A. Matseiko*, I. Kharuk
MIPT, Dolgoprudny, Russia
INR RAS, Moscow, Russia

***Email: matseiko.av@phystech.edu**
Telegram: AlbertMac280
GitHub: AlbertMatseiko/NeutrinoSelection

Application of machine learning methods in Baikal-GVD: selection of neutrino-induced events

Abstract

Baikal-GVD is a large (~ 1 km3) underwater neutrino telescope located in Lake Baikal, Russia. This work presents a neural network for separating events caused by extensive air showers (EAS) and neutrinos. By choosing appropriate classification threshold, we preserve 50% of neutrino-induced events,while EAS-induced events are suppressed by a factor of 10^{-6}. A method for estimating the neutrino flux with minimal error based on neural network predictions has also been developed. The developed neural network employ the causal structure of events and surpass the precision of standard algorithmic approaches.

Baikal-GVD experiment and neutrino selection

The goal of Baikal-GVD is to study events related to astrophysical neutrinos with energies on the order of TeV-PeV, with a sensitivity comparable to the IceCube and KM3NeT-ARCA experiments. The telescope consists of 10 clusters, each of which consists of 8 strings in the shape of a regular heptagon with a center. Each string is equipped with 36 optical modules (OMs). OMs detect Cherenkov radiation from particles produced by neutrino interactions with water, as well as EAS-induced particles. The registered flux of the particles of EAS origin is approximately *10^6* times greater. Since only neutrinos can produce particles with an up-going momentum after passing through the Earth, strong cuts based on the reconstructed angle are applied to distinguish them. **In this work, a neural network approach to that task is considered.**

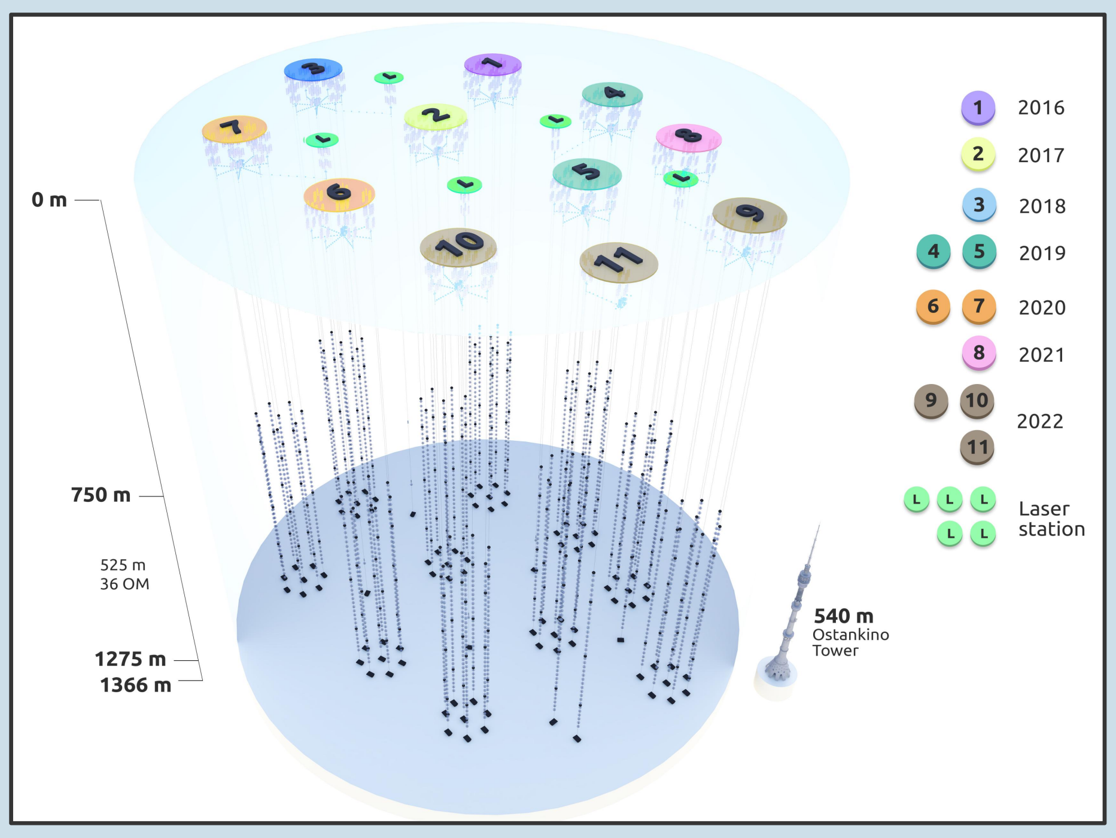


Fig.1. Structure of Baikal-GVD. By 2023, 12 clusters were deployed.

