The use of conditional variational autoencoders for simulation of EASs images from IACTs

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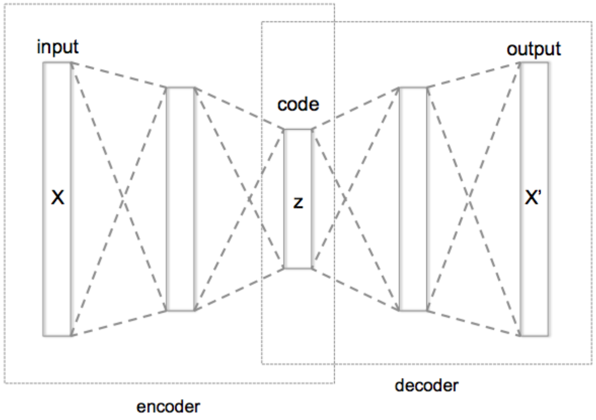
In gamma astronomy, the analysis of extensive area shower (EAS) images recorded by imaging atmospheric Cherenkov telescopes (IACTs) can be improved and for some methods requires synthetic images with known parameters of the primary particles. Typically the synthetic images are constructed using Monte Carlo simulation of the events.

We are developing methods for using conditional variational autoencoders (CVAEs) to generate synthetic IACT images corresponding to both gamma and hadron events. To be useful, the resulting images need to reproduce both the explicitly specified conditional parameters and the general distributions of some characteristics of the images.

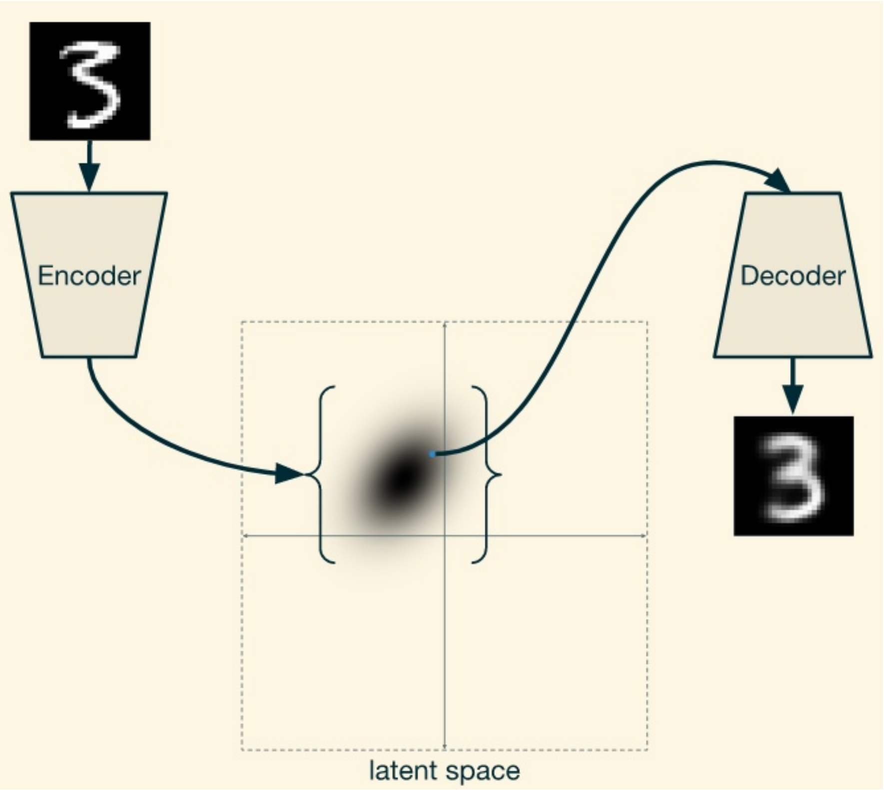
Autoencoders

Autoencoders are artificial neural networks that learn efficient encodings of the input data. An autoencoder consists of an encoder that maps the input into a low-dimensional vector called latent vector or code, and a decoder that attempts to reconstruct the input from the code. Trained autoencoders learn to ignore insignificant data and are useful in e.g. image denoising or data compression.



Variational autoencoders

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.



Conditional variational autoencoders

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. However, 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.

Input data

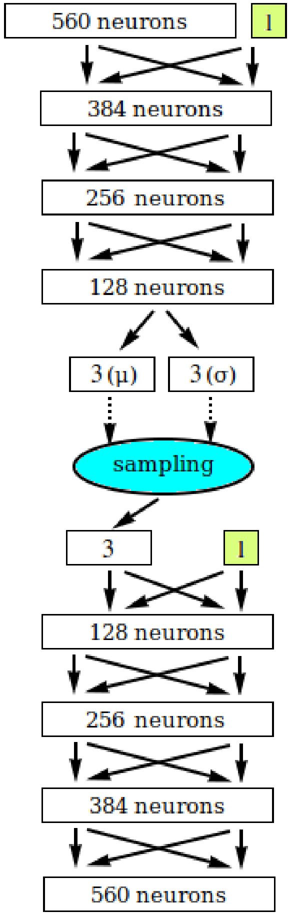
The CVAEs were trained on a subset of 39443 gamma images and 28439 proton images simulated by Monte Carlo software for an IACT of the TAIGA experiment. The energy of the gamma quanta was 1.5–60 TeV, and the energy of the protons was 2–100 TeV.

