

Weekly Update

June 27, 2025

Leo Zhu, Denaisha Kraft

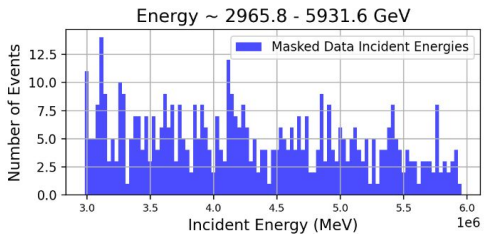
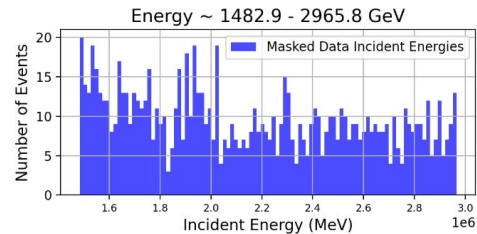
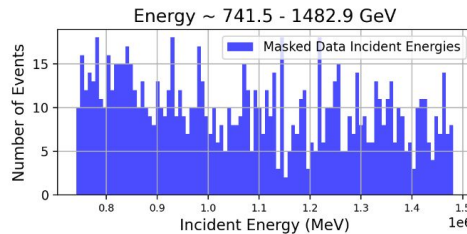
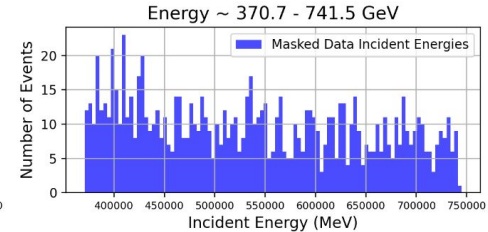
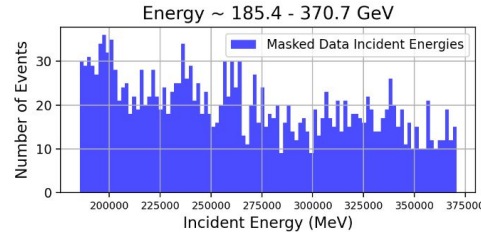
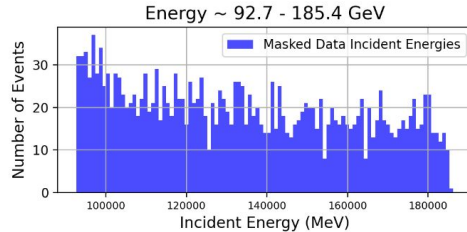
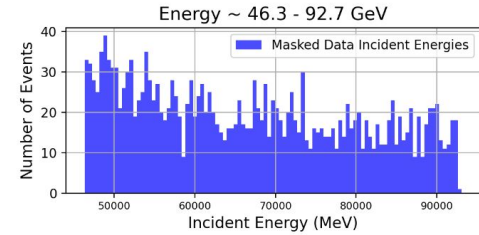
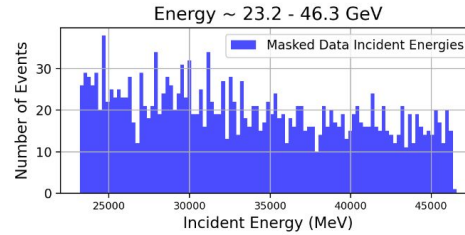
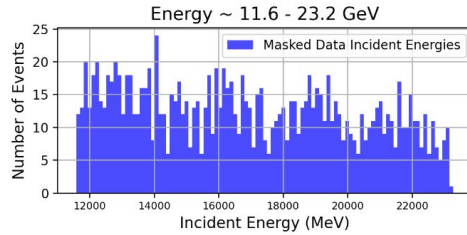
Science Week Abstract

The search for new physics and precision studies of the Higgs boson during the High-Luminosity Large Hadron Collider (HL-LHC) run will require fast and accurate particle-detector simulations. Traditional simulation methods are computationally intensive, with estimates reaching millions of CPU-years annually. To address this, we developed a quantum-assisted deep generative model that integrates quantum simulations with deep learning techniques. Our framework employs a variational autoencoder with a conditioned Restricted Boltzmann Machine (RBM) in the latent space, enabling sampling from D-Wave's Zephyr quantum annealer. This design enhances the modeling capacity of the latent space and allows for realistic, energy-conditioned electromagnetic shower generation. The model is trained on high-granularity ATLAS electromagnetic calorimeter datasets to generate energy-conditioned shower simulations. We validate the performance of our framework using metrics such as sparsity index, energy ratio, and deposited energy distributions, demonstrating promising agreement with ground-truth simulations. This approach achieves speed-ups of three to six orders of magnitude over traditional Geant4 simulations while preserving high fidelity, making it a powerful tool for simulation in high-energy physics.

