

Using Generative Neural Networks to Simulate IACT Images in Gamma Astronomy

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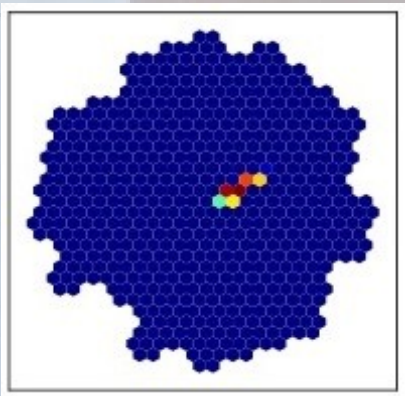
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Air showers detection with IACT

Charged cosmic rays and high energy gamma rays interact with the nuclei of the atmosphere. The result is extensive air showers (EAS) of secondary particles emitting Cherenkov light. Imagine Atmospheric Cherenkov Telescopes (IACT) register the light.

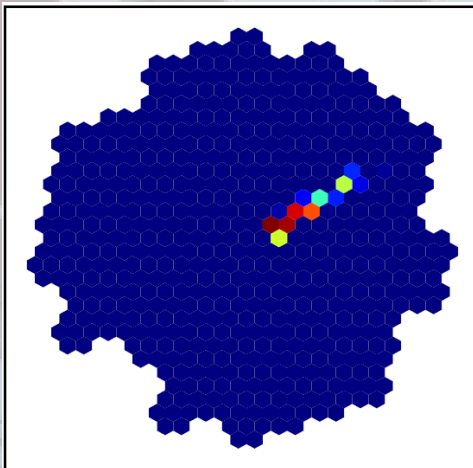


Detected data form "images" of the air shower

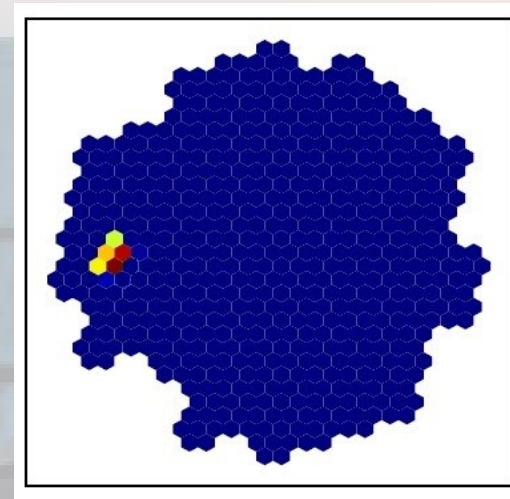
Gamma images and hadron images

There are two types of primary particles producing EAS:

- high energy gamma quanta
 - the particles of interest (0.01% of all particles)
- hadrons background (mostly protons)



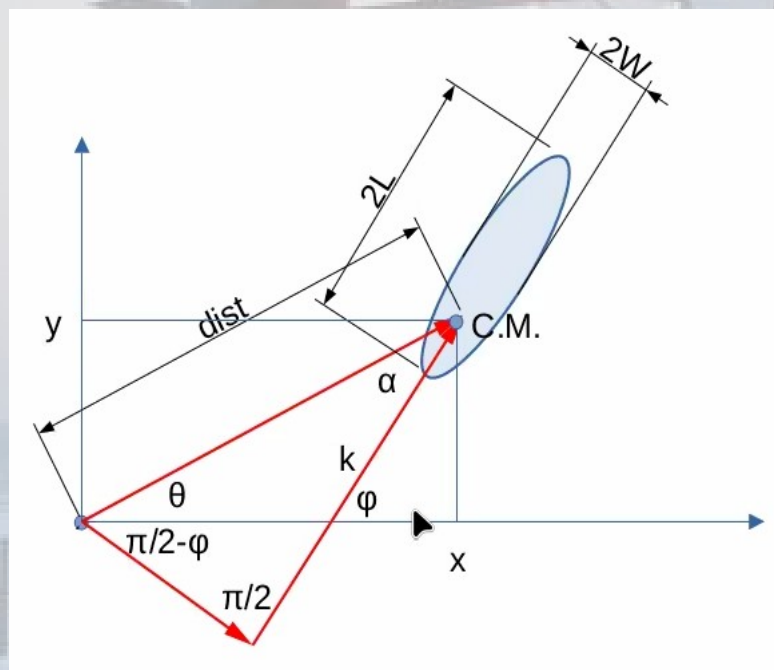
Gamma image



Proton image

Gamma image and Hillas 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
- Distance
- Angles: alpha, phi, theta

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

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 (usual CORSIKA) 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 neural networks significantly reduce the time to generate images

In this work we focus on generation of artificial images using conditional GANs and VAEs.