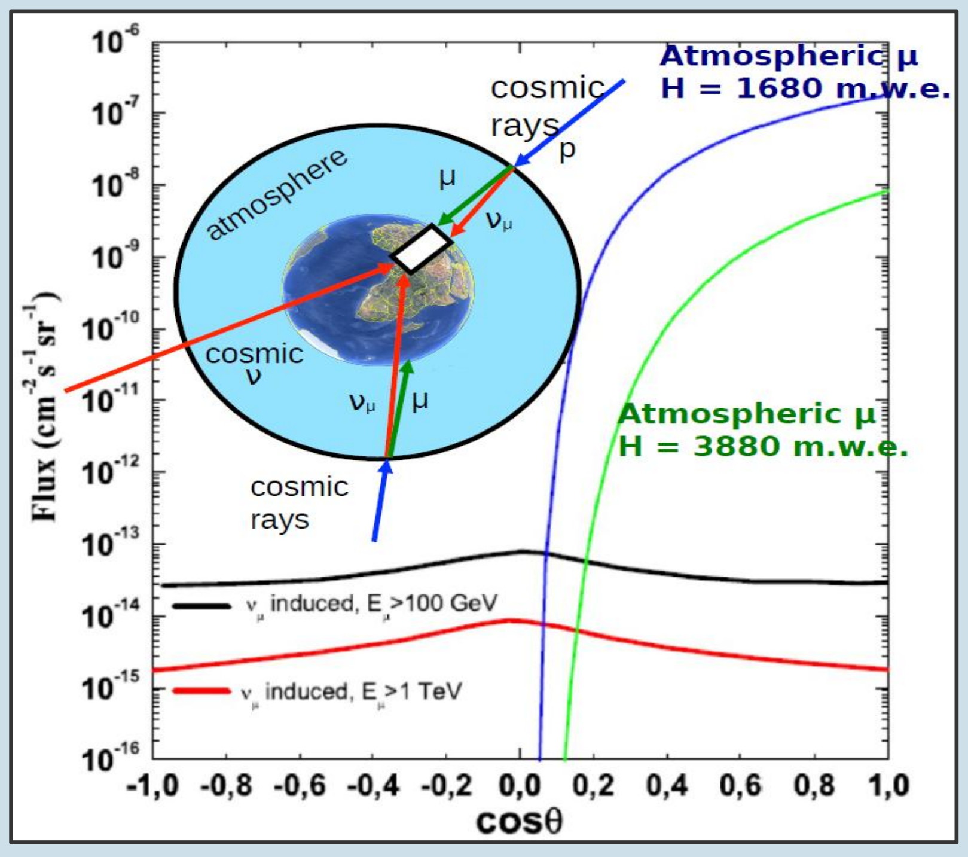


Fig.2. Types of events. The curves show the angular distributions of particle fluxes

Data

Approximately $2*10^7$ Monte Carlo simulations of track trajectories of up-going muon neutrinos and down-going EAS-induced muons are utilized. Only single-cluster events, which account for approximately 90% of the recorded events, are considered.
For input into the neural network, events are represented as a time-ordered array of hits, with each hit containing the coordinates and time of the triggered optical module (OM) and the recorded charge. The signals are cleaned from noise hits. The filtration process is performed by another neural network in practice.

