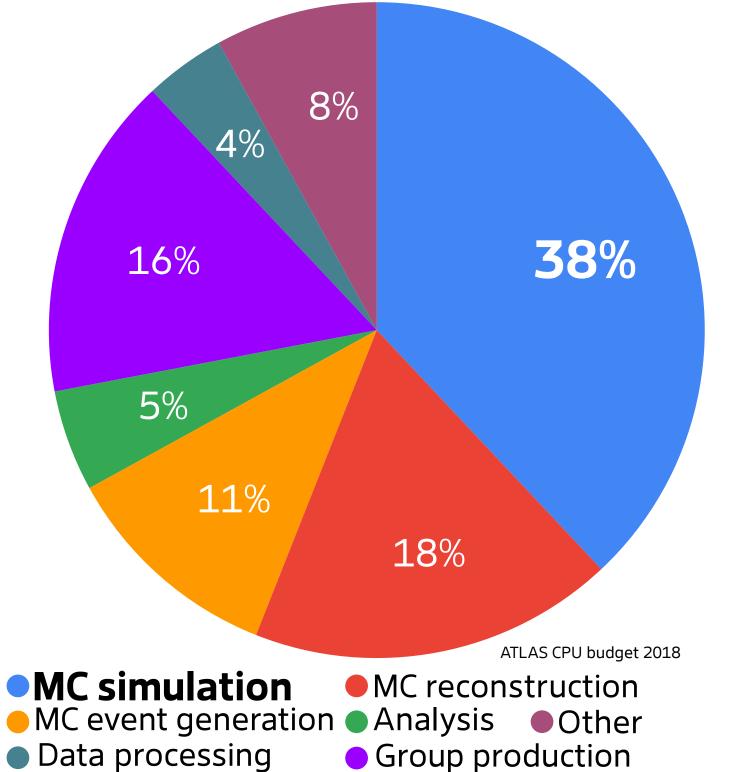
## Fast calorimeter shower simulation with generative Machine Learning