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

We presented the results obtained by two types of neural networks

- Generative adversarial networks
- Variational Autoencoders

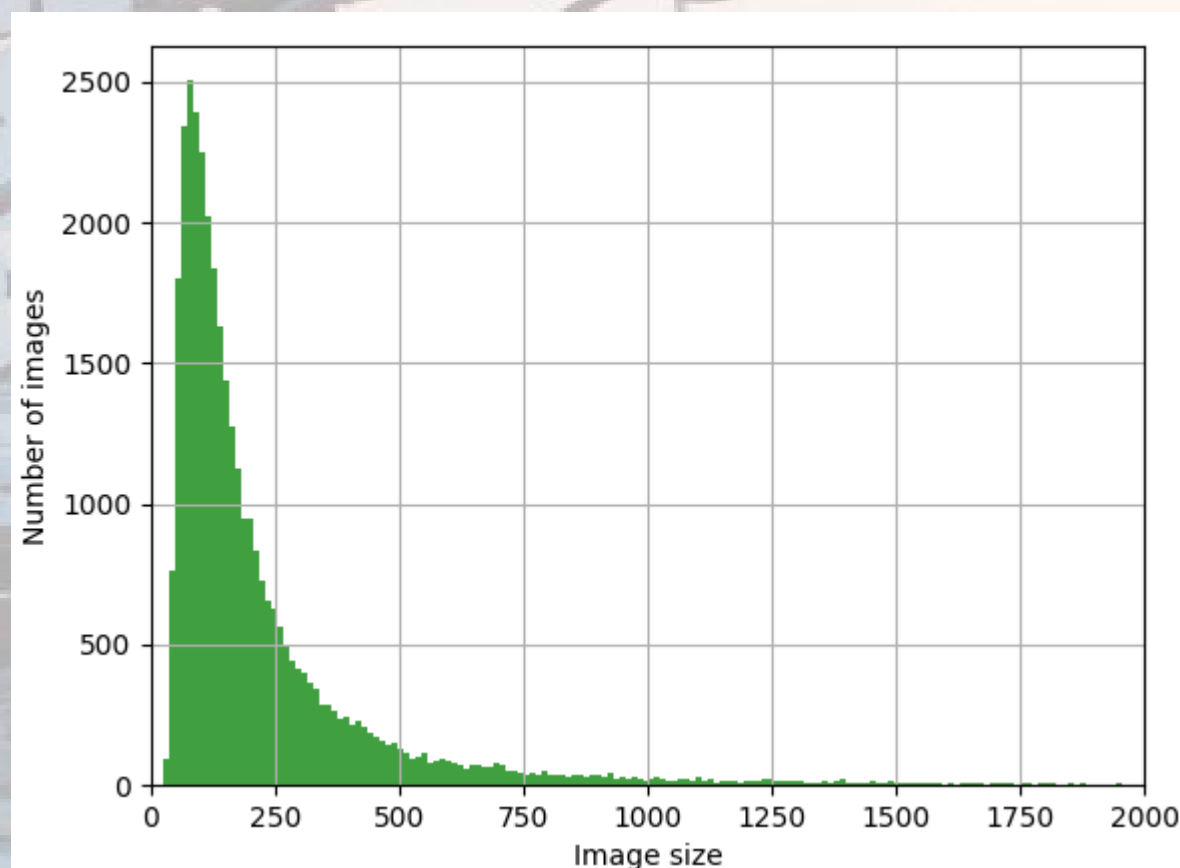
Size distribution of reference images

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

The plot shows the distribution of these images by size

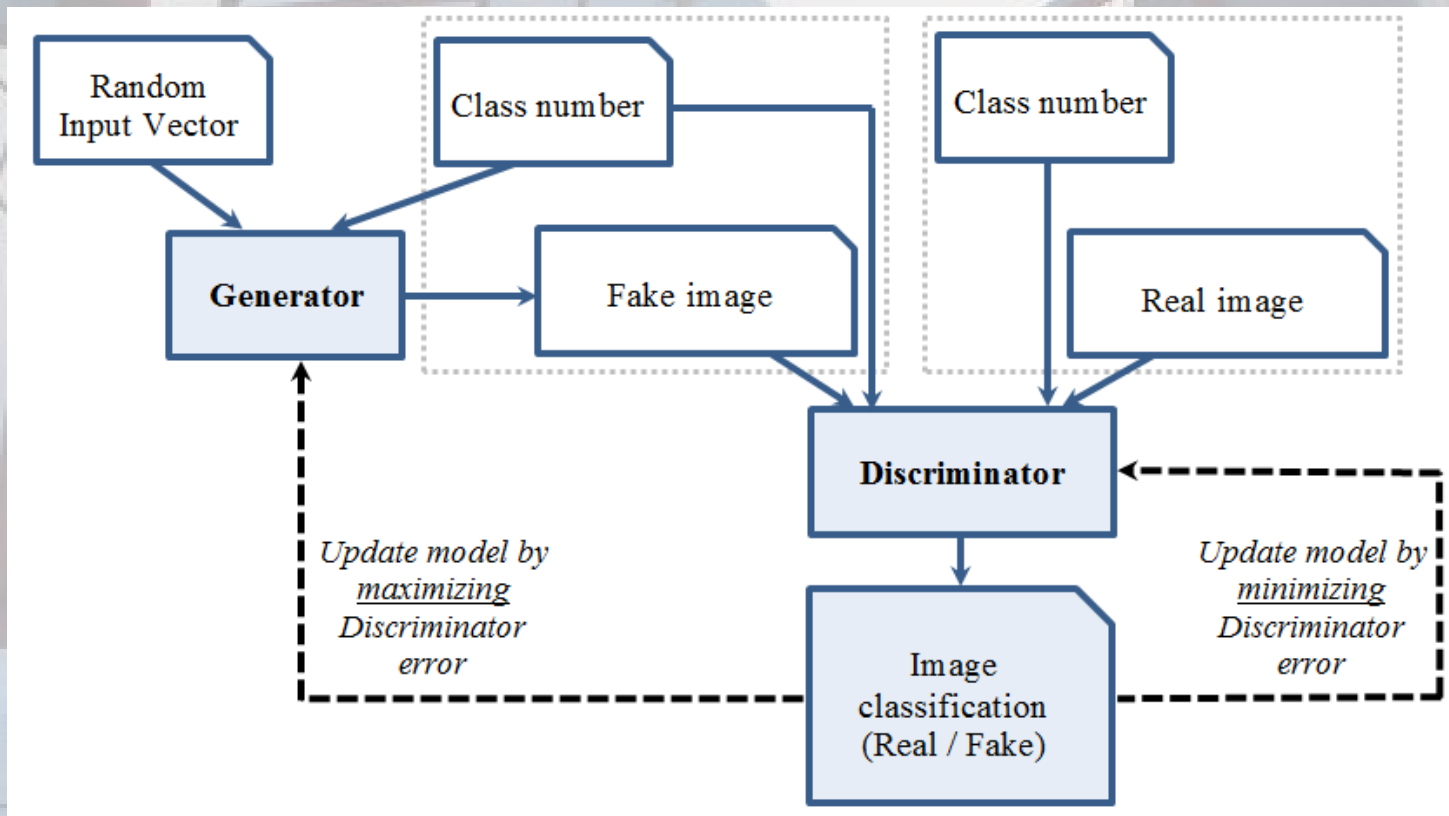
This distribution is very uneven and asymmetrical

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



Conditional generative adversarial network (cGAN)

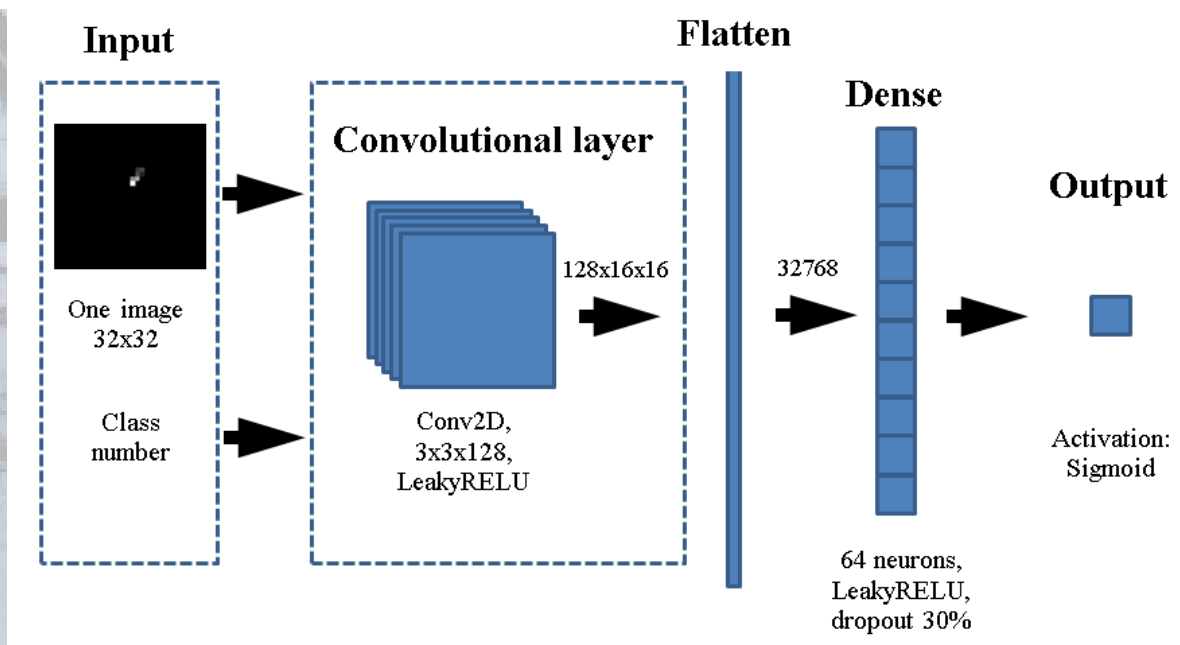
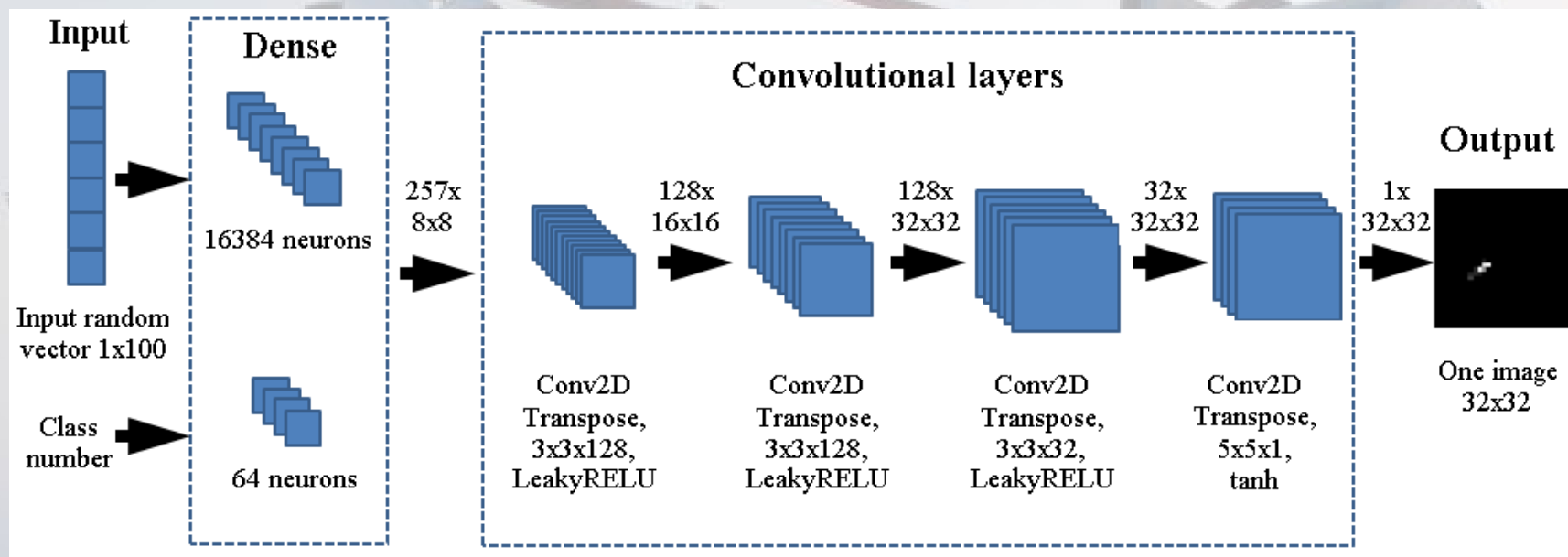
cGAN is a modification of a traditional GAN that allows you to divide images into multiple classes according to the value of some property of the image



