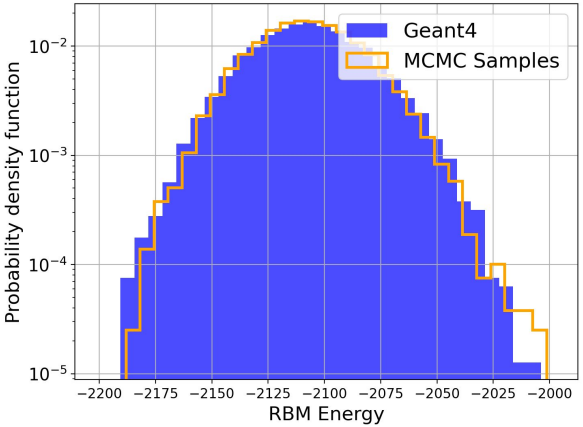
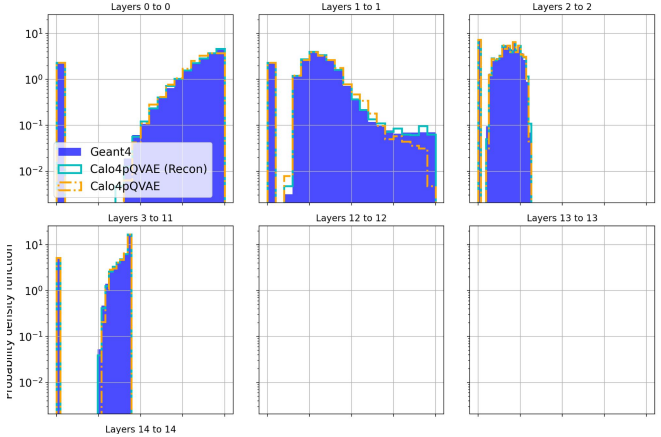
Weekly Update

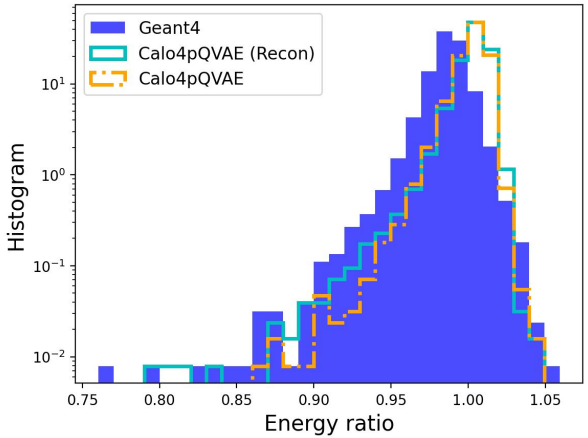
June 6, 2025

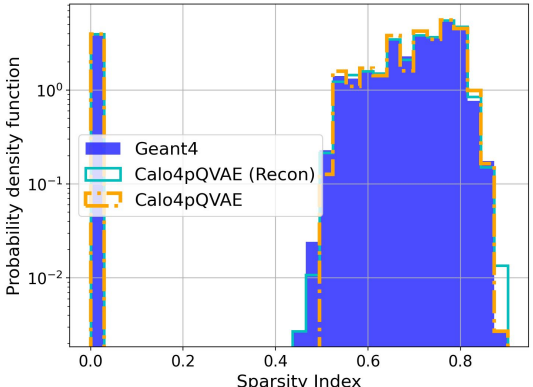
Leo Zhu, Denaisha Kraft

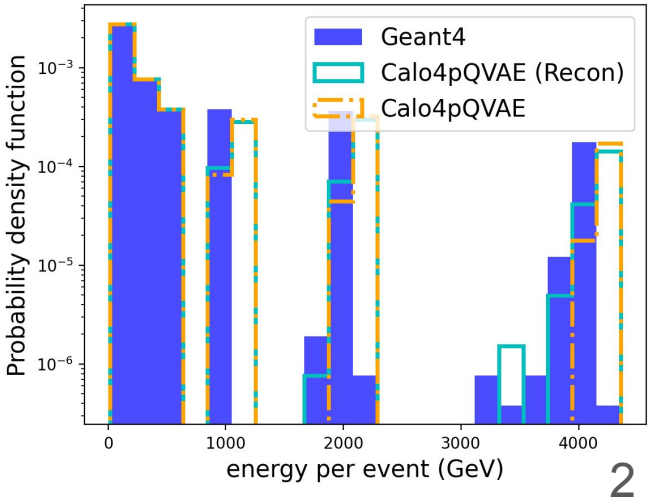
New Model (170 Epochs)



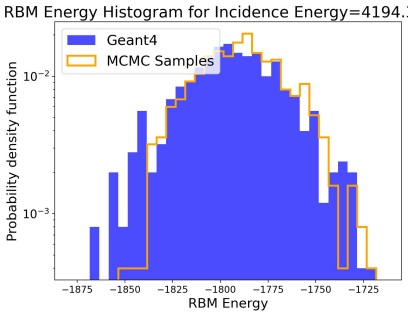


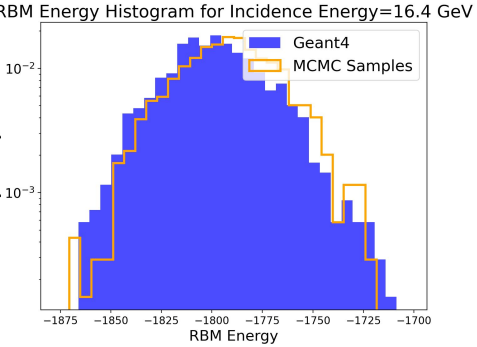


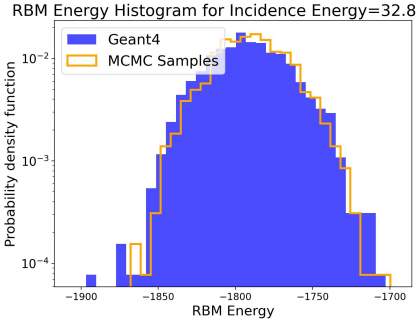


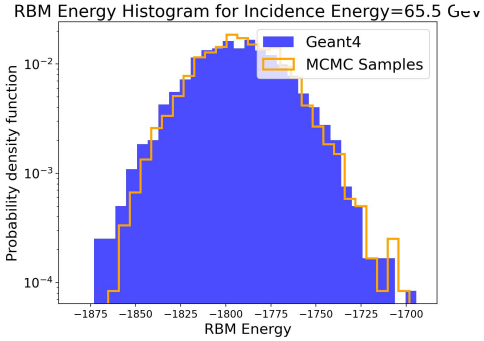


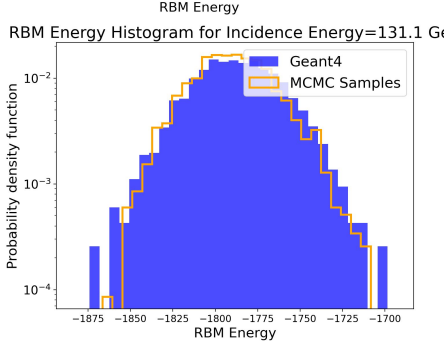
Conditioned Samples (RBM Energies)

