

MACHINE LEARNING METHODS FOR THE ANALYSIS OF TAIGA EXPERIMENT DATA[†]

A.Kryukov^{1,*}, A.Demichev¹, E.Gres^{1,2}, A.Vlaskina^{1,3},
Ju.Dubenskaya¹, S.Polyakov¹

¹Lomonosov Moscow State University, Skobeltsyn Institute of Nuclear Physics,

²Irkutsk State University,

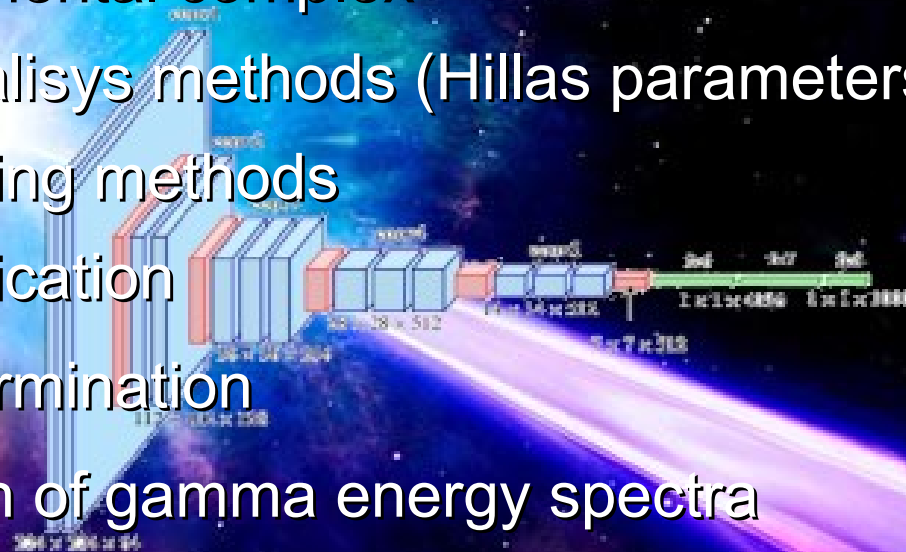
³Lomonosov Moscow State University, Physics Faculty

*kryukov@theory.sinp.msu.ru

[†]The work was supported by RNF, grant #22-21-00442

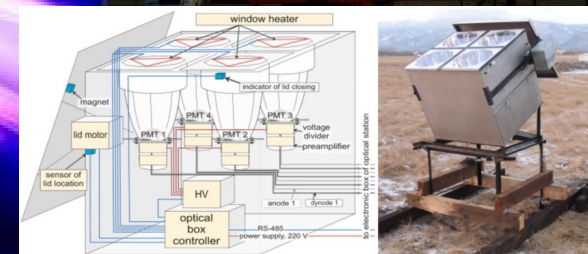
Outlook

- ▶ TAIGA experimental complex
- ▶ Traditional analysis methods (Hillas parameters)
- ▶ Machine learning methods
- ▶ Particle identification
- ▶ EAS axis determination
- ▶ Reconstruction of gamma energy spectra
- ▶ IACT event simulation
- ▶ Conclusion



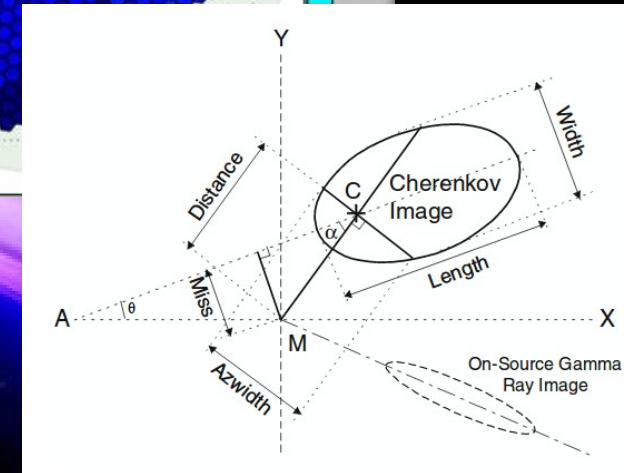
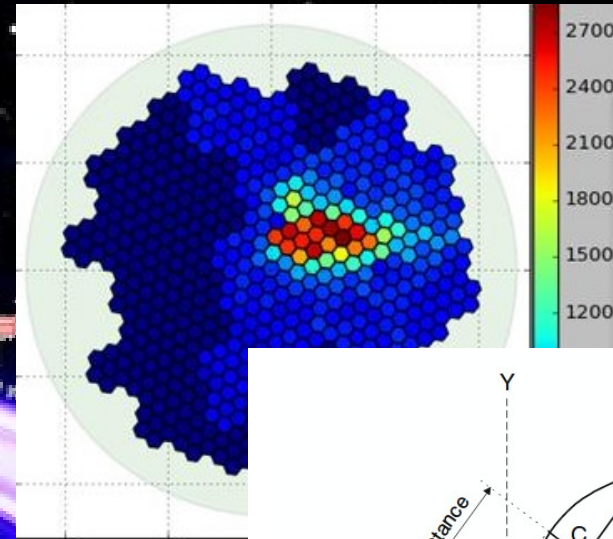
TAIGA experimental complex

- ▶ The main goal is to study the sources of cosmic gamma rays and their nature.
- ▶ Multi-purpose complex for registration of cosmic radiation of various nature.
- ▶ The main installations of the complex
 - ▶ Imaging Atmospheric Cherenkov Telescopes
 - ▶ Currently the 3 IACT's are operating.
 - ▶ HiSCORE - an array of wide-angle Cherenkov detectors