The TAIGA IACT located in Tunka valley, Russia

The CVAE architecture

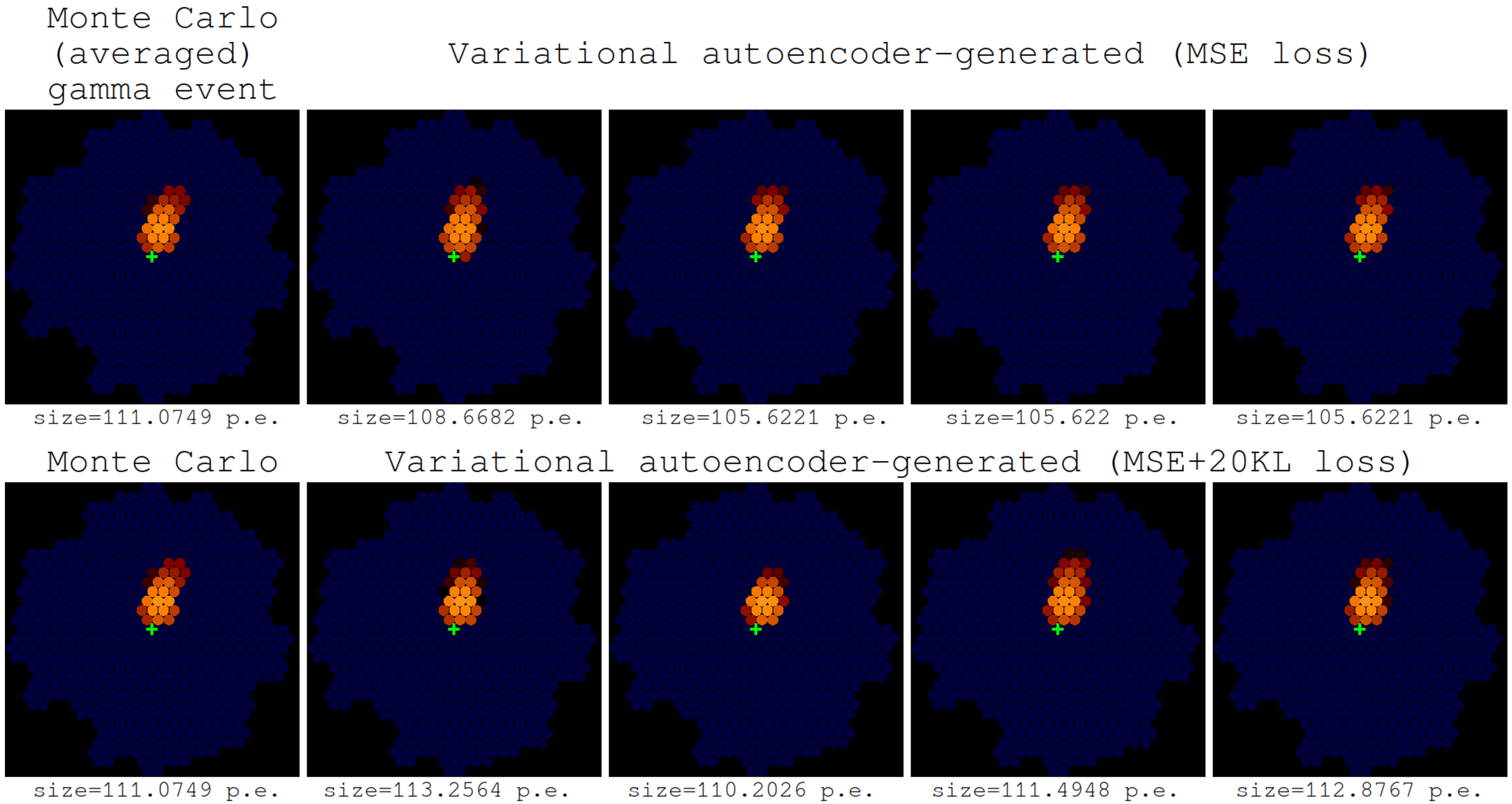
TThe CVAEs had three fully connected layers both in the encoder and the decoder. For gamma images, the latent space had 3 dimensions (as shown on the figure). For proton images, it had 24 dimensions.

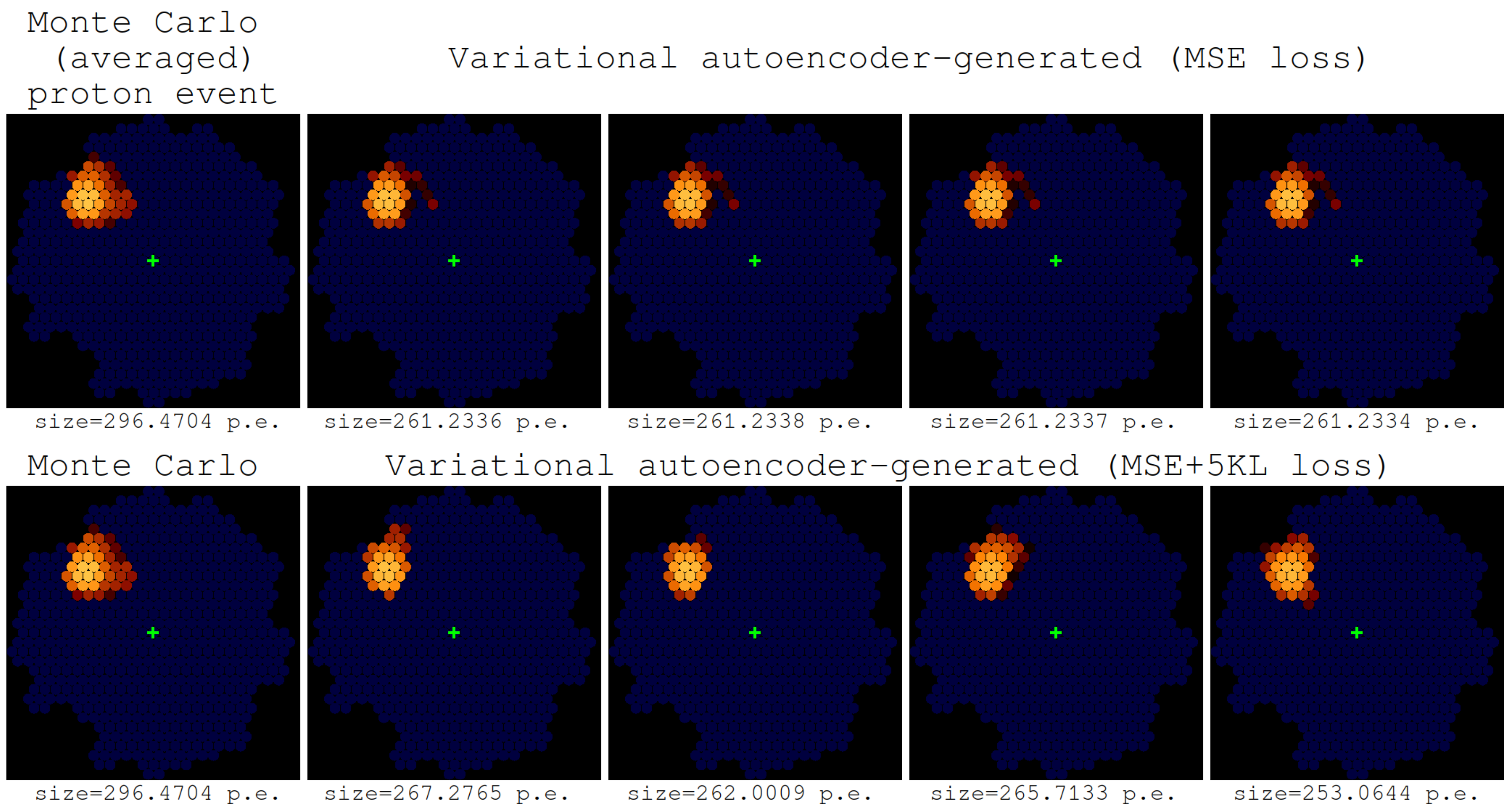
The sum of the pixel amplitudes, or size, was used as the conditional parameter.



