Generating Synthetic Images of Gamma-Ray Events for Imaging Atmospheric Cherenkov Telescopes Using Conditional Generative Adversarial Networks

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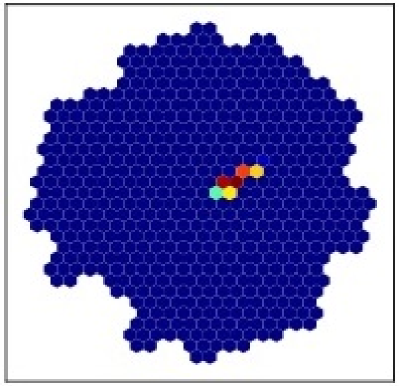
Air showers detection with IACT

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

The result is extensive air showers (EAS) of secondary particles emitting Cherenkov light

Imagine Atmospheric Cherenkov Telescopes (IACT) detect the light

The figure on the right shows the reflecting telescope of the TAIGA-IACT project



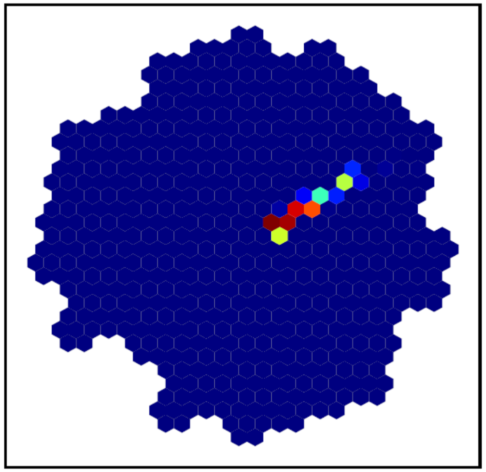
The data detected by the telescope's camera form "images" of the air shower

Gamma images and hadron images

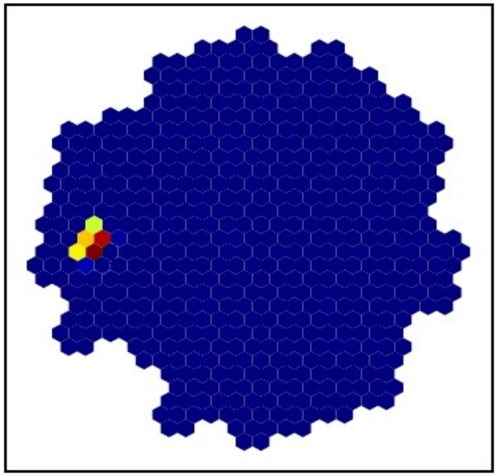
There are two types of primary particles producing EAS:

- high energy gamma quanta: the particles of interest (0.01% of all particles)

- hadrons (mostly protons): background



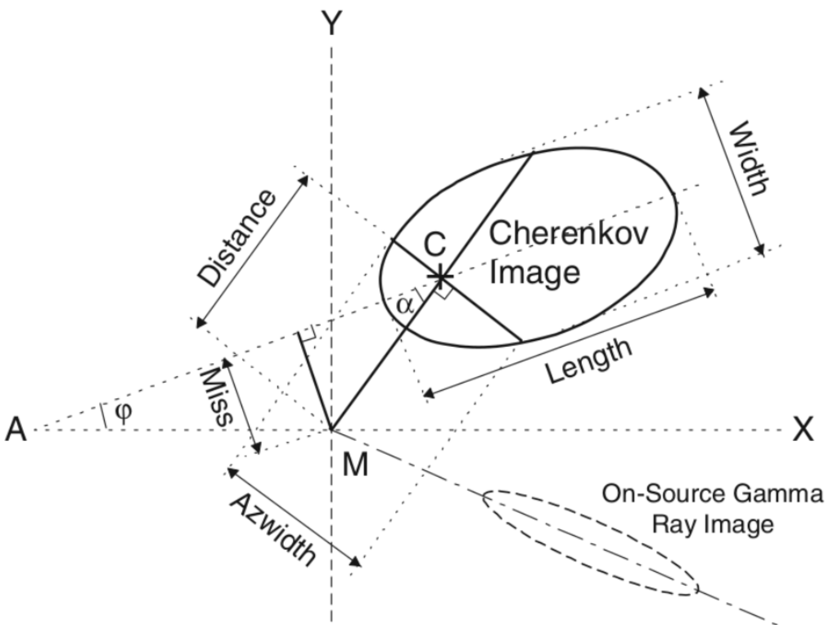
Gamma image



Proton image

Event image and its parameters

For each event image we can calculate the so-called Hillas parameters, which form a set of geometric features of the image



These parameters are widely used in gamma-ray astronomy for gamma/hadron separation

The most important Hillas parameters are:

- Image brightness (called image size)
- Width and length of the ellipse
- Number of triggered pixels and distance
- Angles: alpha, phi

The key parameter is the energy of the primary particle (can not be directly calculated but correlates with the image size)

As a first approximation, it is convenient to use the image size instead of the energy

Artificial images generation task

For each IACT to operate correctly a large amount of experimental data, including simulated data, is required

Traditionally, event images are modeled using a special programs that perform detailed direct simulation of extensive air showers, thereby producing reasonably accurate but resource-intensive and time-consuming results

Machine learning techniques such as generative adversarial networks (GANs) significantly reduce the time to generate images

In this work we focus on <u>generation</u> of artificial <u>gamma images</u> using conditional GANs

The main practical goals of image generation

When generating artificial images we are aiming to:

- generate images similar to those taken by the IACTs
- reproduce the Hillas parameters of the set of real (or properly simulated) images

Thus, the requirements are imposed both on each individual image and on the entire sample of images