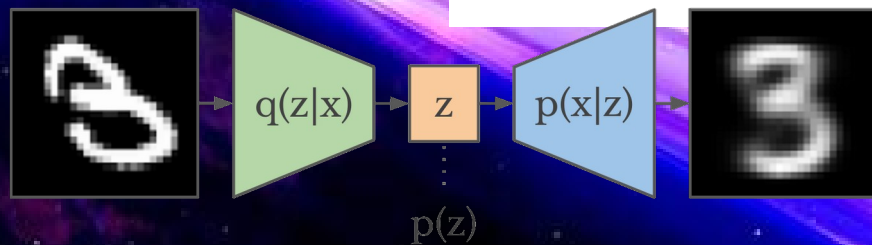
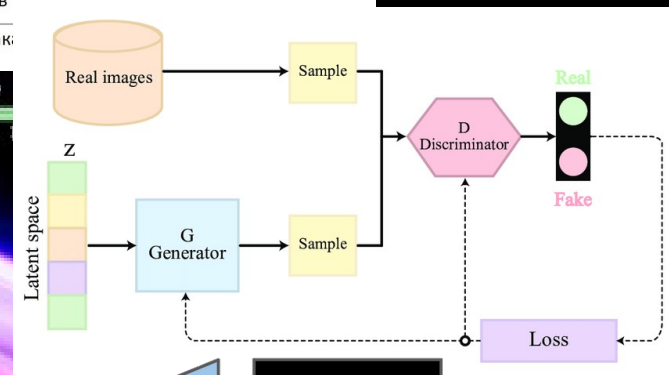
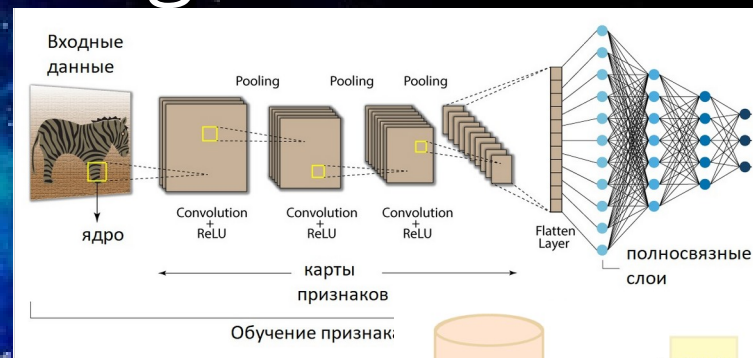
Traditional analysis method (Hillas parameters)

- ▶ The image of a gamma event looks like an ellipse. Its main axis is directed towards the center of the camera.
- ▶ Most valuable criterias are α angle and eccentricity.



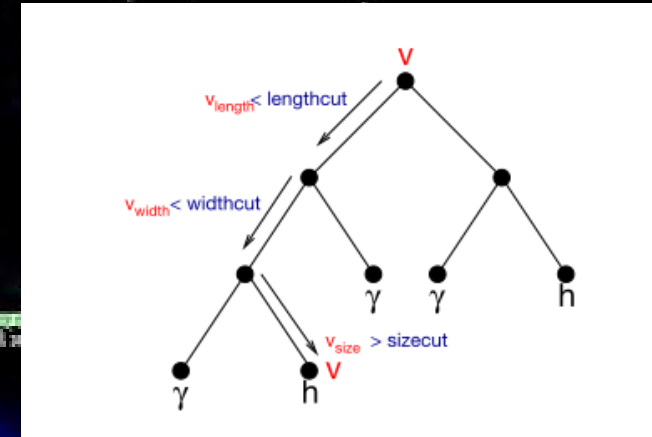
Machine learning methods

- ▶ Boosted Decision Trees (BDT)
 - ▶ We not use them
- ▶ Convolutional Neural Network (CNN)
- ▶ Generative adversarial network (GAN)
- ▶ Variational AutoEncoder (VAE)



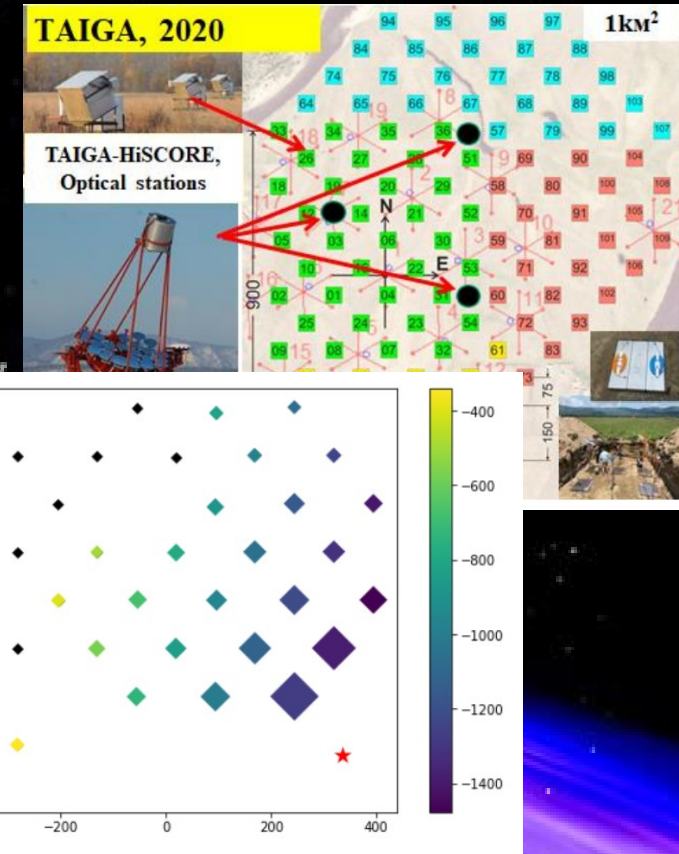
Boosted Decision Trees

- ▶ Events are "sieved" through the graph depending on the conditions
- ▶ Tree ensembles are used to improve the accuracy of the method.
- ▶ BDT can be considered as an improved version of cutoffs by parameters
- ▶ See for example: J. Albert and et. al. // ArXiv: 0709.3719