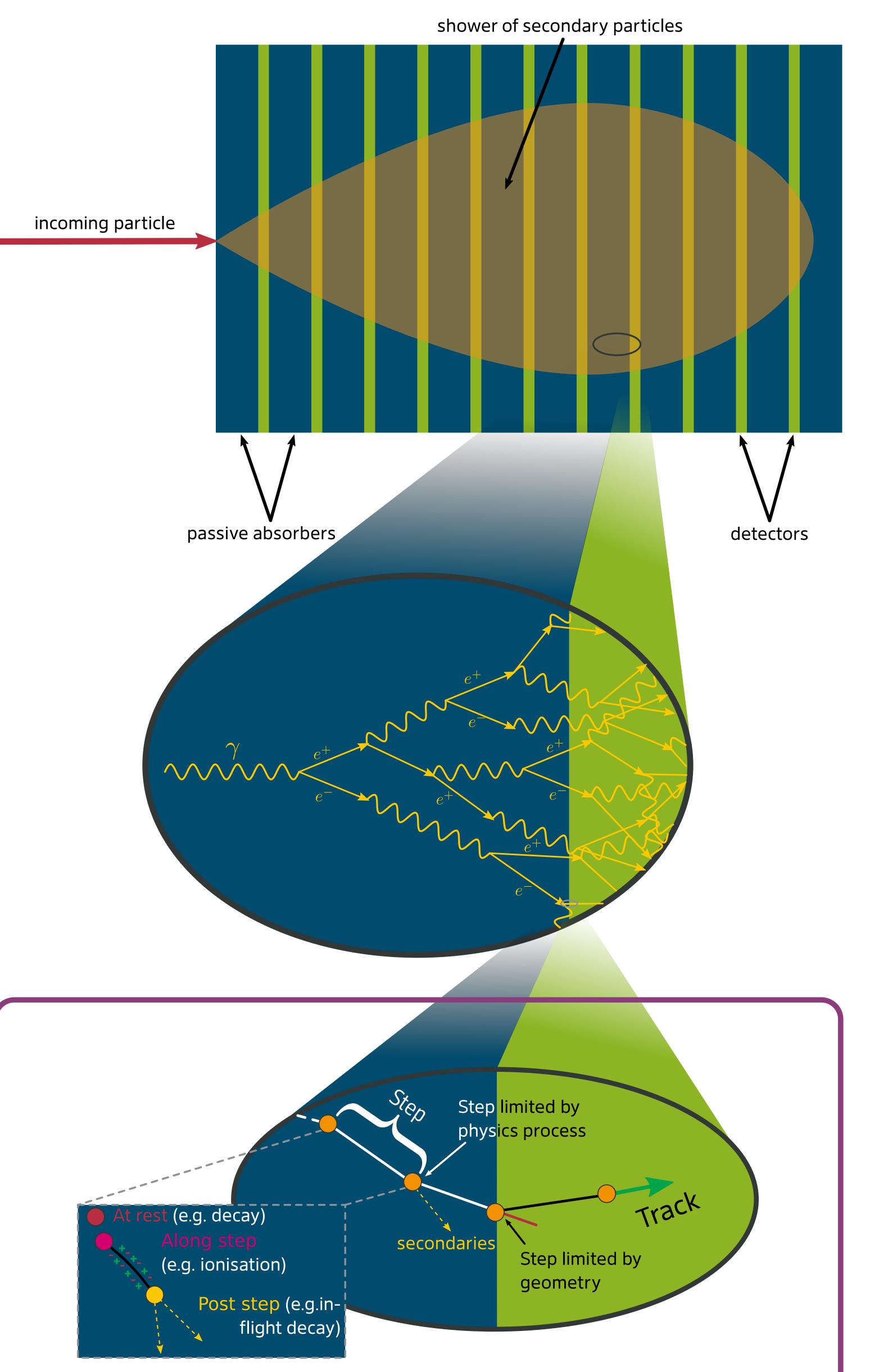
#### **Computing Resources**

• HEP experiments require vast amounts of computing resources • majority of resources spent on detector (MC) simulation • calorimeter simulation is the most expensive part by far



#### Sampling calorimeter

• alternating layers of passive absorber and sensitive detector material • materials can be separately chosen to optimize performance • only a fraction (few percent) of the total deposited energy is measured