Smearing Irregularities Fixed

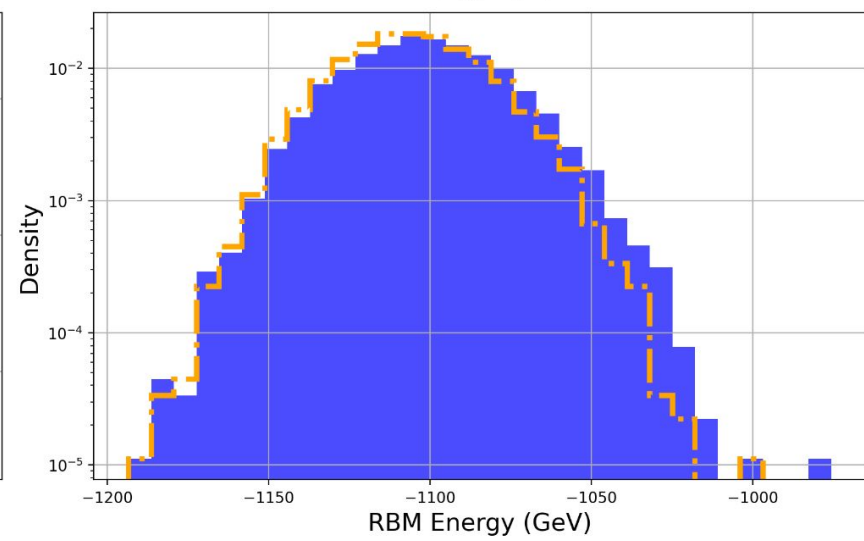
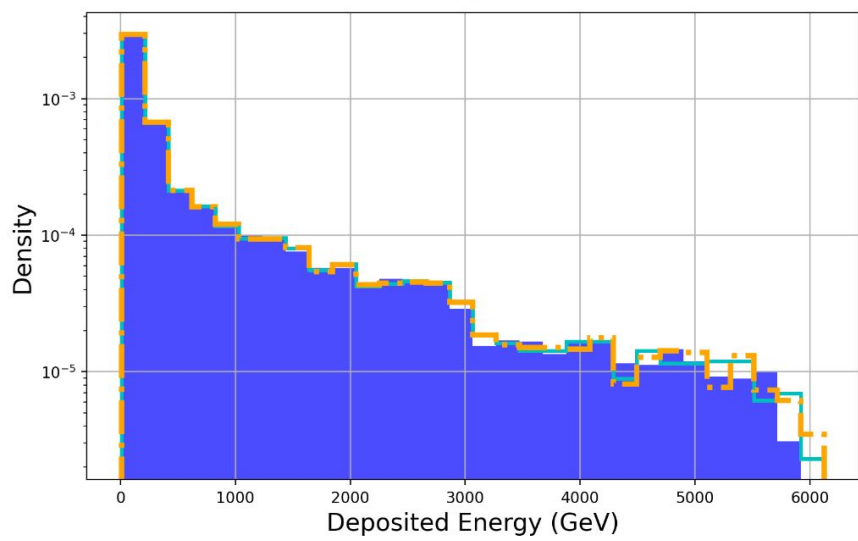
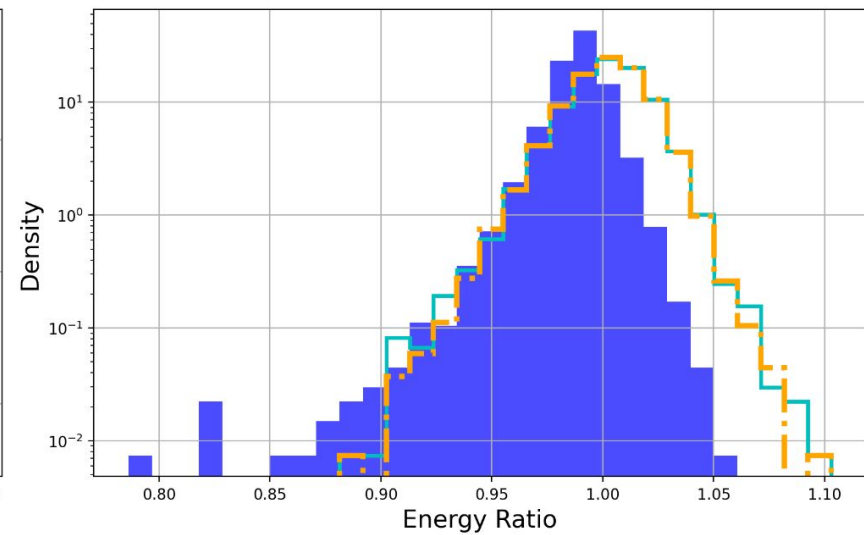
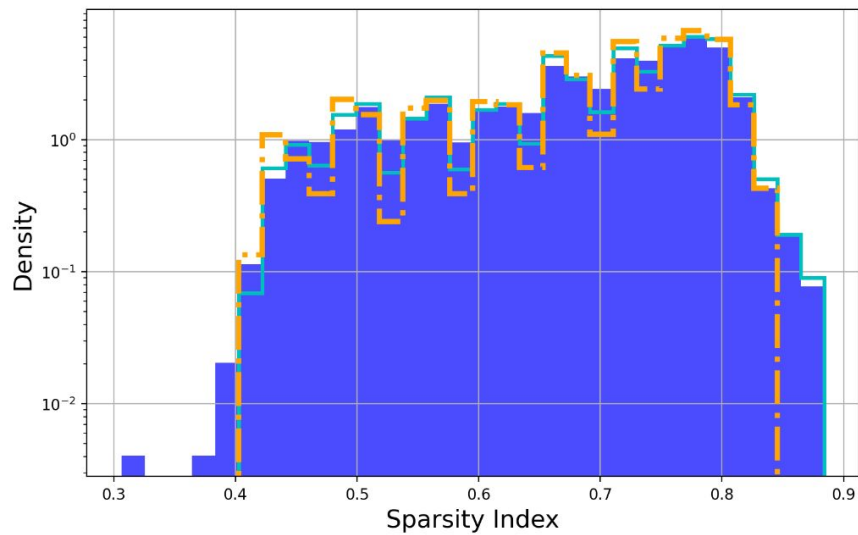
```
noise = torch.empty_like(incident_energies).uniform_(-0.5, 0.5)
perturbed_energies = 2**(torch.log2(incident_energies) + noise)
scale = perturbed_energies/incident_energies
```

- Fixed mistake with base e versus base 2

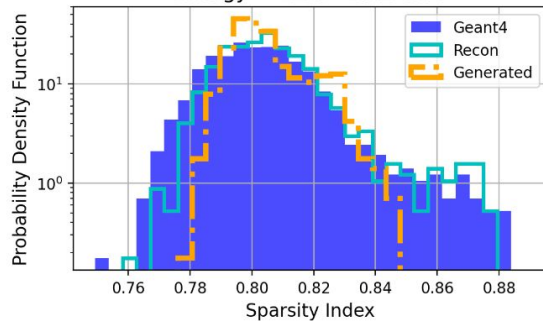


Model Results

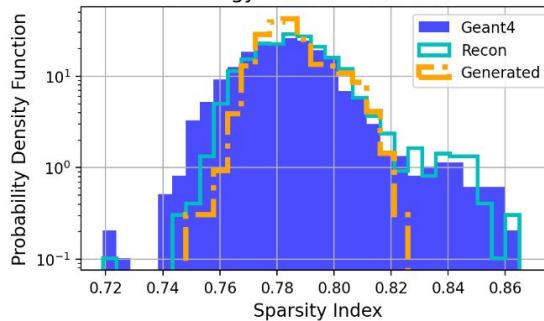
(Eta 0.40, Epoch 210)