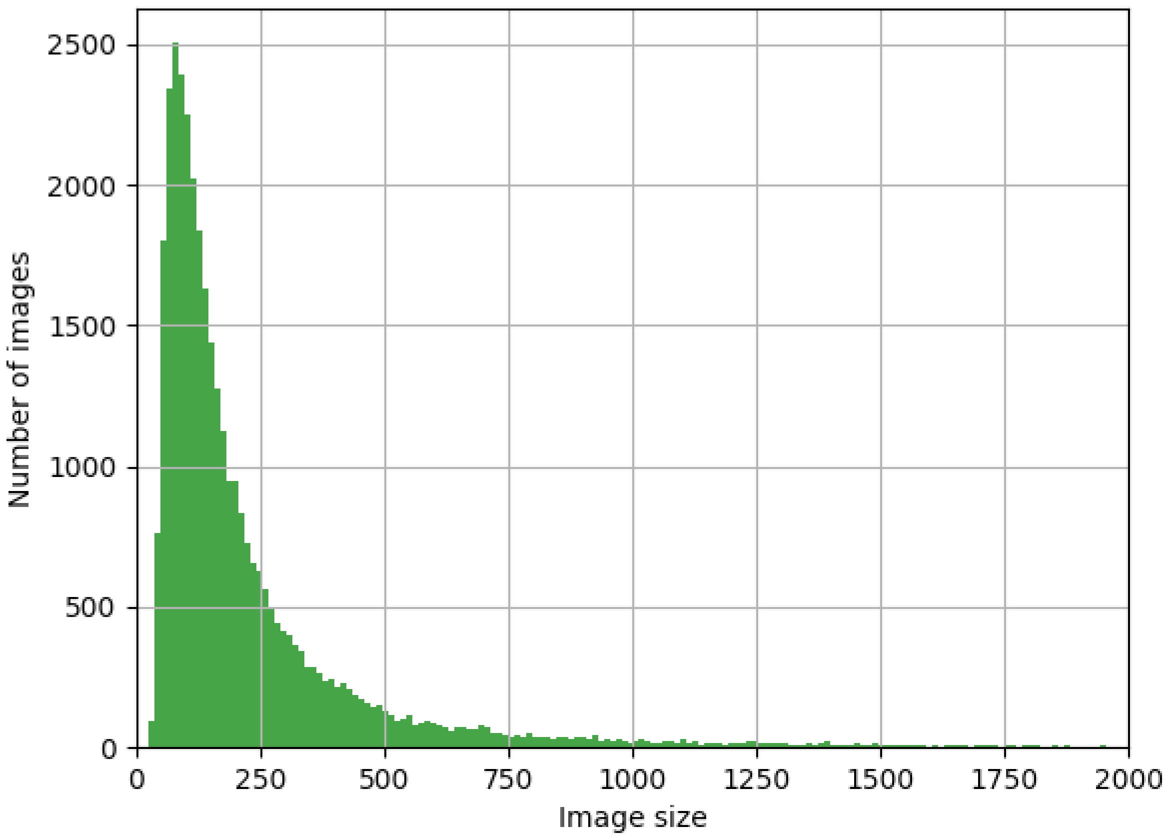
Size distribution of reference images

As reference, we use a sample of 35000 two-dimensional gamma images obtained using TAIGA Monte Carlo simulation software

The plot shows the distribution of these images by image size

This distribution is very uneven and asymmetrical

This is the distribution that we are trying to reproduce when generating new images



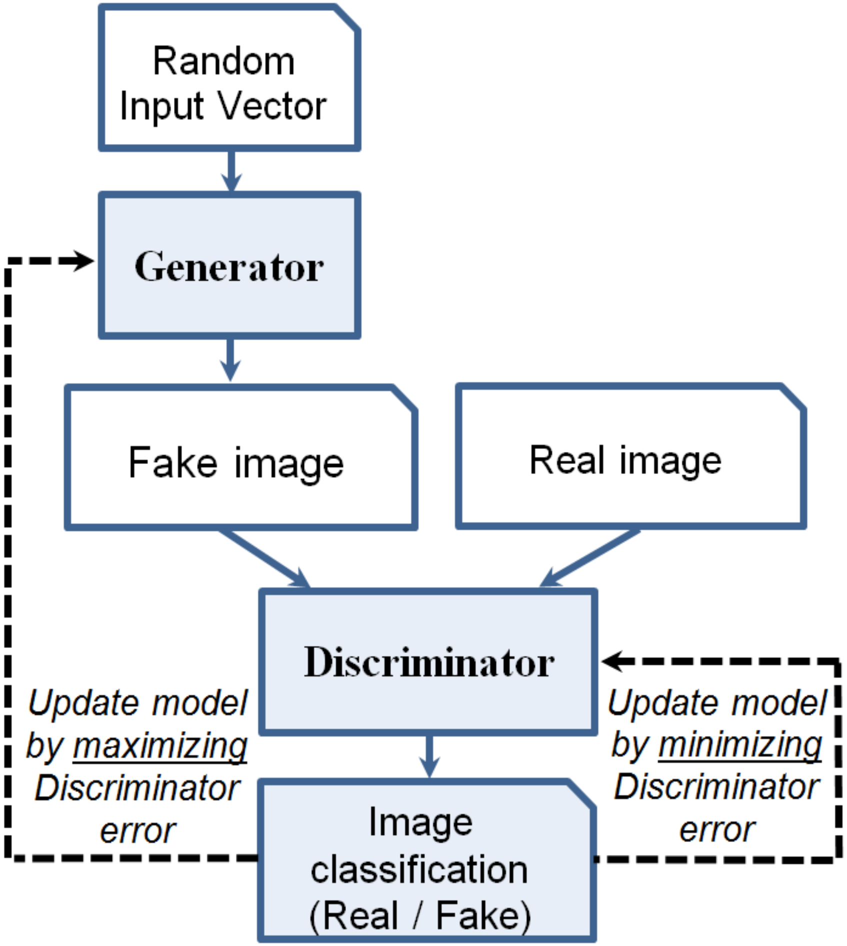
Generative adversarial network (GAN)

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

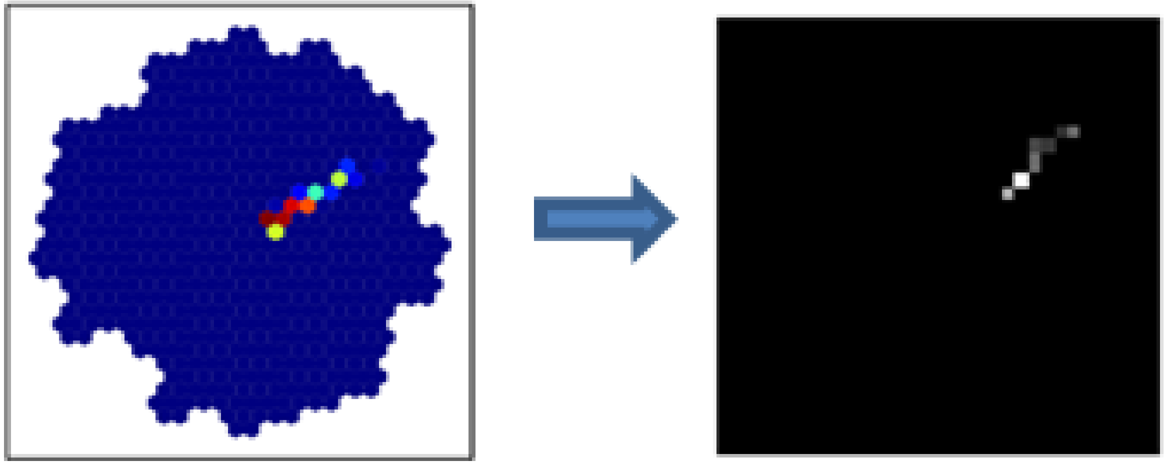
Discriminator:
a neural network that tries to distinguish between real images and those produced by the generator

