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Fast Simulation of the FoCal-H detector with Machine Learning

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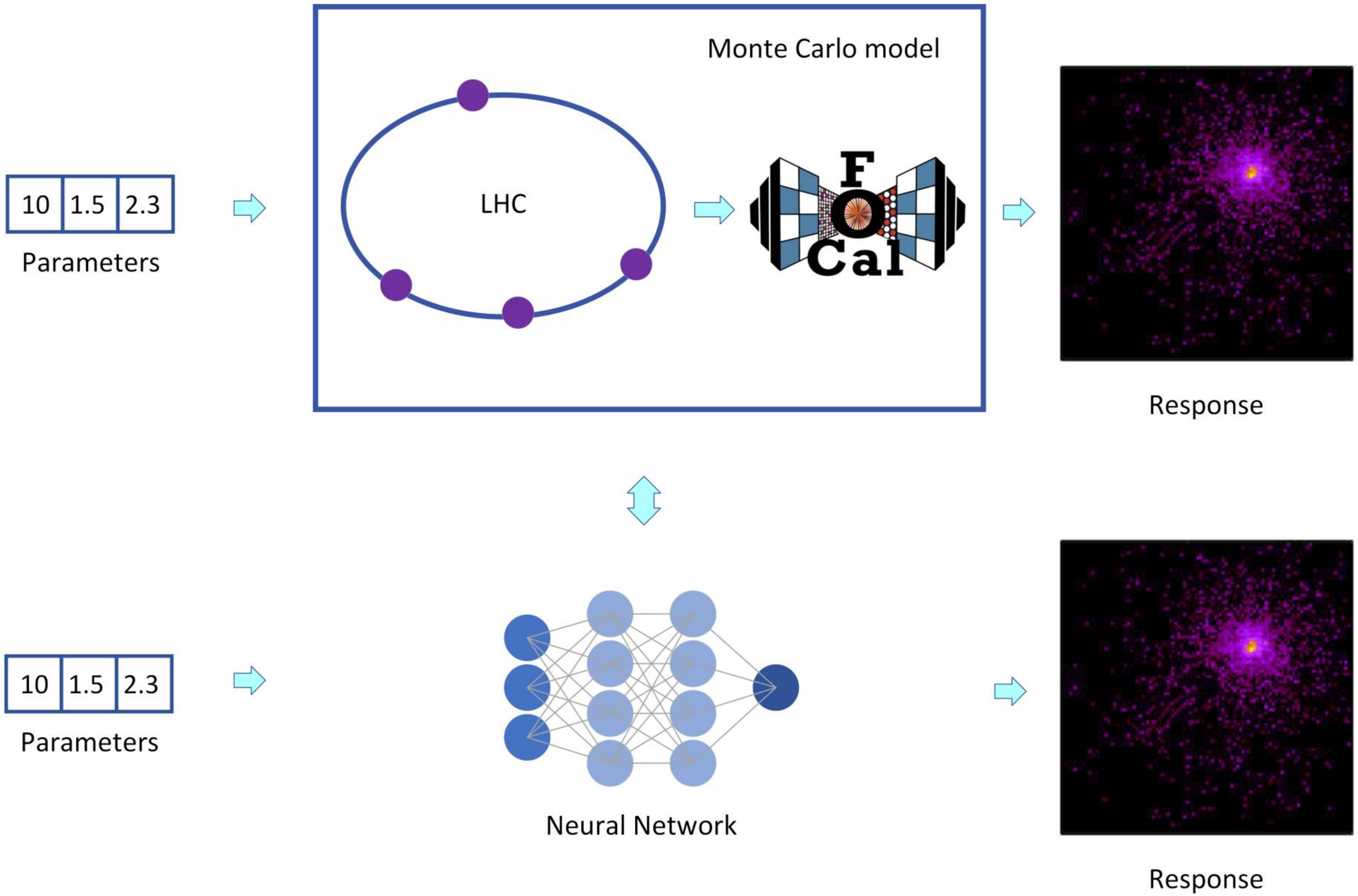
What do we do?