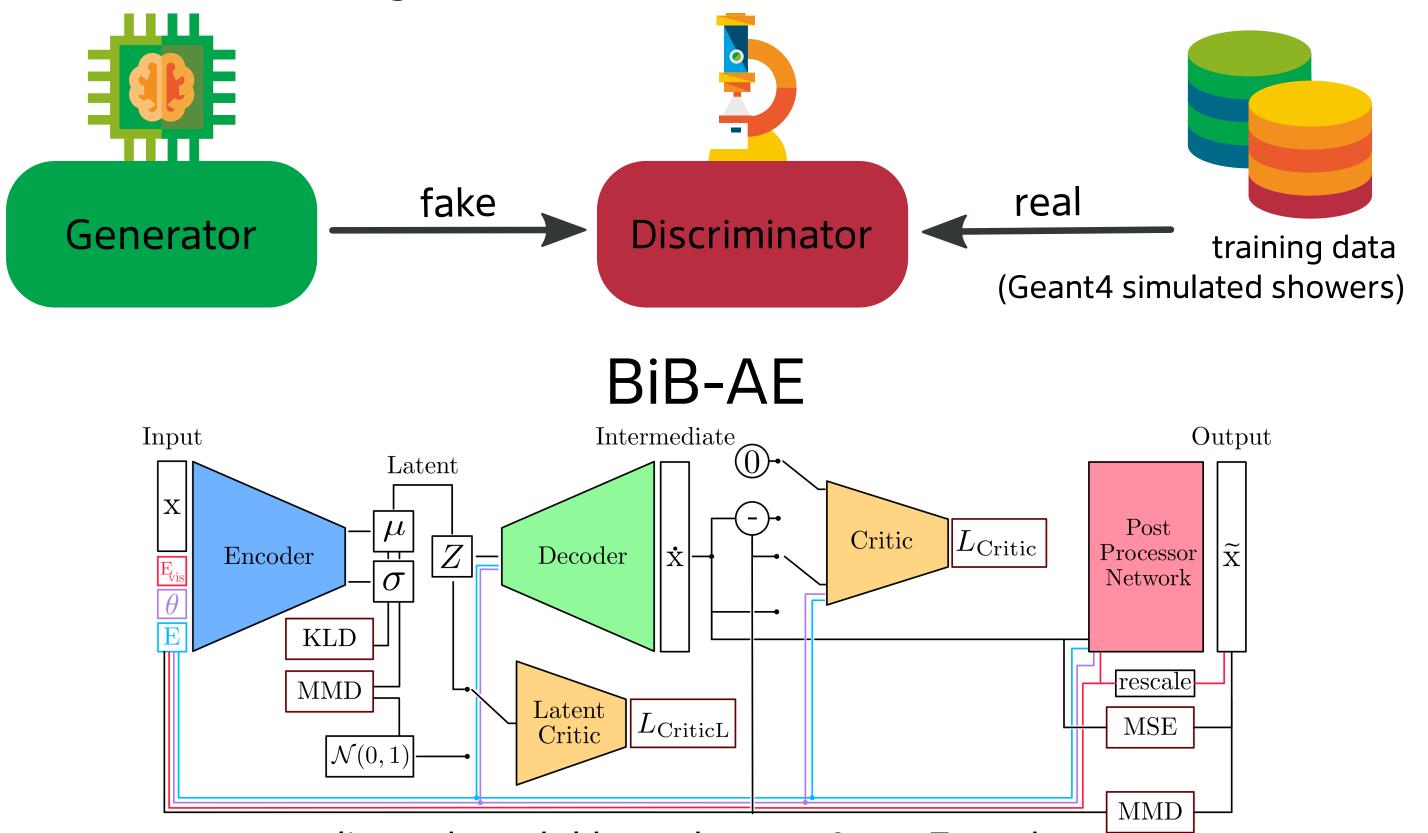


#### Generative Machine Learning

• ML has the potential to speed up simulation by orders of magnitude reduce the required computing resources and increase sustainability • generative models can be used for fast calorimeter shower simulation • generate calorimeter response directly or energy deposits for further processing • conditioned on e.g. incident particle energy, direction, etc.

### Generative Adversarial Networks and Auto-Encoders

• powerful generative models that learn how to generate "fake" data • basic principle: try to fool discriminator with the generated fake showers • discriminator and generator trained in tandem



- complicated model based on an Auto-Encoder
- generates the detector response directly
- model with best physics performance at the moment

### Diffusion Model

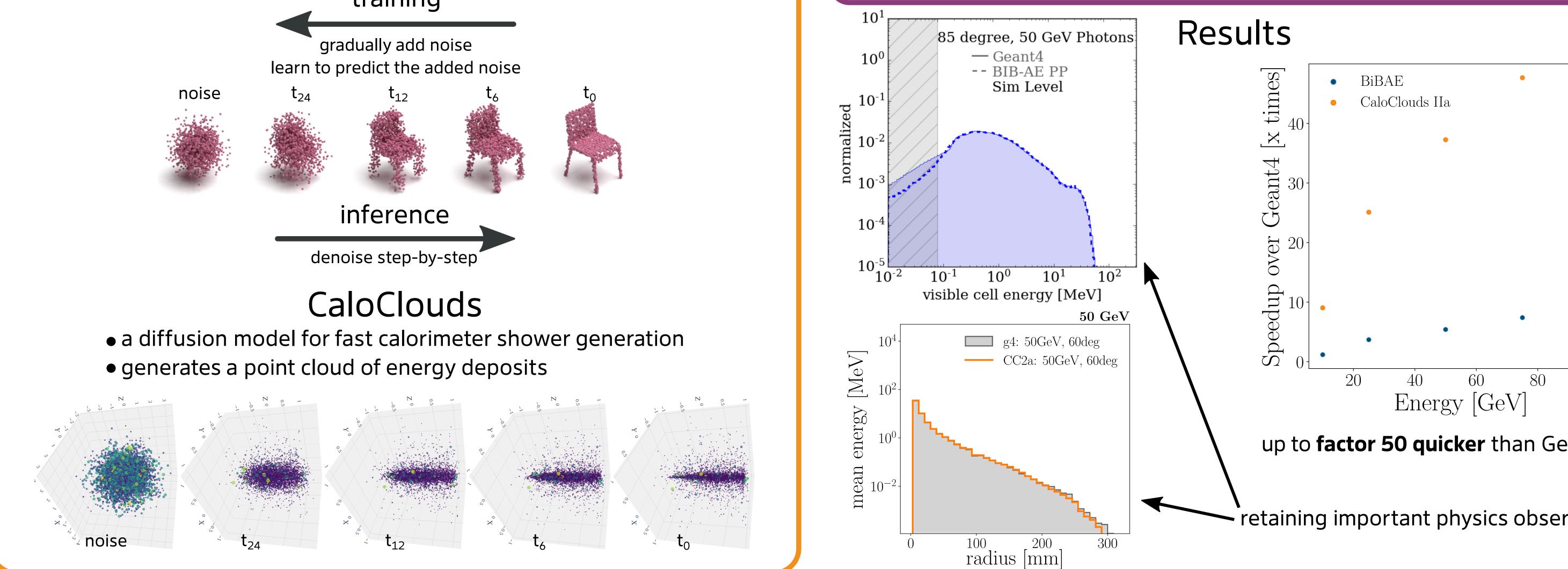
• state of the art ML technique that became popular in the last few years • used e.g. by Stable Diffusion (StabilityAI), Dall-E & Sora (OpenAI), etc.