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

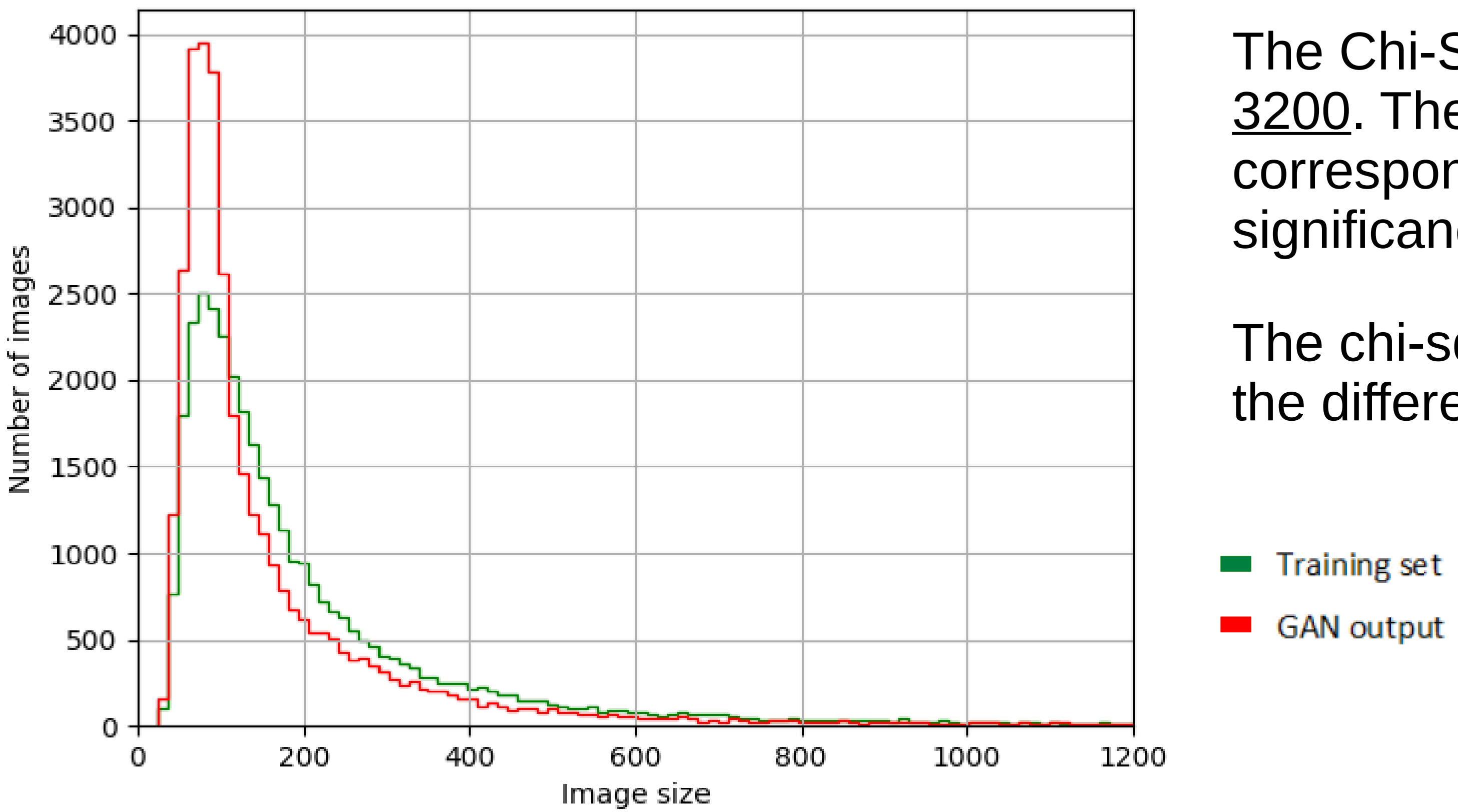
The original hexagonal images were transformed into images with a size of 32 by 32 pixels by transition to an oblique coordinate system



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

Image size distribution for samples generated by GAN

Problem: the size distribution for the generated sample is different from the distribution of the training set