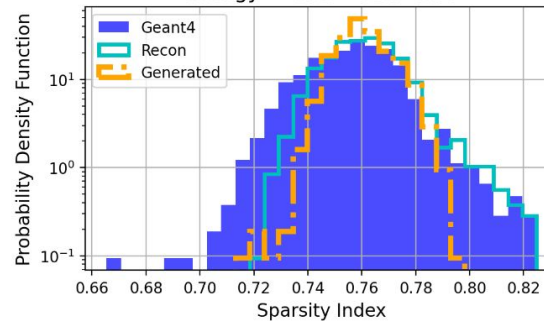
Energy ~ 11.6 - 23.2 GeV



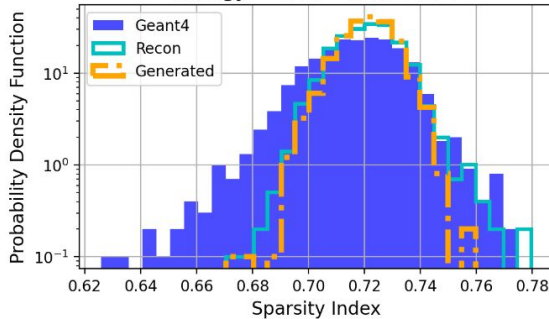
Energy ~ 23.2 - 46.3 GeV



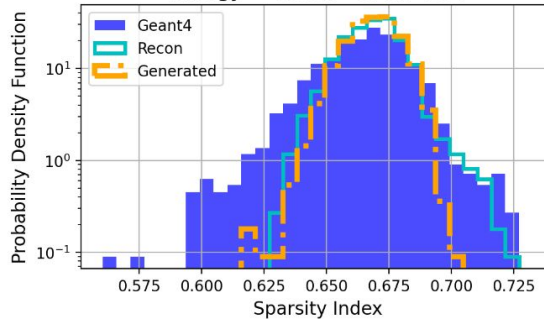
Energy ~ 46.3 - 92.7 GeV



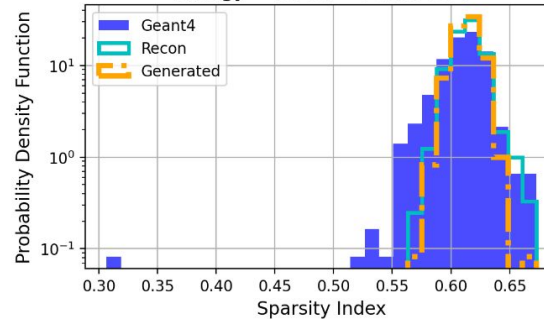
Energy ~ 92.7 - 185.4 GeV



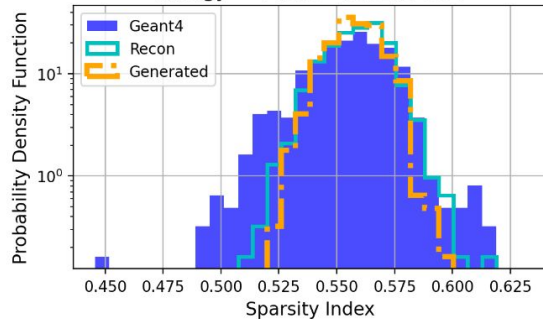
Energy ~ 185.4 - 370.7 GeV



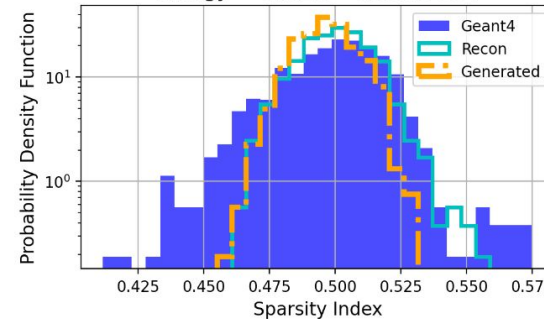
Energy ~ 370.7 - 741.5 GeV



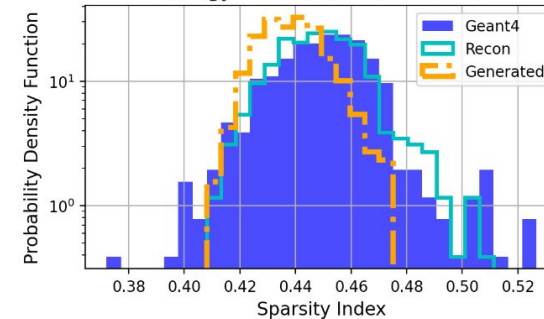
Energy ~ 741.5 - 1482.9 GeV



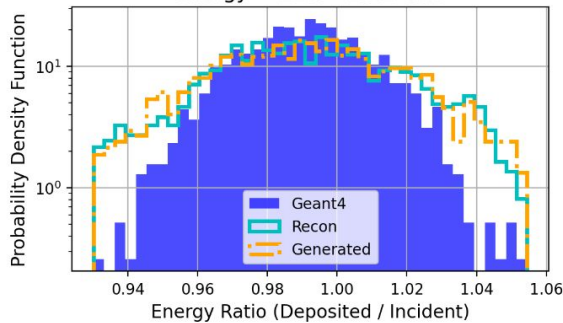
Energy ~ 1482.9 - 2965.8 GeV



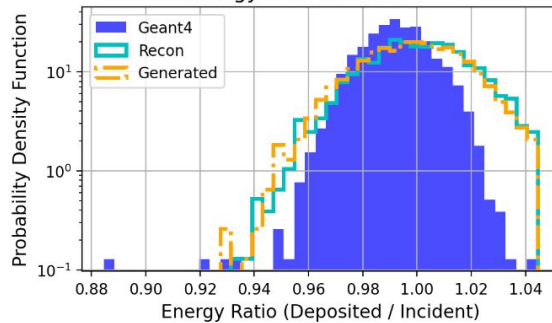
Energy ~ 2965.8 - 5931.6 GeV



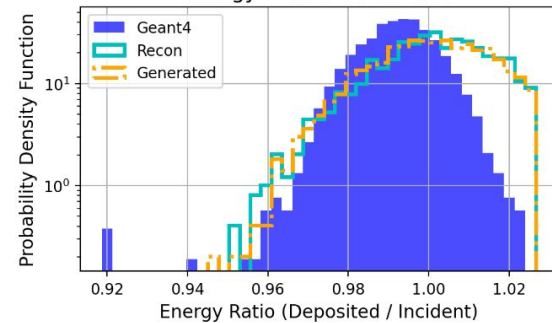
Energy ~ 11.6 - 23.2 GeV



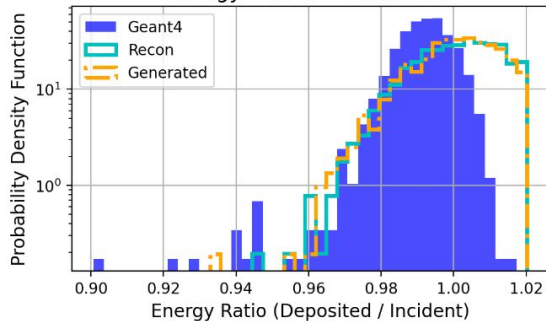
Energy ~ 23.2 - 46.3 GeV



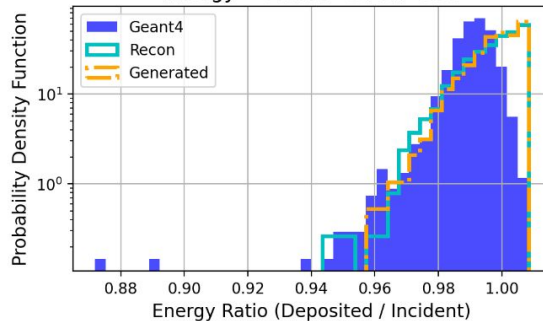
Energy ~ 46.3 - 92.7 GeV



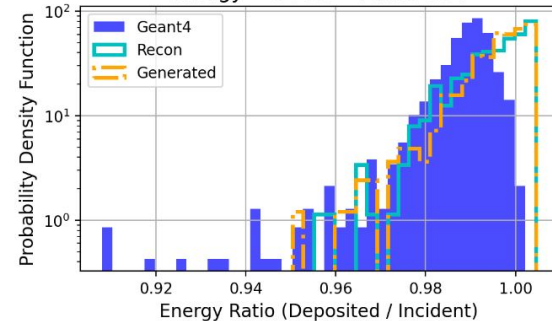
Energy ~ 92.7 - 185.4 GeV