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1.5
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Parameters
Monte Carlo model
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10
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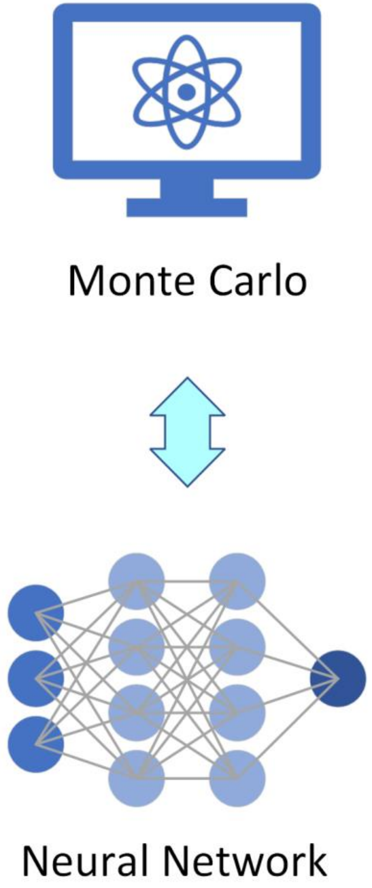
Parameters
Neural Network
Response

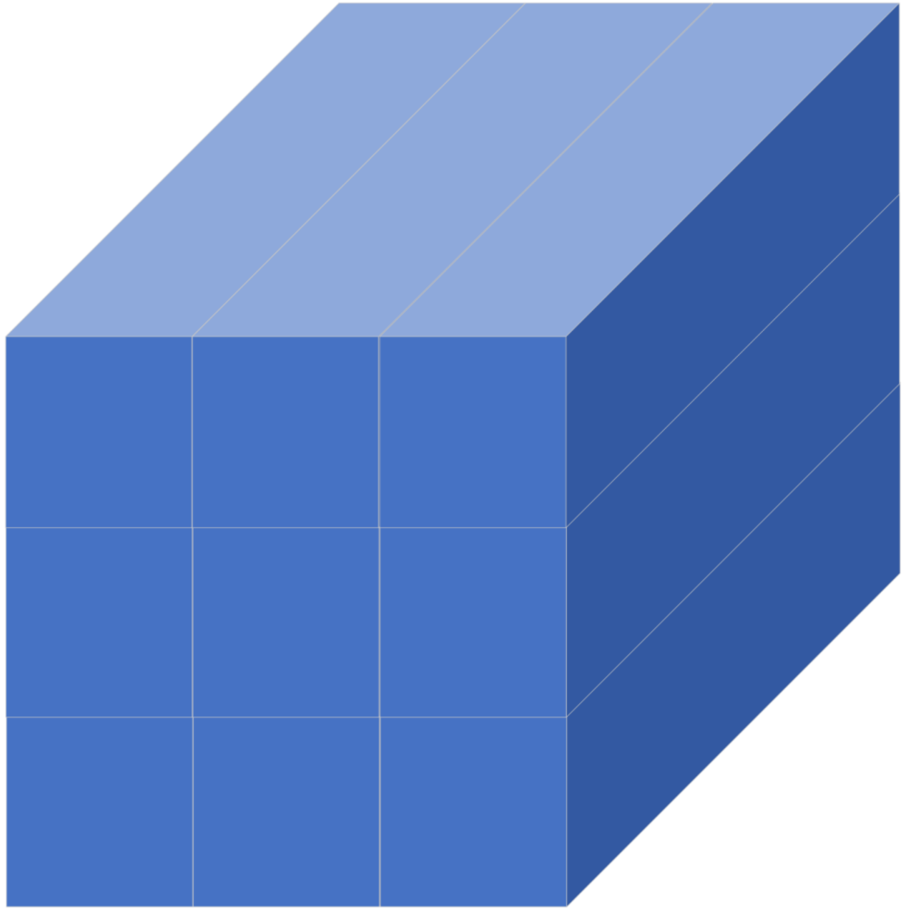
Fast simulations

- Using a surrogate of the whole mathematical model or its part.
  - The most computationally-intensive part → a faster surrogate.
- Fast simulations at CERN.
  - Existing approaches at different experiments.
  - DNN surrogates.
    - VAEs, GANs, NFs, Diffusion-based, Flow Matching.
- There's still a gap to fill!
  - Research done mostly on other experiments' calorimeters.
  - Physics-inspired machine learning.