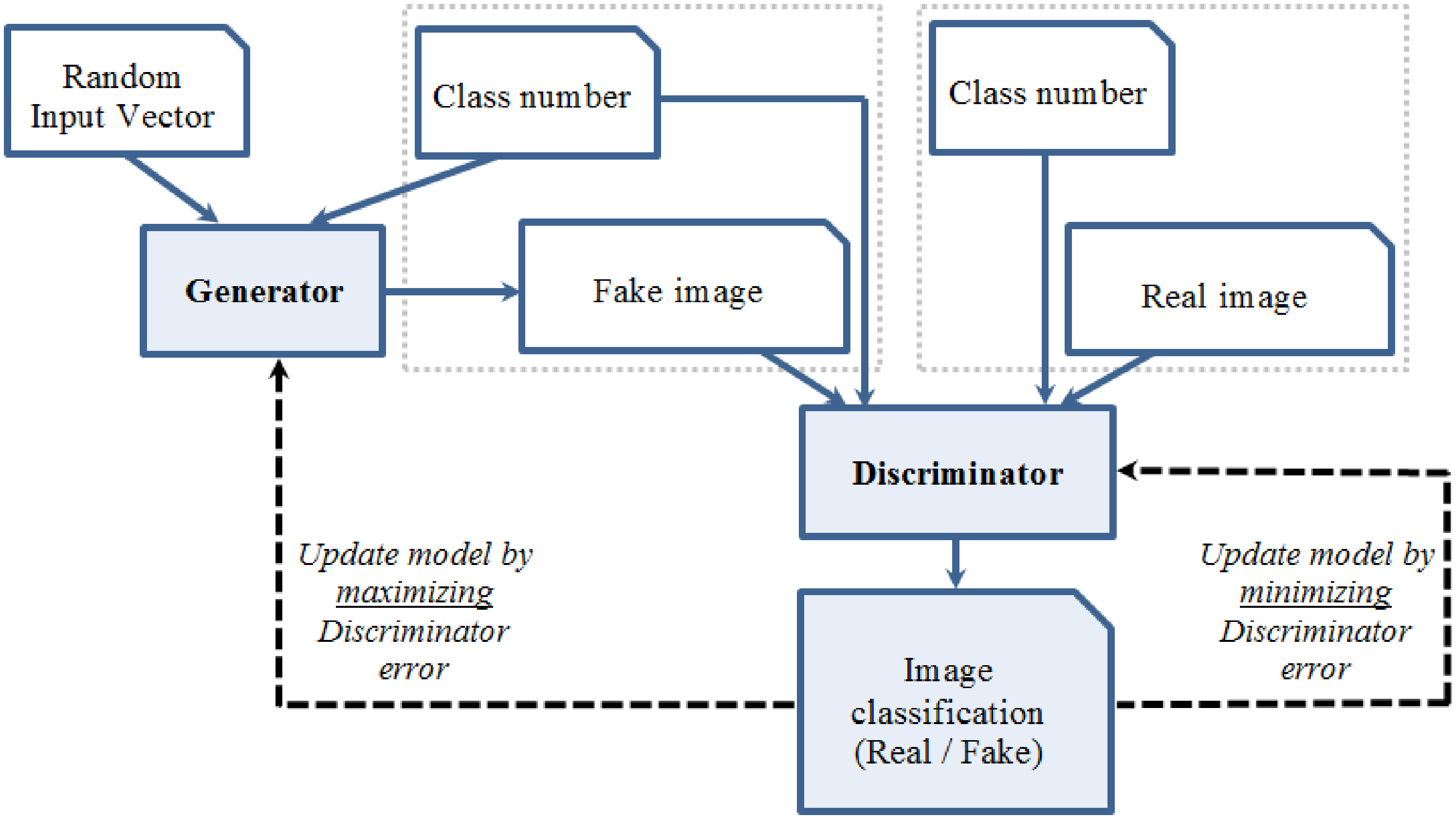


The Chi-Square test statistic is 3200. The critical value corresponding for a 5% significance level is 124,34

The chi-square test shows that the difference is significant

Conditional generative adversarial network (cGAN)

cGAN is a modification of a traditional GAN that allows you to <u>divide images</u> into <u>multiple classes</u> according to the value of some property of the image

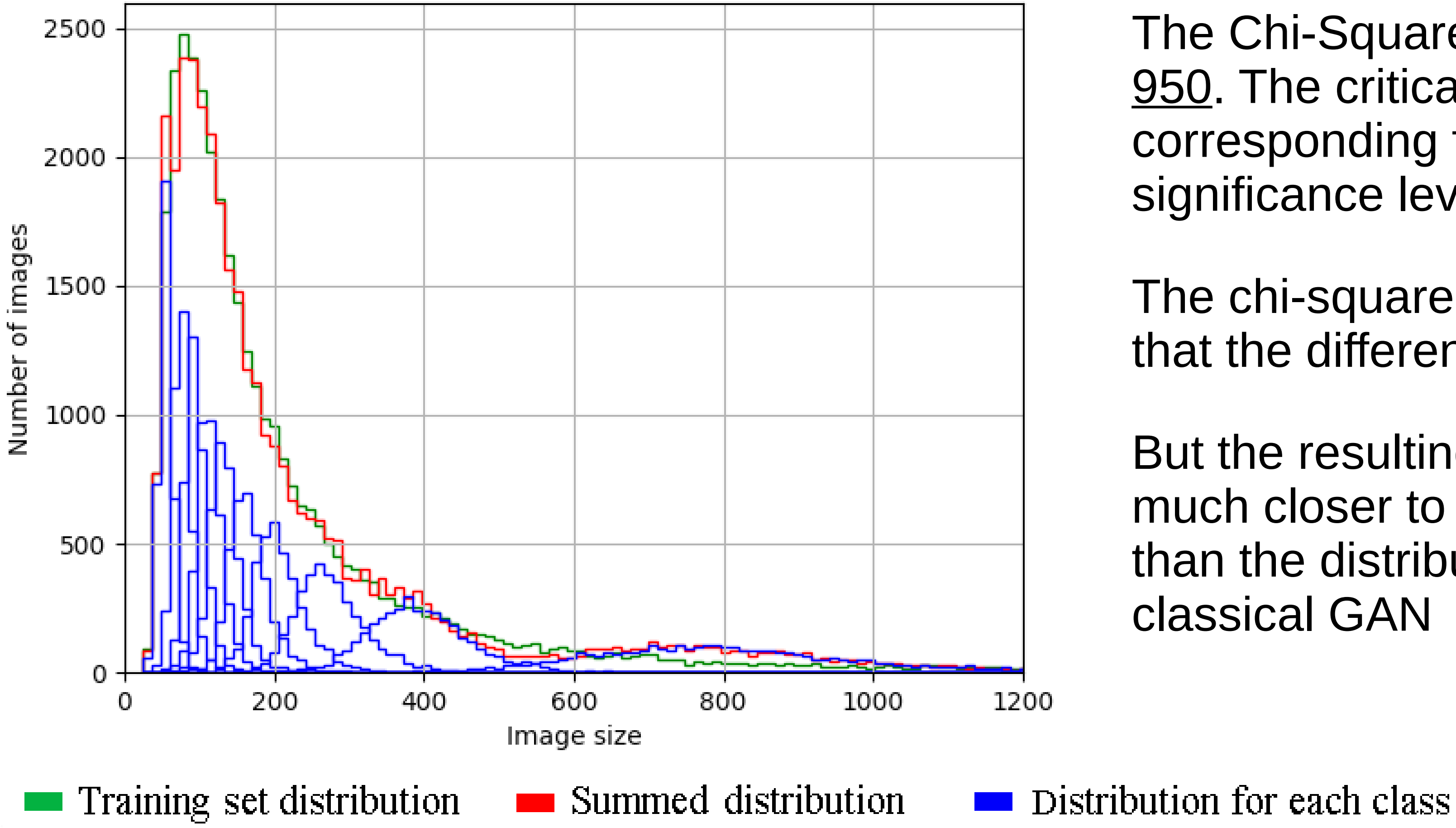


We divided our sample of gamma images by <u>image size</u>, so that the images with the similar size fall into the same class

We divided the images into classes so that each class has the same number of images

Image size distribution for samples generated by cGAN with 10 classes

The size distribution summed over all classes is close to the original distribution in the training set

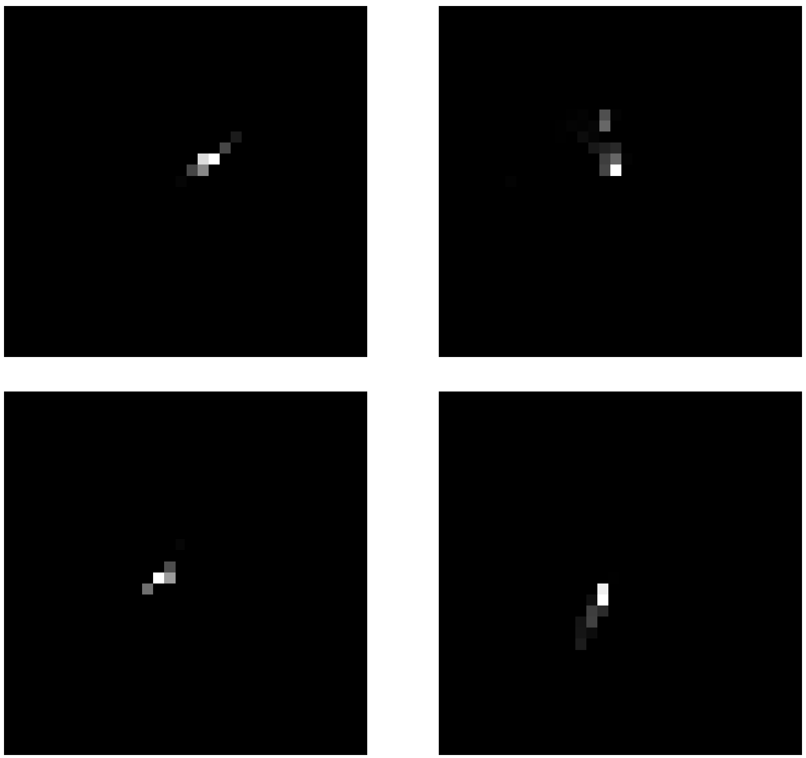


The Chi-Square test statistic is <u>950</u>. The critical value corresponding for a 5% significance level is 124,34

