Modeling images of proton events for the TAIGA project using a generative adversarial network: features of the network architecture and the learning process

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Air showers and its' detection

Charged cosmic rays and high energy gamma rays interact with the atmosphere.

The result is extensive air showers of secondary particles emitting Cherenkov light.

TAIGA-IACT telescopes detect the light.

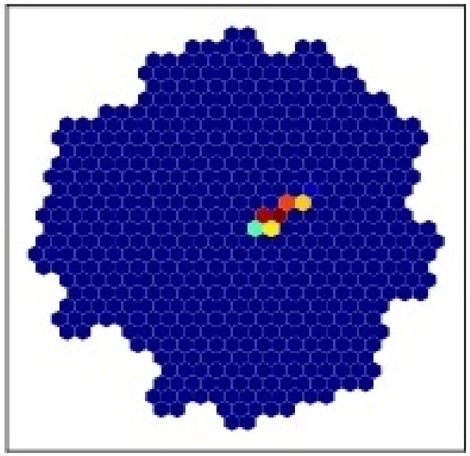
Detected data form "images" of the air shower.

Types of events observed

- gamma-quanta — events of interest

- hadrons - background events
  - most of the observed hadronic events are proton events

Identifying the type of event



gamma event

?

proton event

array of simulated data

gamma events

proton events

Task and goal setting

Current situation:

Images of proton events are modeled using a special program (CORSIKA) that performs detailed direct simulation of extensive air showers, thereby producing reasonably accurate but resource-intensive and time-consuming results.

Only about 1000 images are generated in an hour!

Our goal: simulate images of proton events quickly and still accurately

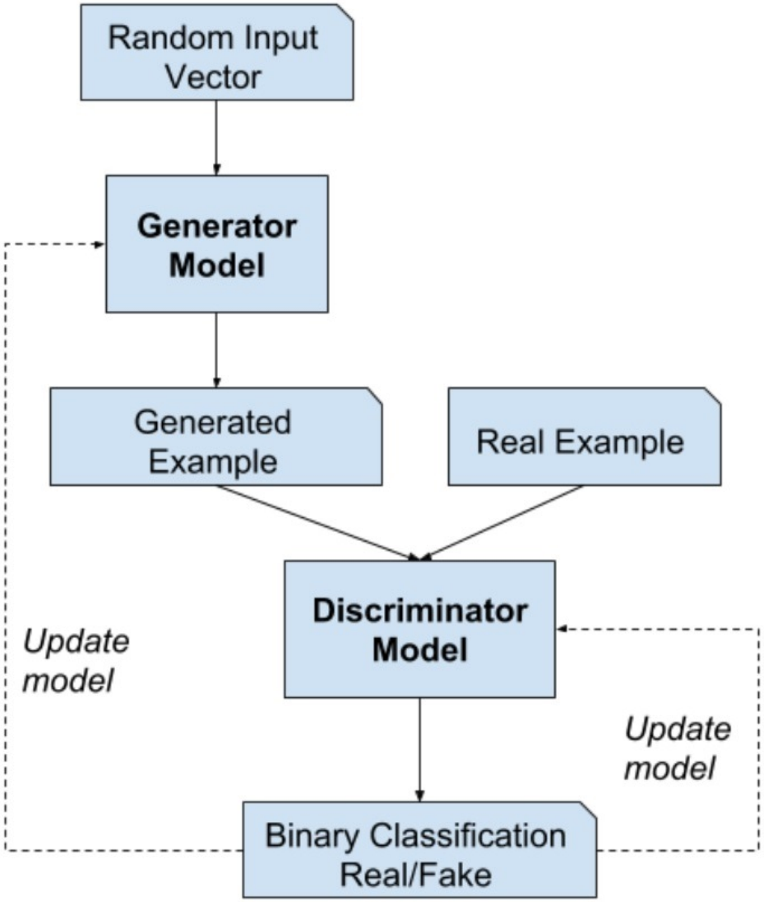
Generative adversarial network (GAN)

GANs are an approach to generative modeling using deep learning methods, such as neural networks. Each GAN consists of two parts: a generator and a discriminator.

Generator:
a neural network that tries to transform its random input into images similar to the real ones

Discriminator:
a neural network that tries to distinguish between real images and those produced by the generator

Generator and Discriminator are trained together on real images in an adversarial game, until the discriminator model is fooled about half the time, meaning the generator model is generating plausible examples.