Loss functions

The CVAEs use a two-component loss function: the first component, called image loss, 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.


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.



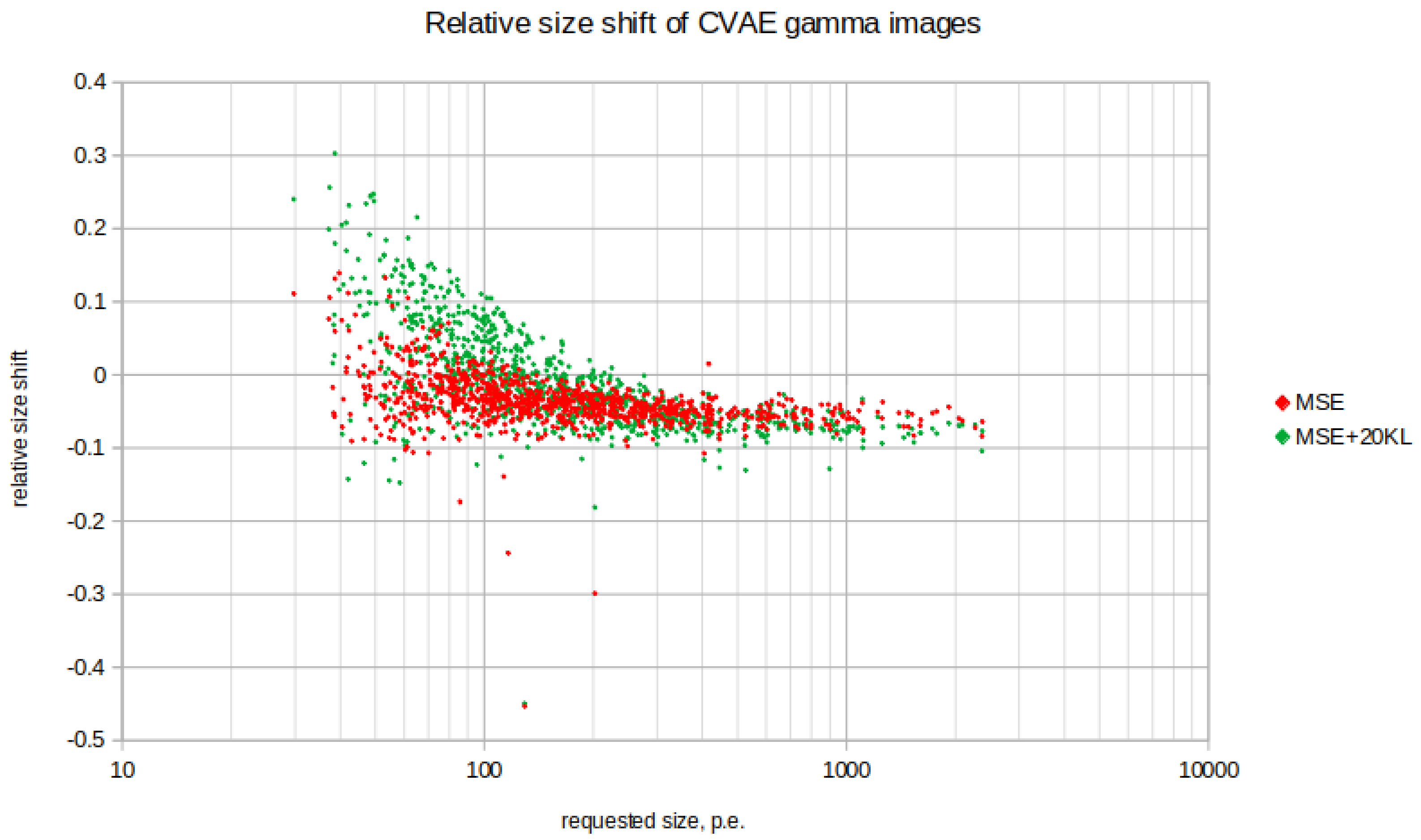
Monte Carlo (averaged) proton event
Variational autoencoder-generated (MSE loss)
size=296.4704 p.e.
size=261.2336 p.e.
size=261.2338 p.e.
size=261.2337 p.e.
size=261.2334 p.e.
Monte Carlo
Variational autoencoder-generated (MSE+5KL loss)
size=296.4704 p.e.
size=267.2765 p.e.
size=262.0009 p.e.
size=265.7133 p.e.
size=253.0644 p.e.