The chi-square test still shows that the difference is significant

But the resulting distribution is much closer to the input one than the distribution for the classical GAN

Change in cGAN training: increasing number of classes to 100



We increased the number of classes to 100 to make the output size distribution more similar to the original distribution for higher sizes

There were doubts that this would lead to training problems, since for our sample there were only 350 images left in each class

But in terms of generating individual images (shown in the figure on the left), the network learned well

Every generated image can be easily converted back to hexagonal form

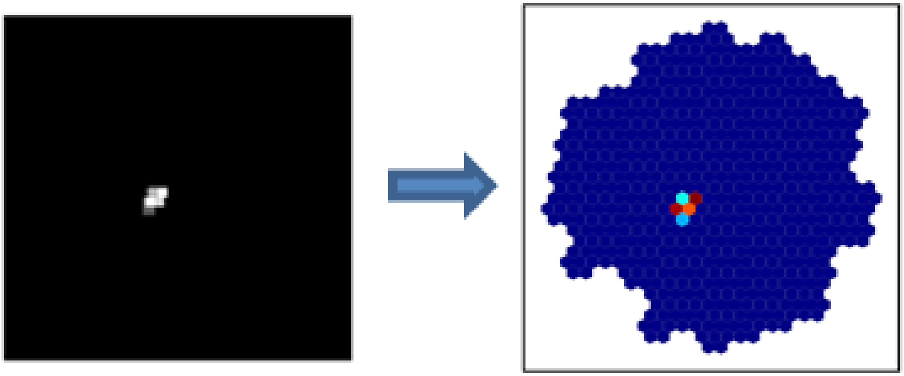
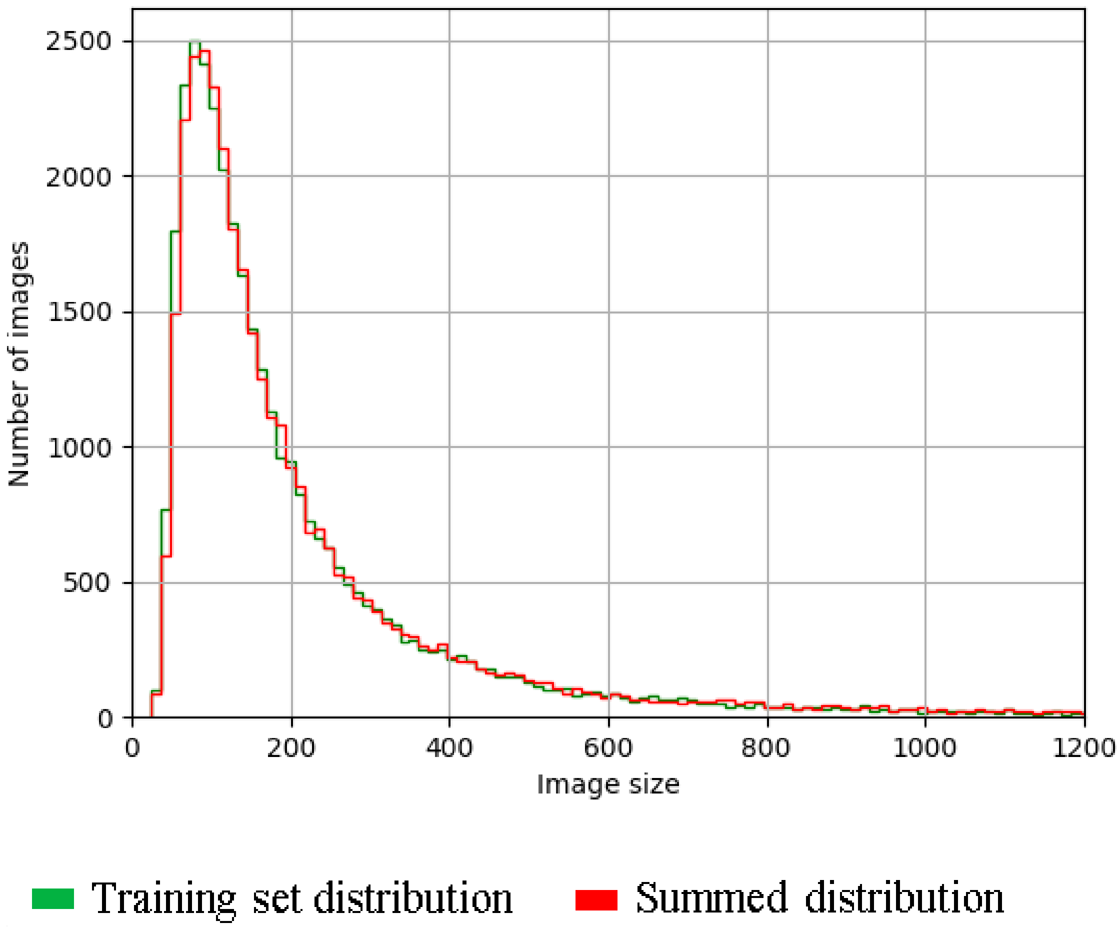


Image size distribution for samples generated by cGAN with 100 classes

The size distribution summed over all classes is close to the original distribution in the training set