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

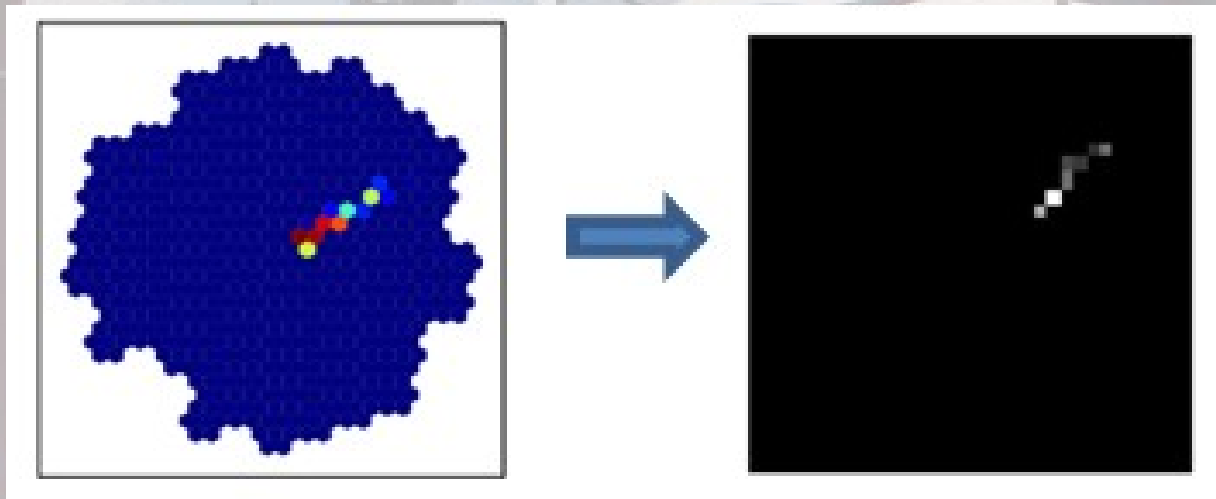
We divided the images into classes so that each class has the same number of images

cGAN architecture



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 image brightness differing by orders of magnitude, we had to switch to a logarithmic scale:

$$X \rightarrow \ln(1+x)$$

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 3950. The critical value corresponding for a 5% significance level is 124,34
- The chi-square test shows that the difference is significant

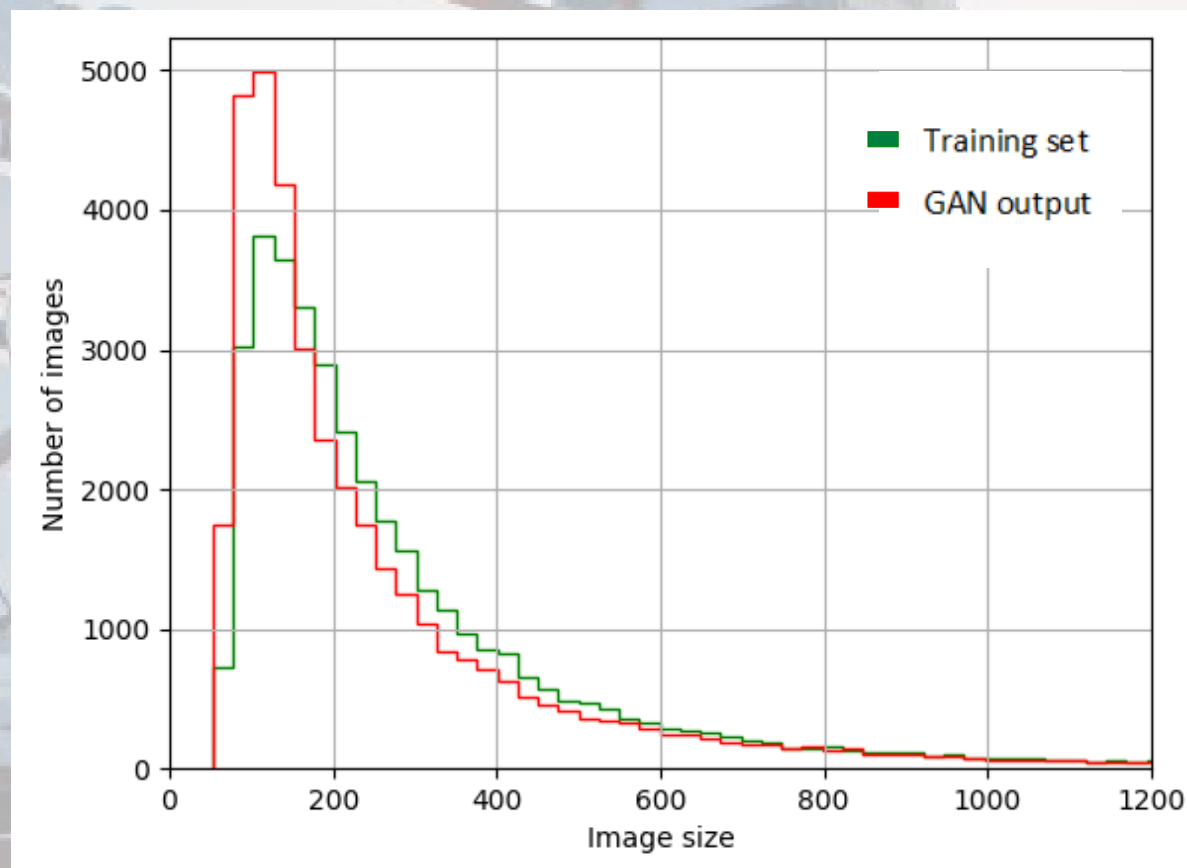
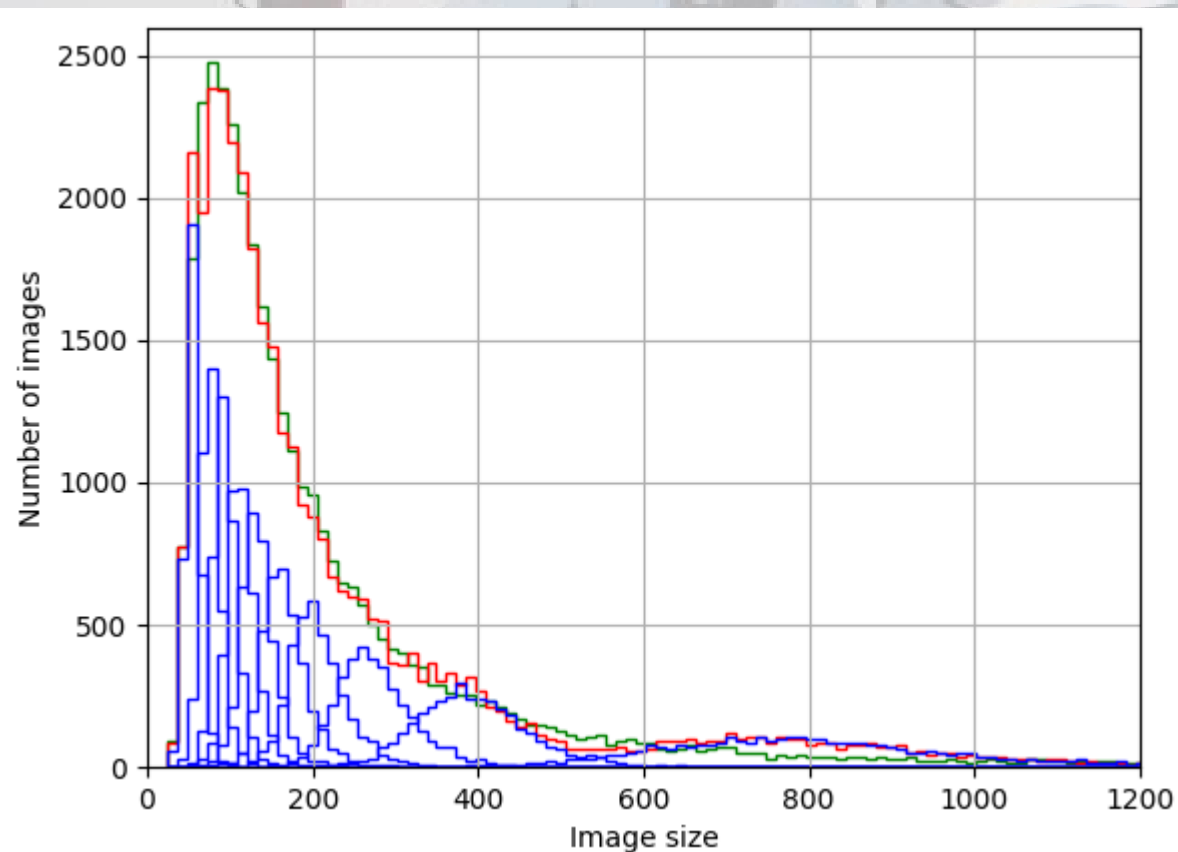


Image size distribution for samples generated by cGAN with 10 classes

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



■ Training set distribution

■ Summed distribution

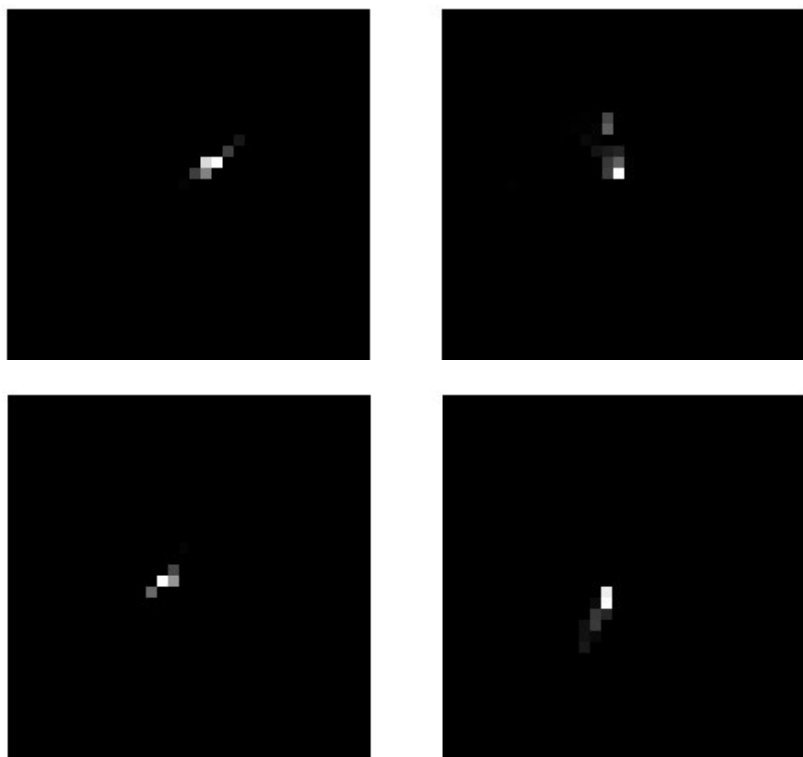
■ Distribution for each class

The Chi-Square test statistic is 950. 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, the network learned well