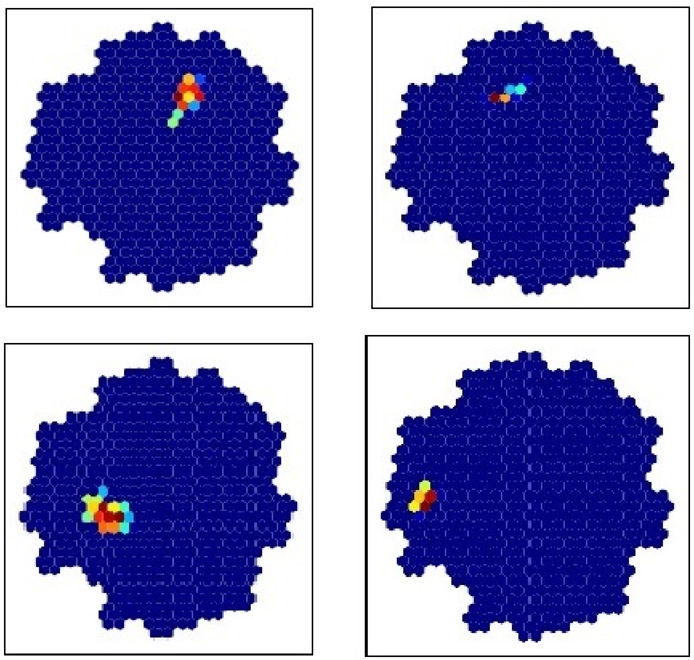
Training dataset preparation

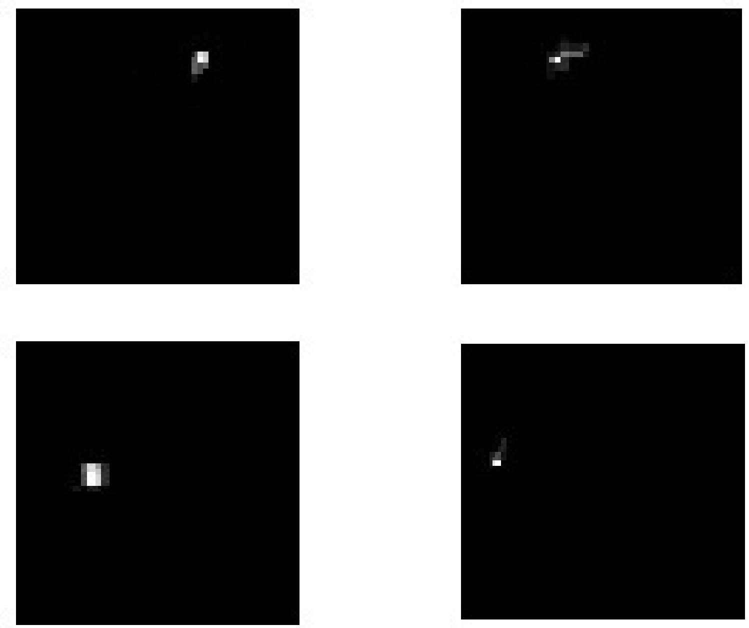
Our GAN was trained on a sample of two-dimensional images obtained using TAIGA Monte Carlo simulation software, containing about 25,000 proton events.

The original images recorded by the telescope's hexagonal lattice were transformed into images with a size of 31 by 30 pixels by transition to an oblique coordinate system. Because GANs work best with square images, each image has been converted to 32 by 32 pixels by adding zeros.