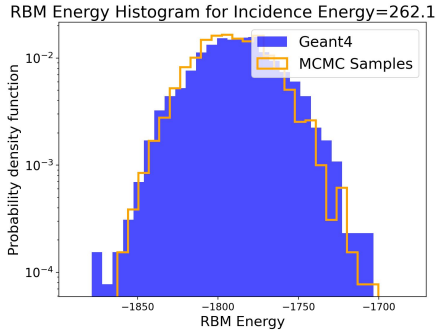


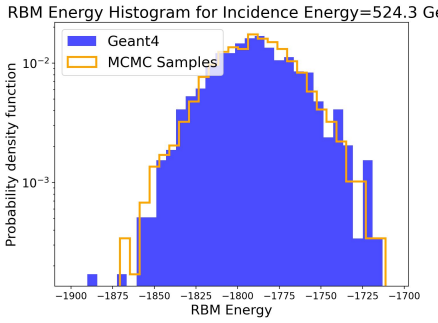


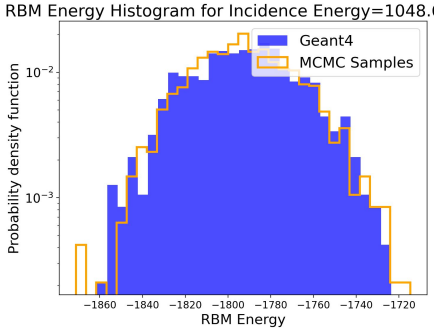


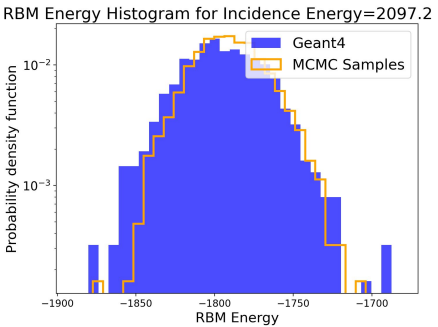




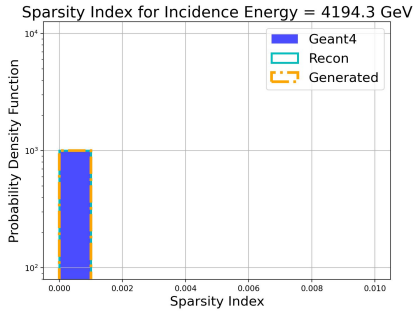


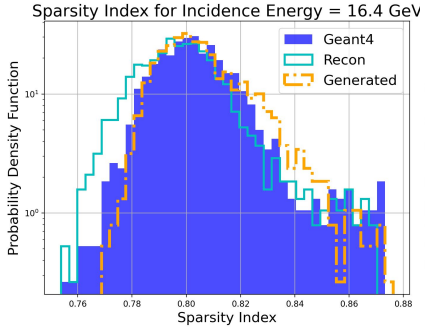


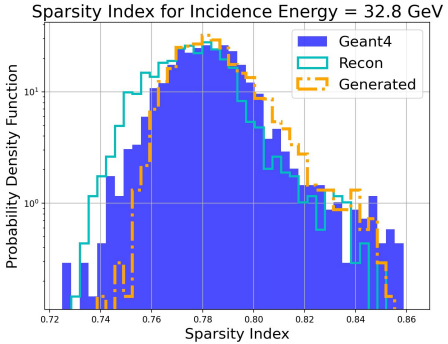


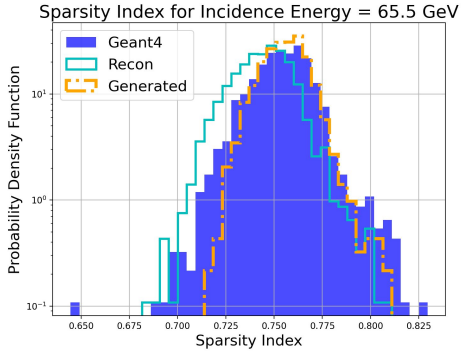


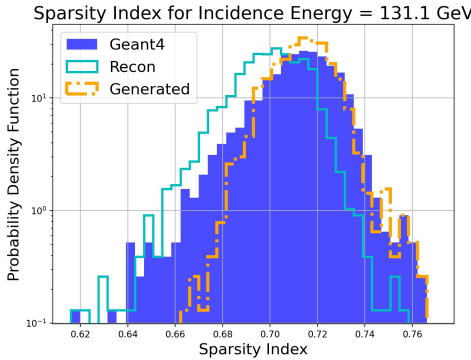
Conditioned Samples (Sparsity)

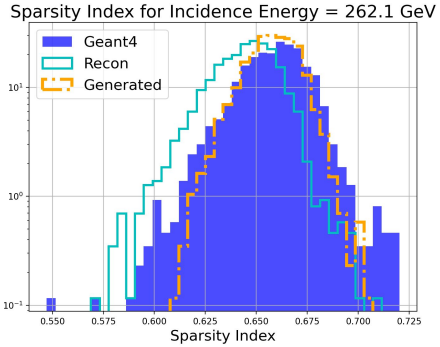


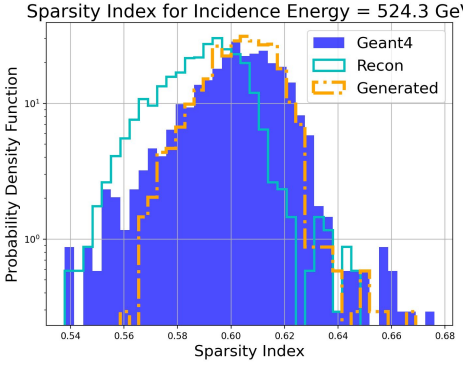


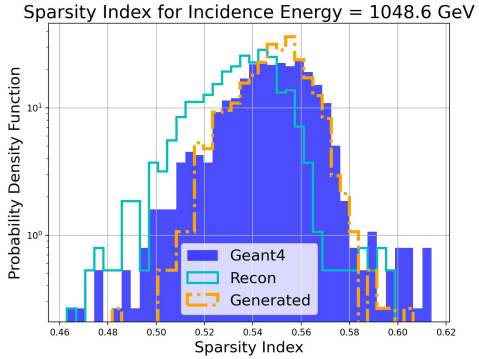


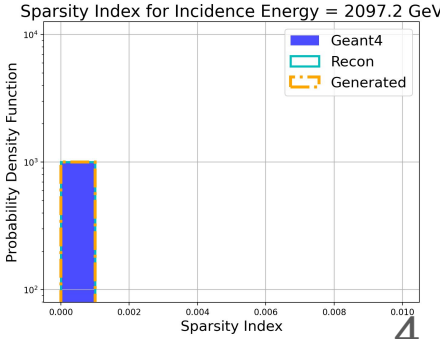




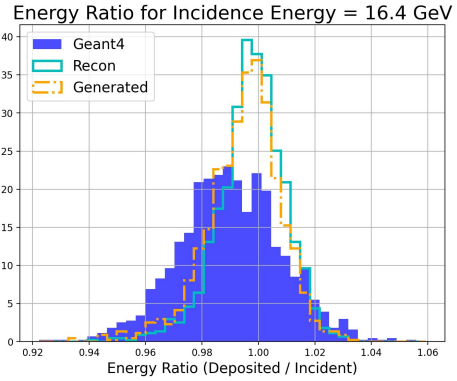


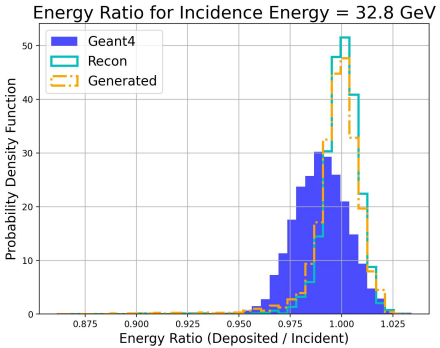


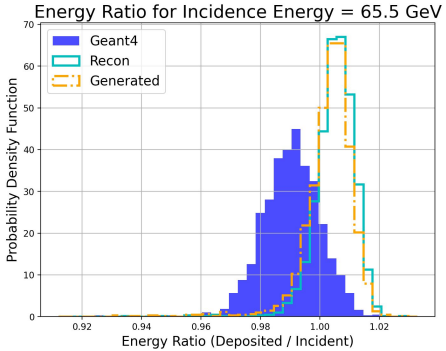


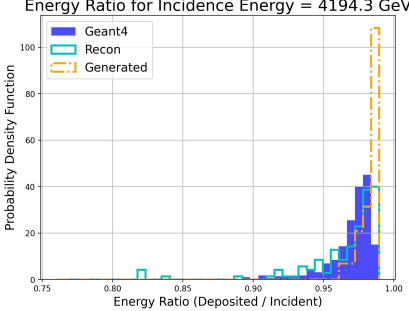


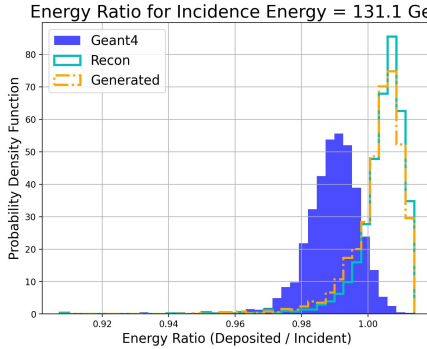
Conditioned Samples (Energy Ratio)