Every generated image can be easily converted back to hexagonal form

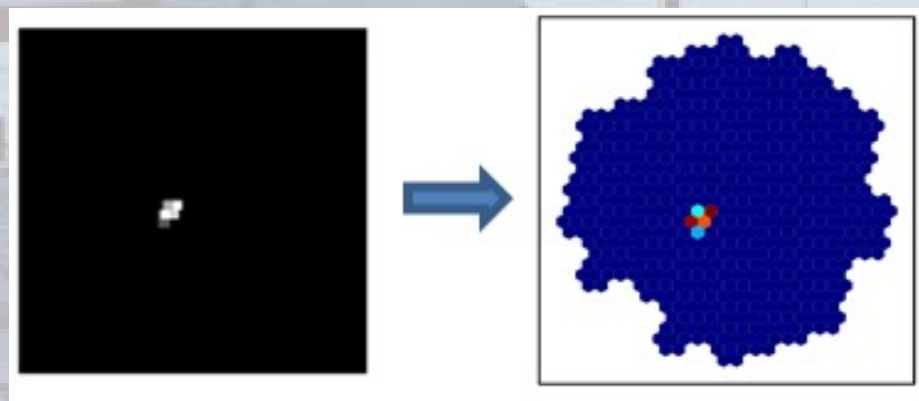
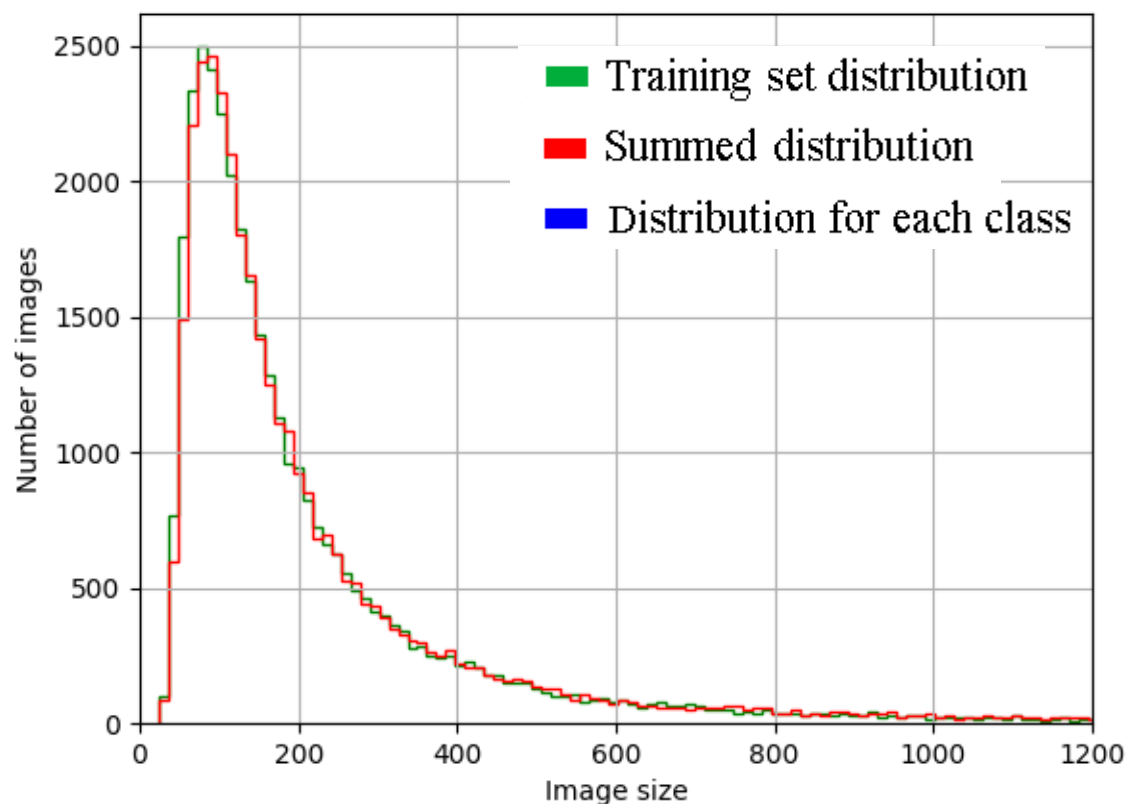


Image size distribution for samples generated by cGAN with 100 classes

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



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

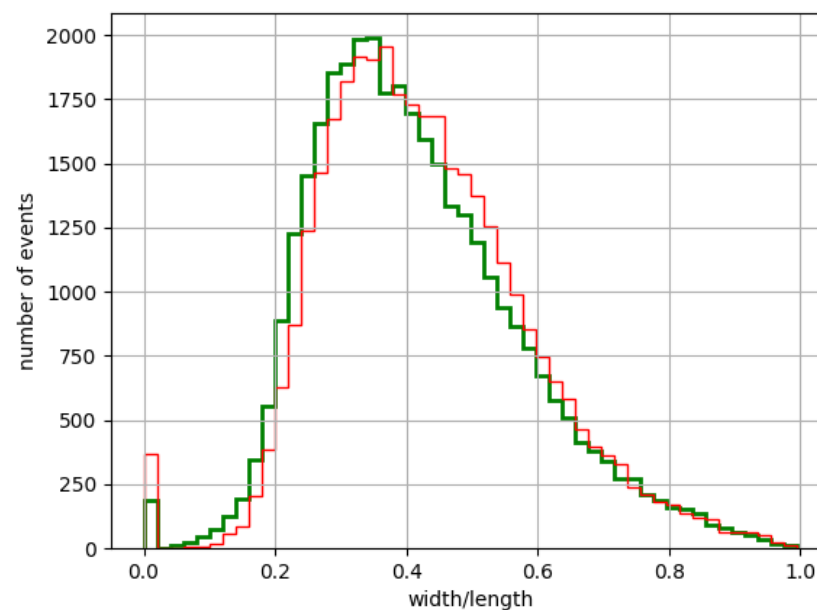
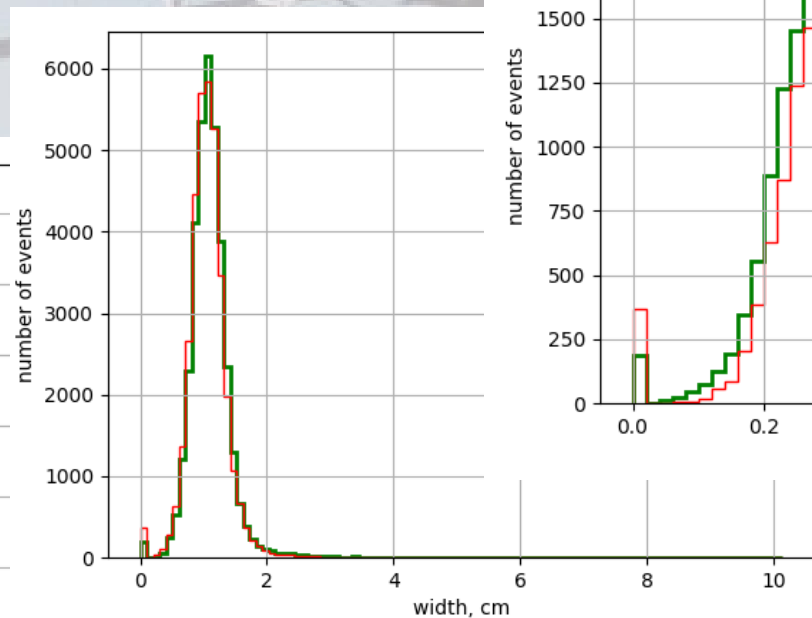
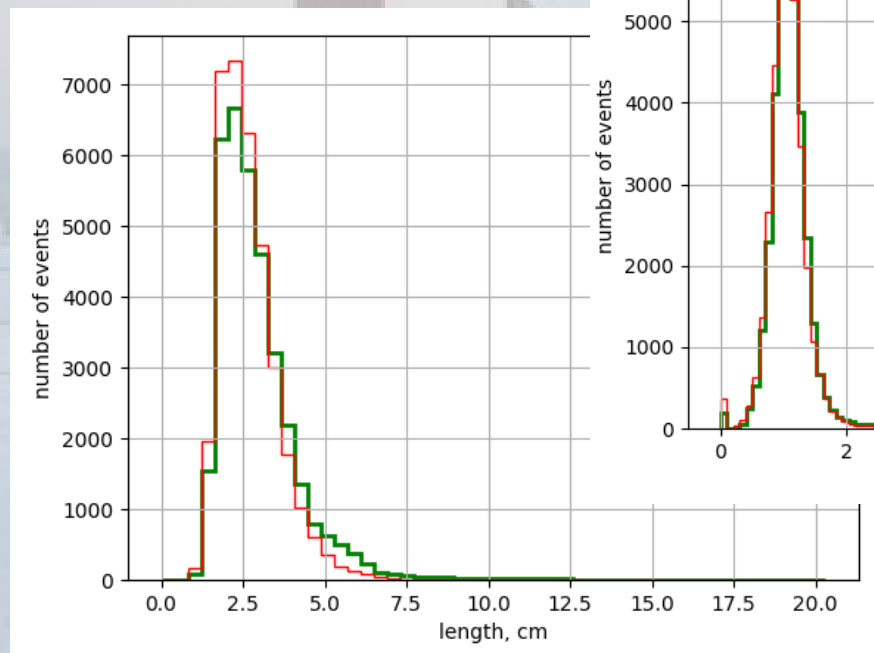
The chi-square test shows that the difference is not significant

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

cGAN with 100 classes. Hillas parameters.