Image size

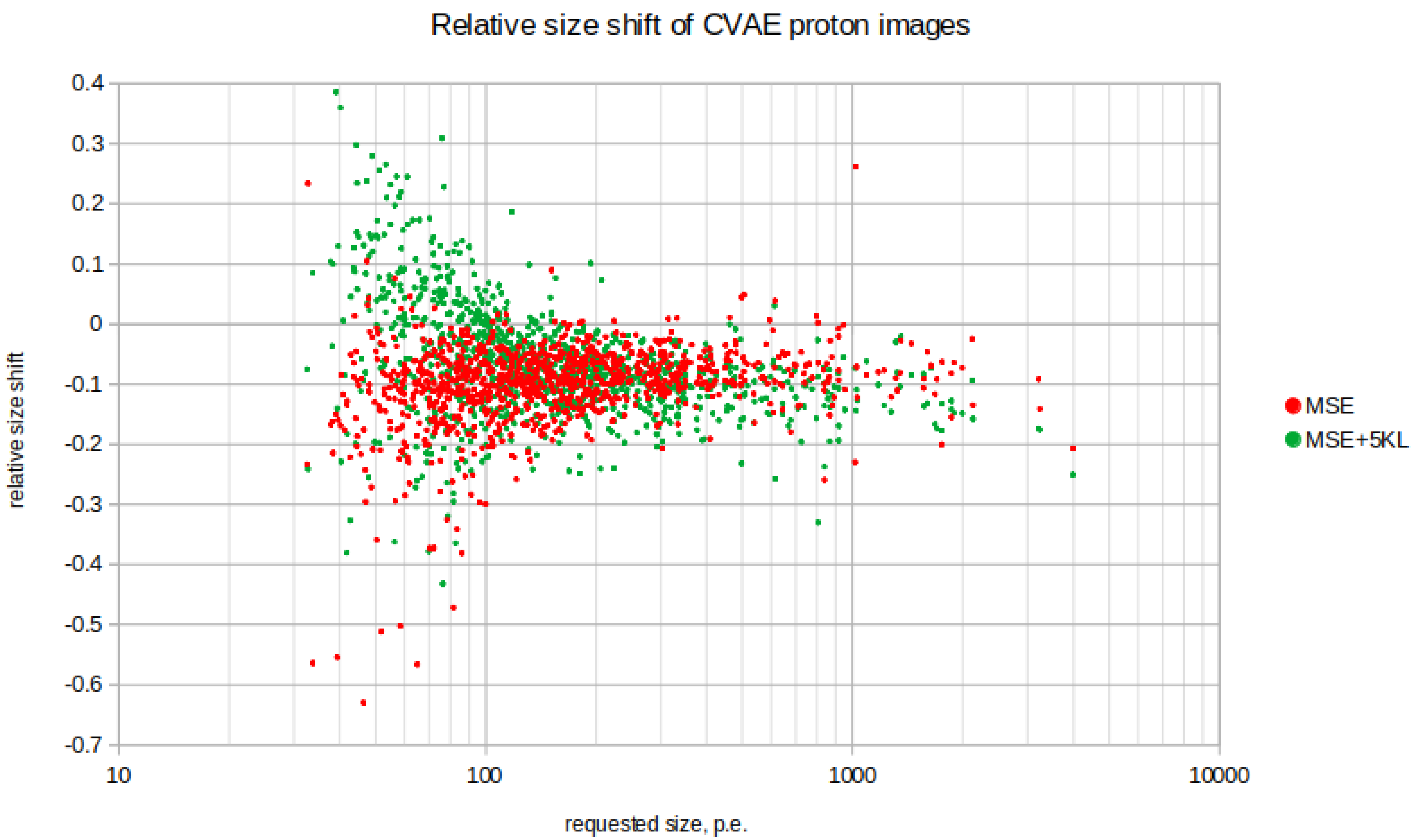
CVAE-generated images tend to have lower size than the value of the conditional parameter used to generate them.

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.



Relative size shift of CVAE gamma images
relative size shift
requested size, p.e.
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
10
100
1000
10000
MSE
MSE+20KL


Relative size shift of CVAE proton images
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-0.7
relative size shift
10
100
1000
10000
requested size, p.e.
MSE
MSE+5KL