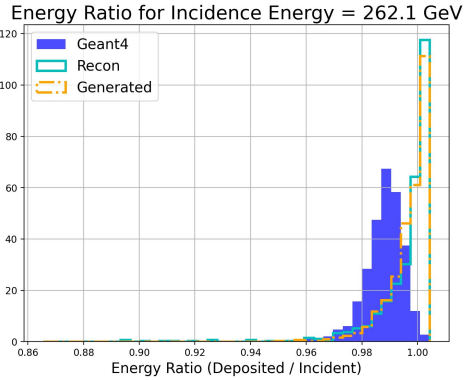


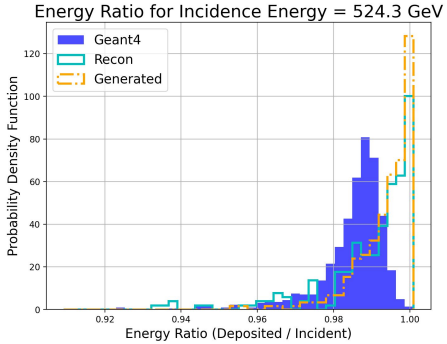


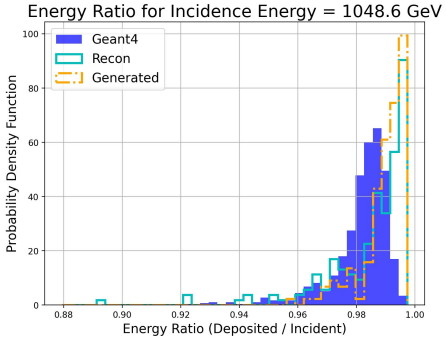


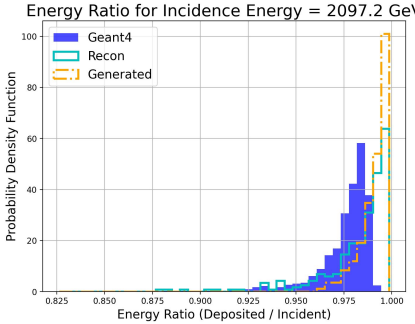




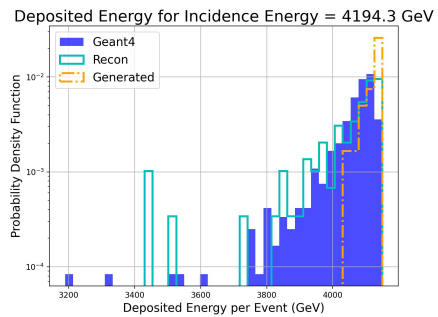


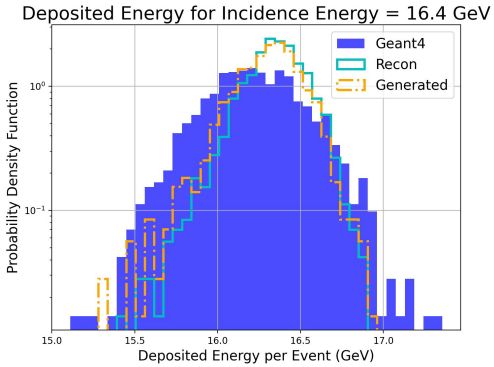


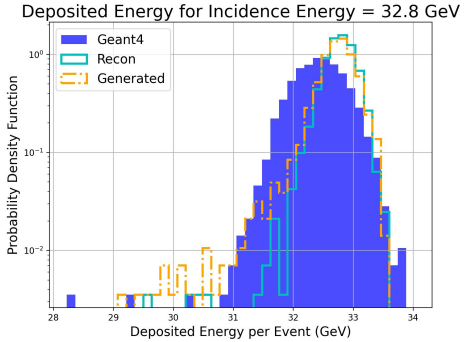


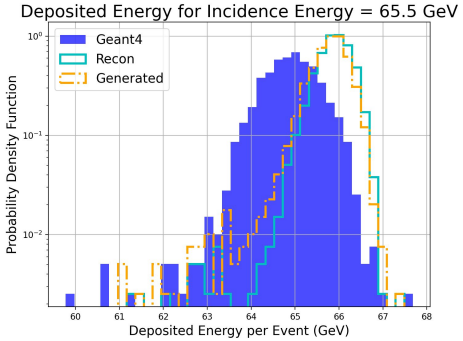


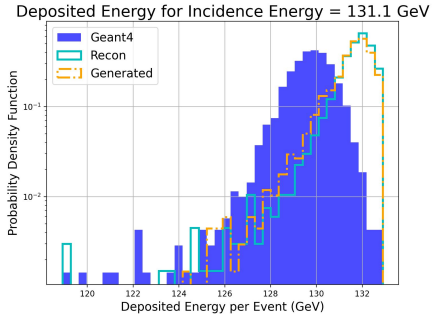
Conditioned Samples (Deposited Energy)

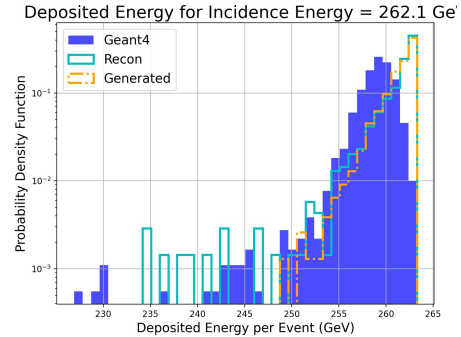


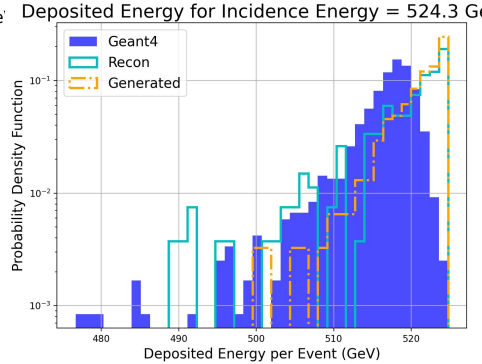


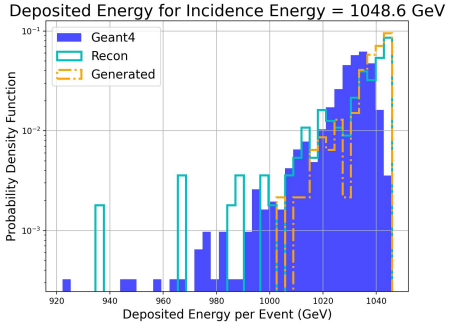


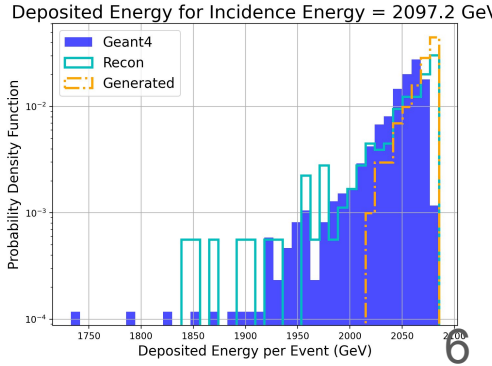




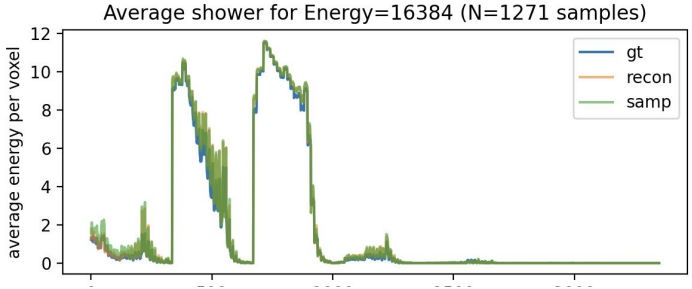


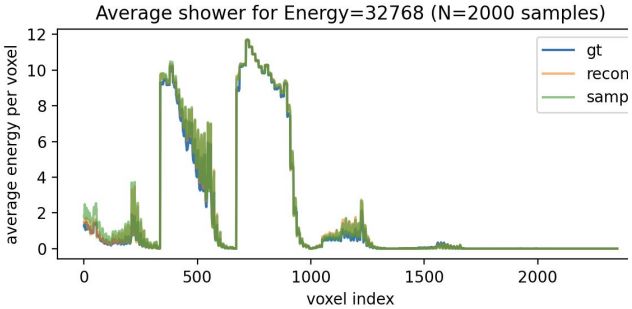


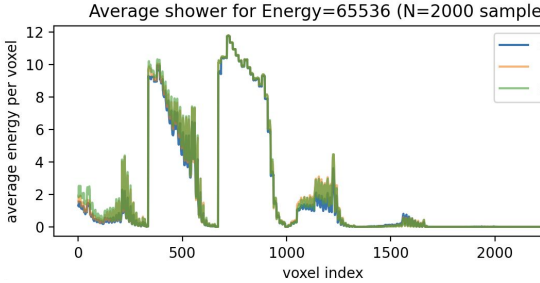


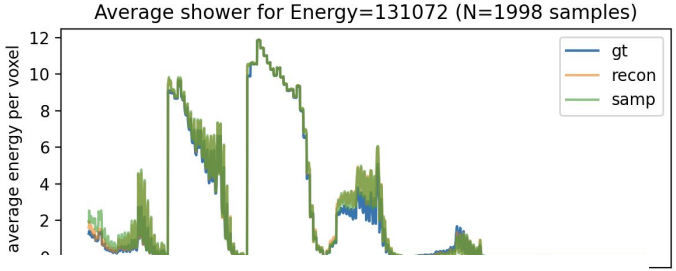


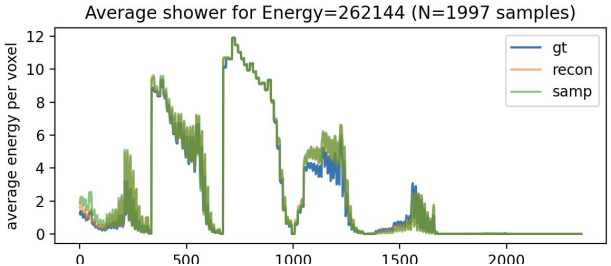
Conditioned Samples (Showers Over Voxels)