■ Training set distribution

■ Summed distribution



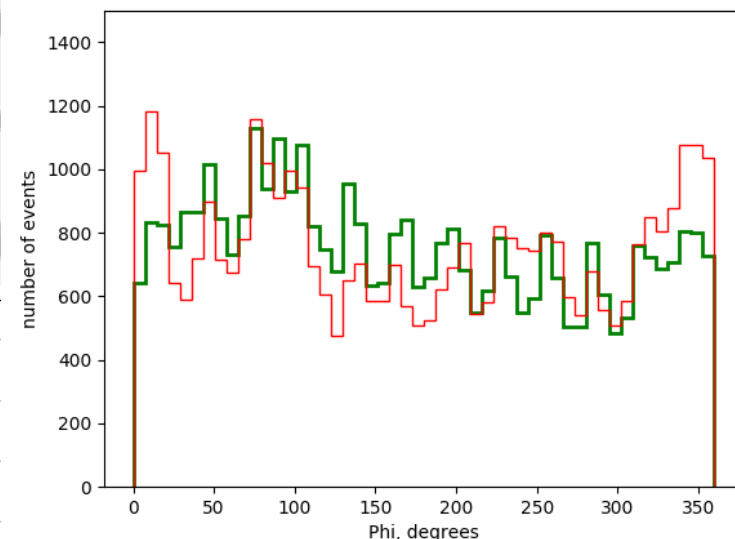
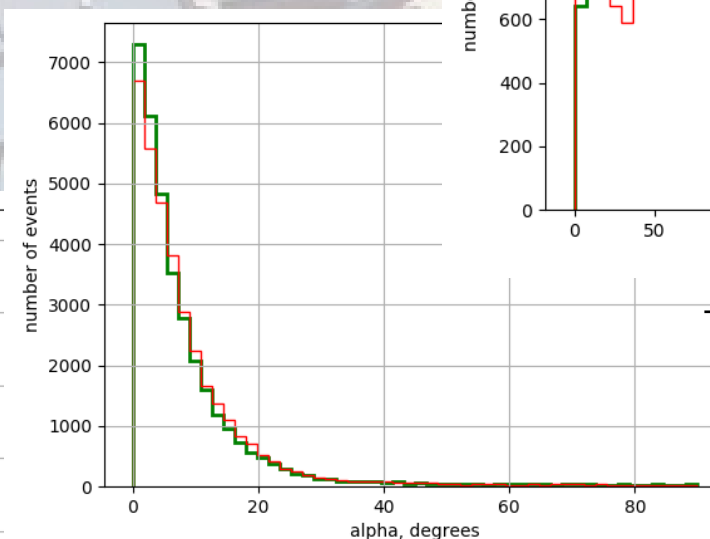
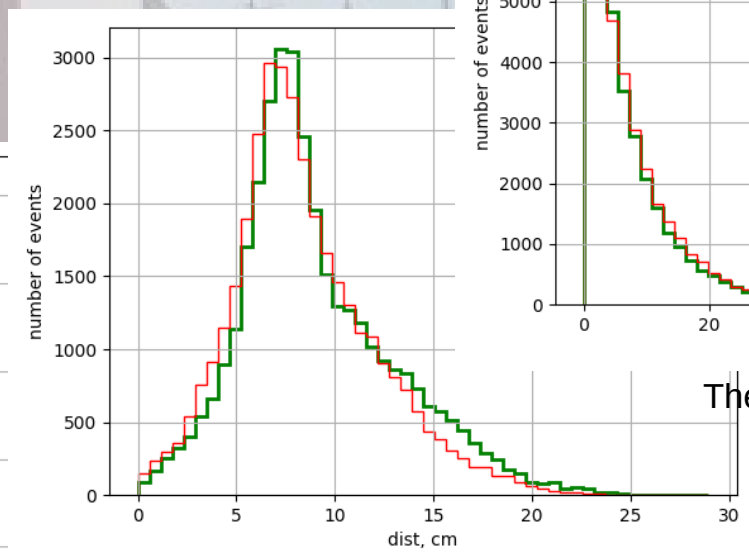
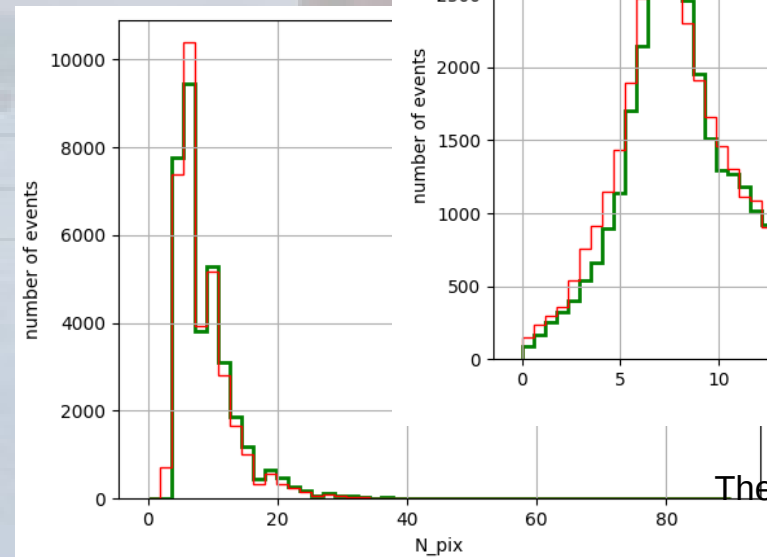
The Chi-Square test statistic is 261

The Chi-Square test statistic is 759

cGAN with 100 classes. Hillas parameters.

■ Training set distribution

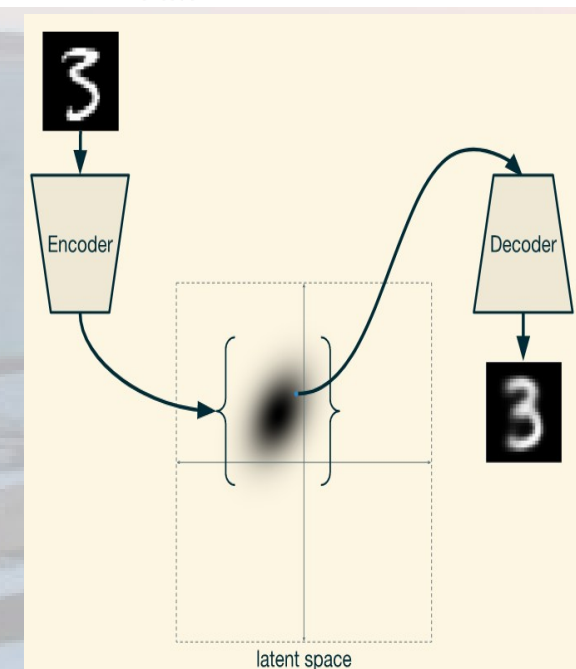
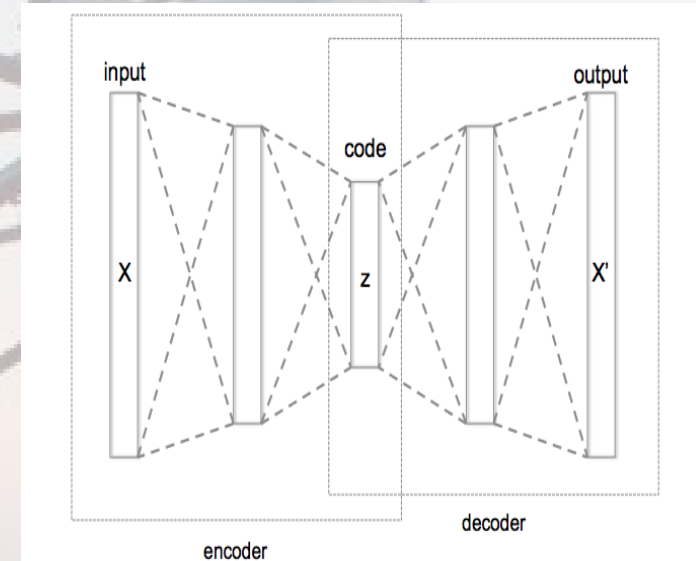
■ Summed distribution



