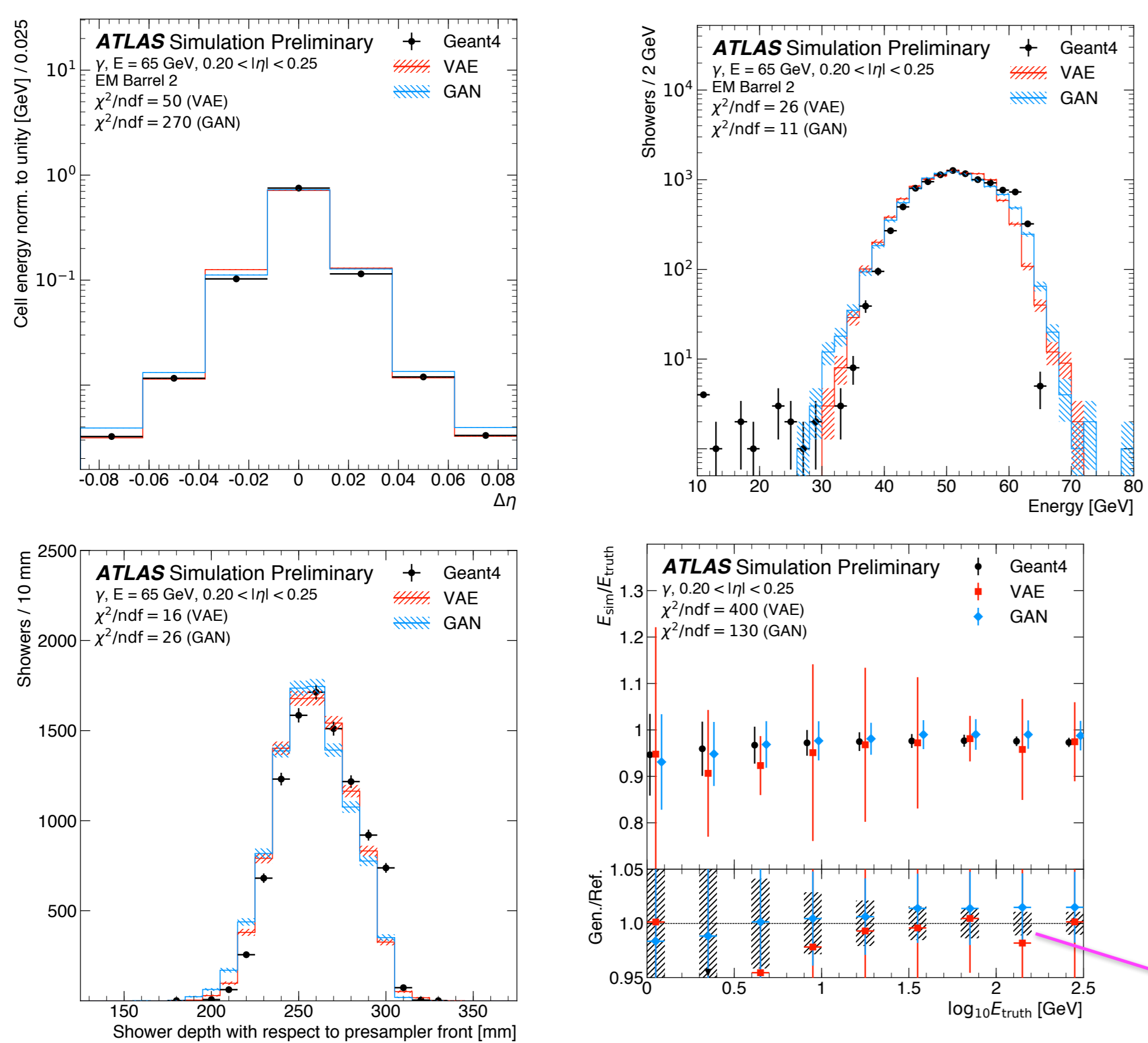
Gulrajani et al. 2017



Let AI supervise AI



## Results from Summer 2018



Look at single photon showers at {1,2,4,8,16, 32, 65, 131, 262} GeV

Assume Geant4 is ideal

Compare VAE, GAN to Geant4