FoCal

- FoCal consists of two detectors: electromagnetic (FoCal-E) and hadronic (FoCal-H).
- FoCal-H: copper tubes arranged in a grid of size ~ $100\times100\times110$ cm^3.
  - Needed for photon isolation and jet measurements.
- To be installed during LS3 for data-taking in 2027-2029.



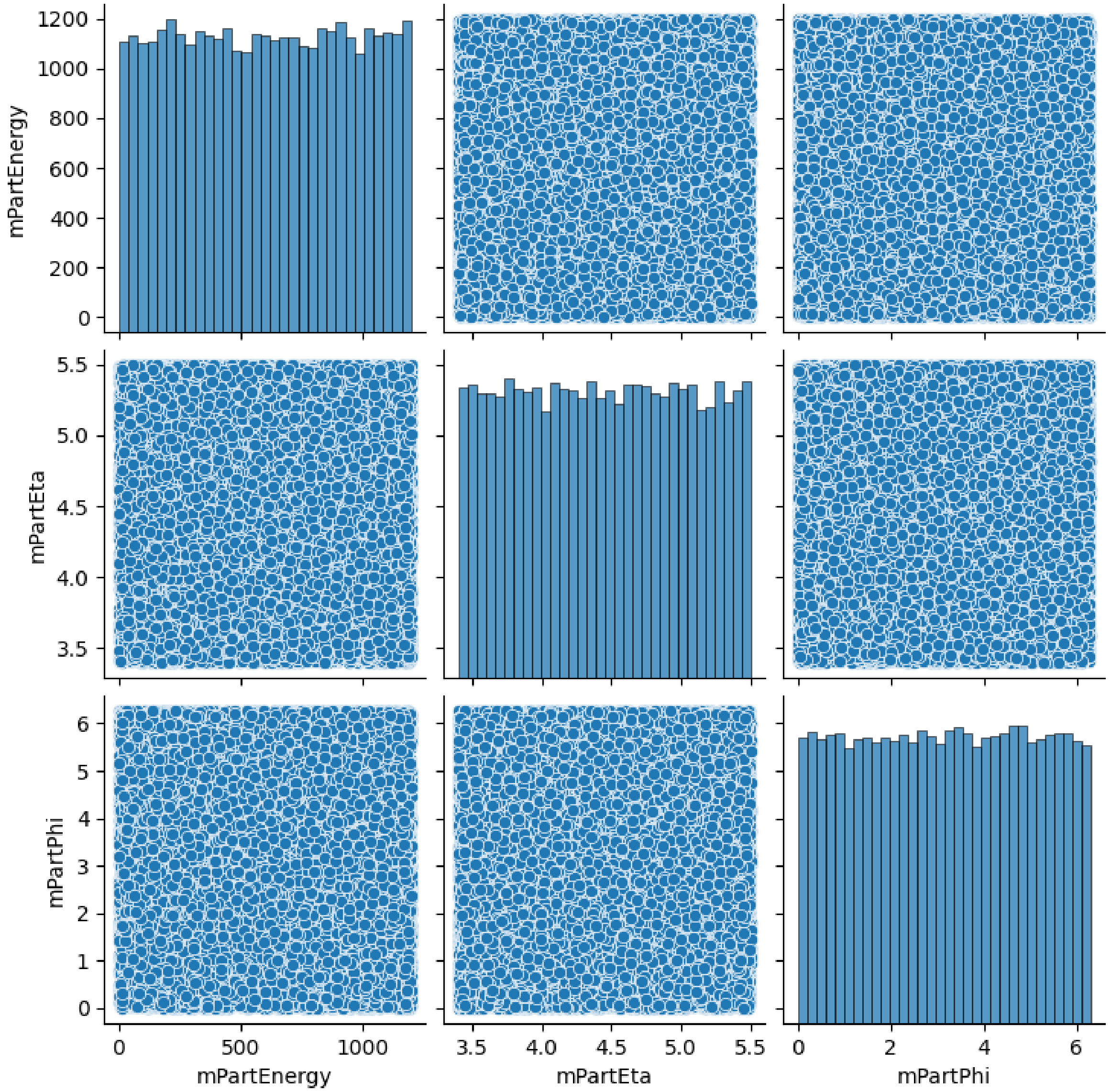
FoCal-H simulation

- Simulated using Monte Carlo approach.
  - Computationally expensive method!
- Detector measures energy deposited in each fiber by particles passing through it.
- Simulation of such structure is a perfect task for generative neural networks.