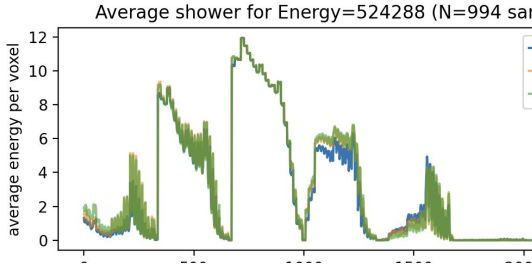


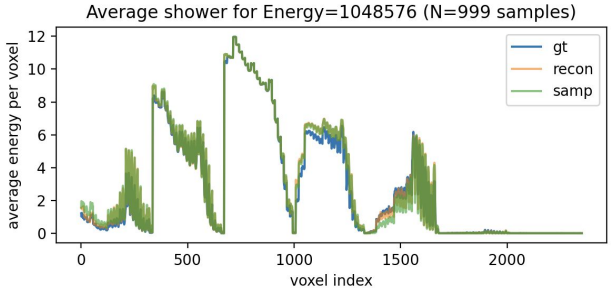


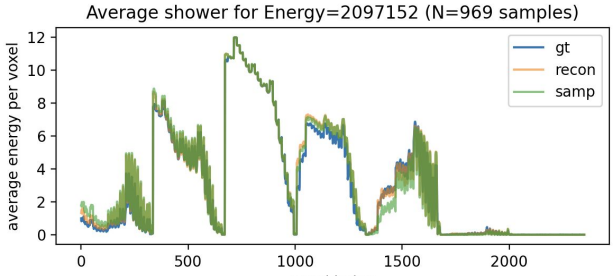


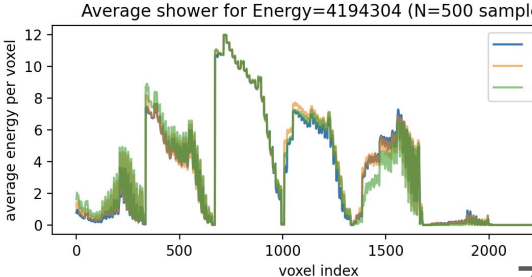




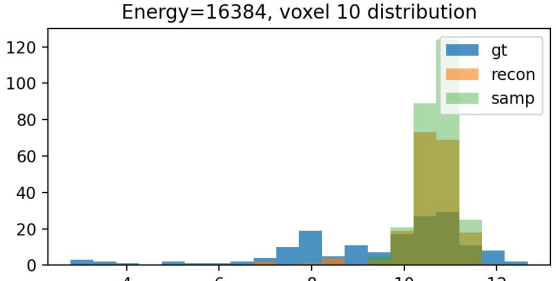


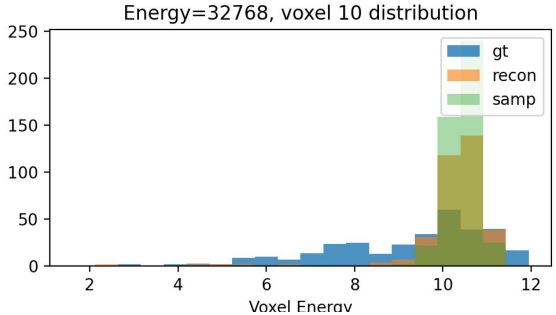


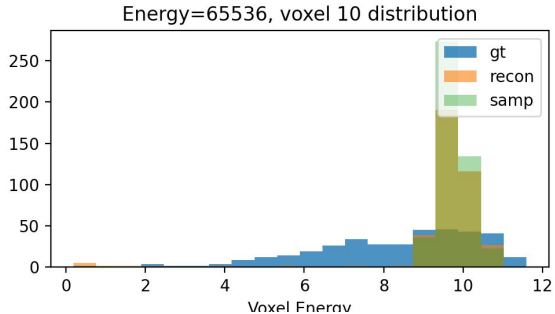


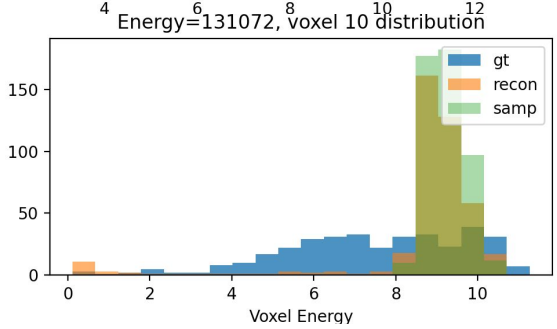


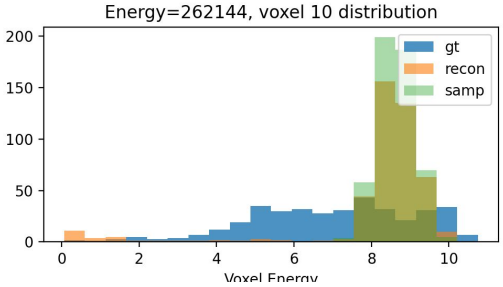
Conditioned Samples (Energy of Single Voxel)

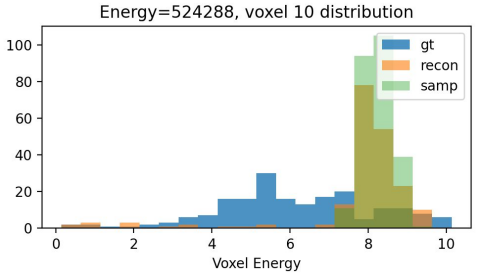


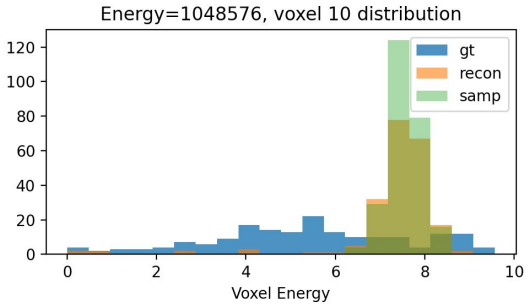


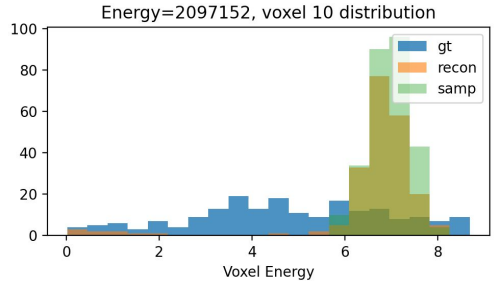


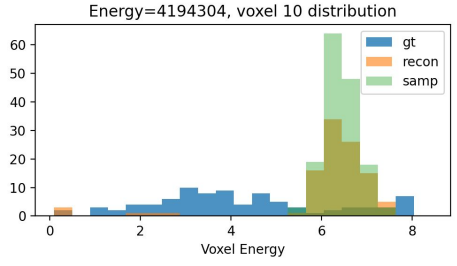








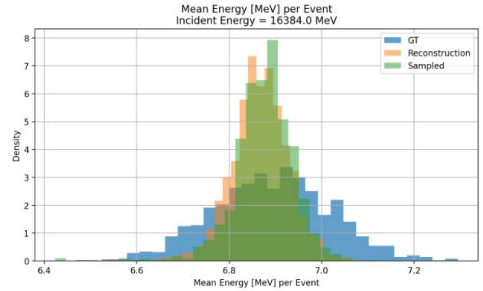


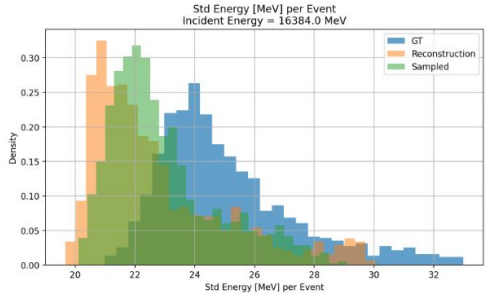


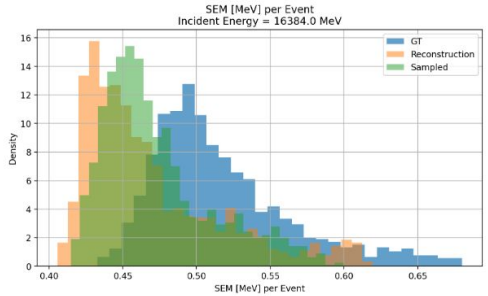
Metrics

- Mean voxel energy, standard deviation, and standard error of the mean for each event
- Done for each incident energy
- This is for the lowest incident energy in val_loader