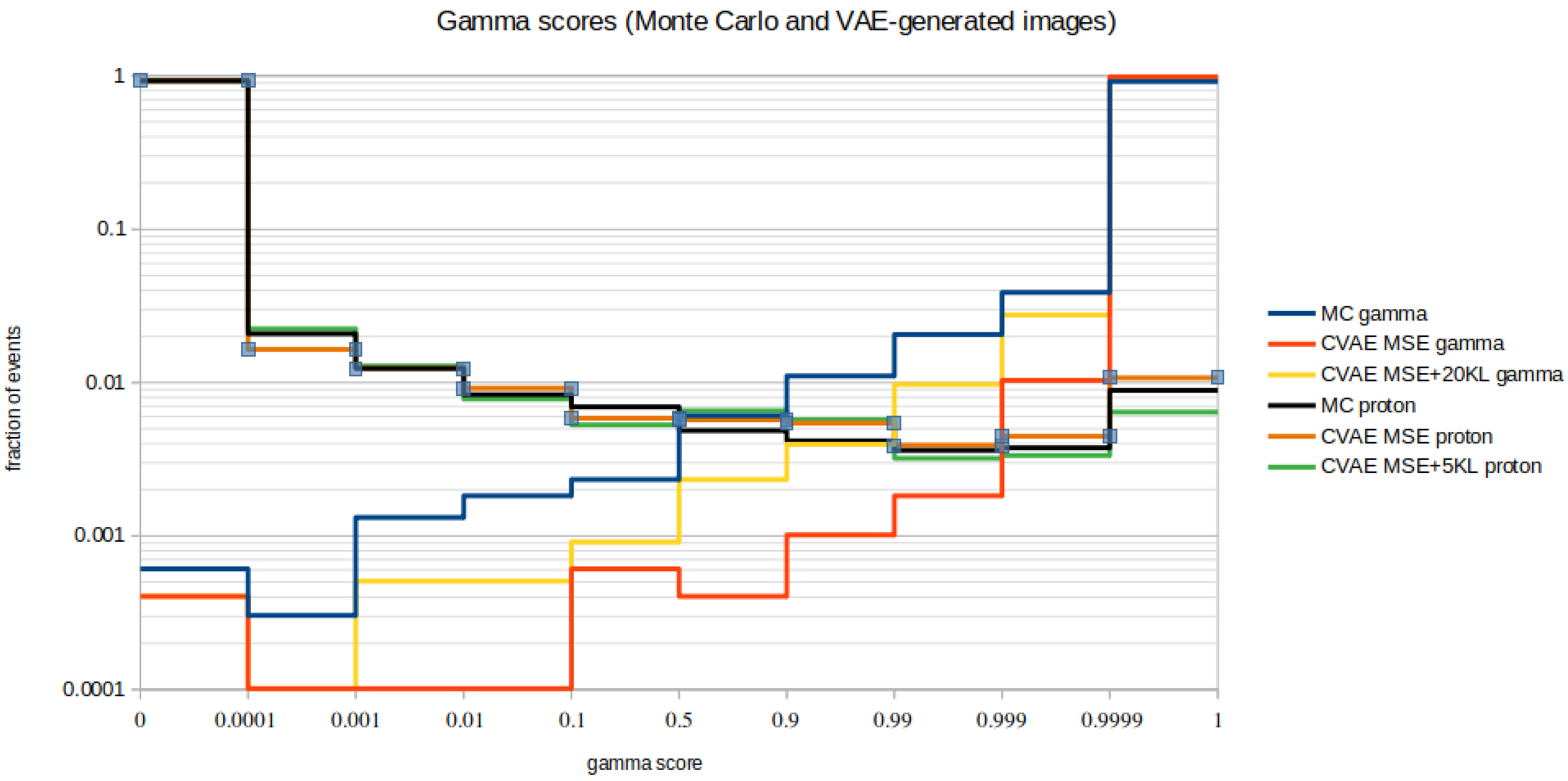
Gamma score

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.

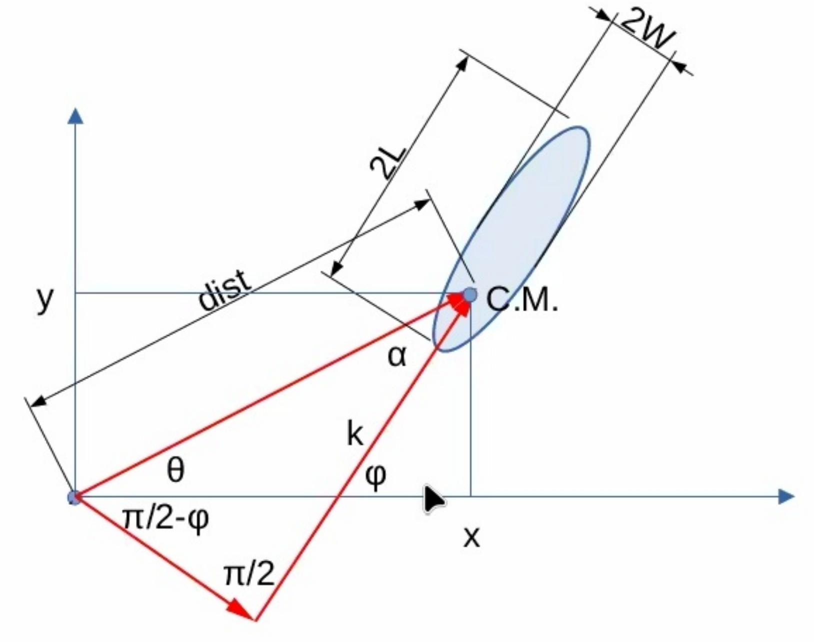
For the CVAE-generated proton images the average gamma score is 0.03032 for the MSE autoencoder and 0.02485 for the MSE+5KL autoencoder, respectively.

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.