Dataset

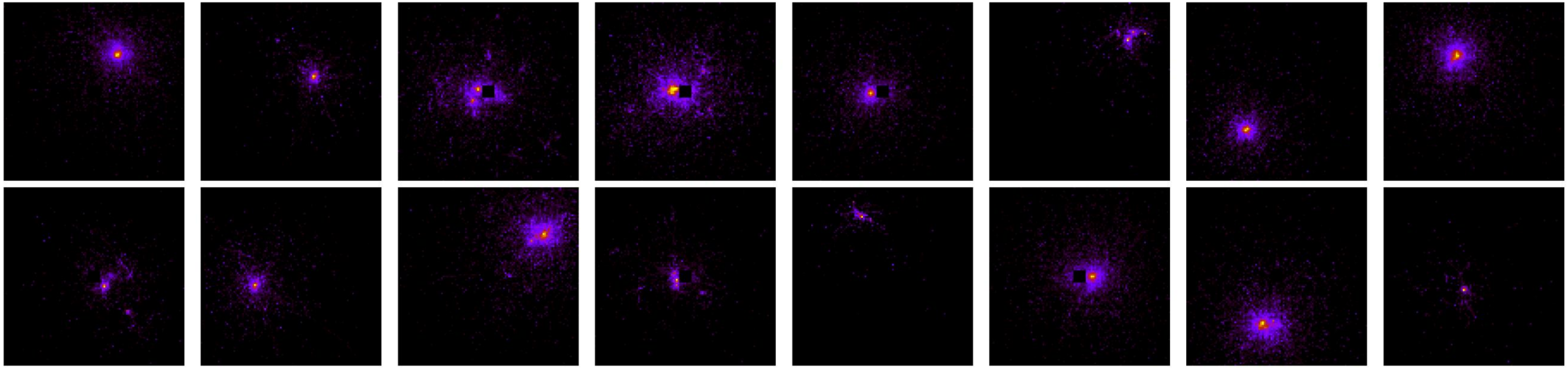
- 30 000 samples with simulation of π+ particles.
- Three input features:
  - particle energy.
  - pseudorapidity η - determines the polar angle θ with respect to the beam axis.
  - azimuthal angle ϕ - describes the rotation around the beam axis.

η and ϕ describe the kinematics of particles in a collider experiment.