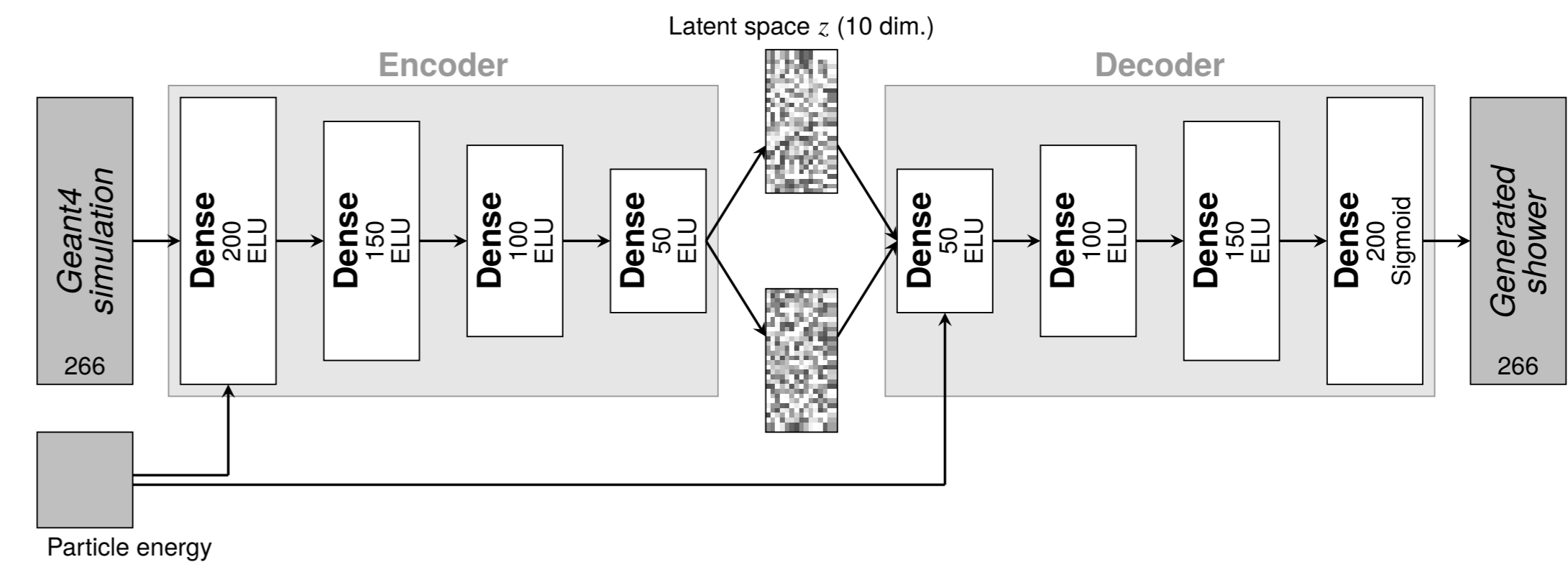
Energy resolution too wide

PUB Note: ATL-SOFT-PUB-2018-001

## Variational Auto-Encoder

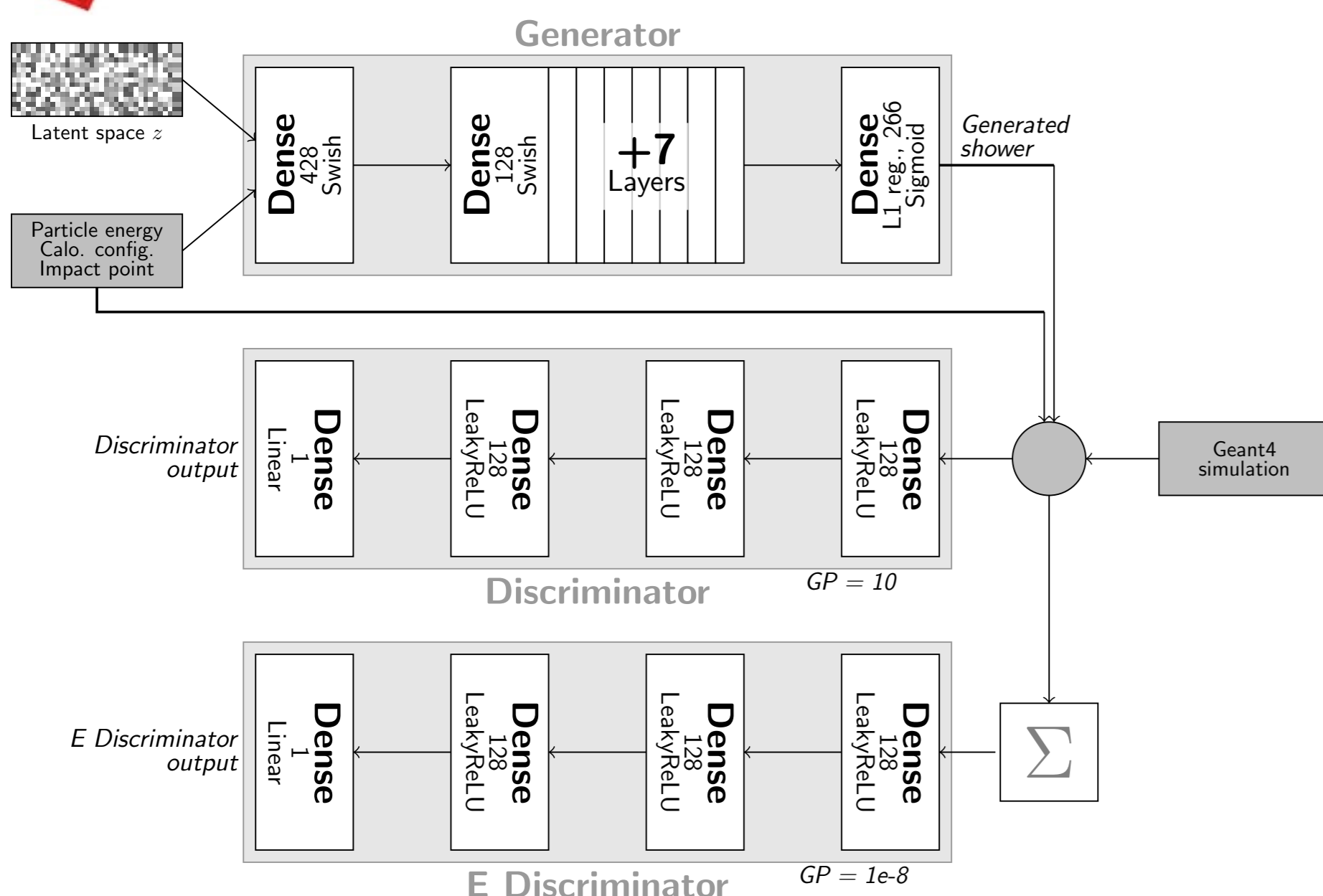
Kingma et al. 2013