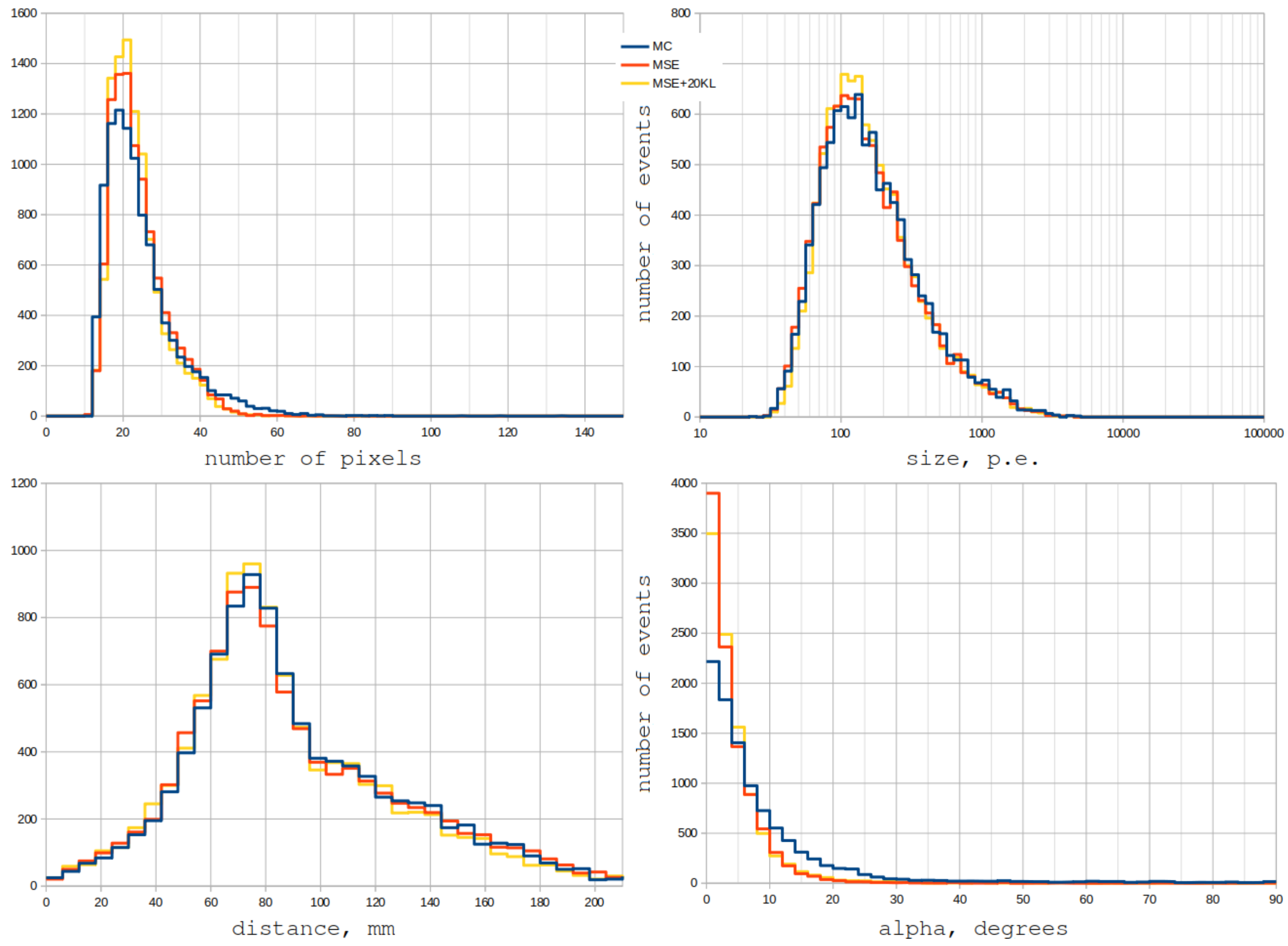

Gamma scores (Monte Carlo and VAE-generated images)
1
0.1
0.01
0.001
0.0001
fraction of events
0
0.0001
0.001
0.01
0.1
0.5
0.9
0.99
0.999
0.9999
1
gamma score
MC gamma
CVAE MSE gamma
CVAE MSE+20KL gamma
MC proton
CVAE MSE proton
CVAE MSE+5KL proton