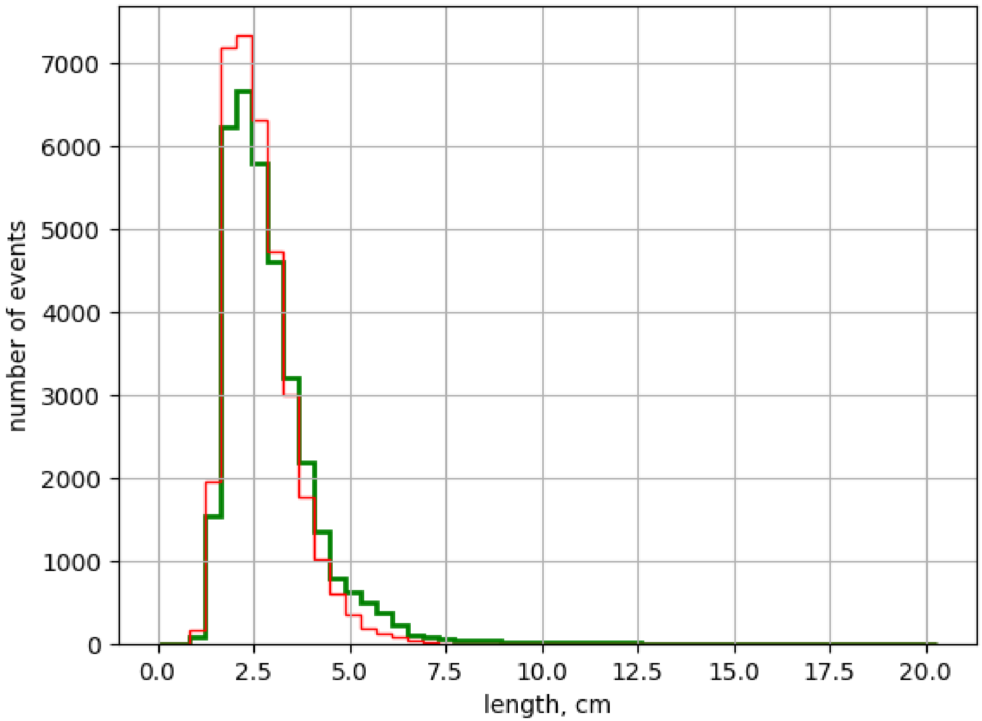
The Chi-Square test statistic is <u>121</u>. The critical value corresponding for a 5% significance level is 124,34

The chi-square test shows that the difference is not significant

The resulting distribution by size is very close to the input one

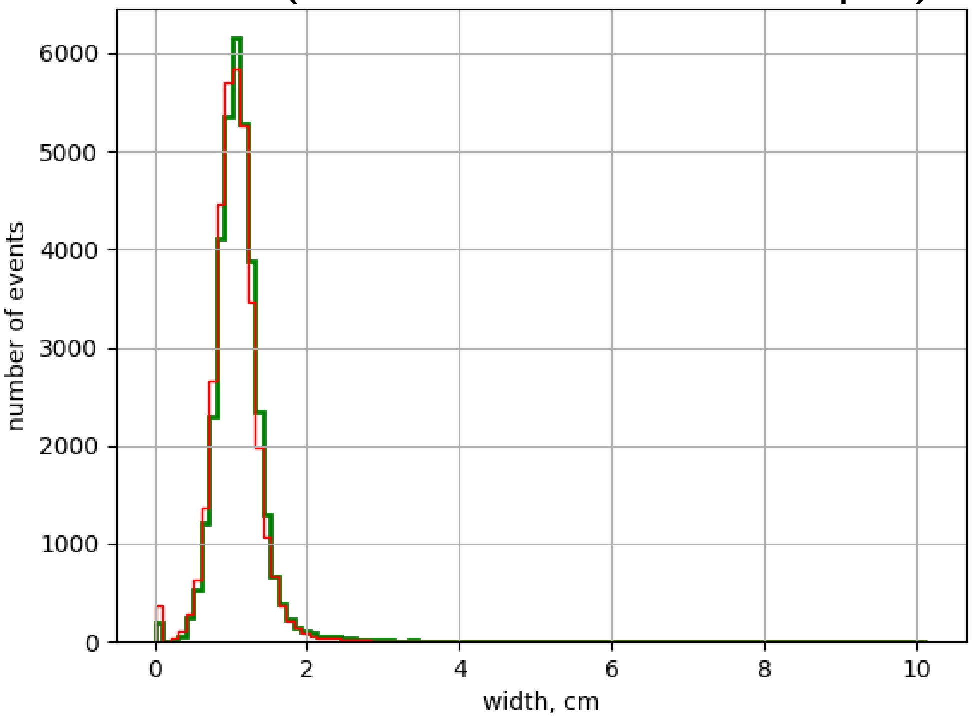
cGAN with 100 classes. Hillas parameters. Length and width

Length (semi-major axis of the ellipse)



The Chi-Square test statistic is 559

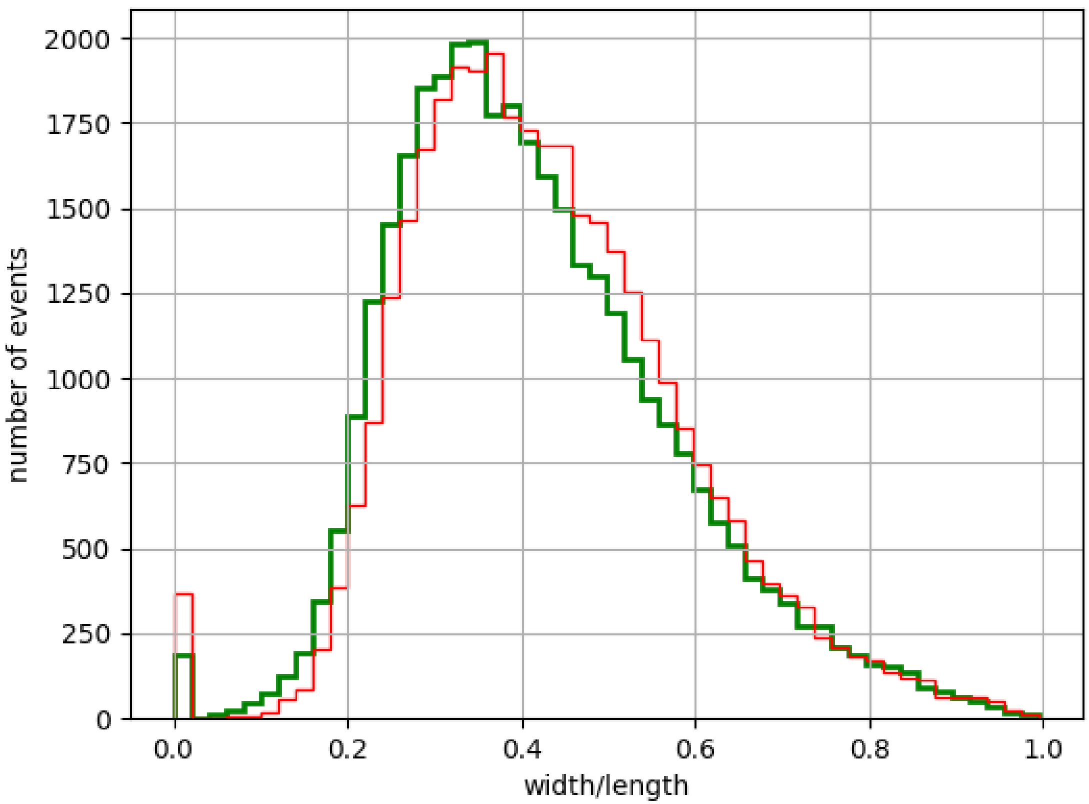
Width (semi-minor axis of the ellipse)