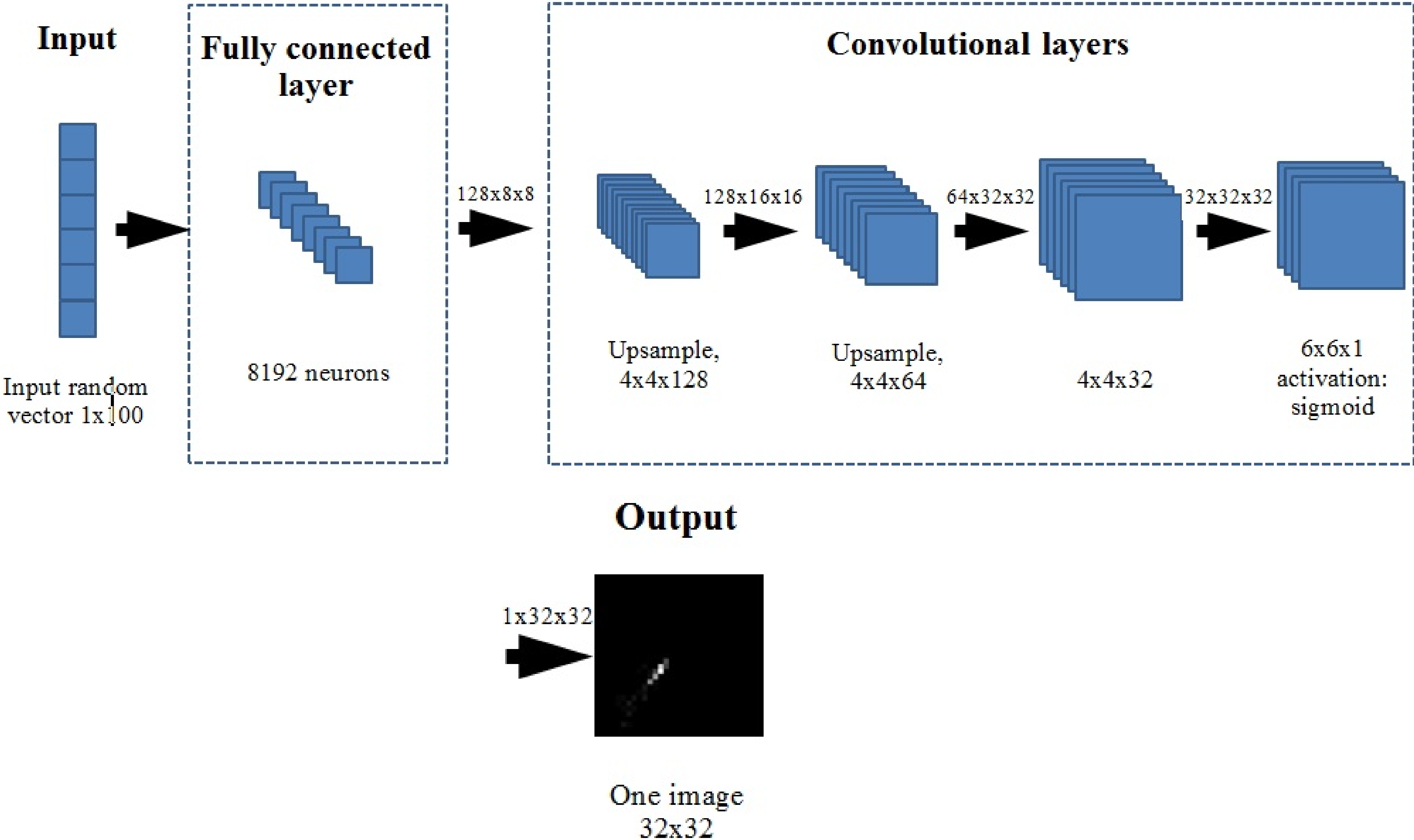
Since the training set contains images with different energies, we had to switch to a logarithmic scale by applying the logarithm function to each pixel of each image: $\ln(1+x)$.