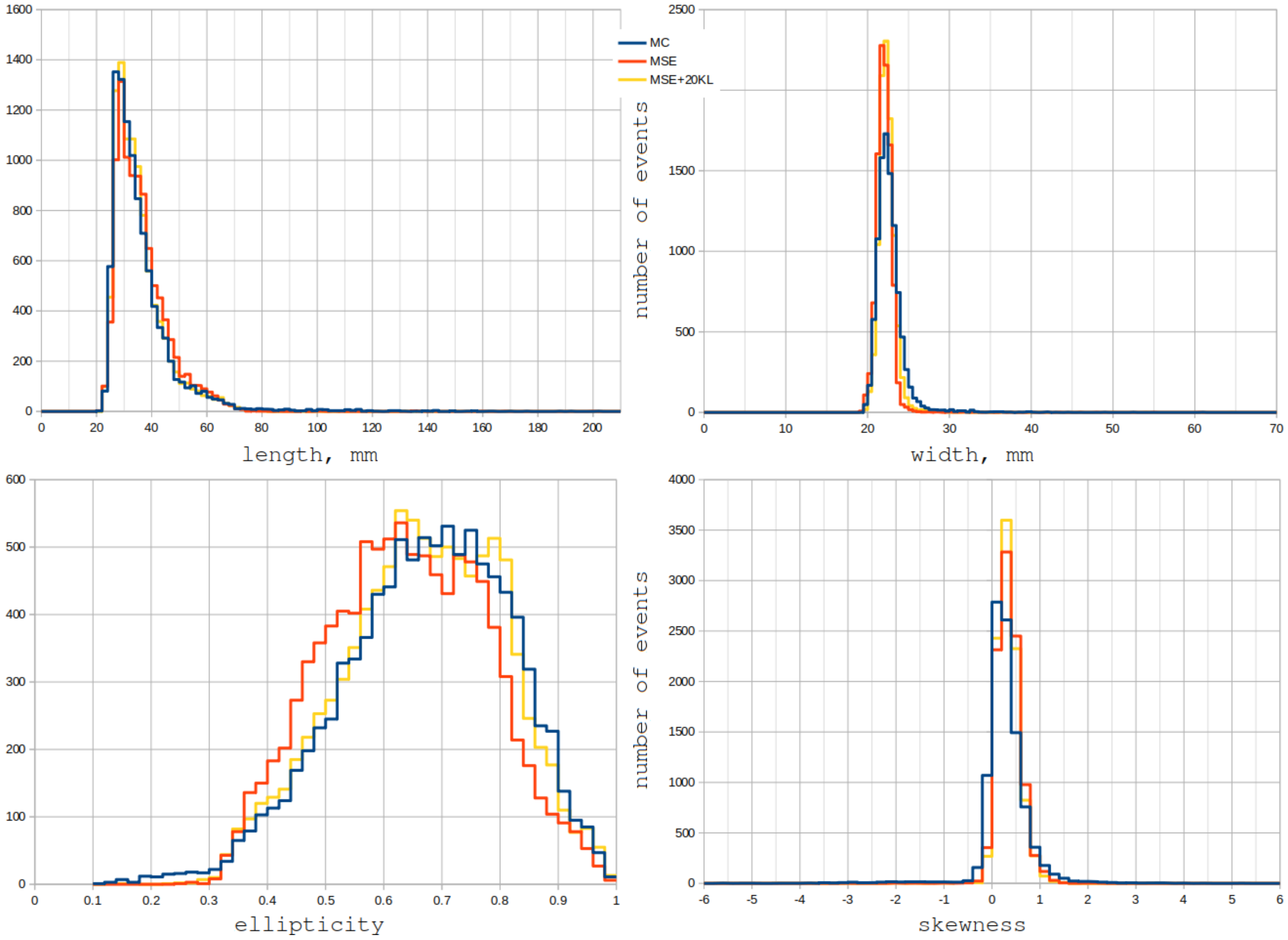
Hillas parameters

IACT images are often analyzed using Hillas parameters.

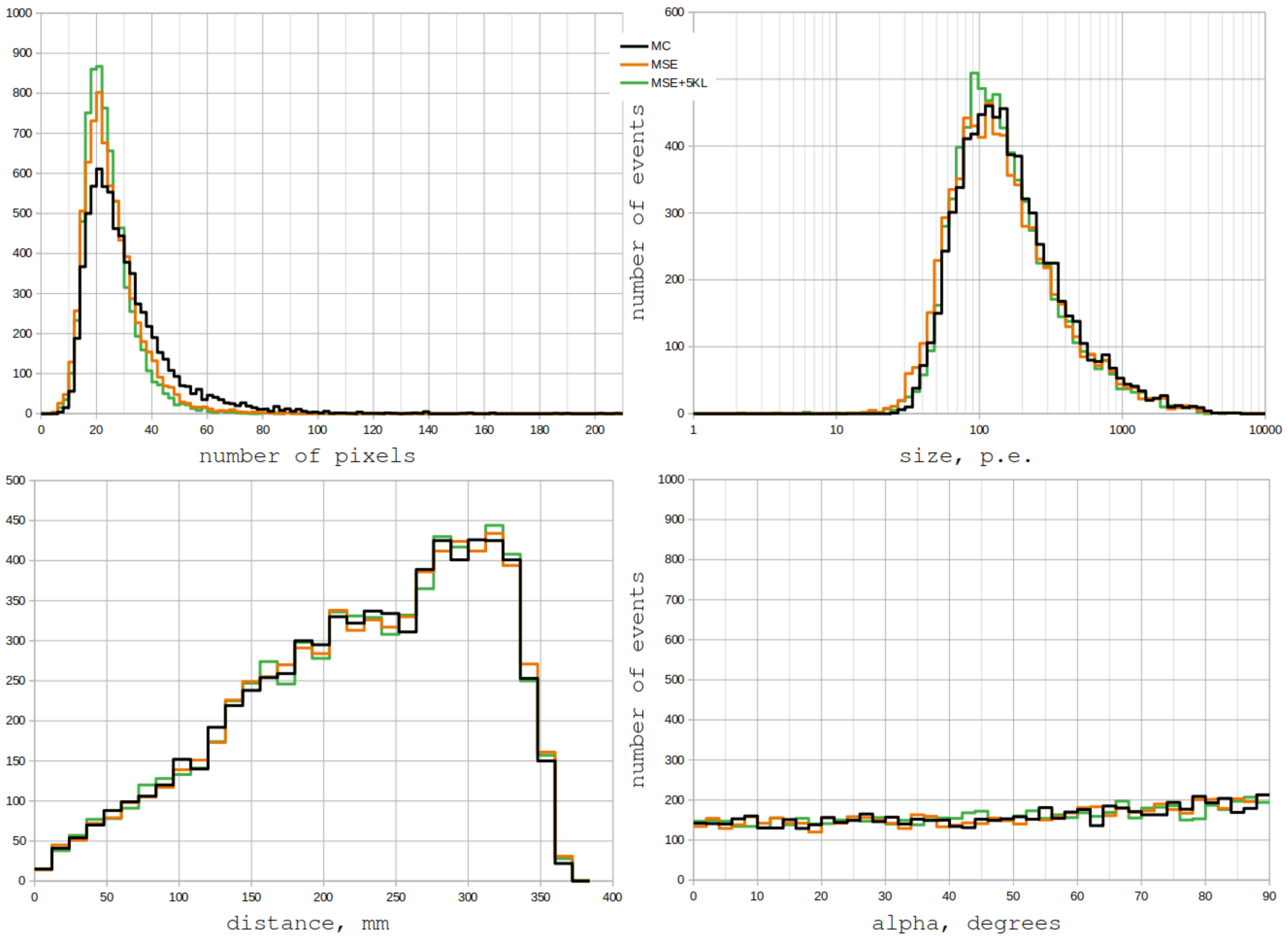


We use them to analyze distributions of CVAE-generated images.