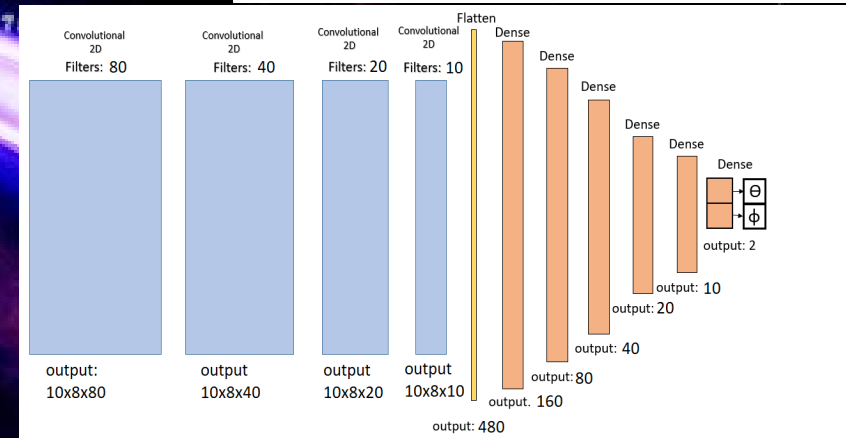
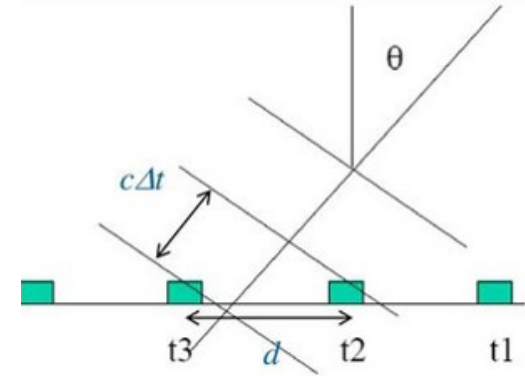
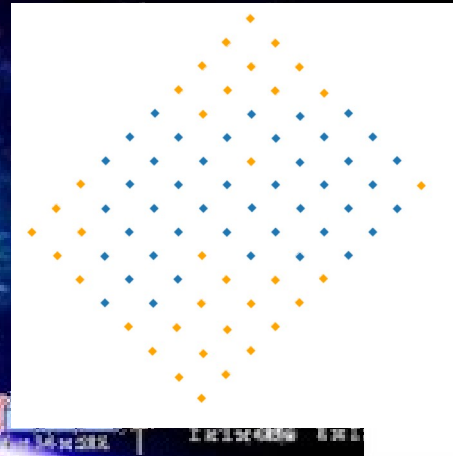
EAS axis determination in HiSCORE

- ▶ We consider the HiSCORE event as a multilayer image.
 - ▶ arrival registration times of signal;
 - ▶ their amplitudes;
 - ▶ auxiliary layers.
- ▶ For network training and validation, model data sets obtained using the CORSIKA program were used.
- ▶ The sample consists of 12216 events, the simulation was performed for 44 HiSCORE stations
- ▶ The sample contains events in which at least four stations were triggered.



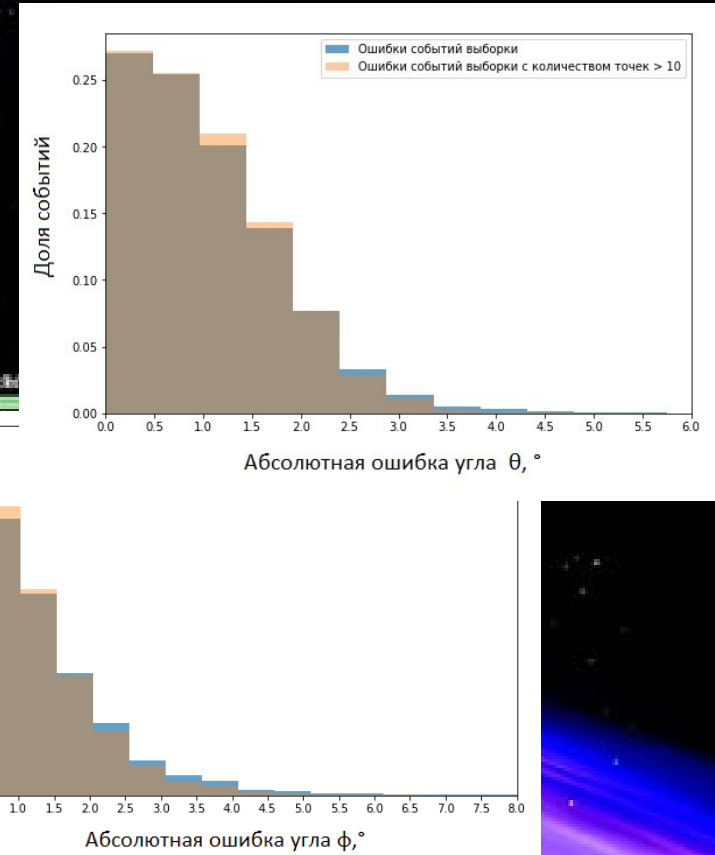
EAS axis determination in HiSCORE

- ▶ To use the advantages of convolutional neural networks in processing data with a grid topology, the array of stations is extended to a rectangular shape: points with zero values are added, the coordinate axes are rotated by 45°
- ▶ The network receives as input data on the EAS signal registration time for each triggered station in the event.
- ▶ At the output, we expect to get the angles of the EAS axis θ and ϕ determined by the neural network



EAS axis determination in HiSCORE

- ▶ The total mean square error of the model (the result of the neural network): $MSE = 2.85$.
 - ▶ Average absolute error θ : 0.970
 - ▶ Average absolute error ϕ : 1.380
- ▶ Errors for events with different numbers of triggered stations can vary significantly. In this regard, an analysis was made of events with the number of triggered stations more than ten and less than ten.
 - ▶ Number of triggered stations < 10 : $\Delta\theta = 1.34$, $\Delta\phi = 1.68$
 - ▶ Number of triggered stations > 10 : $\Delta\theta = 0.82$, $\Delta\phi = 1.12$



HiSCORE. Spectrum reconstruction

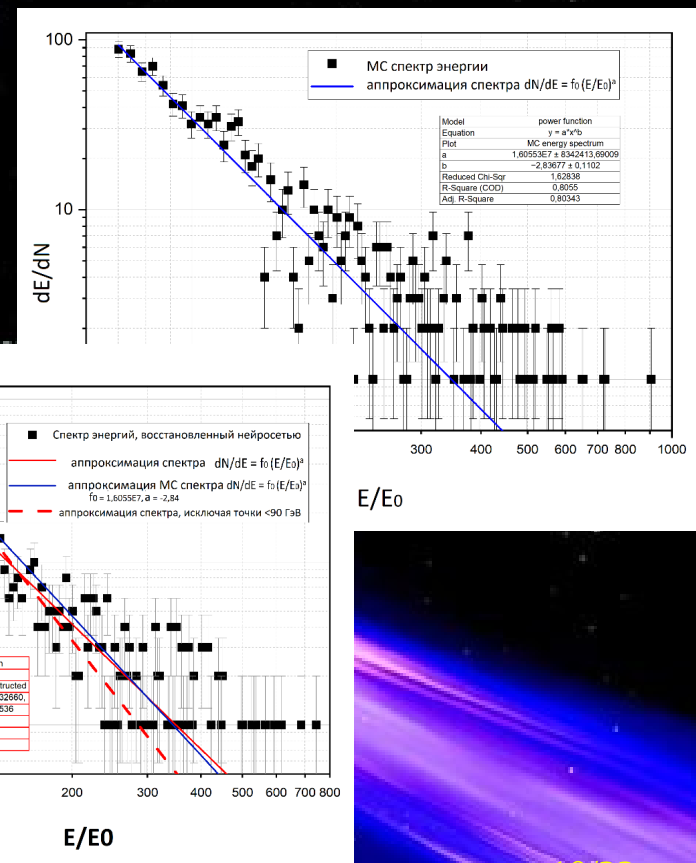
- The graphs show a comparison of the energy spectra of Monte Carlo events and the energy reconstructed by the neural network.