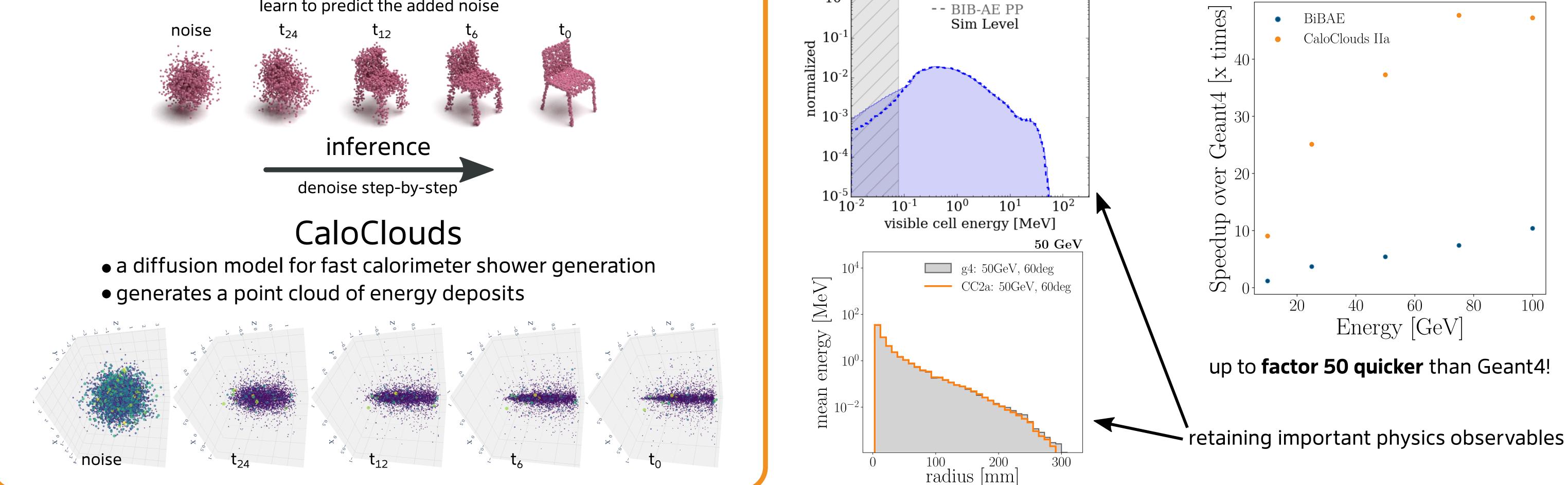
# training gradually add noise learn to predict the added noise

### Geant4 simulation

• standard toolkit for simulations of particles propagating through matter • used in HEP and other areas (e.g. medicine) • detailed simulation of all physics processes on a microscopic scale

• tracking all particles until they have deposited all their energy





## **Come and see it yourself**