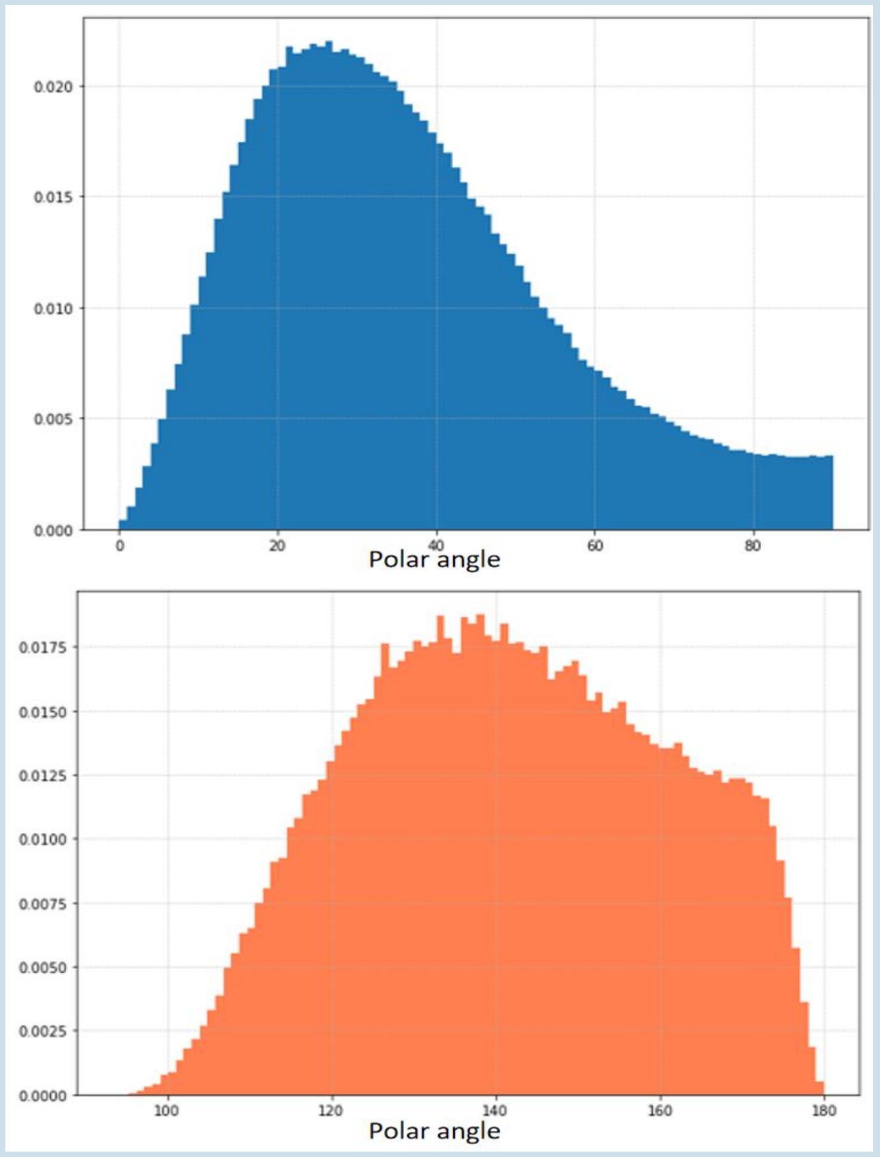
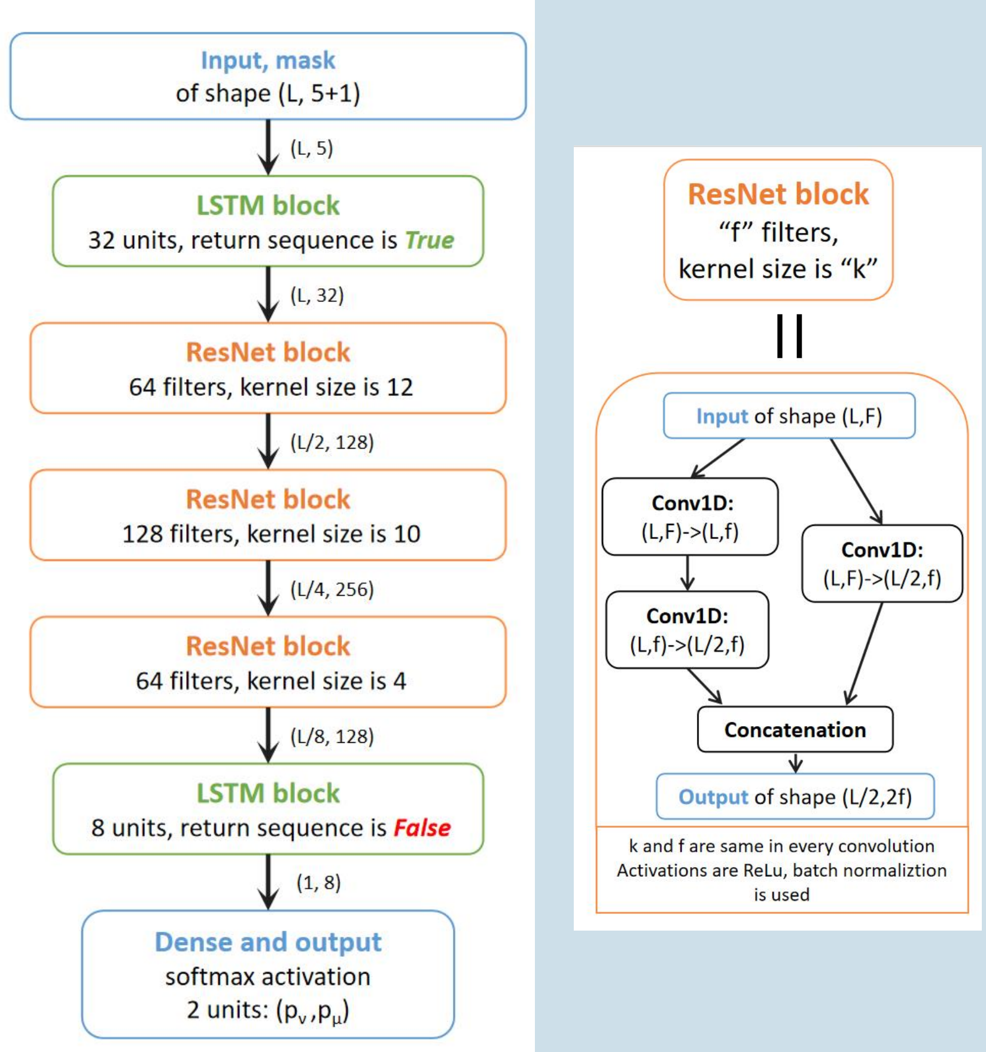