	dN/dE	a	Red. Chi-Sq
MC spectrum		-2.83 +/- 0.11	1.628
CNN spectrum		-2.55 +/- 0.14	2.619
CNN (>90 TэВ)		-3.34 +/- 0.17	1.250
MAGIC spectrum		-2.47 +/- 0.01	1.818

MAGIC spectrum was taking from
J. Aleksić, S. Ansoldi et al., 2015

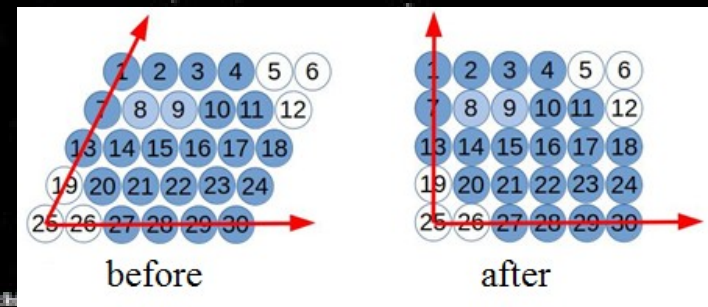
DLCP2022, 06.07.2022

A.Kryukov, SINP MSU



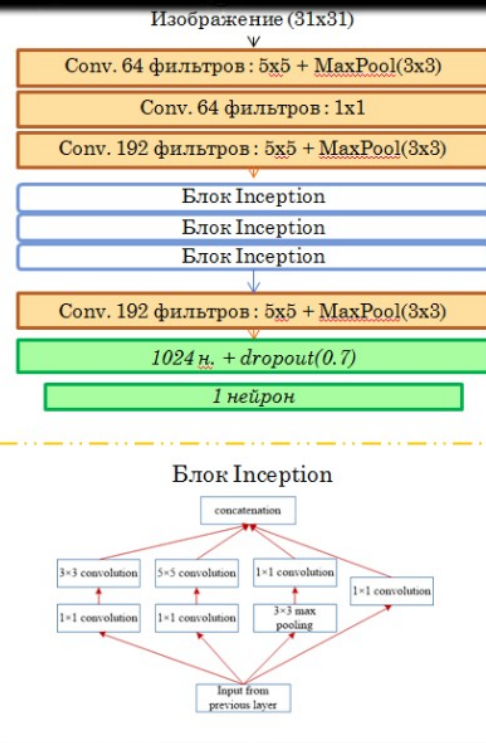
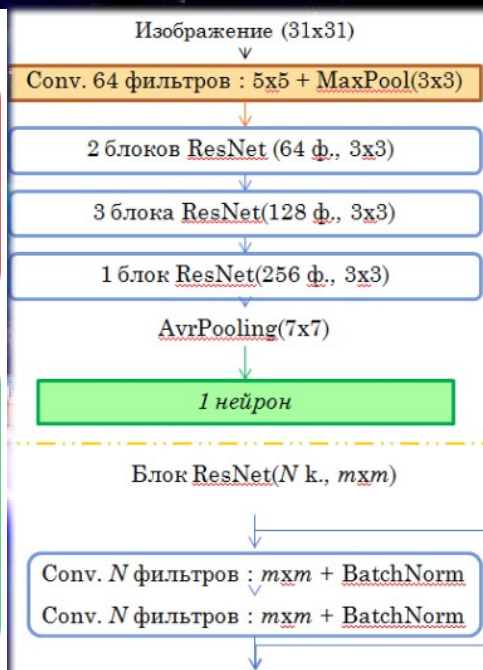
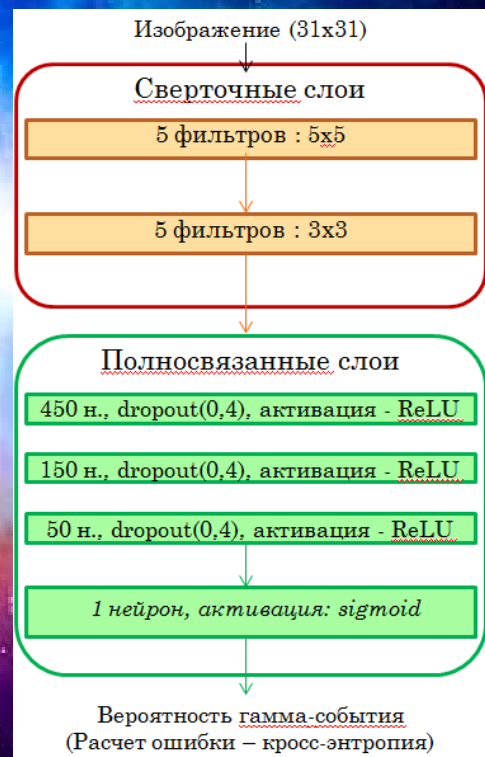
IACT. Data preprocessing

- ▶ Hexagonal detector geometry
- ▶ Augmentation of training set
 - ▶ Important for CNN
- ▶ Rescale
 - ▶ $\log(1+x)$
- ▶ Augmentation
 - ▶ Rotation for 60°



IACT. Classification of primary particles

- For an adequate comparison, ResNet and GoogLeNet were simplified in such a way that the number of weight coefficients for CNN networks approximately coincided. In our case, their number is ~400 thousand.