Dataset

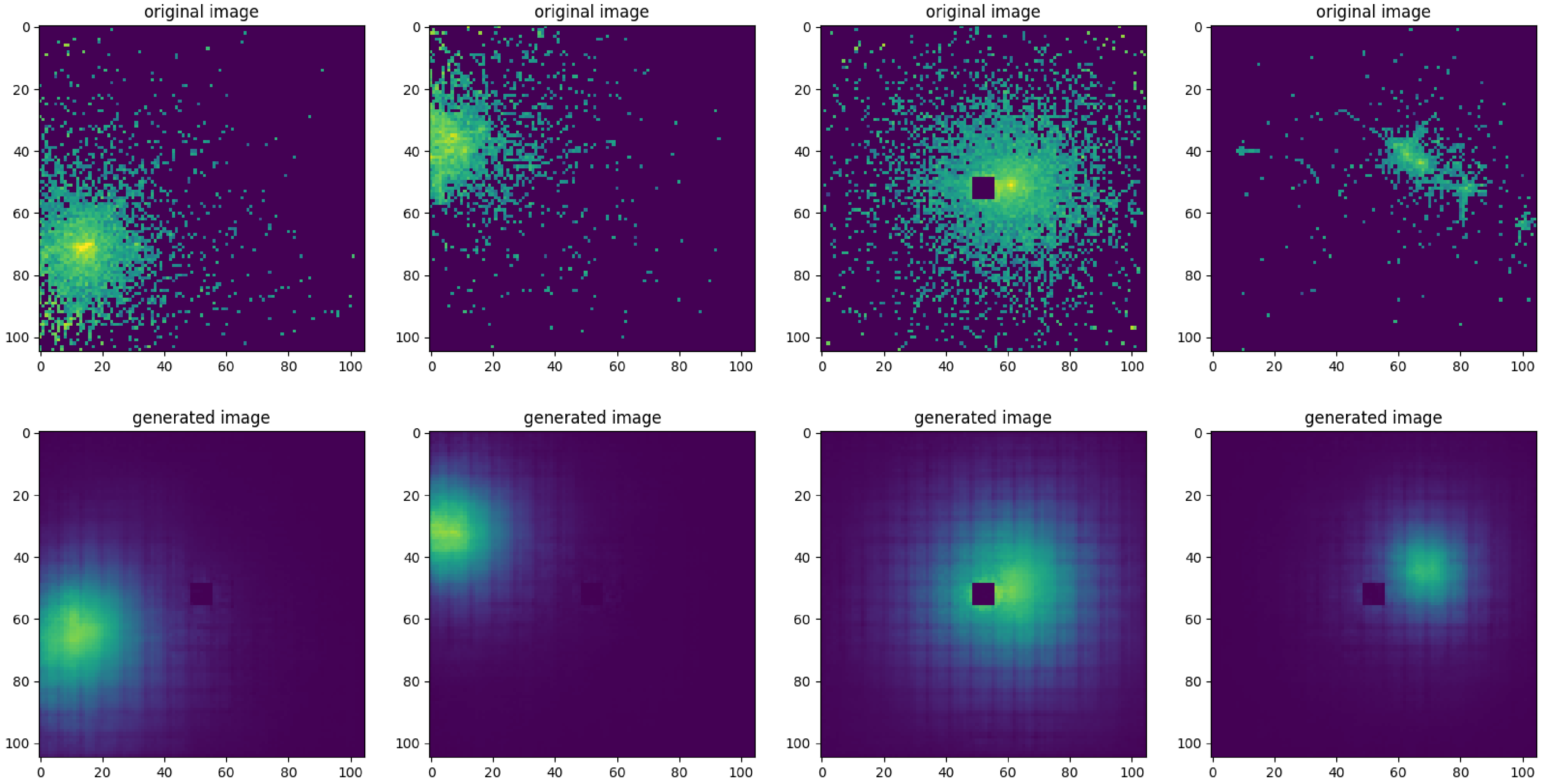
- Output: detector response.
- In this stage of the experiment, we work with 2-dimensional data.



Variational AutoEncoder (VAE) approach

- VAE is a standard and well-established image generation method.
- The main idea behind VAEs is to use an encoder that embeds a training image in latent space while maintaining the continuity of such representation.
- In our case we used the conditional variant of VAE.
- Conditional VAE includes particle properties as additional information for data generation.
- This method is prone to the effect of "blur" but roughly preserves the shape and location of particle shower readings.