Training dataset examples.
Proton images

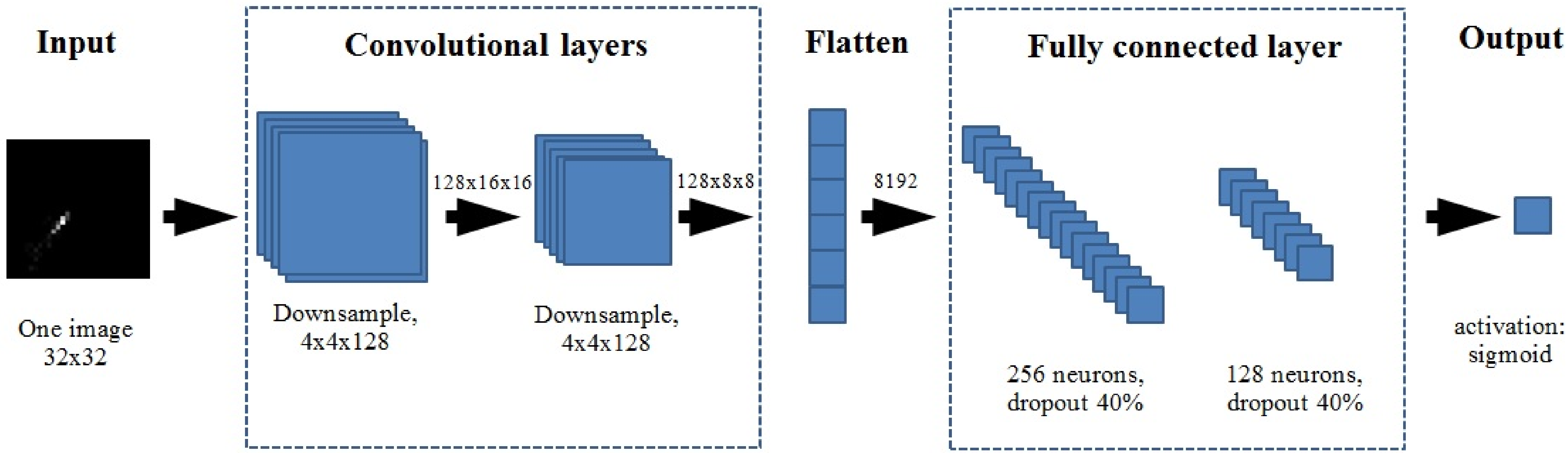




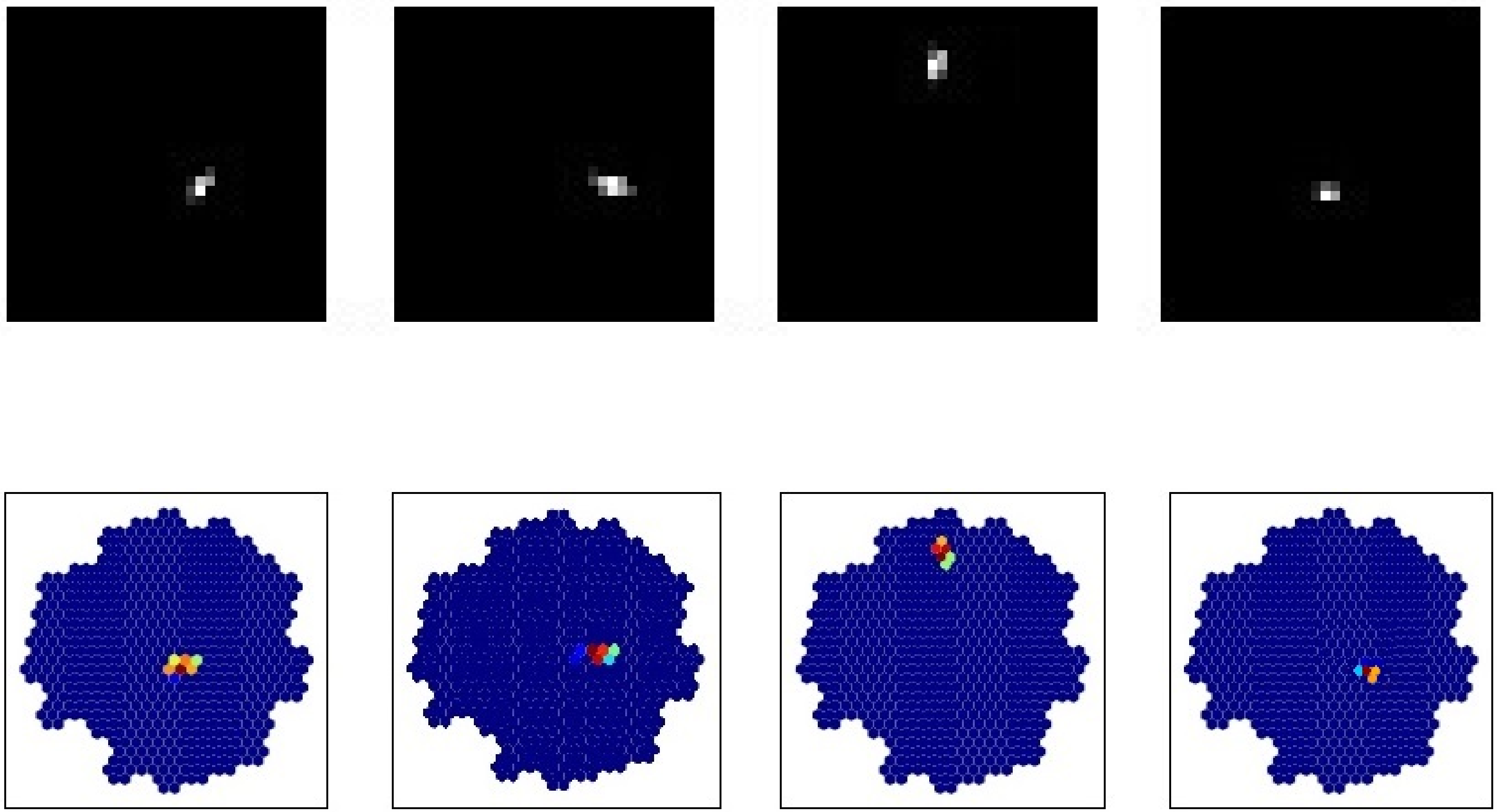
Generator architecture



Discriminator architecture



Generated proton images: network output and the hexagonal images



Number of learning epochs

The number of epochs is a hyperparameter of the learning process that controls the number of complete passes through the training dataset.

The feature of our training dataset is that the events in it are not uniformly distributed over energies. Some events are rare.

Experimentally, we found that the optimal number of epochs is about 300. In this case, the network is trained enough to generate even rare events (but not extremely rare).

Image generation: numerical performance indicators

Network training at the GPU Tesla P100 took about 6 hours.

After training, generation of 4000 events takes about 10 seconds.

Testing the results using third-party software showed that more than 90% of the generated images were found to be very good, another 5% were acceptable.

Conclusion

Generative adversarial networks simulate proton events images for the TAIGA experiment with a reasonable degree of accuracy.

Most of the generated events are indistinguishable from the ones generated using the traditional method.

At the same time, the rate of events generation using GAN is more than 1000 times higher than the rate of generation by the traditional method.

Thank you for attention!