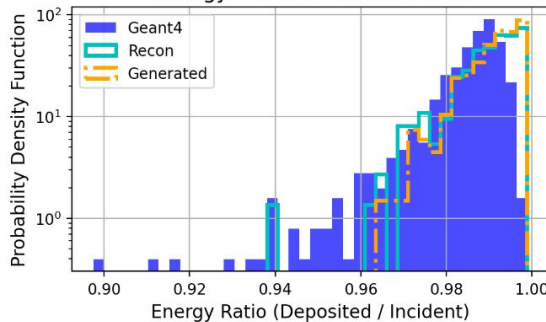
Energy ~ 185.4 - 370.7 GeV



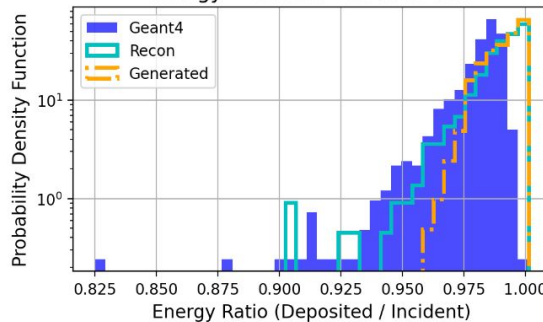
Energy ~ 370.7 - 741.5 GeV



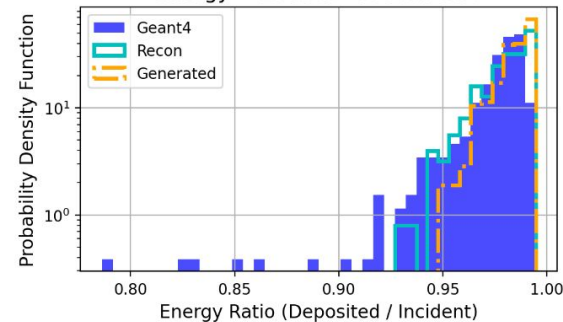
Energy ~ 741.5 - 1482.9 GeV

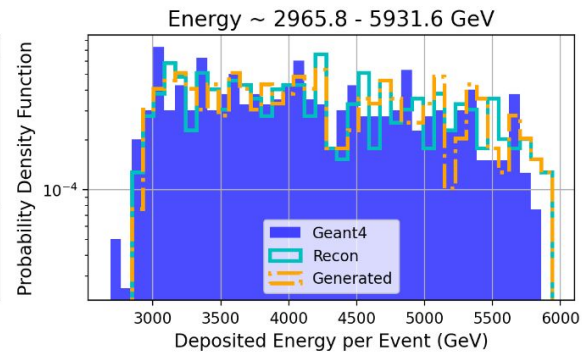
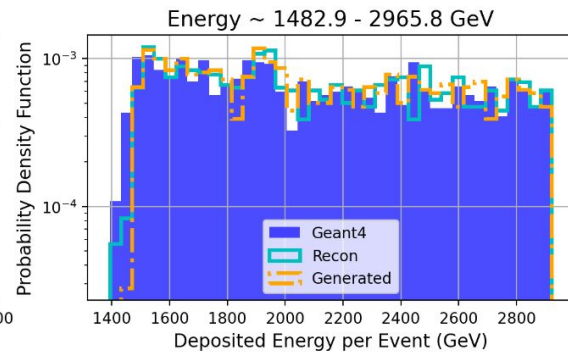
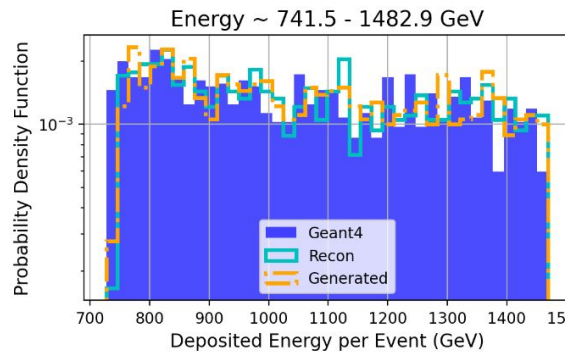
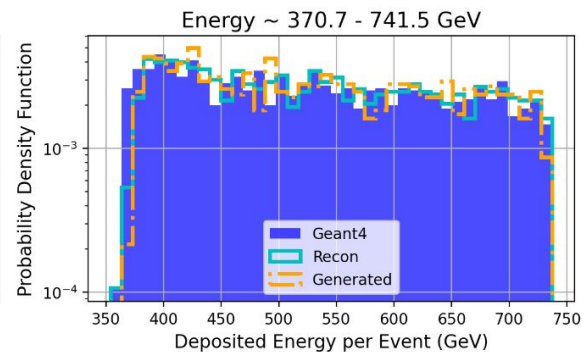
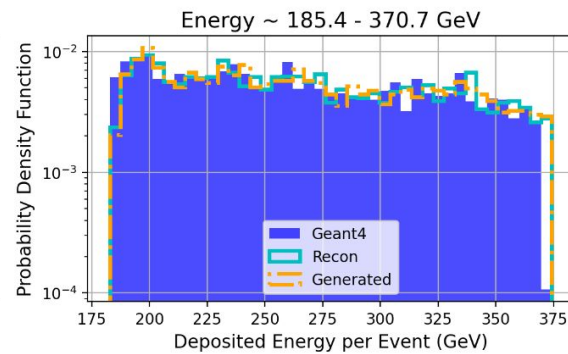
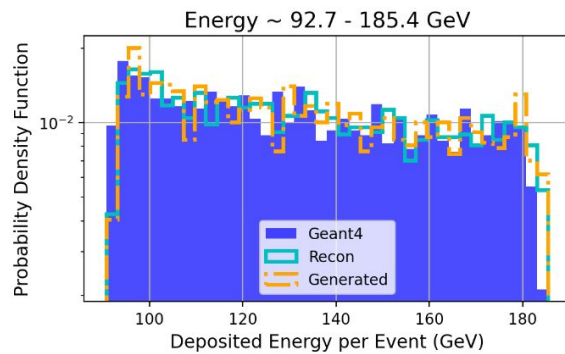
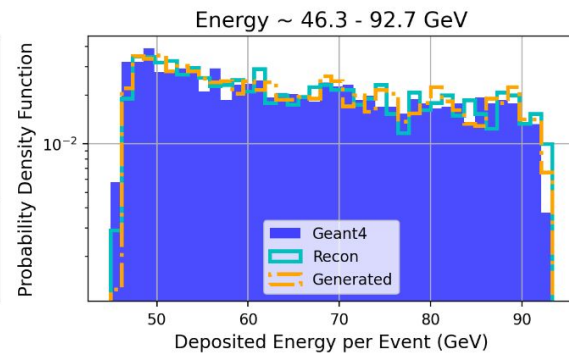
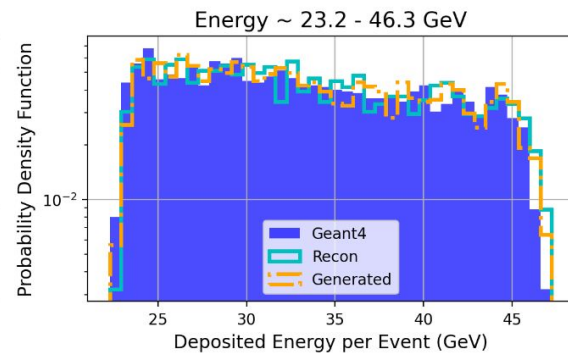
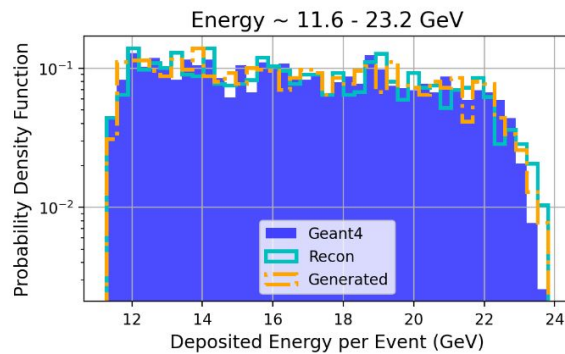


Energy ~ 1482.9 - 2965.8 GeV

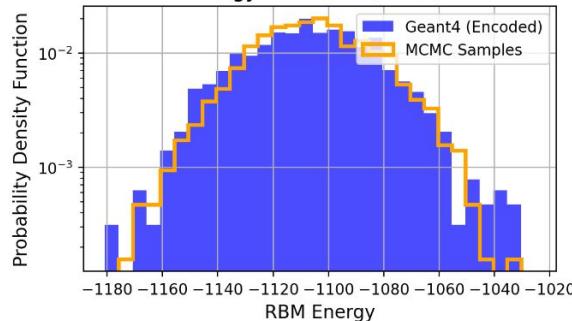


Energy ~ 2965.8 - 5931.6 GeV

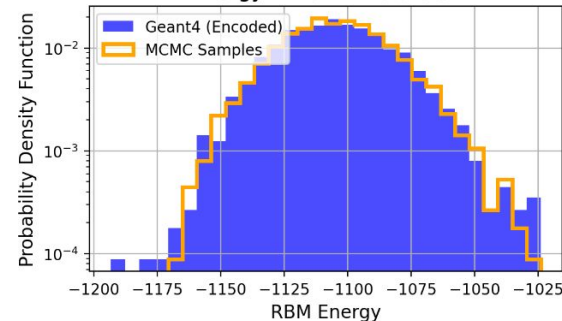




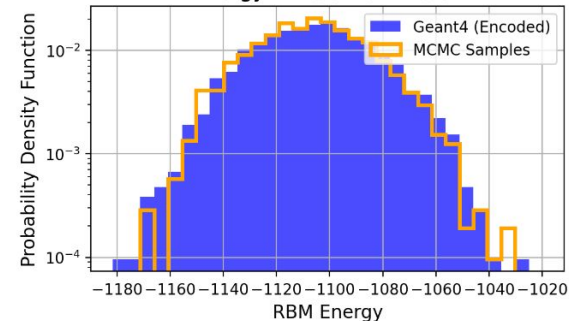
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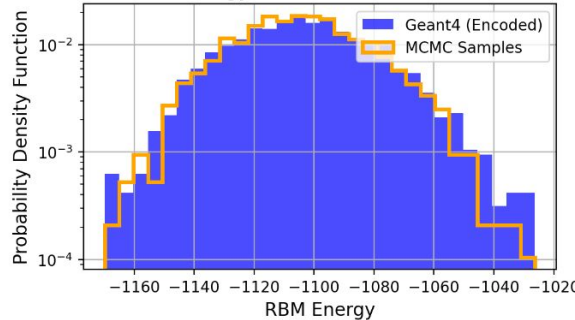
Energy ~ 23.2 - 46.3 GeV