The Chi-Square test statistic is 261

Training set distribution   Summed distribution

cGAN with 100 classes. Hillas parameters. The ratio of width to length

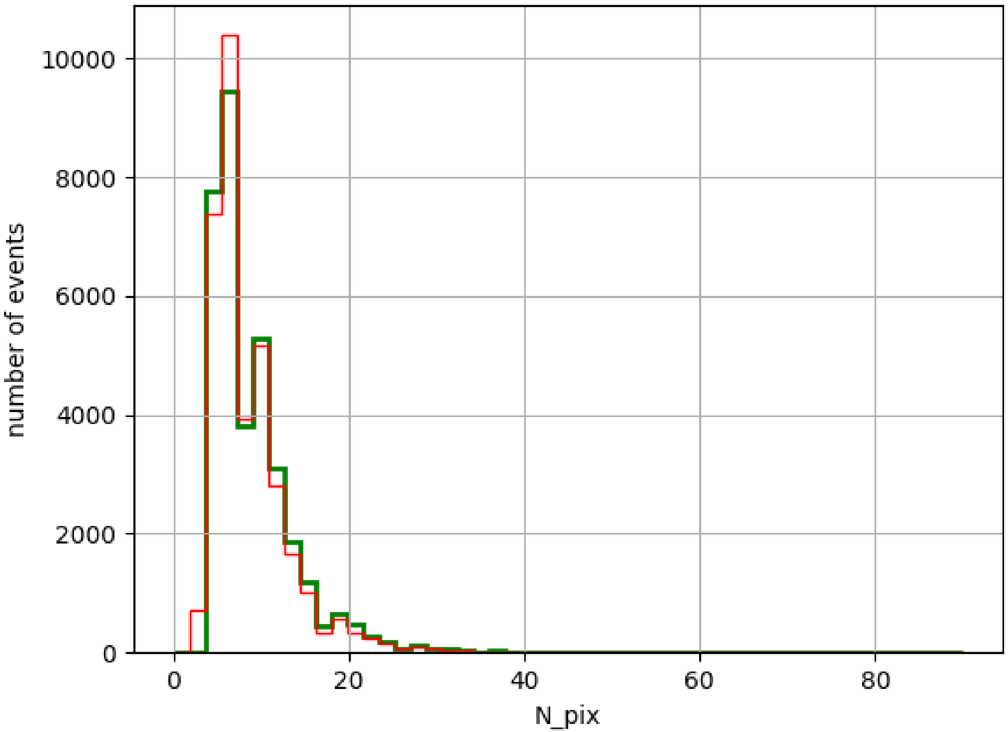


The Chi-Square test statistic is 462

Training set distribution   Summed distribution

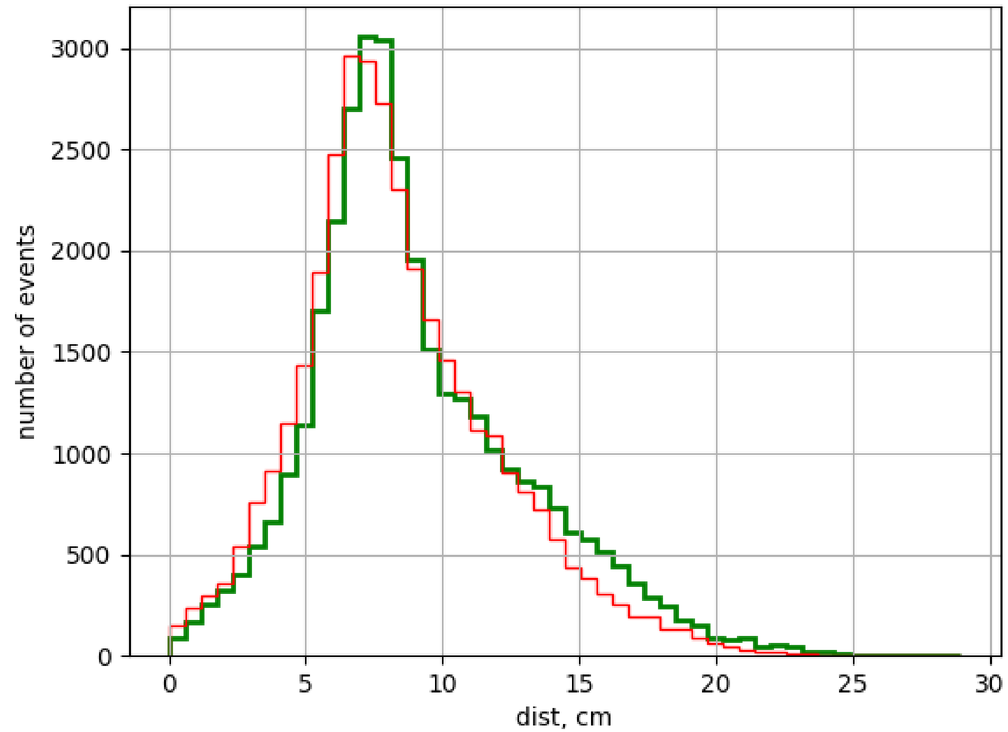
cGAN with 100 classes. Hillas parameters. Number of triggered pixels and distance

