Using convolutional neural networks for HiSCORE events analysis

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Gamma astronomy

Physical problems of gamma astronomy:

- Study of physical phenomena, occurring in extreme conditions
- Principles of acceleration of ultra-high energy particles and the search for their sources in the universe.



Methods: Extensive Air Showers

- Primary high-energetic particle reaches the atmosphere, generating a massive cascade of secondary particles.
- Secondary particles emit Cherenkov light
- Air shower parameters: primary particle type, its arrival direction, position of central axis, particle energy
- Conventional method of parameter determination: Hillas parametrization



TAIGA experiment (Tunka Advanced Instrument for cosmic rays and Gamma Astronomy)

- Instrument for ground-based astronomy from a few PeV to several TeV
- •Consists of Cherenkov Telescopes (TAIGA-IACT), Cherenkov stations (TAIGA-HiSCORE), scintillation counters and other instruments.

TAIGA-IACT and TAIGA-HiSCORE





IACT-event (Monte-Carlo simulation)

Artificial Neural Networks (ANN)

Value of the hidden layer node:

 $n_k = w_{k1}x_1 + w_{k2}x_2 \dots + w_{kn}x_n + w_0$

The goal of training is to find the local minimum of the error function of the weights. To find the local minimum, the gradient descent method is used.



Convolutional Neural Network (CNN)

The main feature of CNN is operation of convolution. It is used mostly for data with grid topology, such as images.



Conventional analysis methods

Traditional method of analysis: Searching for the EAS front



Proposed method

- We consider a set of times of signal arrival registration as an "image".
- We are looking for a time isoline and use them to restore the direction of the EAS axis
- For time isoline determination, deep learning technologies can be used, in particular, we propose the use of a CNN



Data: Monte-Carlo events

We use the time of registration of the signal by the station as input data

- At the output of the network, we expect the values
- of the polar and azimuthal angles
- We work with data for 44 stations
- It is necessary to bring the grid of stations to a rectangular form



150 м

400

Model architecture

N⁰	Layer type	Output shape	Number of output filters	Activation function
1	Convolutional 2D	9x9x27	27	ReLU
2	Convolutional 2D	9x9x9	9	ReLU
3	Convolutional 2D	9x9x3	3	ReLU
4	Flatten	243	-	-
5	Dense	72	-	ReLU
6	Dense	36	-	ReLU
7	Dense	18	-	ReLU
8	Dense	2	-	ReLU

Model architecture

Kernel size: 3 x 3

Total number of parametrers: 23612

Optimizer: ADAM (Adaptive Moment Estimation);

learning rate = 0,001

Loss:
$$MSE = \frac{1}{n} \sum_{i}^{n} (y_{true} - y_{pred})^2$$



ReLU activation function



Training results

Events with more than 10 points:

Mean absolute error for Theta: 1.30°

Mean absolute error for Phi: 1.76°

Events with less than 10 points:

Mean absolute error for Theta: 1.85°

Mean absolute error for Phi: 2.79°



loss: 3.0585246086120605 accuracy: 0.9760000109672546 Mean absolute error for Theta: 1.0384769001007081 Mean absolute error for Phi: 1.7023339276313783

100

Training results

Number of stations: below 10.

Training set: 8736 events

Validation set: 500 events

Number of epochs: 100

Mean absolute error for Theta: 2.32°

Mean absolute error for Phi: 3.85°



loss: 21.11964225769043 accuracy: 0.921500027179718 Mean absolute error for Theta: 2.3196171808242796 Mean absolute error for Phi: 3.8468647526502604

Conclusions

Achieved accuracy of angle determination: 95% CNN applications in TAIGA experiment has promising results Perspectives:

- Taking into account that real grid is irregular: linear interpolation of times is proposed
- •Applying deep learning technologies to determine the EAS energy, the position of the EAS axis
- Considering different network architectures for pattern recognition



Thank you for your attention!