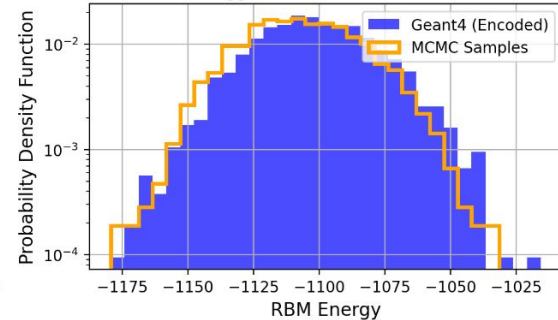
Energy ~ 46.3 - 92.7 GeV



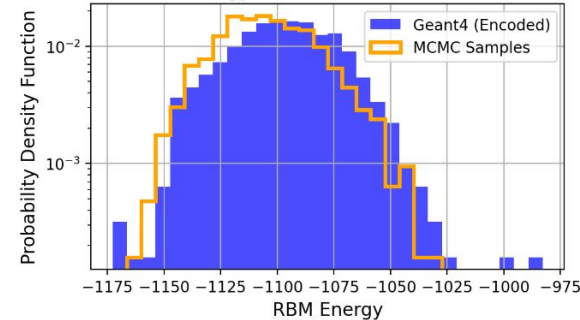
Energy ~ 92.7 - 185.4 GeV



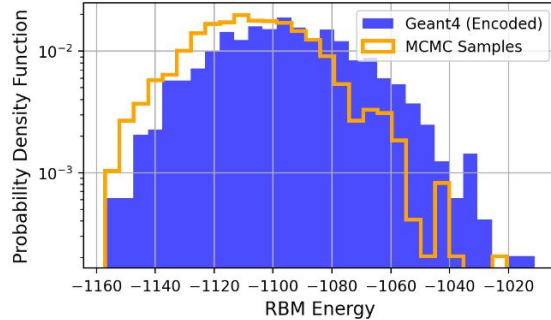
Energy ~ 185.4 - 370.7 GeV



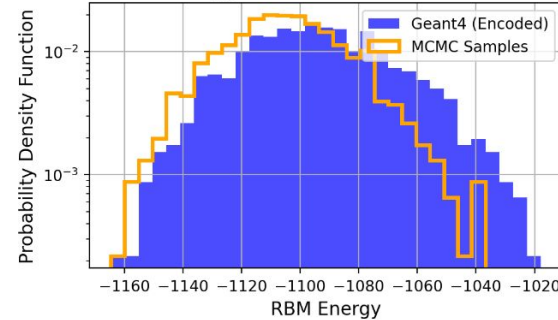
Energy ~ 370.7 - 741.5 GeV



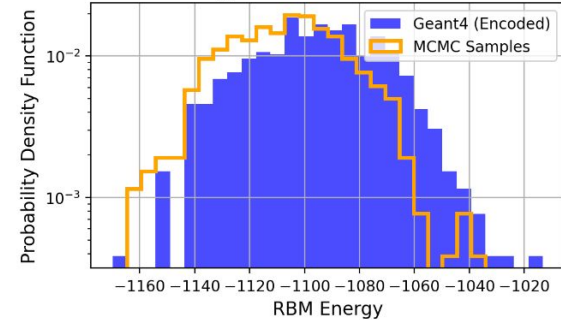
Energy ~ 741.5 - 1482.9 GeV



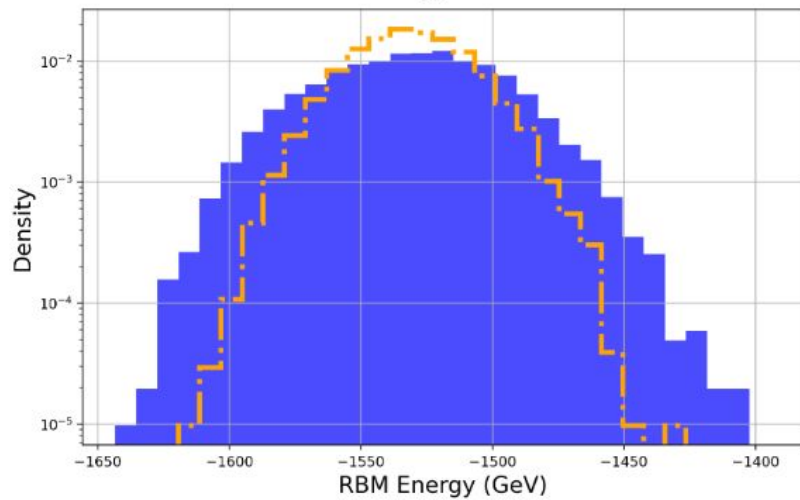
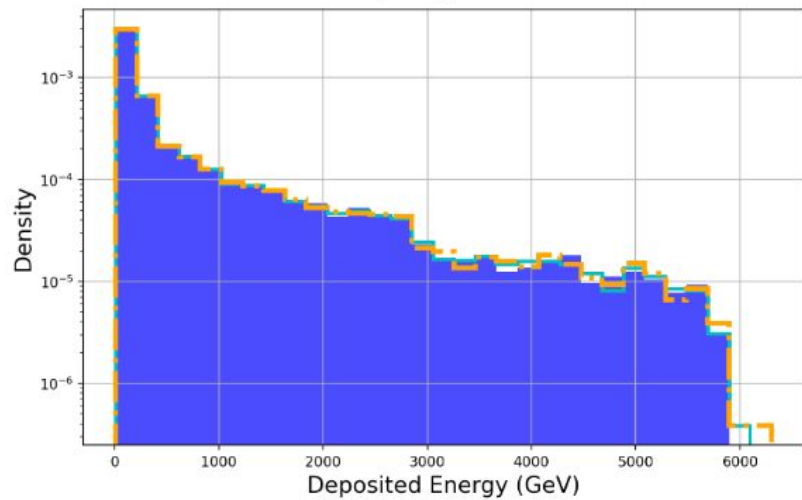
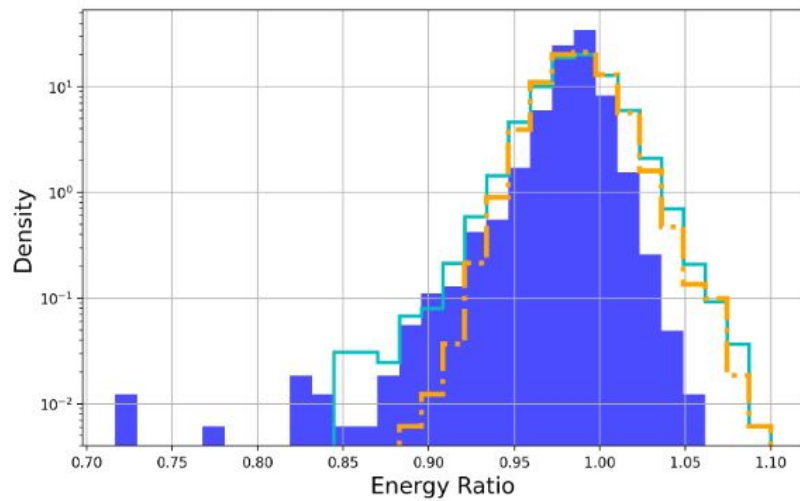
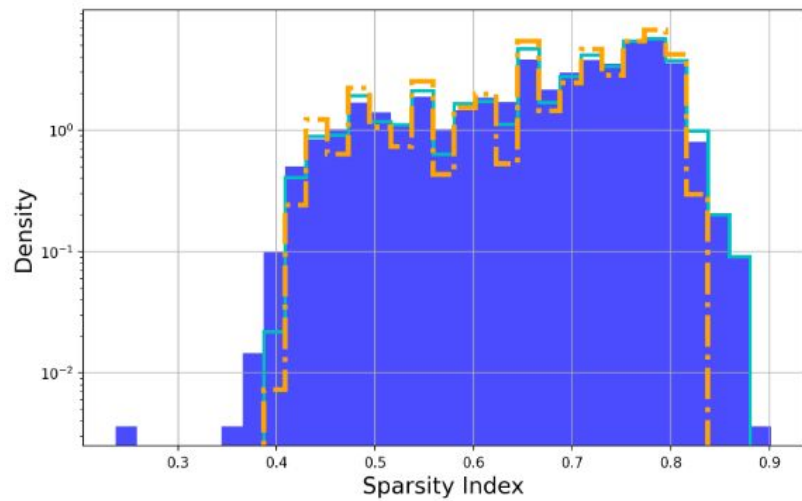
Energy ~ 1482.9 - 2965.8 GeV