The Chi-Square test statistic is 677

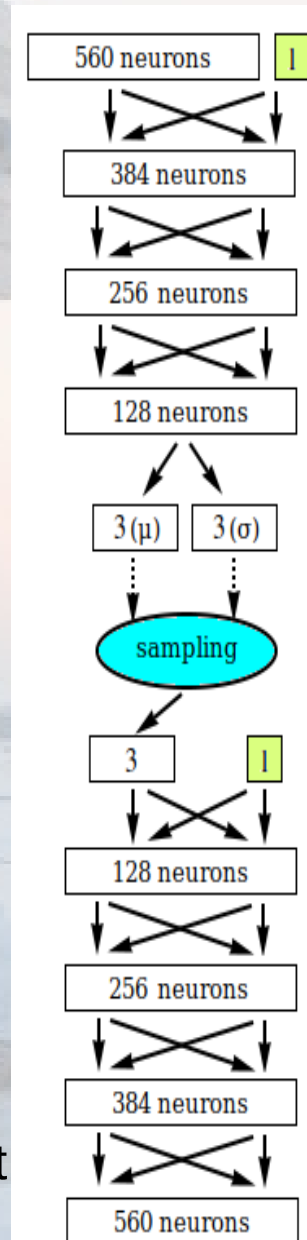
Variational AE / Conditional VAE

- Variational autoencoder is a probabilistic generative model. It is similar to autoencoders, consisting of an encoder and a decoder. However, in a variational autoencoder the encoder maps the input into a distribution in latent variable space, and the decoder reconstructs some image from a vector sampled from this distribution.
- In addition to the latent variables learned by the variational autoencoder, some parameters of the input data can be specified explicitly during training. These parameters are passed both to the encoder and the decoder and can be continuous as well as discrete (e.g. the energy and the type of a primary particle, respectively). When the trained CVAE is used to generate images, the desired values of the parameters can be specified.
 - Unlike constrained variational autoencoders, CVAEs only use these parameters as additional data rather than restrict the resulting images to have the specified values of the parameters.



CVAE Architecture

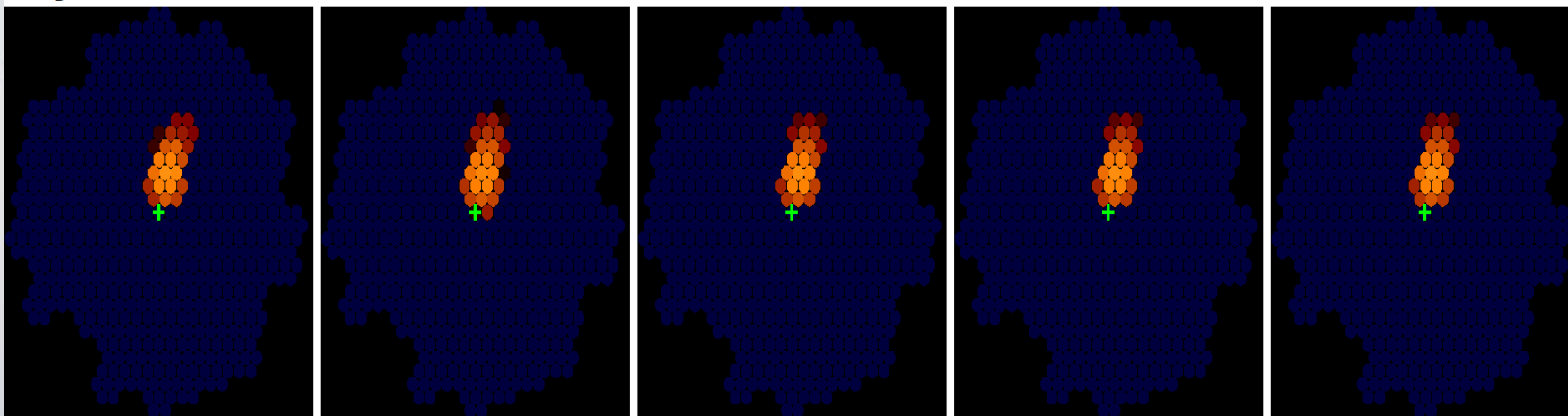
- The CVAEs had three fully connected layers both in the encoder and the decoder. For gamma images, the latent space had 3 dimensions (as shown on the figure). For proton images, it had 24 dimensions.
- The sum of the pixel amplitudes, or size, was used as the conditional parameter.
- The CVAEs were trained on a subset of 39443 gamma images and 28439 proton images simulated by Monte Carlo software for an IACT of the TAIGA experiment. The energy of the gamma quanta was 1.5–60 TeV, and the energy of the protons was 2–100 TeV.
- The CVAEs use a two-component loss function.
 - The first component corresponds to the differences between the input image and the image generated by the decoder. We primarily used mean squared error (MSE) as the image loss.
 - The second component of the loss function, called Kullback-Leibler loss (KL), restricts the shape of the latent distributions produced by the encoder.
 - By varying the relative weights of the components we can get different results.



Gamma events

Monte Carlo
(averaged)
gamma event

Variational autoencoder-generated (MSE loss)



size=111.0749 p.e.

size=108.6682 p.e.

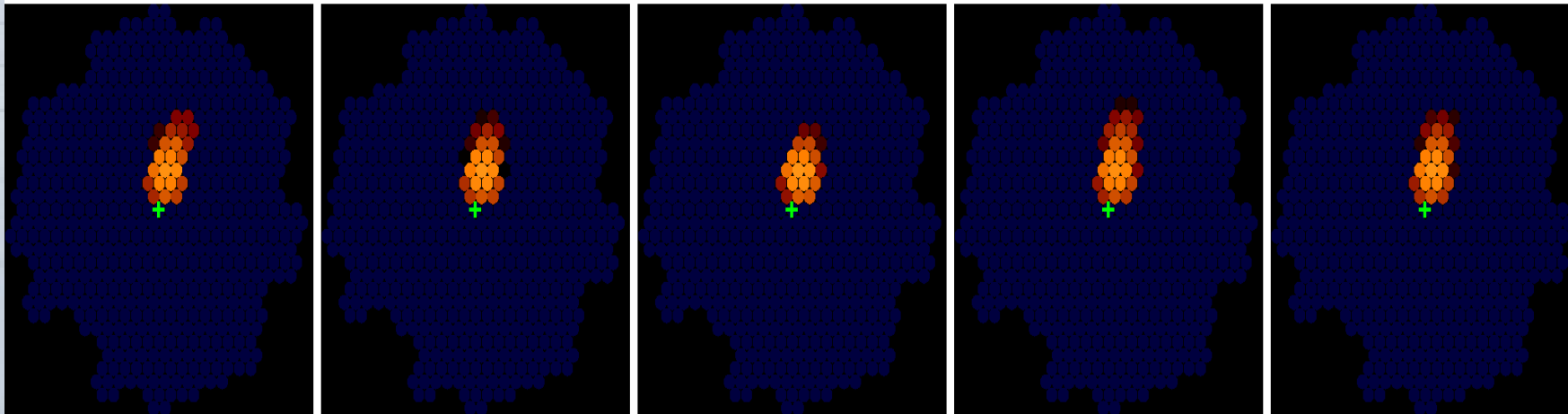
size=105.6221 p.e.

size=105.622 p.e.

size=105.6221 p.e.

Monte Carlo

Variational autoencoder-generated (MSE+20KL loss)



size=111.0749 p.e.

size=113.2564 p.e.

size=110.2026 p.e.

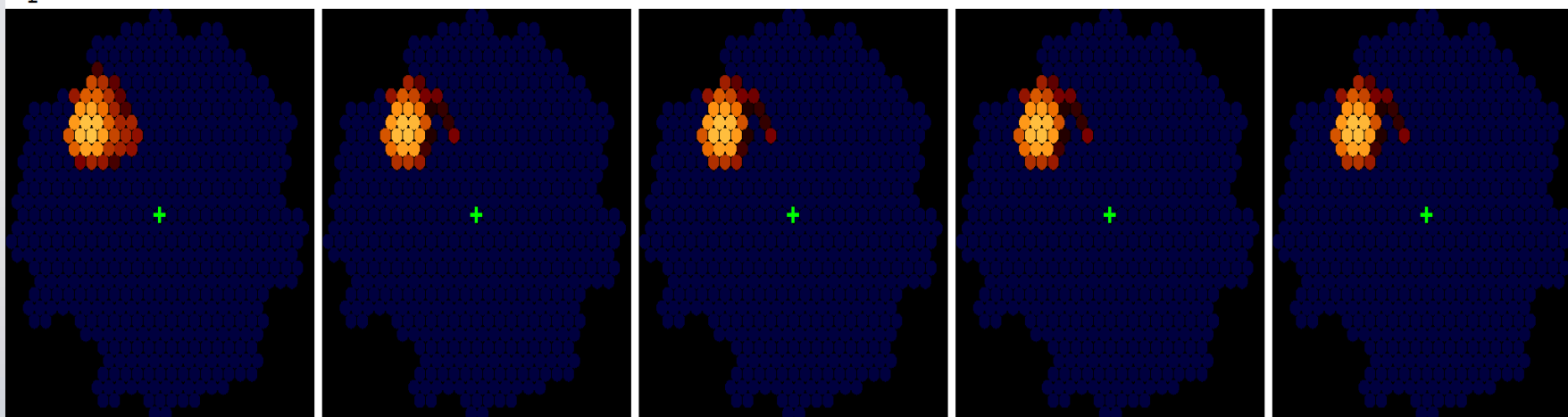
size=111.4948 p.e.

size=112.8767 p.e.