IACT. Classification of primary particles

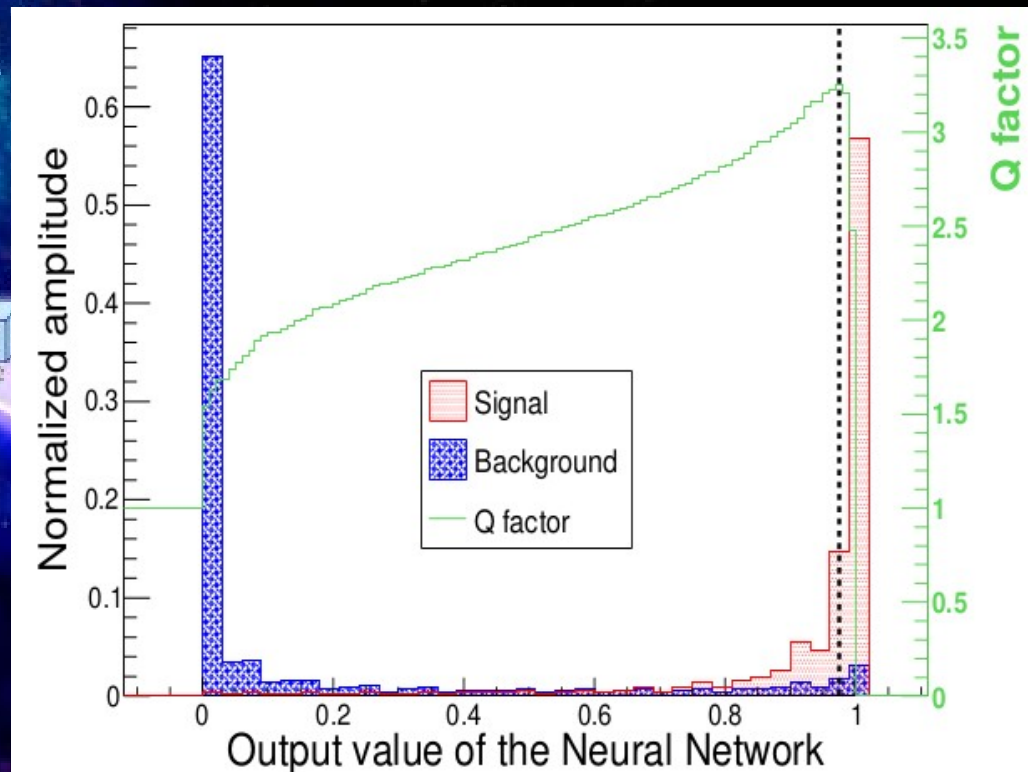
Метод отбора	N_{total}	N_g	N_h	N_{g_g}	N_{h_g}	S_{after}	$Q=S_{after} / S_{before}$
User CNN	40 000	20 000	20 000	11677	180	275,6	2,22
	4 182	58	4 124	25	21	4,71	5,22
	36 783	35	36 748	13	187	0,94	5,15
ResNet	36 783	35	36 748	18	279	1,07	5,84
GoogLeNet	36 783	35	36 748	19	262	1,16	6,35

where

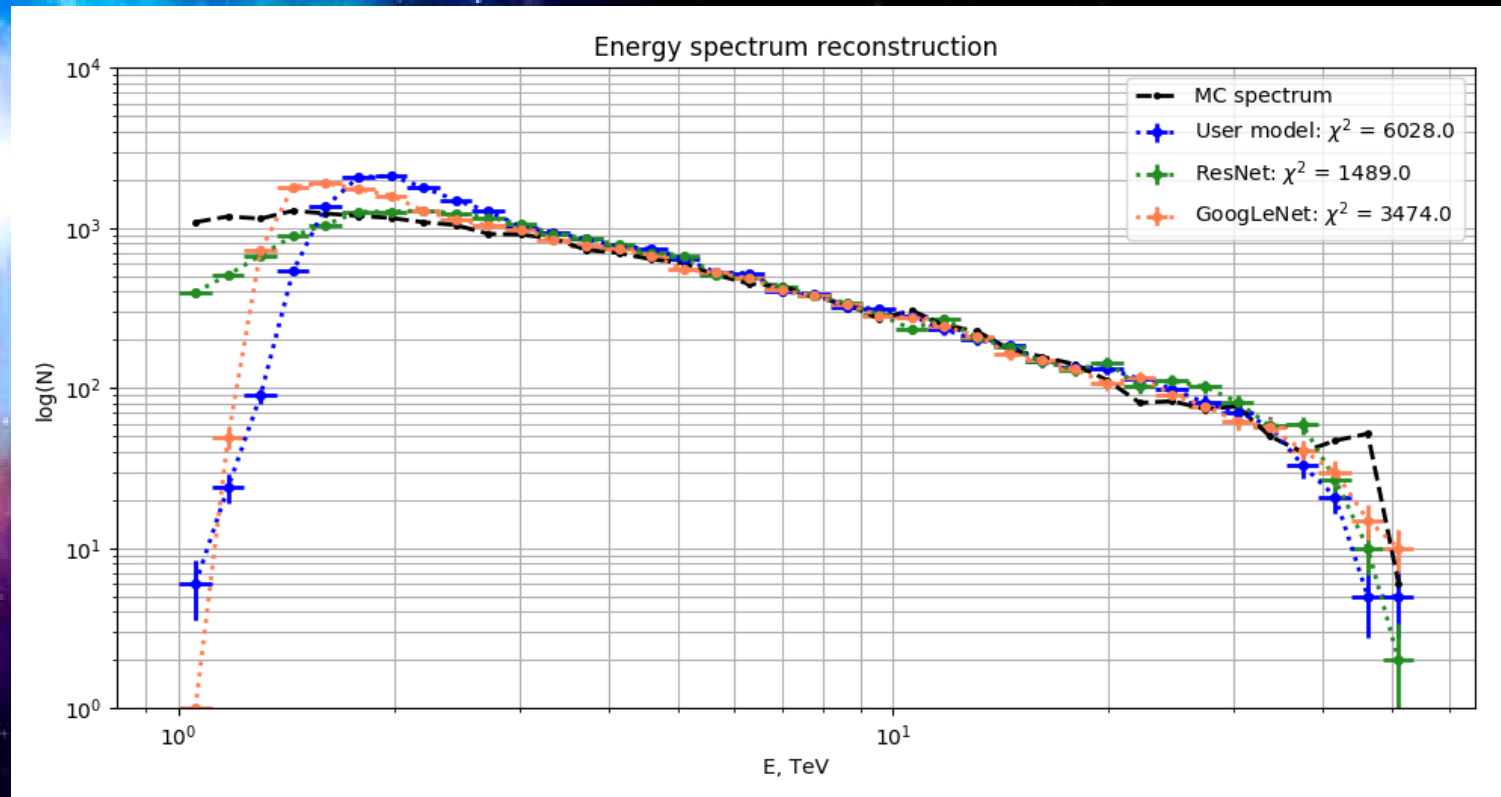
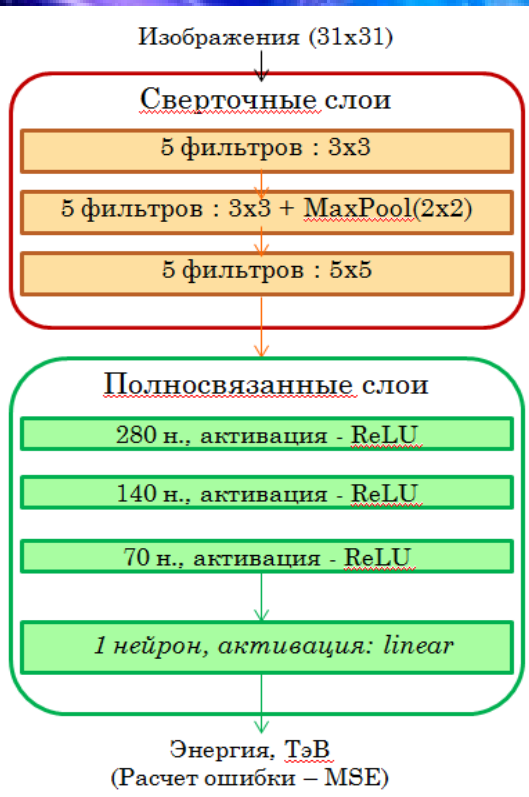
$$S_{after} = \sqrt{2 \left((N_{g_g} + N_{h_g}) \ln \left(1 + \frac{N_{g_g}}{N_{h_g}} \right) - N_{g_g} \right)}$$