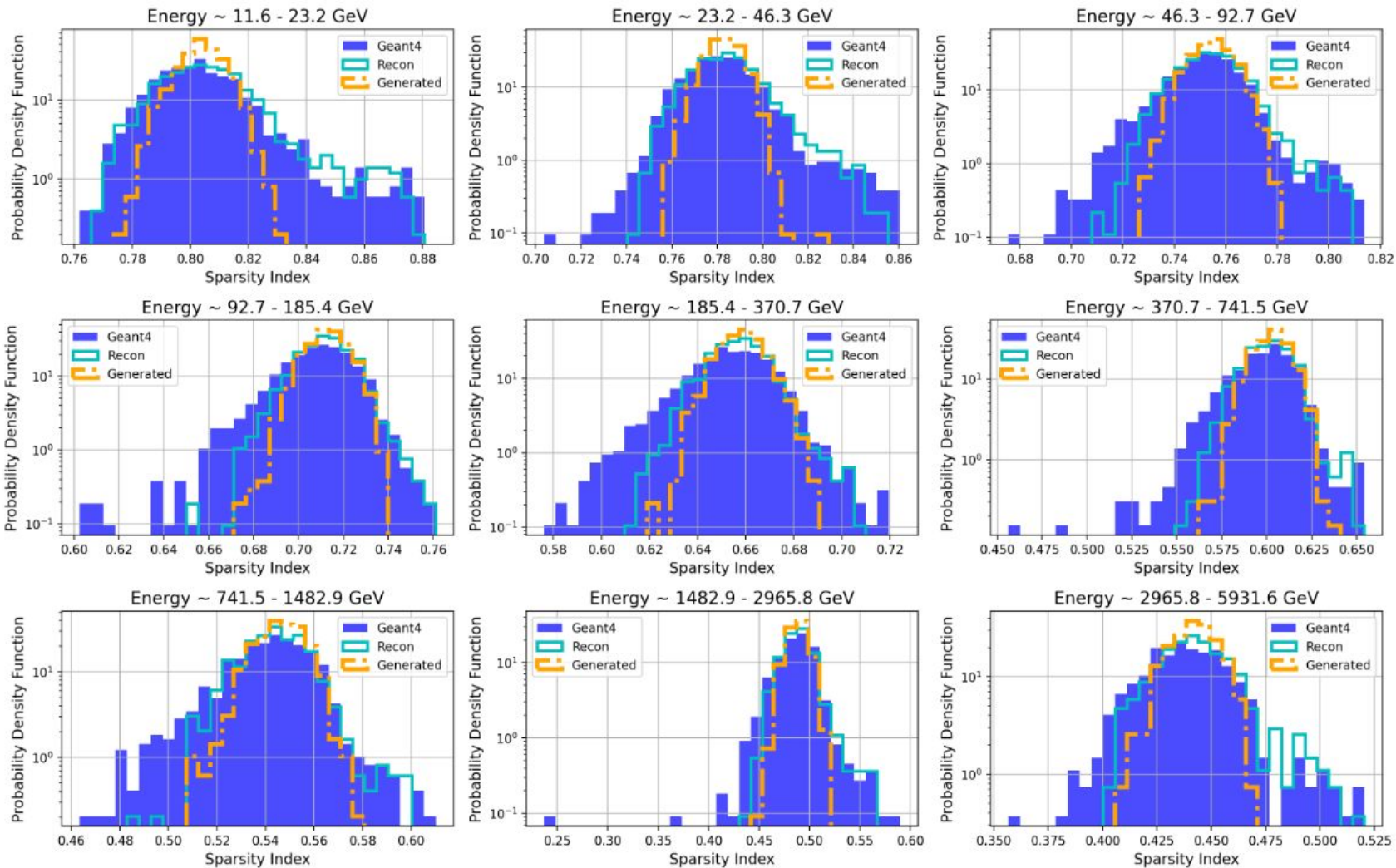


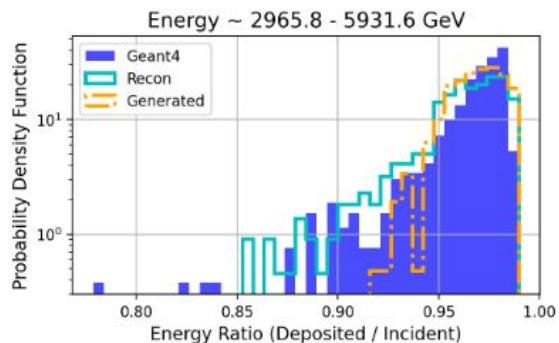
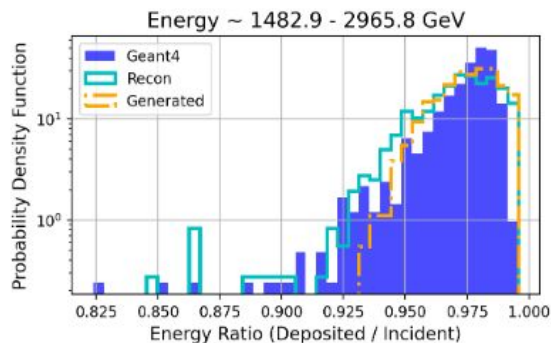
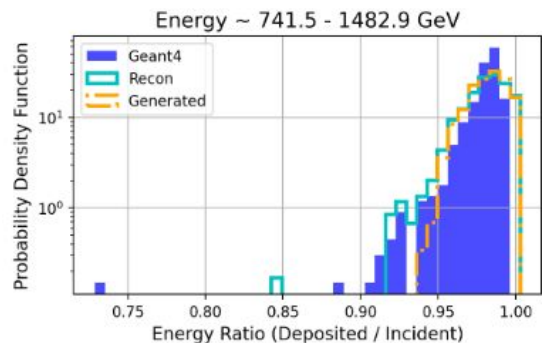
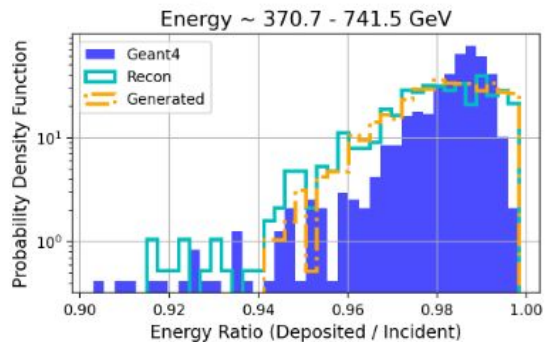
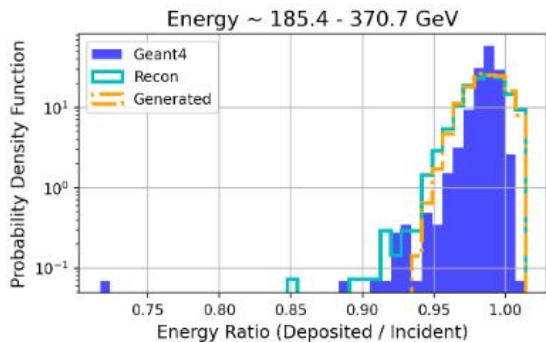
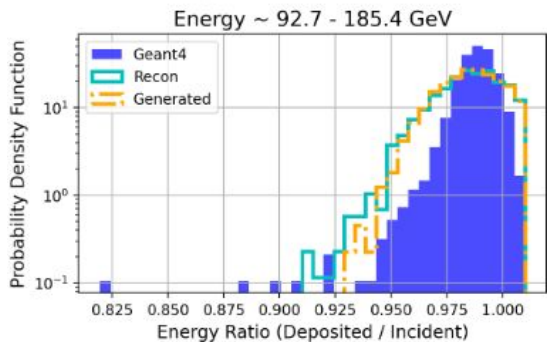
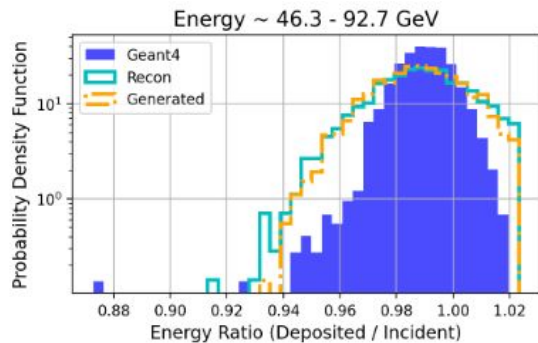
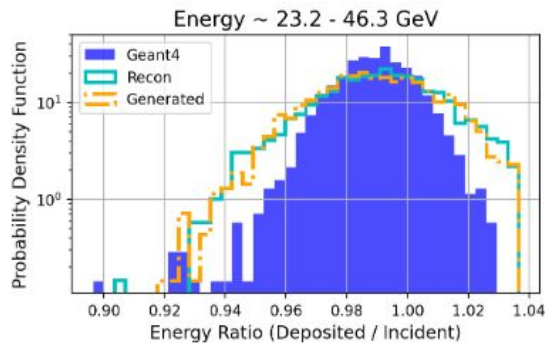
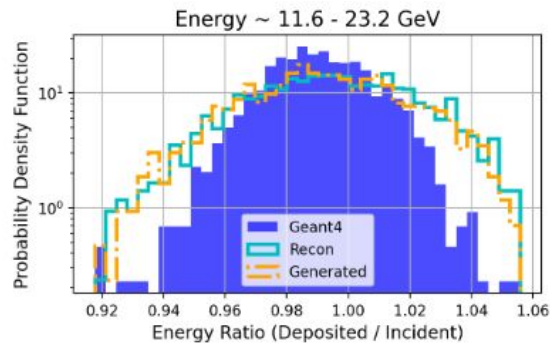