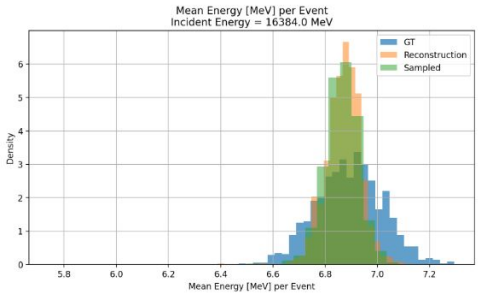
Epoch 30

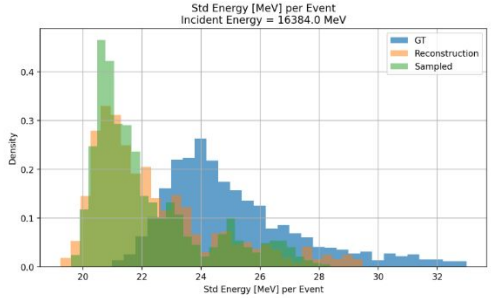


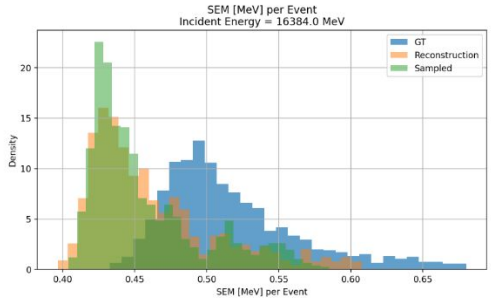




Epoch 70



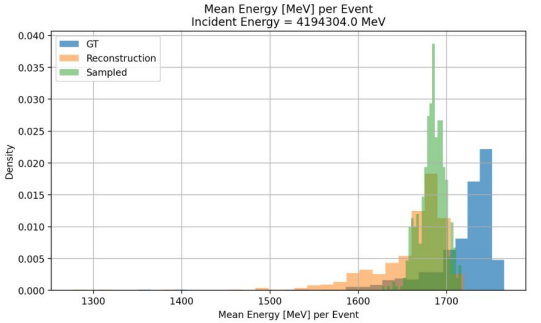


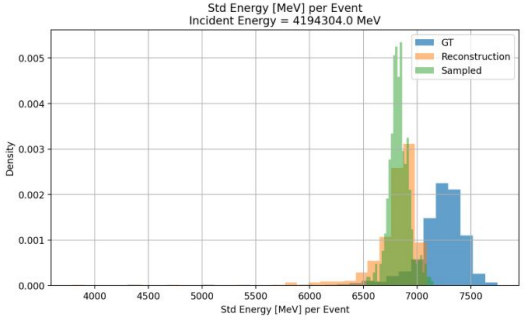


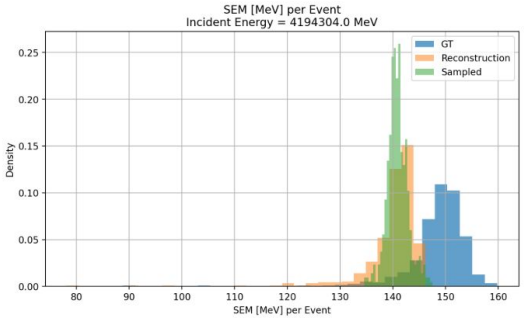
Metrics

- Same metrics but now for the highest incident energy in val_loader

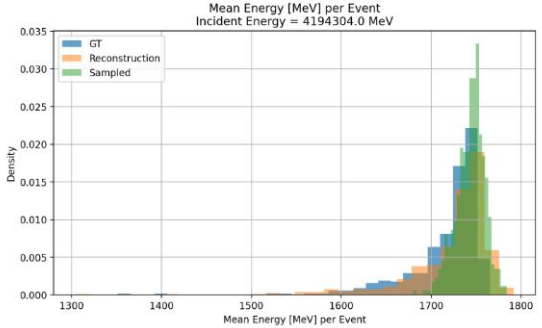
Epoch 30

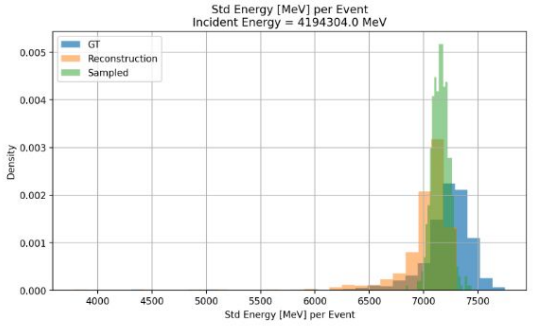


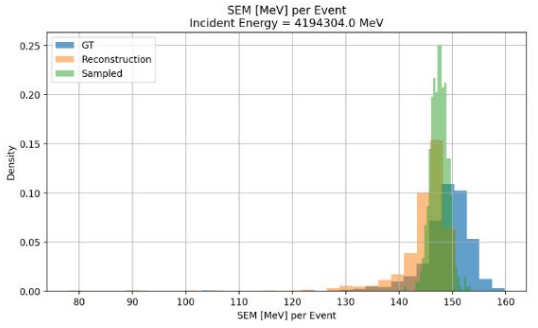




Epoch 70







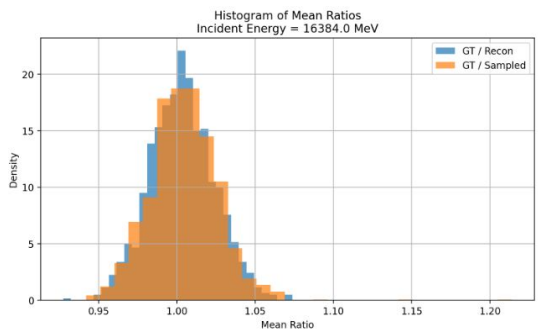
Ratio Metrics

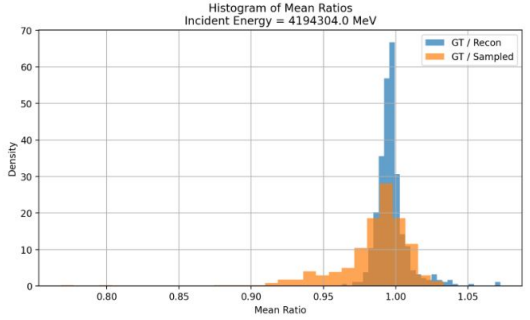
- Epoch 70

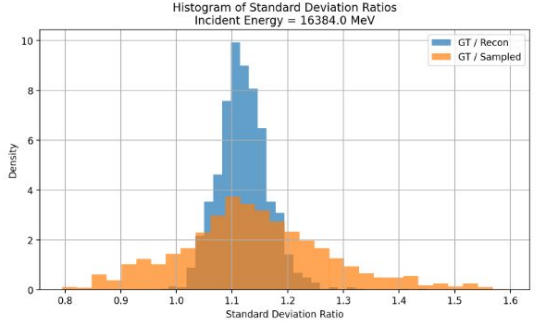
- Comparing ratio of mean voxel energy, standard deviation, and standard error of the mean

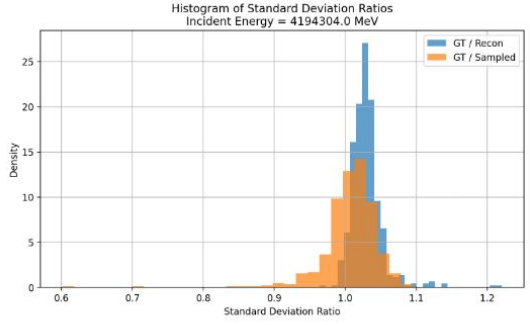
Lowest incident energy

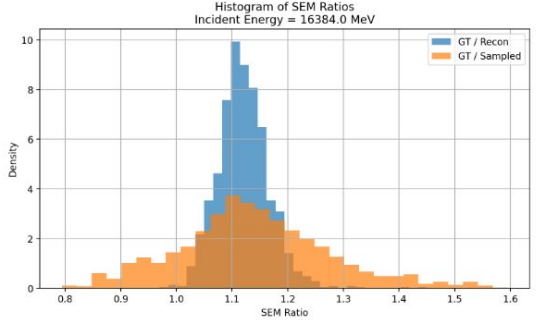
Highest incident energy

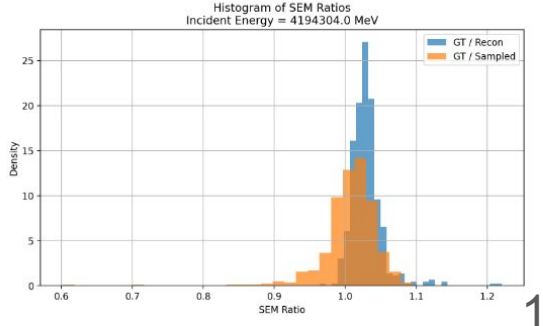








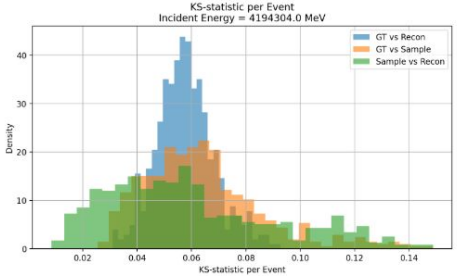


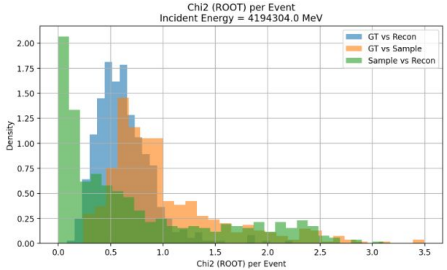


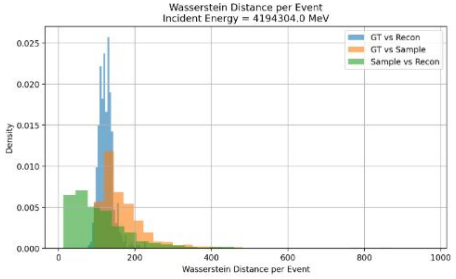
Other Metrics

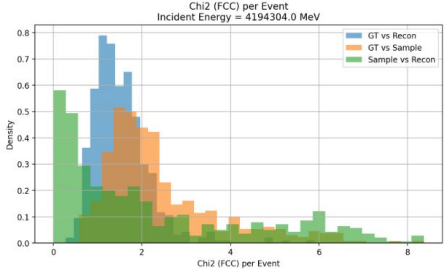
- Epoch 70
- Chi squared (two methods)
- Wasserstein statistic
- KS-statistic
- Done for each incident energy