Classification of primary particles

- Source^ R. Alfaro and et.al. // ArXiv: 2205.12188

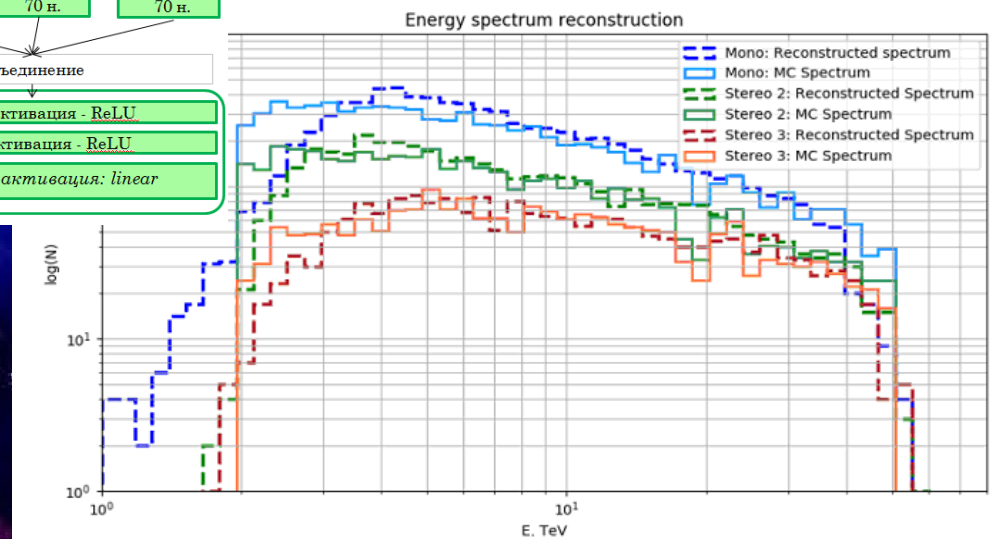
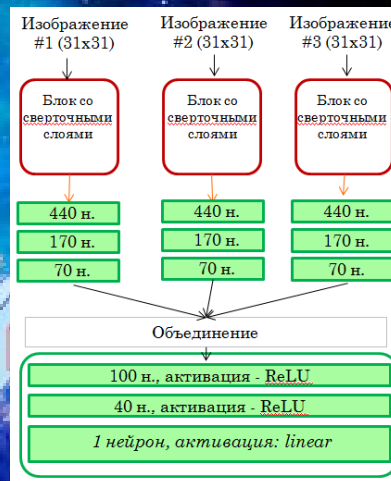


IACT. Reconstruction of gamma ray energy spectra in mono mode



IACT. Reconstruction of gamma ray energy spectra

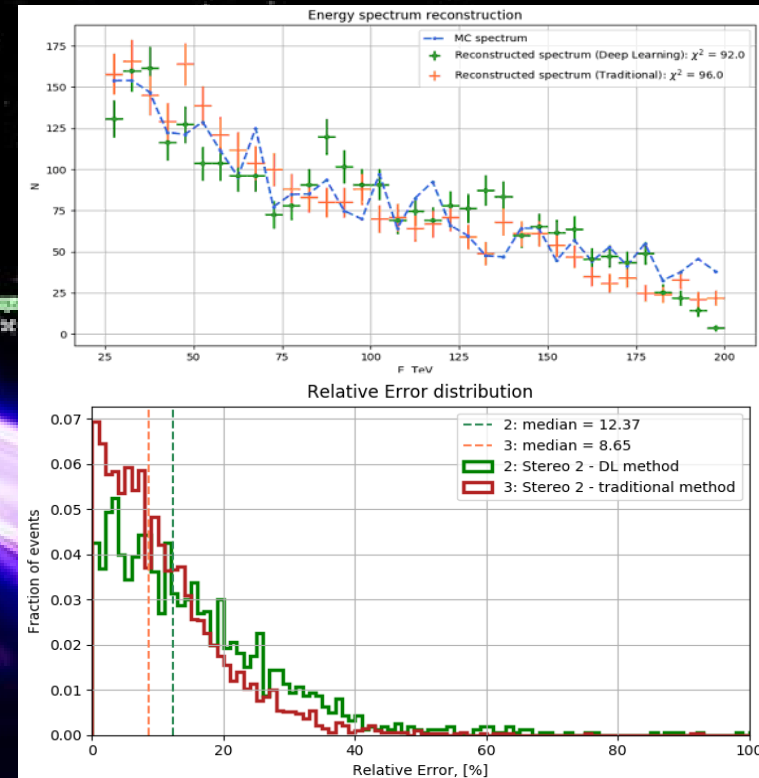
- ▶ Reconstruction of the event energy and the energy spectrum was carried out by a custom three-channel CNN.
- ▶ The values χ^2 in mono mode are 1,546
- ▶ In the case of "stereo-2" - 495
- ▶ In "stereo-3" - 156.
- ▶ The error decreased from 26% to 15%.