Proton events

Monte Carlo
(averaged)
proton event

Variational autoencoder-generated (MSE loss)



size=296.4704 p.e.

size=261.2336 p.e.

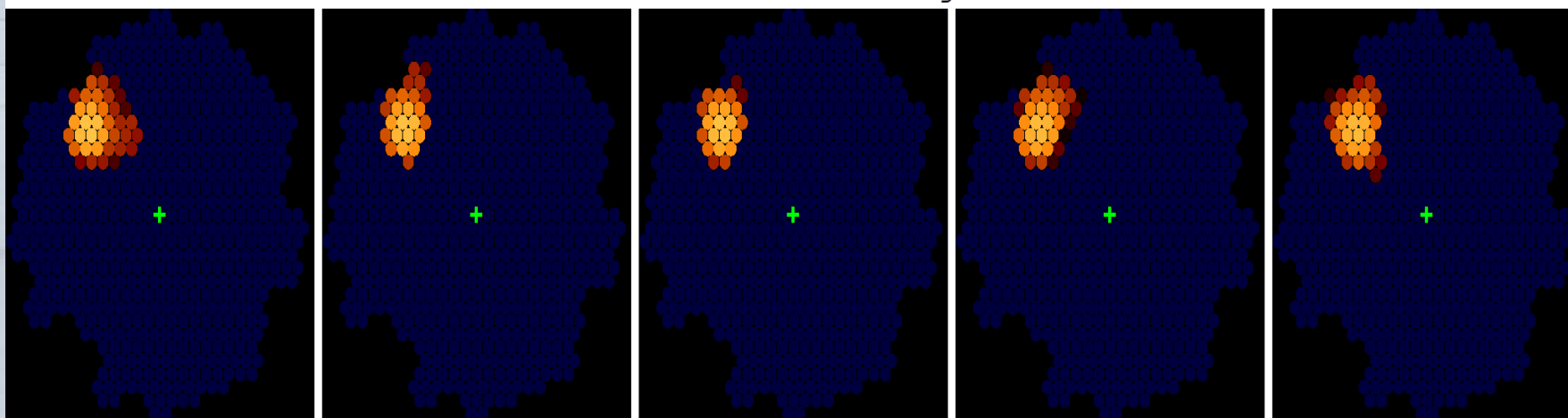
size=261.2338 p.e.

size=261.2337 p.e.

size=261.2334 p.e.

Monte Carlo

Variational autoencoder-generated (MSE+5KL loss)



size=296.4704 p.e.

size=267.2765 p.e.

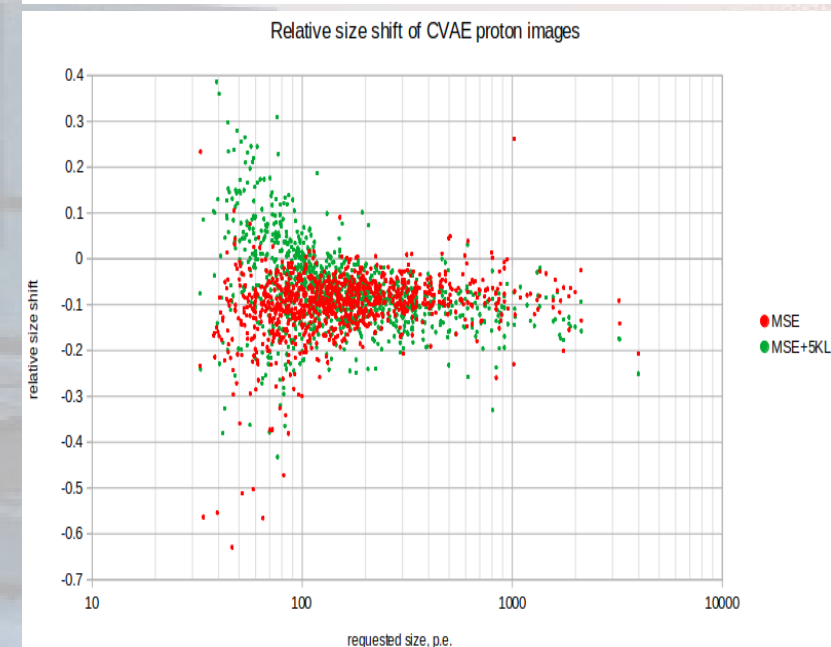
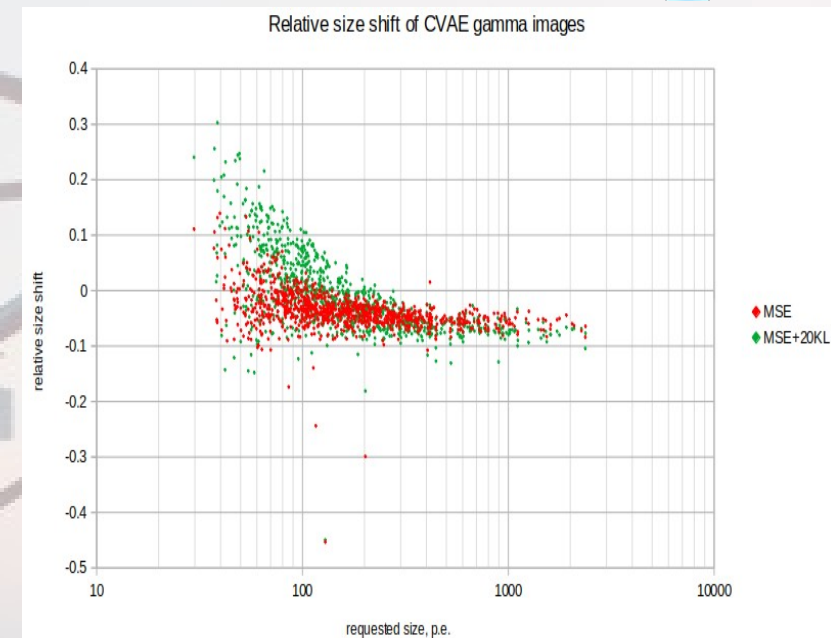
size=262.0009 p.e.

size=265.7133 p.e.

size=253.0644 p.e.