Energy ~ 2965.8 - 5931.6 GeV

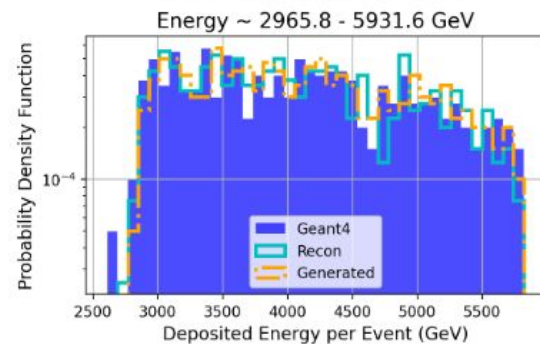
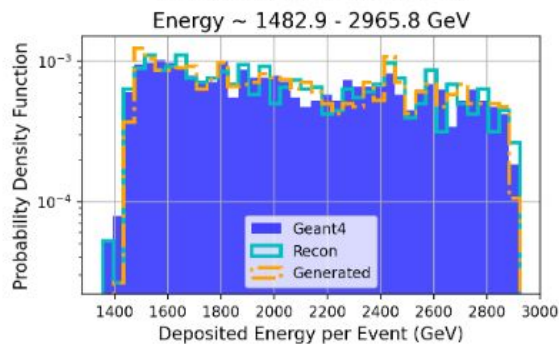
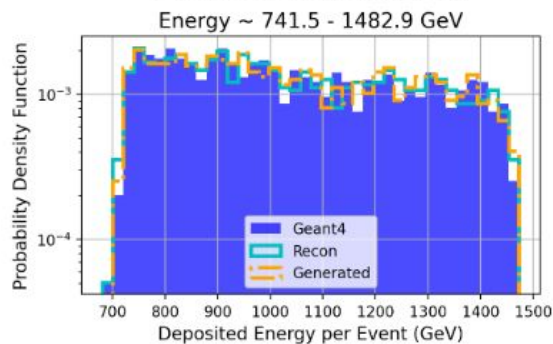
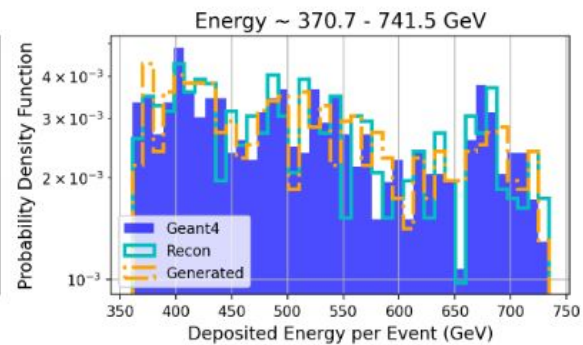
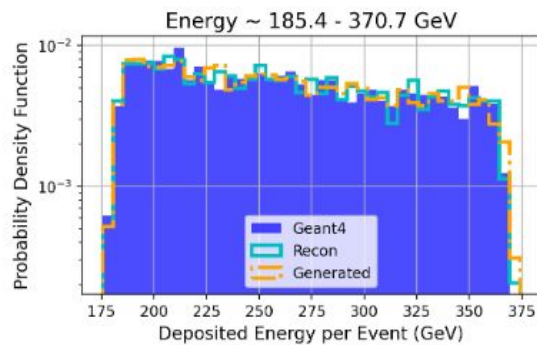
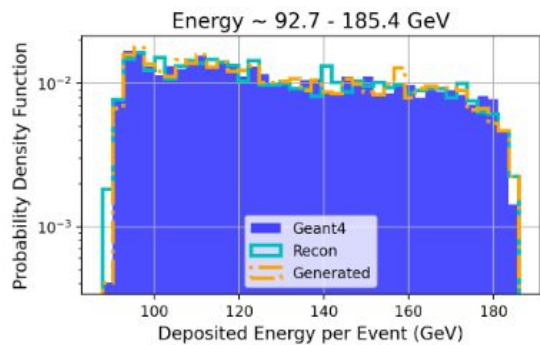
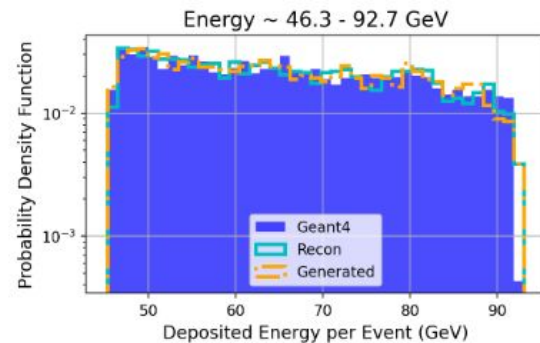
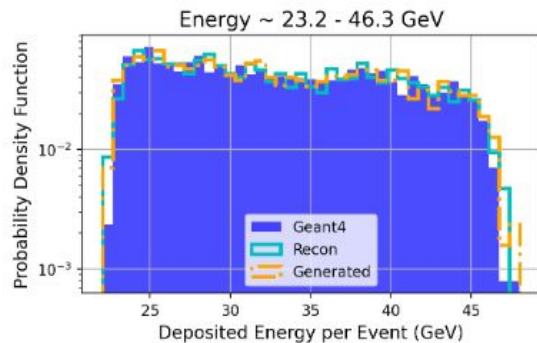
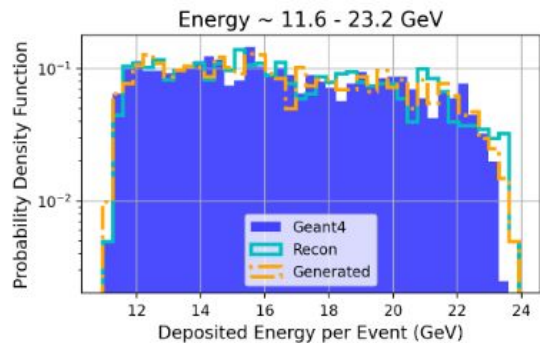