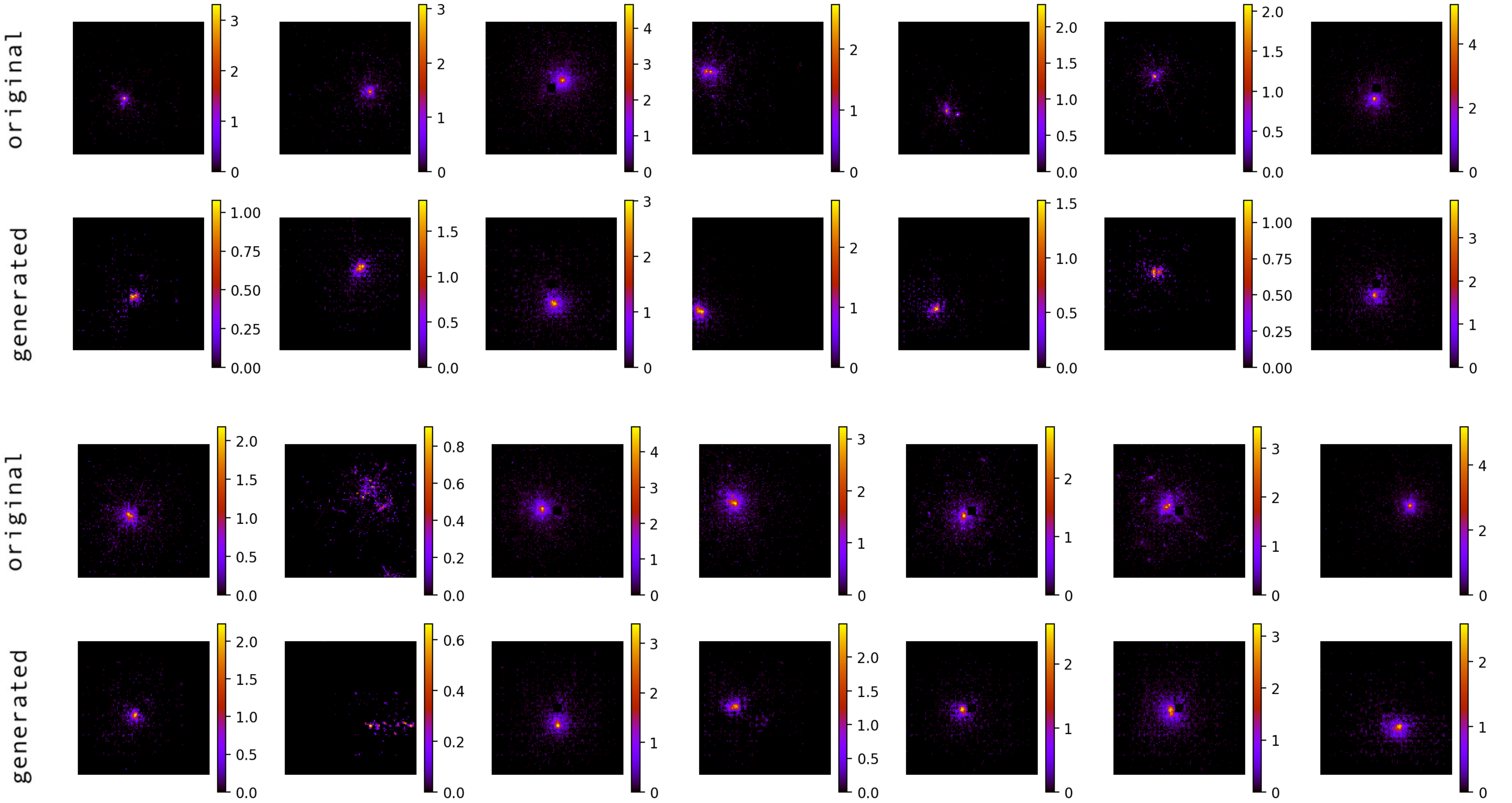
VAE example results



Generative Adversarial Network (GAN) approach

- Often a baseline method for calorimeter simulation.
- The training process involves two networks – a generator which learns to create realistic data that mimics the original training set, and a discriminator which learns to distinguish between real and fake data.
- Fast, yet usually more recent methods provide higher-quality results.
- Unstable training.