Highest incident energy

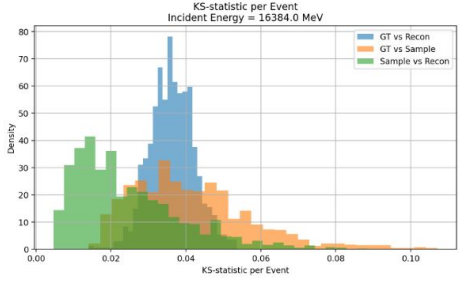


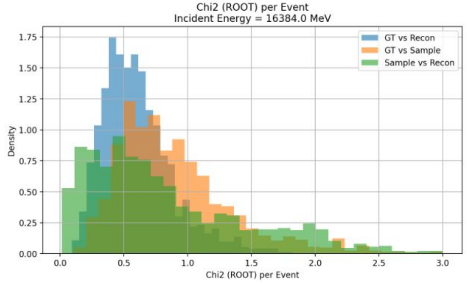


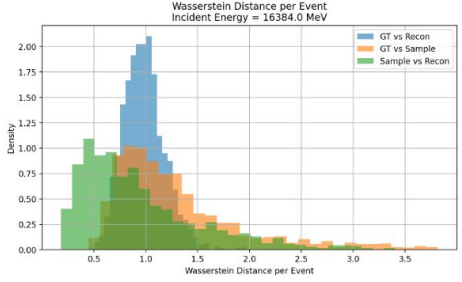


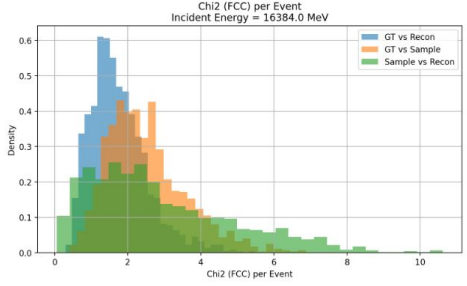


Lowest incident energy

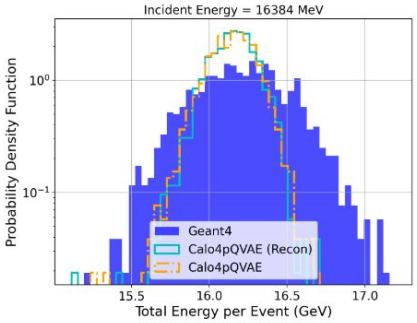


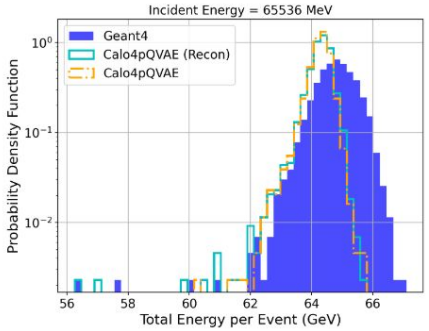


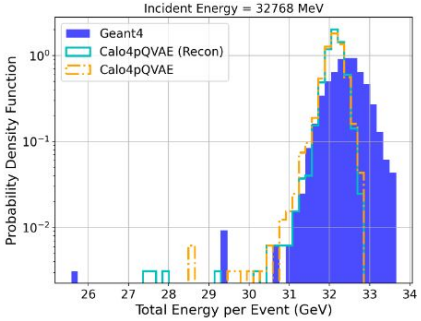


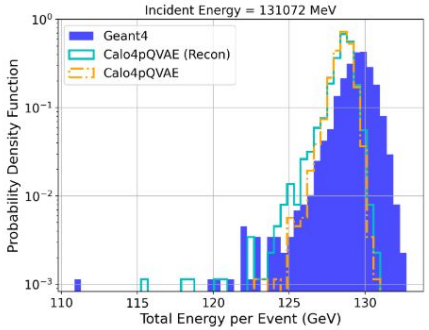


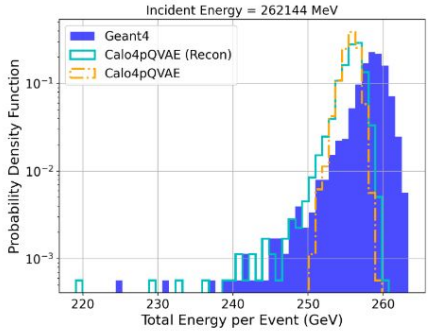
Conditioned Samples (Deposited Energy)

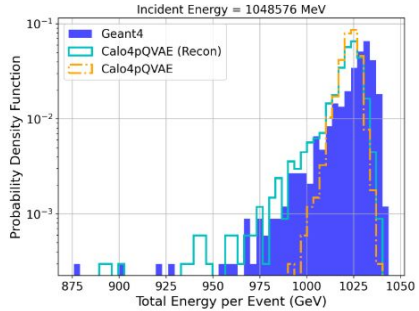


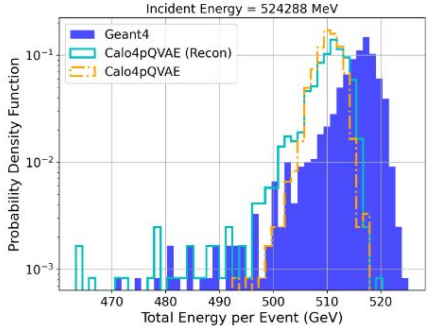


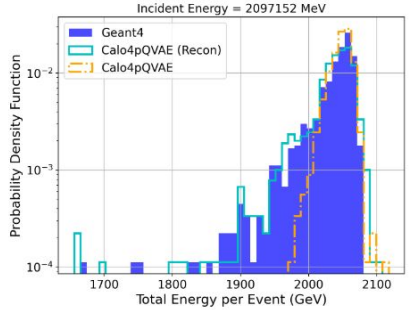


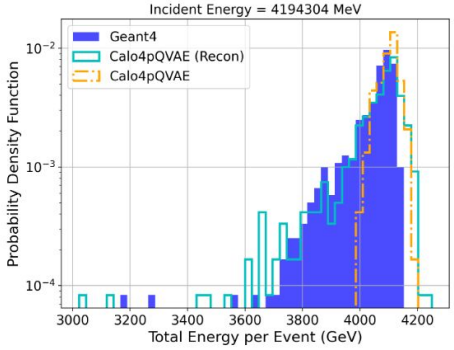


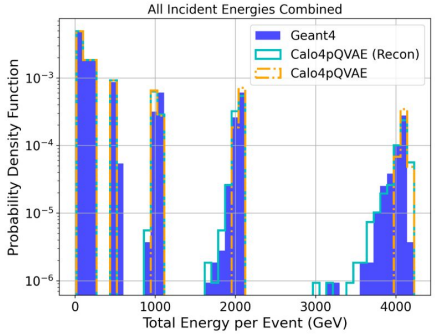




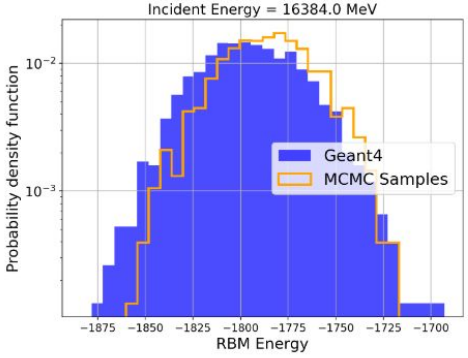


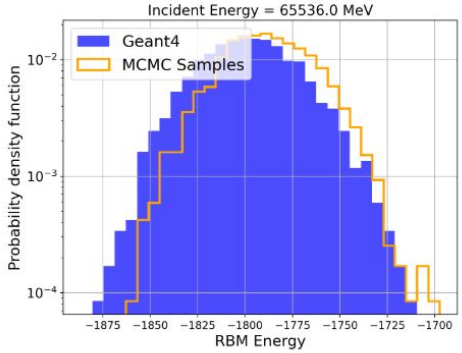


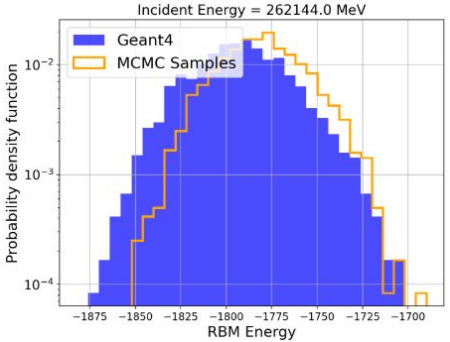


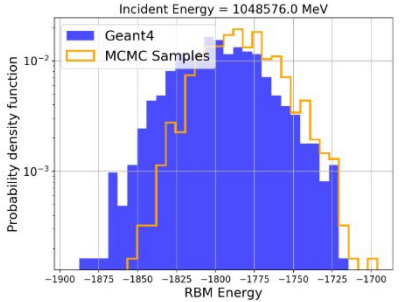


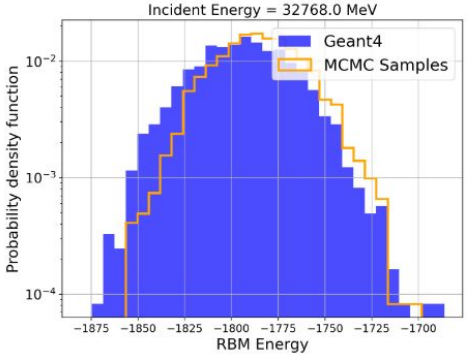
Conditioned Samples (RBM Energy)