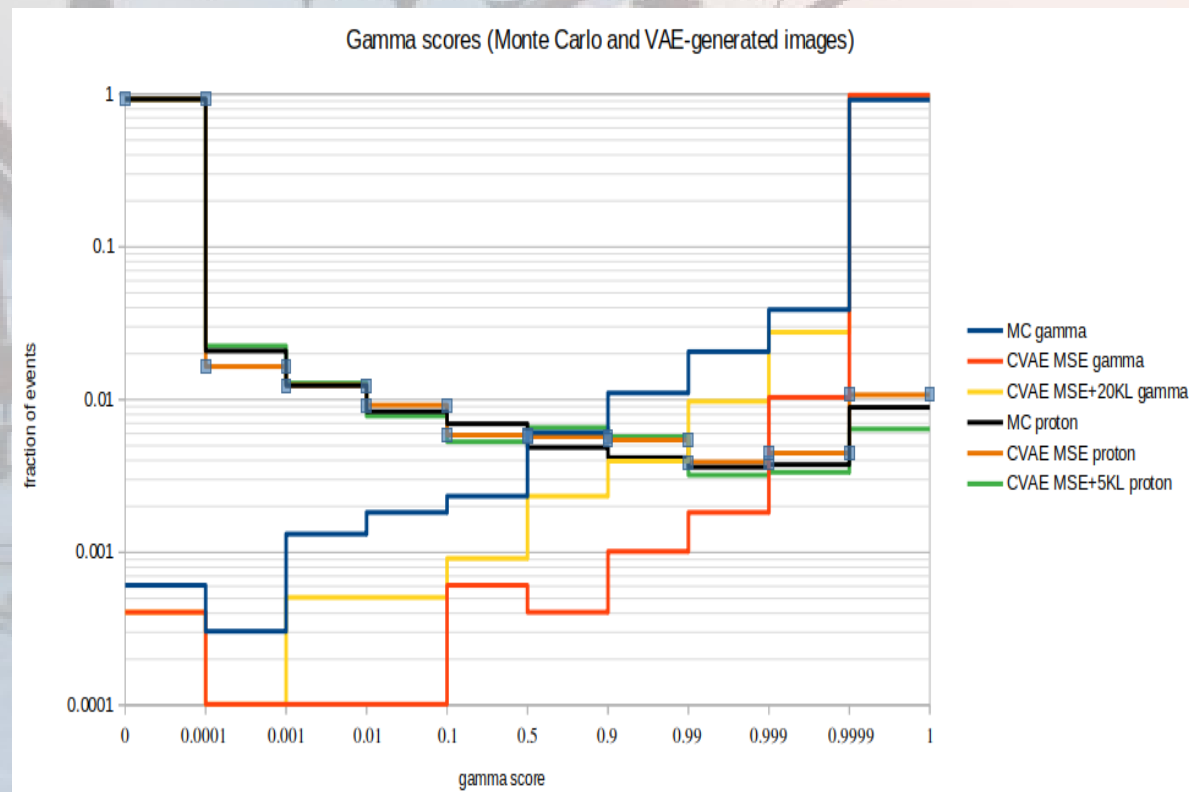
Image size

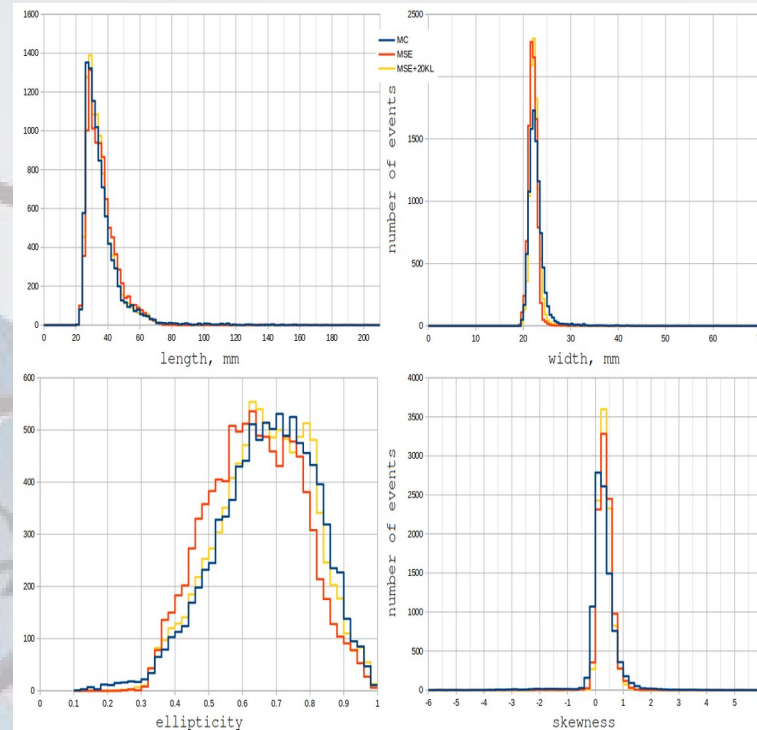
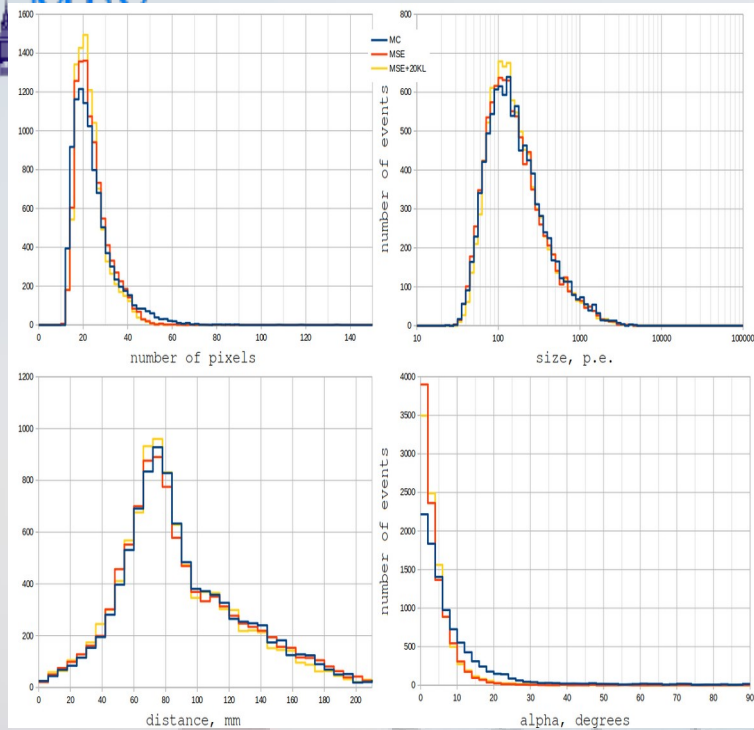
- CVAE-generated images tend to have lower size than the value of the conditional parameter used to generate them.
- For gamma images, the CVAE trained with MSE loss generates images with the average relative size shift -0.035 and the average relative size error 0.044 , the CVAE trained with MSE+20KL loss generates images with the average relative size shift -0.021 and the average relative size error 0.046 .
- For proton images, the CVAE trained with MSE loss generates images with the average relative size shift -0.09 and the average relative size error 0.105 , the CVAE trained with MSE+5KL loss generates images with the average relative size shift -0.081 and the average relative size error 0.104 .



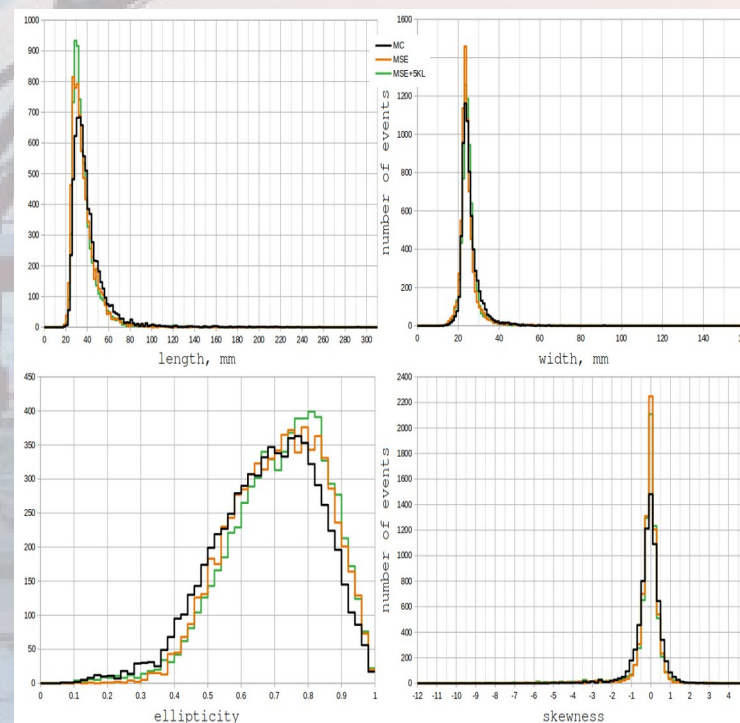
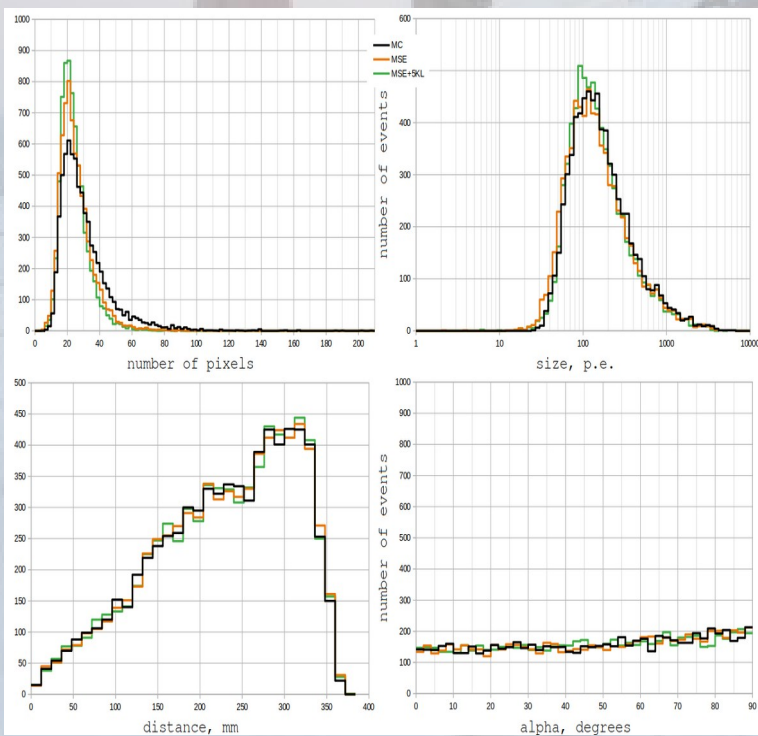
Gamma score

- A classifier neural network was trained on the same set of images as the variational autoencoders.
- The classifier gives the CVAE-generated gamma images the average gamma score 0.99863 for the CVAE with MSE loss and 0.99704 for the CVAE with MSE+20KL loss, respectively.
- For the CVAE-generated proton images the average gamma score is 0.03032 for the MSE autoencoder and 0.02485 for the MSE+5KL autoencoder, respectively.
- For comparison, Monte Carlo-simulated gamma events not used in the training set of the classifier get the average gamma score 0.99227; Monte Carlo-simulated proton events get the average gamma score 0.02612.





Gammas



Protons

Conclusion

- A conditional GAN 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 differ significantly from the corresponding distributions of the training set, but are still close in shape.
- The images generated by the CVAEs are similar enough to the Monte Carlo images
 - their gamma score by a classifier neural network is higher than that of Monte Carlo-simulated images for gamma events, and is close to the score of Monte Carlo-simulated images for proton events.
- The generated images on average have somewhat lower size than the requested values, with the average relative size error less than 5% for gamma events and less than 11% for proton events.
- For most Hillas parameters, the distributions of CVAE-generated images fail to reproduce the distributions of the Monte-Carlo events, but they are broadly similar.
- The rate of images generation using generative neural networks is more than 1000 times higher than the rate of generation by the traditional method.

Thank you!

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