Gamma ray energy spectra.

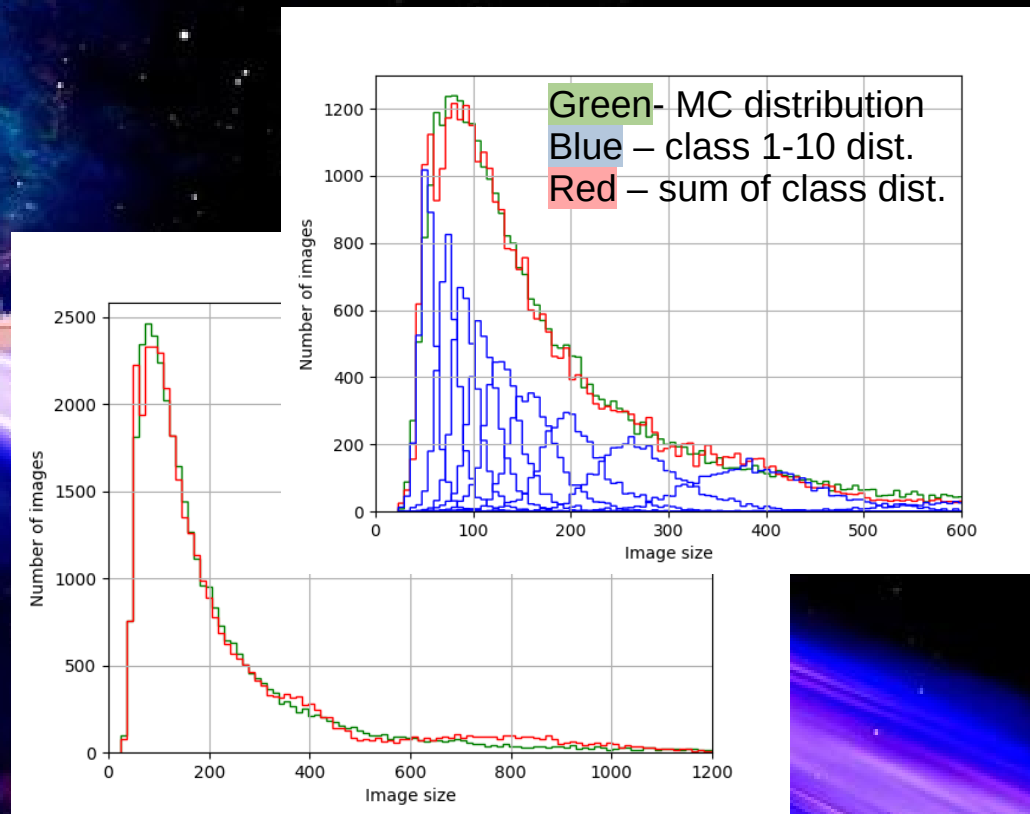
DL vs. Hillas parameters

- ▶ A comparison was made on a sample consisting of gamma rays with an energy of 25-200 TeV.
- ▶ Traditional energy recovery method: for each telescope, approximation by a function depending on some Hillas parameters (spot brightness, size, distance) and EAS characteristics (EAS maximum height).
- ▶ Deep learning method: A custom two-channel CNN (Stereo2) was chosen.



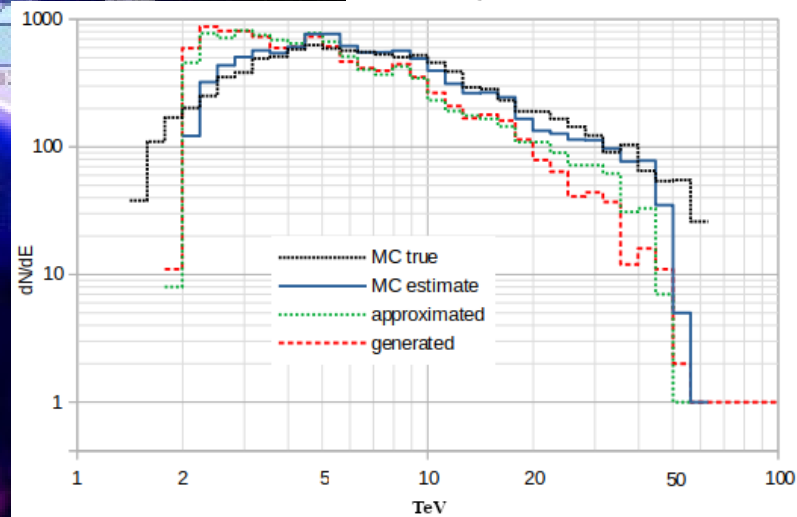
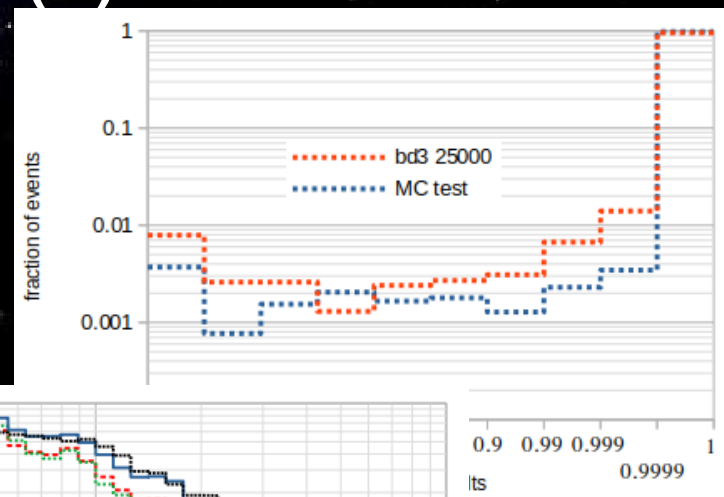
IACT event modelling.(c)GAN