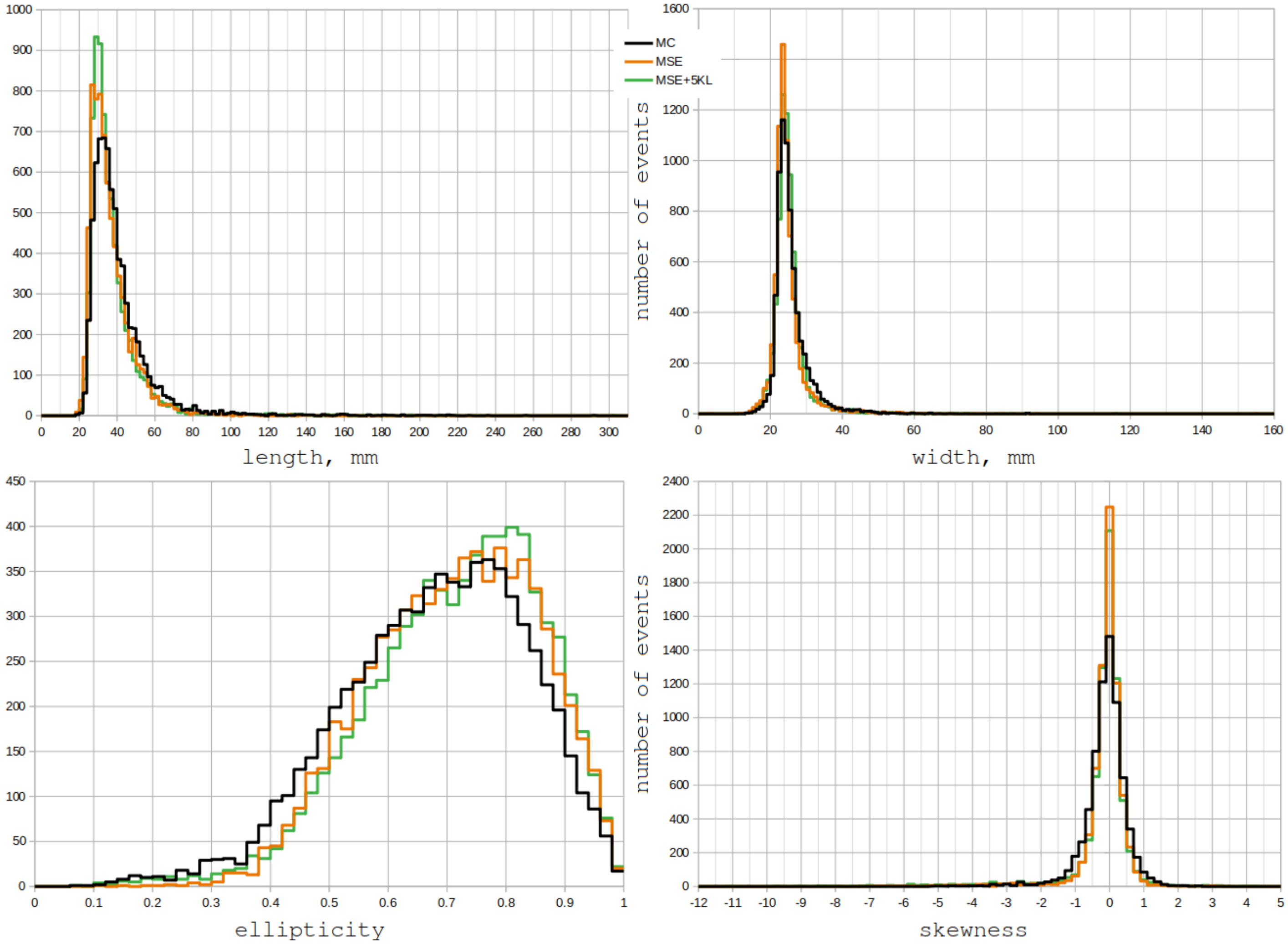

MC
MSE
MSE+20KL
number of events
number of pixels
size, p.e.
distance, mm
alpha, degrees



MC
MSE
MSE+20KL
number of events
length, mm
width, mm
ellipticity
skewness



MC
MSE
MSE+5KL
number of events
number of pixels
size, p.e.
number of events
distance, mm
alpha, degrees



MC
MSE
MSE+5KL
number of events
length, mm
width, mm
number of events
ellipticity
skewness

Conclusion

We trained conditional variational autoencoders (CVAEs) using Monte Carlo-simulated images of gamma and proton events.

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 then 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.

χ^2 values for Hillas parameters

gamma

	MSE	MSE+20KL	df	Critical 5%
N_pix	609.0891058	887.6701627	28	41.337
x_mean	45.80899322	91.63605215	28	41.337
y_mean	70.87416954	80.10969589	29	42.557
dist	101.305579	137.5484785	41	56.942
length	629.7337715	220.0488486	31	44.985
width	2390.013573	1159.529392	25	37.652
azwidth	3460.871162	1585.259318	28	41.337
miss	3643.424663	3179.350418	38	53.384
alpha	2907.222648	2283.443391	44	60.481
Phi	718.0164806	675.006579	44	60.481
Theta	39.22077309	53.71315502	44	60.481
conc	848.1267181	771.2395418	34	48.602
log10(size)	60.56211873	125.6303529	40	55.758
asym	1905.133387	2058.138052	30	43.773
ellipticity	1053.899056	206.1421293	42	58.124

proton

	MSE	MSE+5KL	df	Critical 5%
N_pix	1083.739407	1504.394165	44	60.481
x_mean	6.647549472	13.33494281	29	42.557
y_mean	10.29233941	8.625579024	28	41.337
dist	18.54804439	23.23774	30	43.773
length	1089.561808	724.1048811	34	48.602
width	742.7169116	430.7105854	36	50.998
azwidth	771.0660185	457.2649577	34	48.602
miss	75.55526927	83.62719791	44	60.481
alpha	69.86978251	98.45930057	44	60.481
Phi	95.82918493	128.7052417	59	77.931
Theta	19.82439934	36.63682251	59	77.931
conc	544.3752634	304.8337186	34	48.602
log10(size)	716.40742	288.1304718	42	58.124
asym	1160.133124	1689.022385	30	43.773
ellipticity	393.0378463	441.8909257	43	59.304