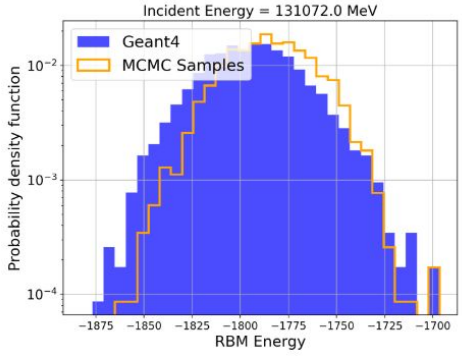


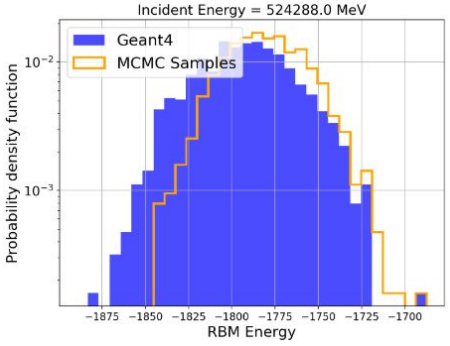


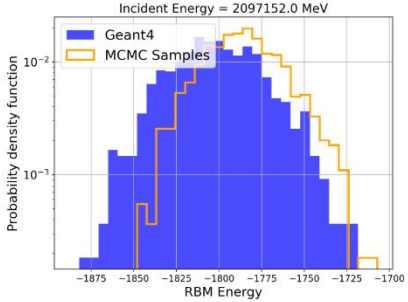


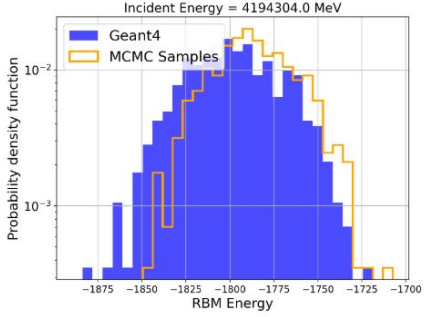




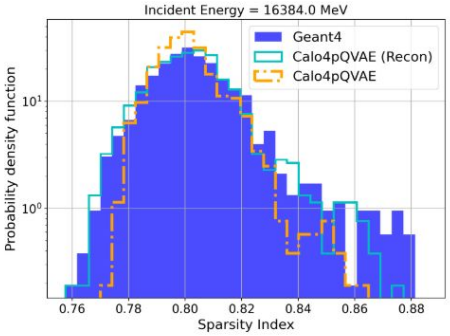


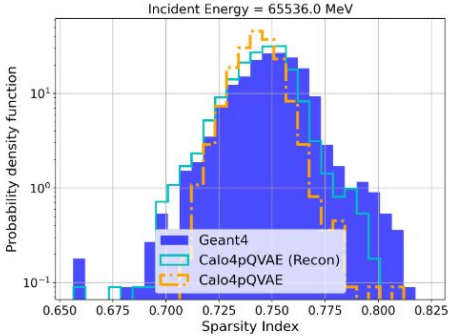


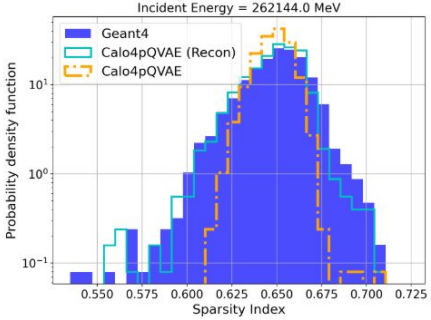


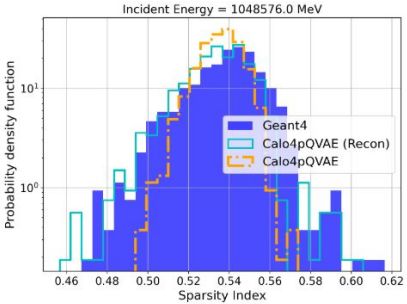


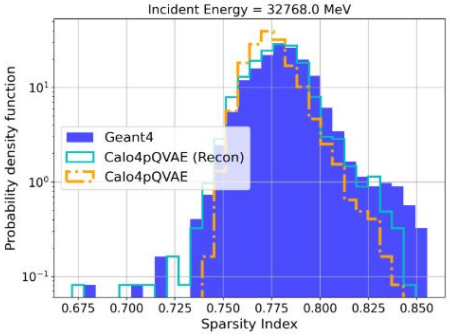
Conditioned Samples (Sparsity Index)

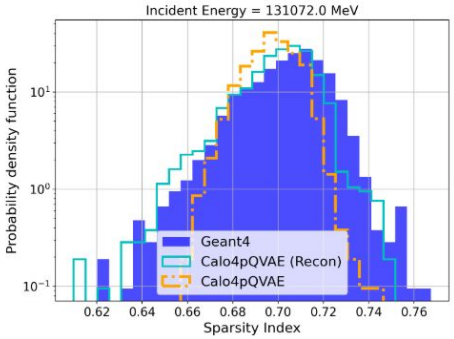


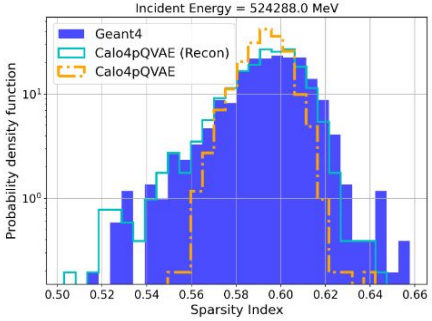


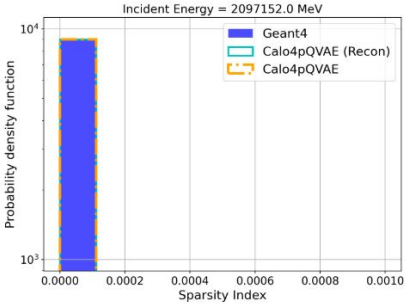


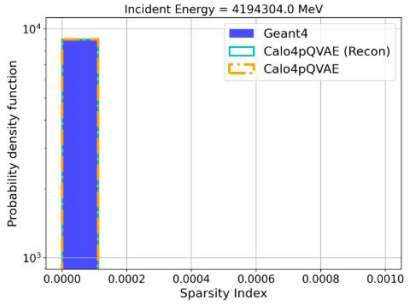




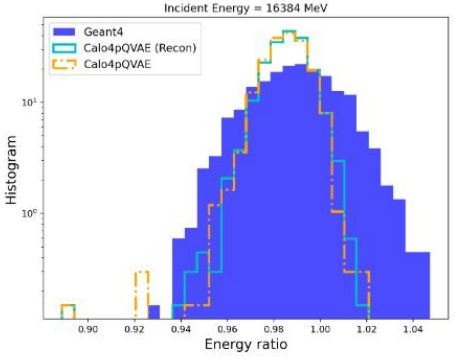


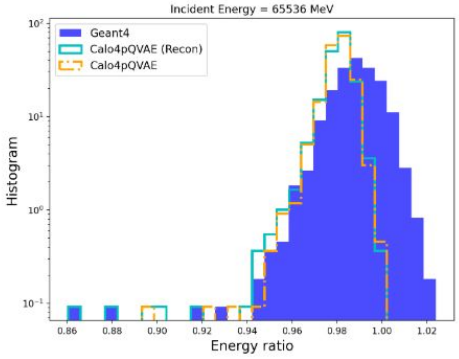


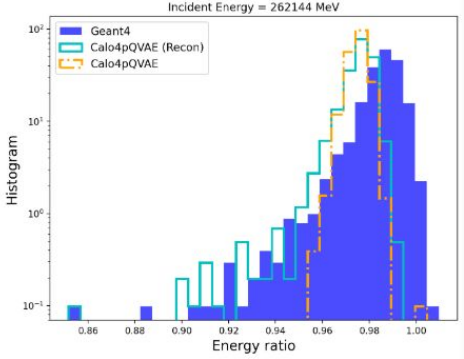


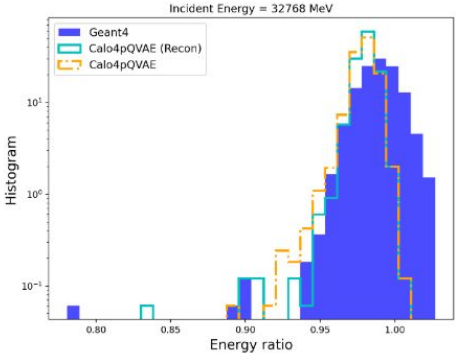


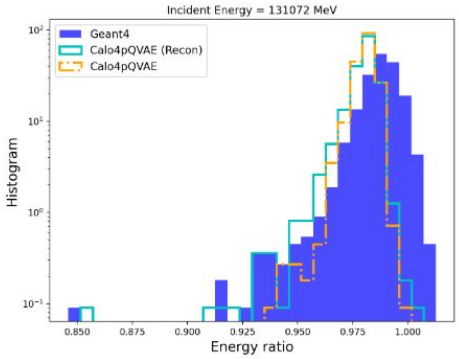
Conditioned Samples (Energy Ratio)