The number of triggered pixels in the image



The Chi-Square test statistic is 477

Distance between the centroid of the ellipse and the center of the field of view

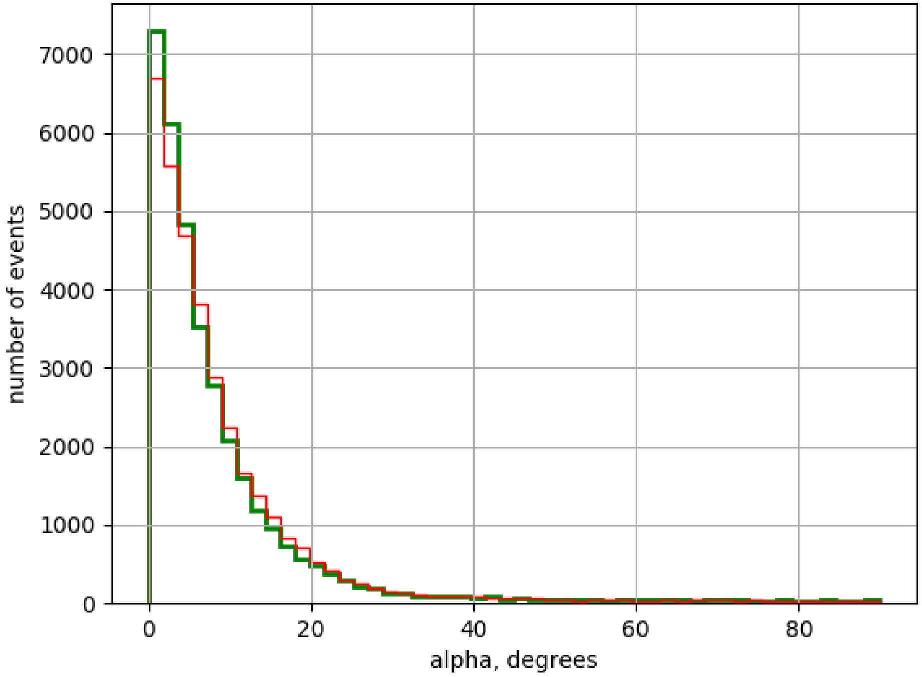


The Chi-Square test statistic is 498

Training set distribution   Summed distribution

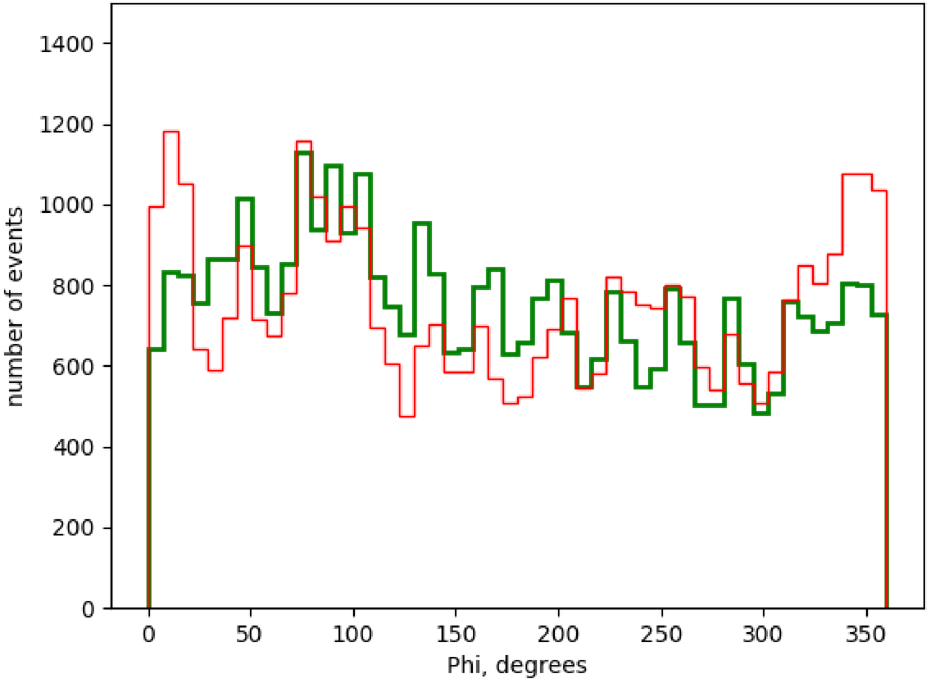
cGAN with 100 classes. Hillas parameters. Angles: alpha, phi

Alpha - the angle between the major axis and the line that connects the centroid of the ellipse with the center of the field of view



The Chi-Square test statistic is 213

Phi - the angle between the major axis of the ellipse and the X-axis of the X-Y coordinate system



The Chi-Square test statistic is 387

Training set distribution
Summed distribution

Conclusion

A conditional generative adversarial network simulate images for the TAIGA-IACT experiment with a very good degree of accuracy

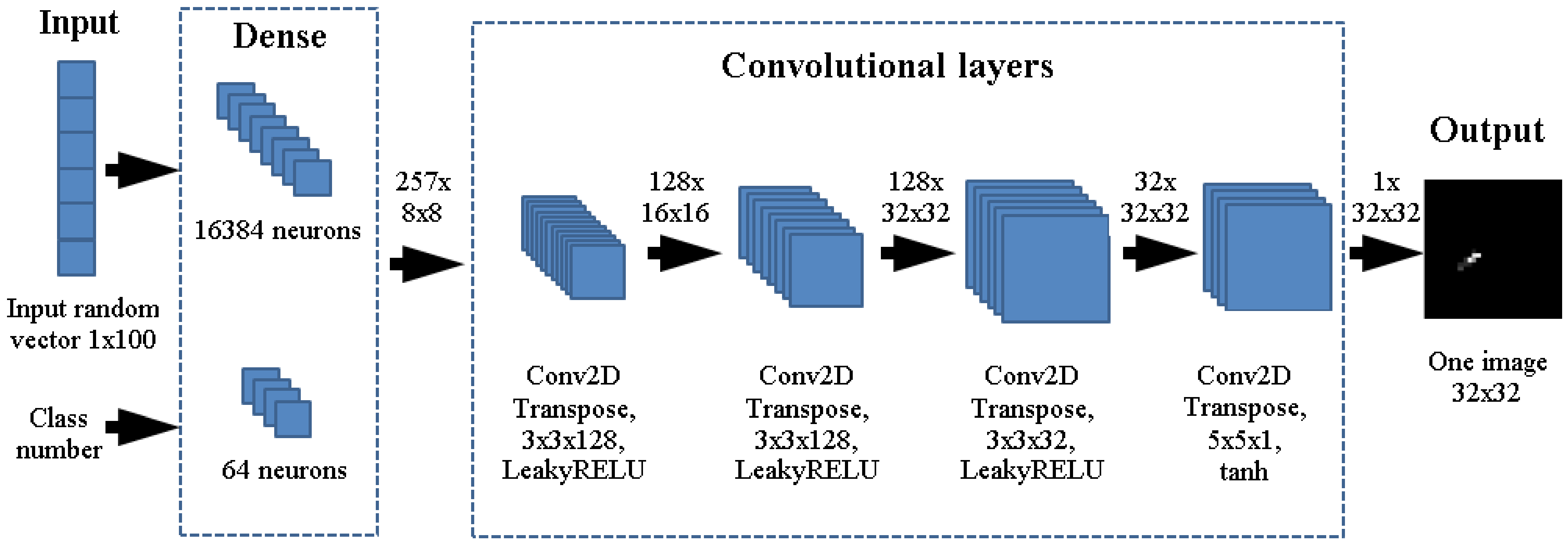
cGAN with 100 classes helps to generate an output sample of images with a size distribution that is statistically indistinguishable to that of the training set

The distributions of the Hillas parameters of the output sample and the corresponding distributions of the training sample are close in shape, although this difference is statistically significant

The rate of images generation using cGAN is more than 1000 times higher than the rate of generation by the traditional method

Thank you for attention!

Generator architecture



Discriminator architecture