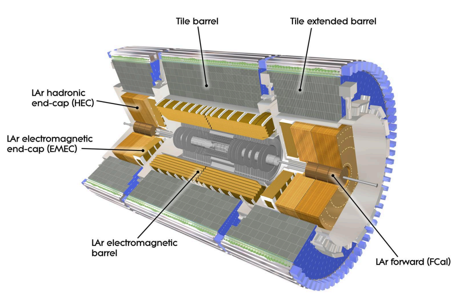
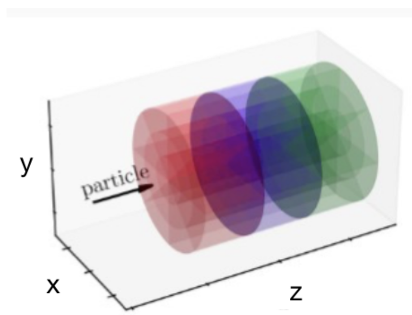
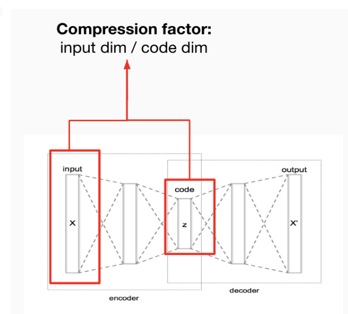
Within particle physics, particle collisions can be experimentally detected and imaged with calorimeters or computationally simulated with current mathematical and physical models. Comparisons between simulated collisions and experimental results can provide new information about the presence of new particles like the Higgs-Boson, and allow researchers to modify current theories of particle physics. A major problem with both collider experiments and simulations are the resource costs to conduct them. More glaringly, given the current Monte-Carlo simulations the need for CPUs to handle the growing amounts of data will increase by 25 times by 2040. The current methodology to conduct these simulations are simply computationally expensive to keep up with the growing amount of data. Our team had worked to tackle these problems by creating a model to speed up simulations based upon previous existing architecture. The previous model was a generative diffusion model and we used its architecture and implemented an autoencoder to build a latent diffusion model pipeline. With our pipeline, we trained 3 different training models on a dataset of images. We utilized our best performing autoencoder to encode, or compress the image, incorporate our diffusion model to perform latent diffusion, and finally decode, or enlarge the image back to its original shape. We measured their losses to track how much we can compress an image into a latent space to speed up the diffusion process without sacrificing model accuracy. With the pipeline, we generated visual plots for comparison of our latent diffusion model's performance "CaloDiffu" to a control performance "Geant4." We hypothesized that compressing the original images before the generative diffusion process would increase the speed of its sampling process.



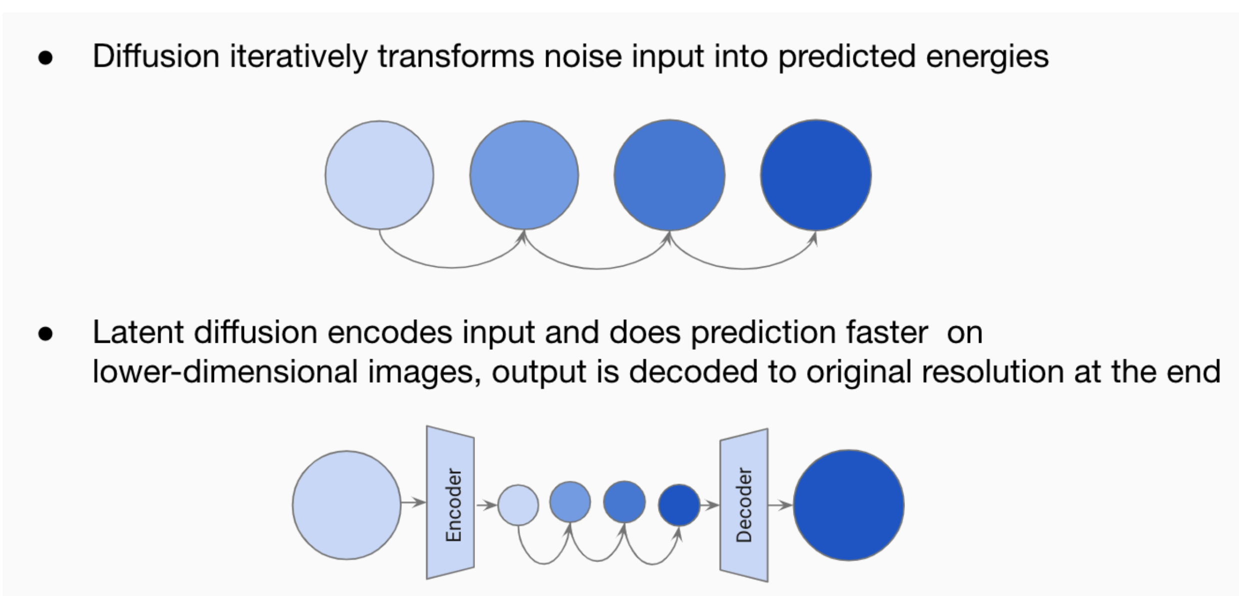
Visualization of Calorimeter



Visualization of Energy Shower



Schematic of Autoencoder



Visualization of Regular and Latent Diffusion Pipeline