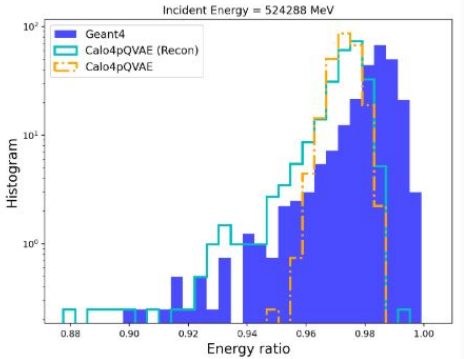


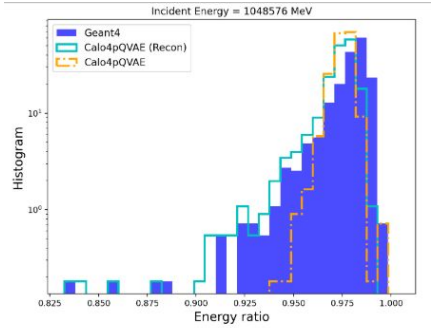


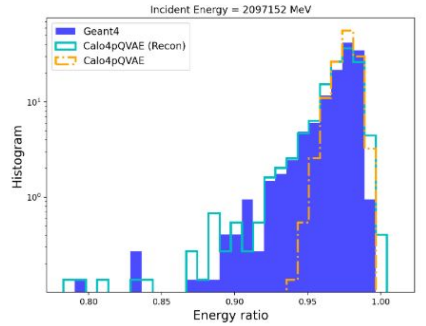


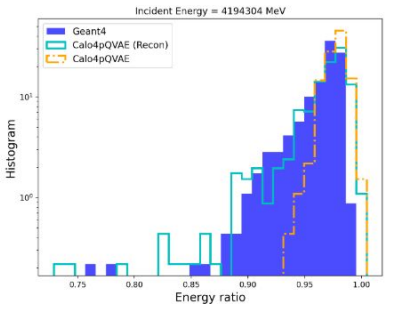




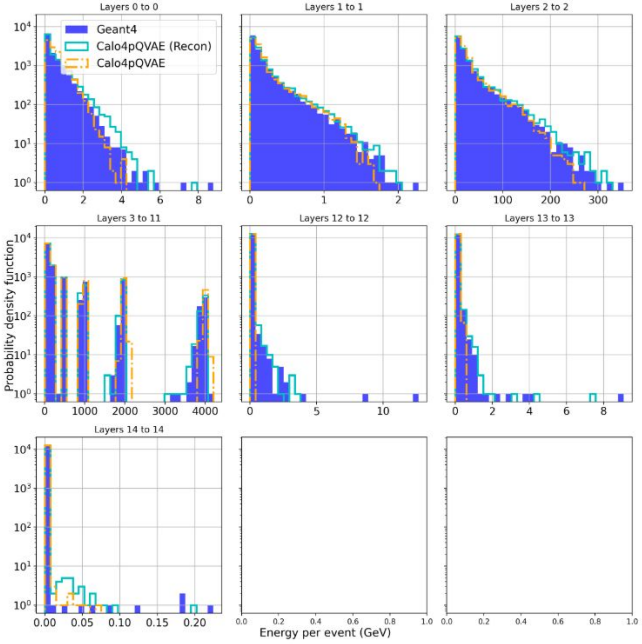


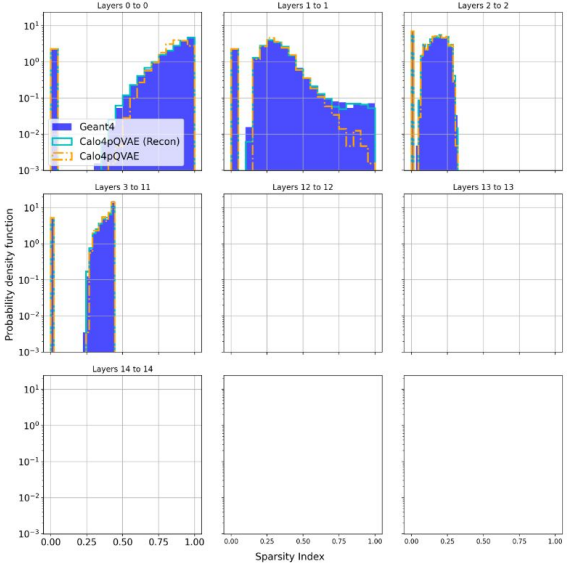


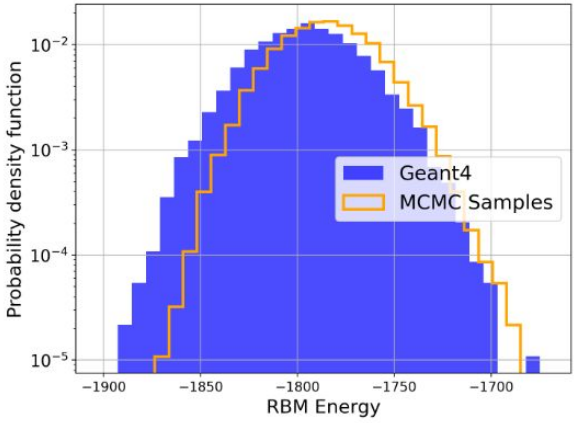


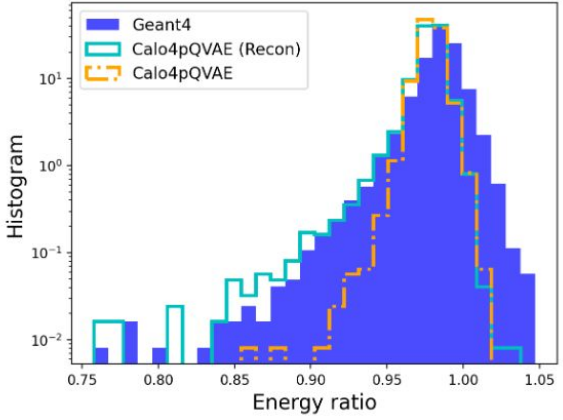


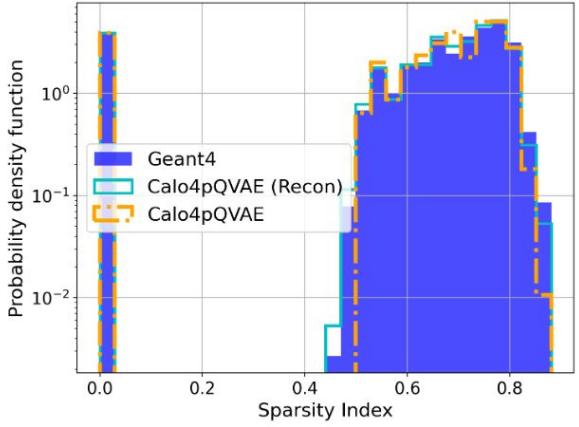
Epoch 70


Layers 0 to 0
Layers 1 to 1
Layers 2 to 2
Layers 3 to 11
Layers 12 to 12
Layers 13 to 13
Layers 14 to 14
Geant4
Calo4pQVAE (Recon)
Calo4pQVAE
Probability density function
Energy per event (GeV)


Layers 0 to 0
Layers 1 to 1
Layers 2 to 2
Layers 3 to 11
Layers 12 to 12
Layers 13 to 13
Layers 14 to 14
Geant4
Calo4pQVAE (Recon)
Calo4pQVAE
Probability density function
Sparsity Index


Probability density function
Geant4
MCMC Samples
RBM Energy


Geant4
Calo4pQVAE (Recon)
Calo4pQVAE
Histogram
Energy ratio


Geant4
Calo4pQVAE (Recon)
Calo4pQVAE
Probability density function
Sparsity Index

Reinforcement Learning

- Actor/Critic method:
  - Actor: CaloQVAE, specifically the RBM
  - Critic: Train a model with labeled batches of showers to predict KPD/FPD
- Training cycle:
  - Generate a batch of showers
  - Pass into critic model and get KPD/FPD score
  - Use REINFORCE algorithm to adjust weights and lower the energy of samples z that correspond to good KPD/FPD
- Goals/Advantages
  - Once decoder has learned to generate samples from latent space, we want to sample well from that latent space
  - Critic model could be useful in general: save compute when comparing many models
  - No inference time or memory cost