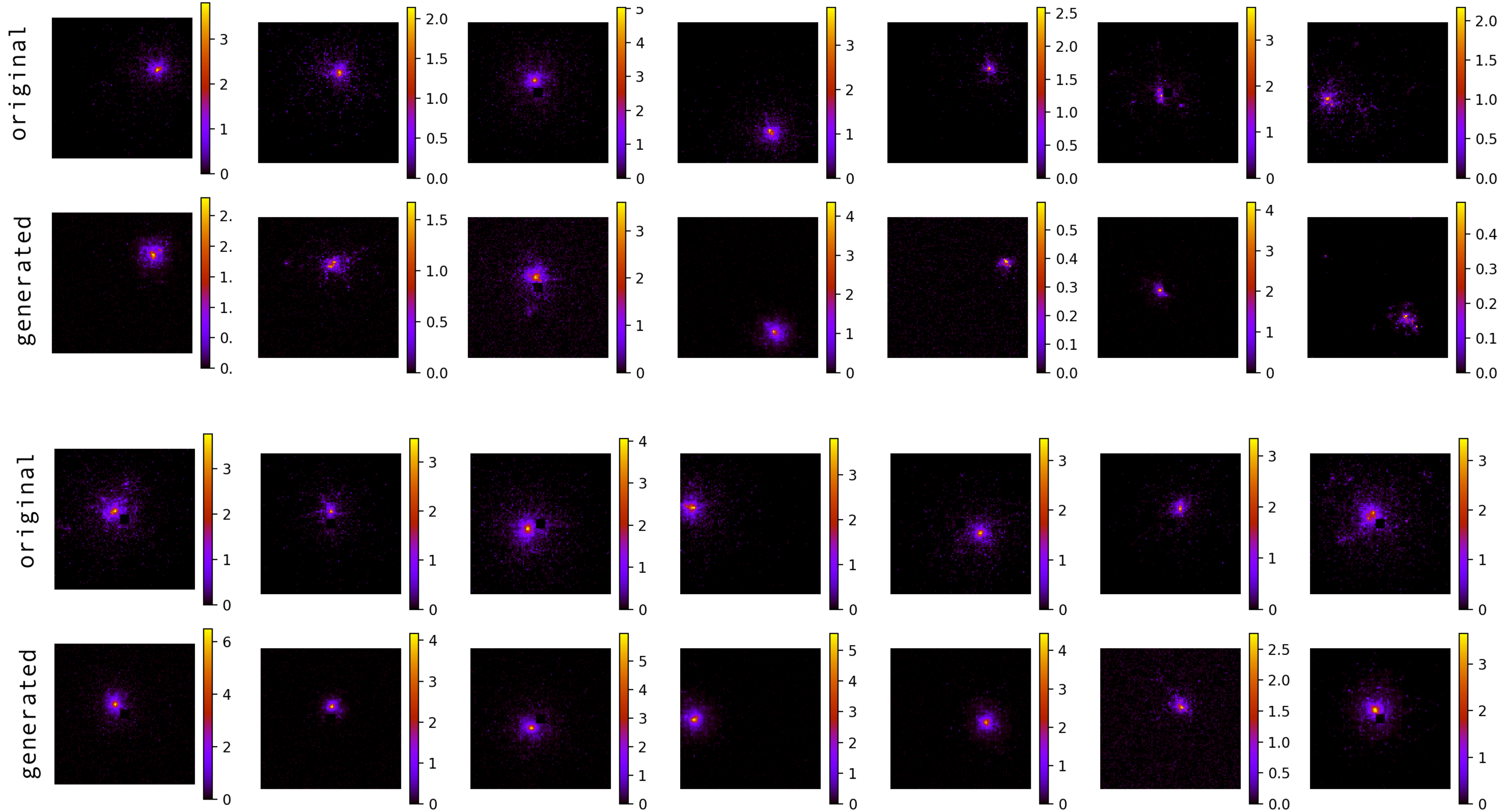
GAN example results



Diffusion approach

- Diffusion methods are particularly suitable for high-quality image generation.
- The main idea is to progressively increase noise in the image and learn to reverse this process.
- It is possible to control generation time and quality of samples by adjusting denoising pace.
- So far, conditional denoising diffusion implicit models (Cond-DDIM) were studied.

Diffusion example results



Theory-inspired approach

- Additional loss: distance between the simulated and expected shower center positions.
- Calculated using azimuthal angle and pseudorapidity:

$$x = z \cdot \tan\left(2 \arctan\left(e^{-\eta}\right)\right) \cdot \cos\phi$$

$$y = z \cdot \tan\left(2 \arctan\left(e^{-\eta}\right)\right) \cdot \sin\phi$$

- Currently under development.

Technological stack & hardware

- Python.
- TensorFlow, PyTorch, JAX, NumPy, scikit-learn and Uproot libraries.
- Weights & Biases platform.
- NVIDIA A100 GPU available on the Athena cluster.

Conclusions and next steps

- Promising results, especially with GANs and diffusion models.
- Further development and optimisation of the models.
- Theory-inspired approach.
- Other architectures: flow matching.

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