- ▶ Conditional GAN
- ▶ During training, all events were sorted by energy and divided into 10 equal parts (about 3500 events per each). Each part was considered a separate class, information about which was used on the training sample.
- ▶ When generating events by the trained network, the same number of events of each class was generated.
- ▶ Generation speed of about 5000 images per second



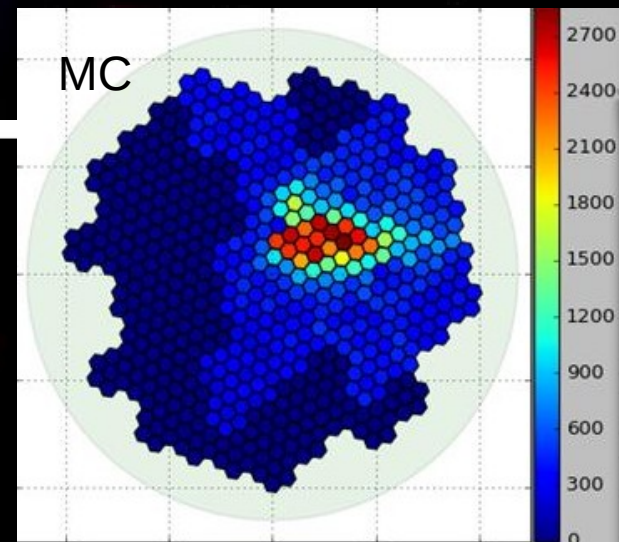
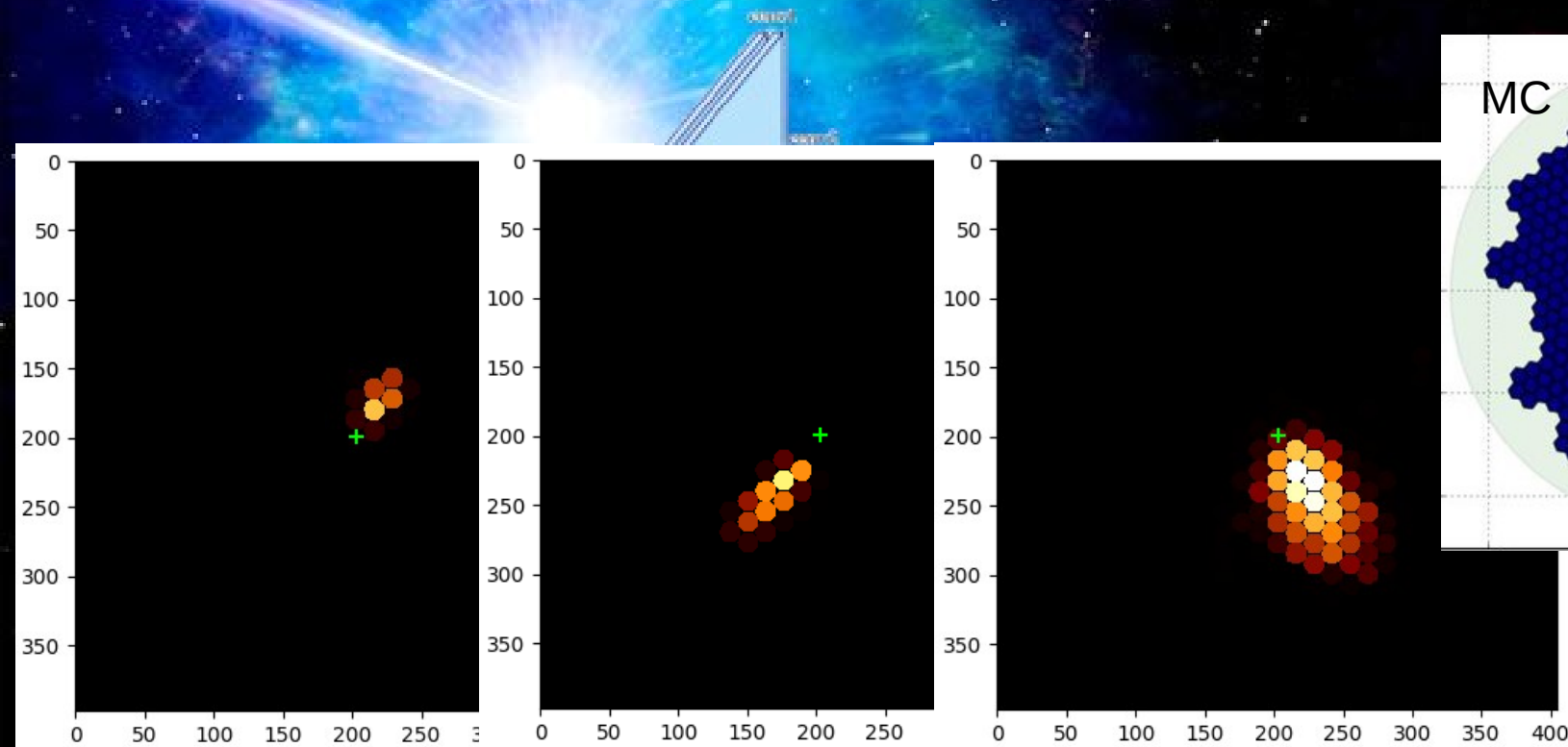
IACT event modelling. (c)VAE

- ▶ The classifier recognizes simulated events as gamma events at or above 0.999.
- ▶ Preliminary spectrum simulates samples is on the figure.



IACT event modelling. (c)VAE

- ▶ Examples of simulated IACT gamma events.



Conclusion

- ▶ In the task of classifying events, deep learning gives a very good result. Due to the strong suppression of proton events, neural networks can be an important tool for event selection.
- ▶ In the problem of restoring the energy spectrum, a good result is achieved in the case of stereoscopic observations. In this mode, neural networks give a good match to traditional methods based on Hillas parameters.
- ▶ Very good prospects for methods based on generative networks for event simulation as an alternative to Monte Carlo simulation. These methods make it possible to speed up the process of modeling good quality events with correct statistics by hundreds and thousands of times.