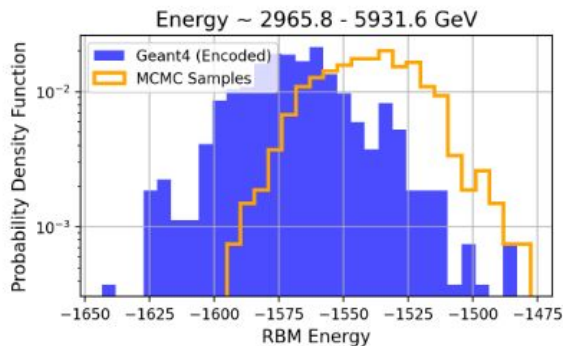
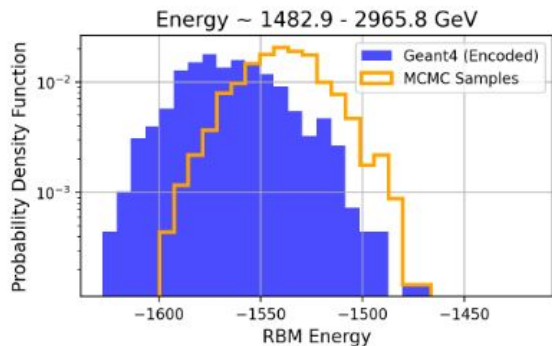
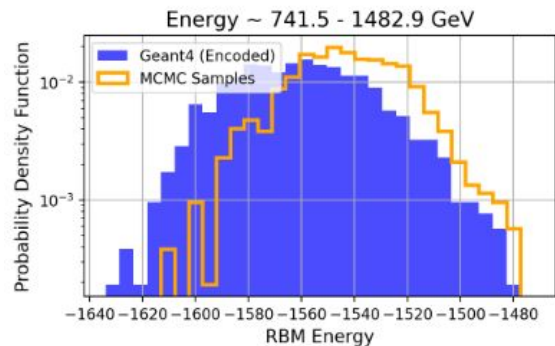
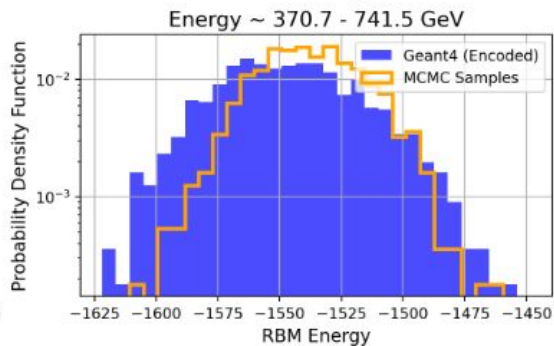
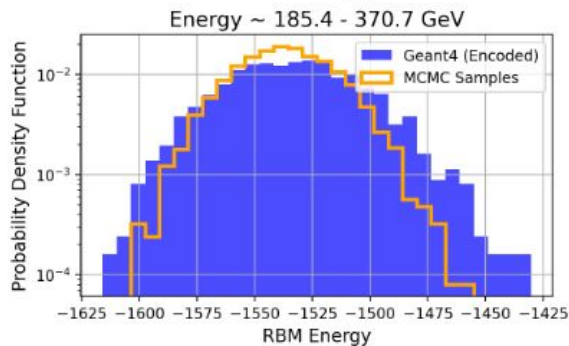
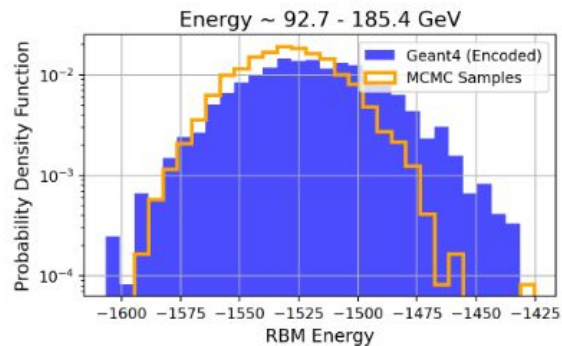
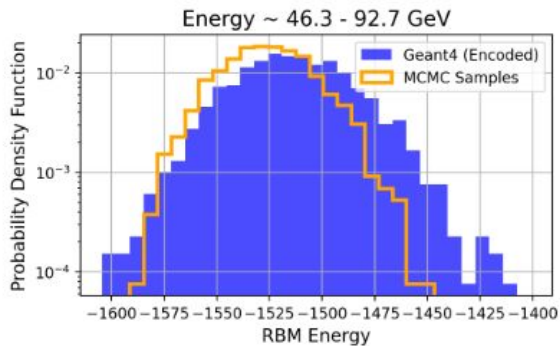
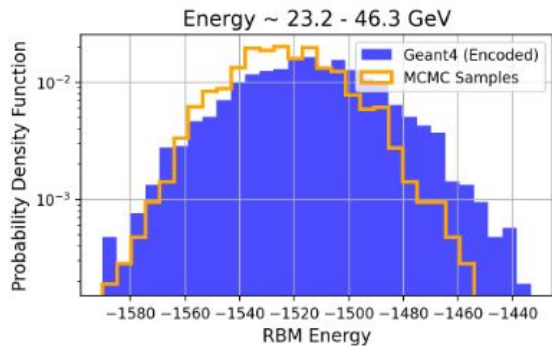
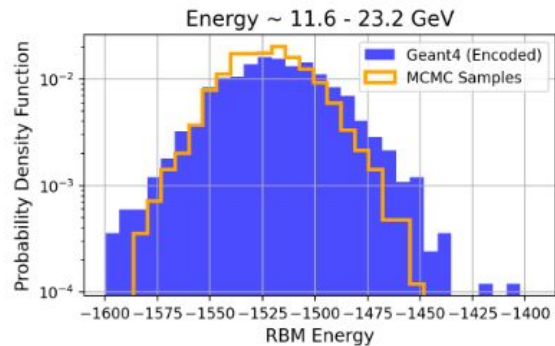
(Eta 0.25, Epoch 220)











Insights from Latent Diffusion

- Their strategy: train VAE to learn latent representation, then train diffusion model on modelling latent space
 - Diffusion model is analogous to RBM in our case
- Training is separate: the VAE is trained by itself, with very minimal ($1e-6$) regularization
 - Supports idea to train RBM after VAE is fully trained
- Additional loss terms for the VAE
 - Perceptual loss term included in typical generative models for images (no good counterpart for particle showers)
 - Discriminator loss, specifically a PatchGAN discriminator
 - For us, patches could be layers or voxel patches?