Force output of encoder (Latent) to be Gaussian distributed



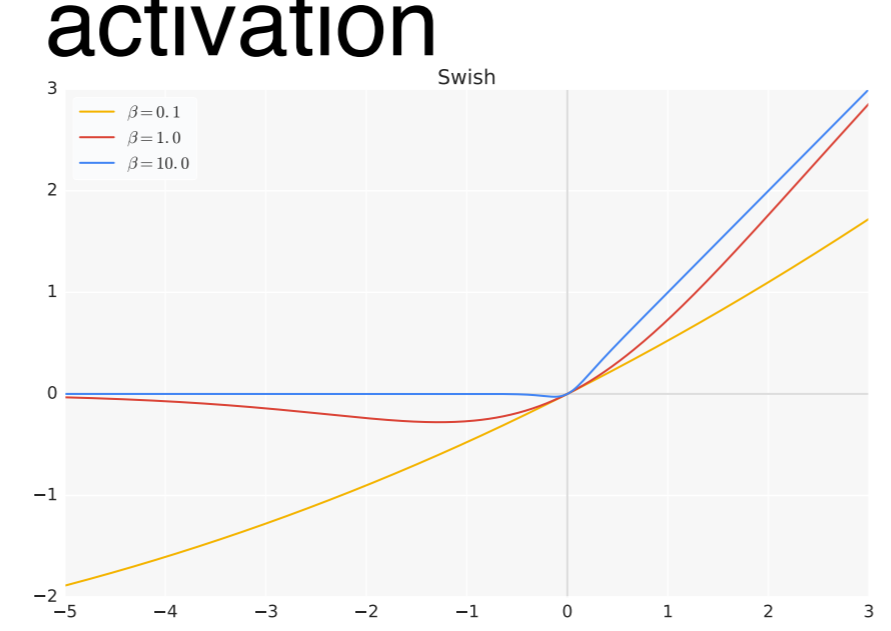
- Combining deep learning with variational Bayesian methods
- Encode 266 cell shower into smaller 10 dim. Gaussian latent space, decode to generate shower

## Update: Revised GAN

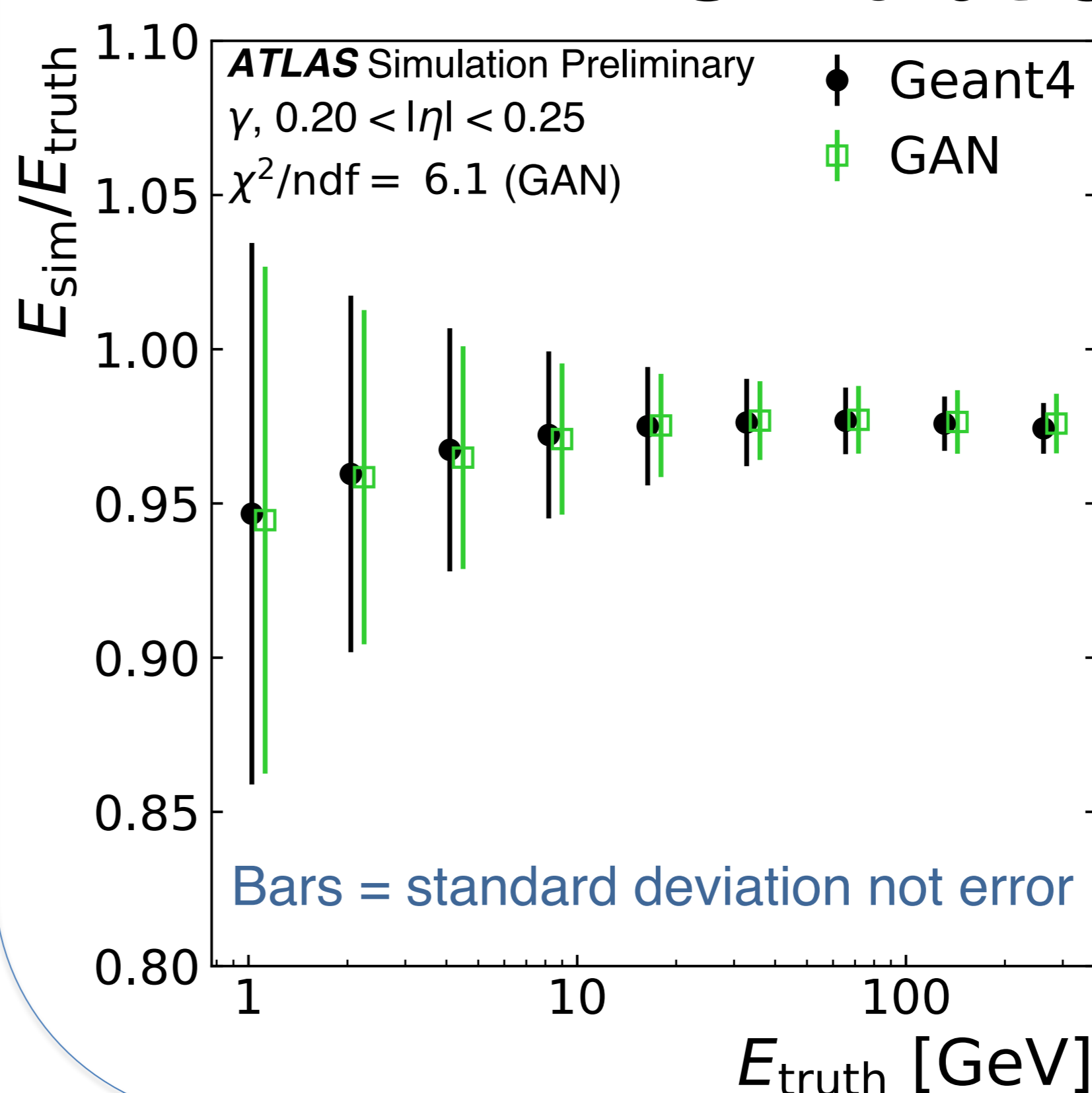


- Add an "E Discriminator" with low gradient penalty to only look at total energy
- Condition on Particle Position
- Deeper Generator with trainable Swish activation

$$\text{Swish}(x) = x \cdot \text{sigmoid}(\beta x)$$



## Update: Detector Resolution Simulation



- The detector resolution is better at higher energies
- GAN reproduces the mean and  $\sigma E \sim 10\% \sqrt{E}$  very well