Fig.2. Polar angle distibutions for neutrino- (blue) and EAS-induced muons (orange) in data.

The neural network

The network predicts a value between 0 and 1, representing its confidence that the given event is caused by a neutrino. By setting a classification threshold, the desired level of suppression of EAS-induced events can be achieved. The architecture consists of a combination of recurrent (LSTM), convolutional (ResNet) blocks, and a dense layer at the output. LSTM effectively captures patterns in temporal sequences and allows for flexibility in the number of triggered optical modules. ResNet enables both deepening the network and aggregating information about the event (encoding).


Input, mask
of shape (L, 5+1)
(L, 5)
LSTM block
32 units, return sequence is *True*
(L, 32)
ResNet block
64 filters, kernel size is 12
(L/2, 128)
ResNet block
128 filters, kernel size is 10
(L/4, 256)
ResNet block
64 filters, kernel size is 4
(L/8, 128)
LSTM block
8 units, return sequence is *False*
(1, 8)
Dense and output
softmax activation
2 units: (p_ν, p_μ)

ResNet block
“f” filters,
kernel size is “k”
||
Input of shape (L,F)
Conv1D: (L,F)->(L,f)
Conv1D: (L,f)->(L/2,f)
Conv1D: (L,F)->(L/2,f)
Concatenation
Output of shape (L/2,2f)
k and f are same in every convolution
Activations are ReLu, batch normaliztion is used

Fig.3. Architecture of the developed neural network

Resulting metrics

The quality of classification are represented by metrics:

- Exposition (***E***) - the part of neutrino-induced events, that were classified correctly (true positive rate)
- Suppression (***S***) - the part of EAS-induced events, that were classified incorrectly (false positive rate)

In Fig.4, the metrics are presented depending on the classification threshold. The desired ***S*** =*10^{-6}* is achieved at the threshold of *0.9996* with ***E*** equal to *50%.*

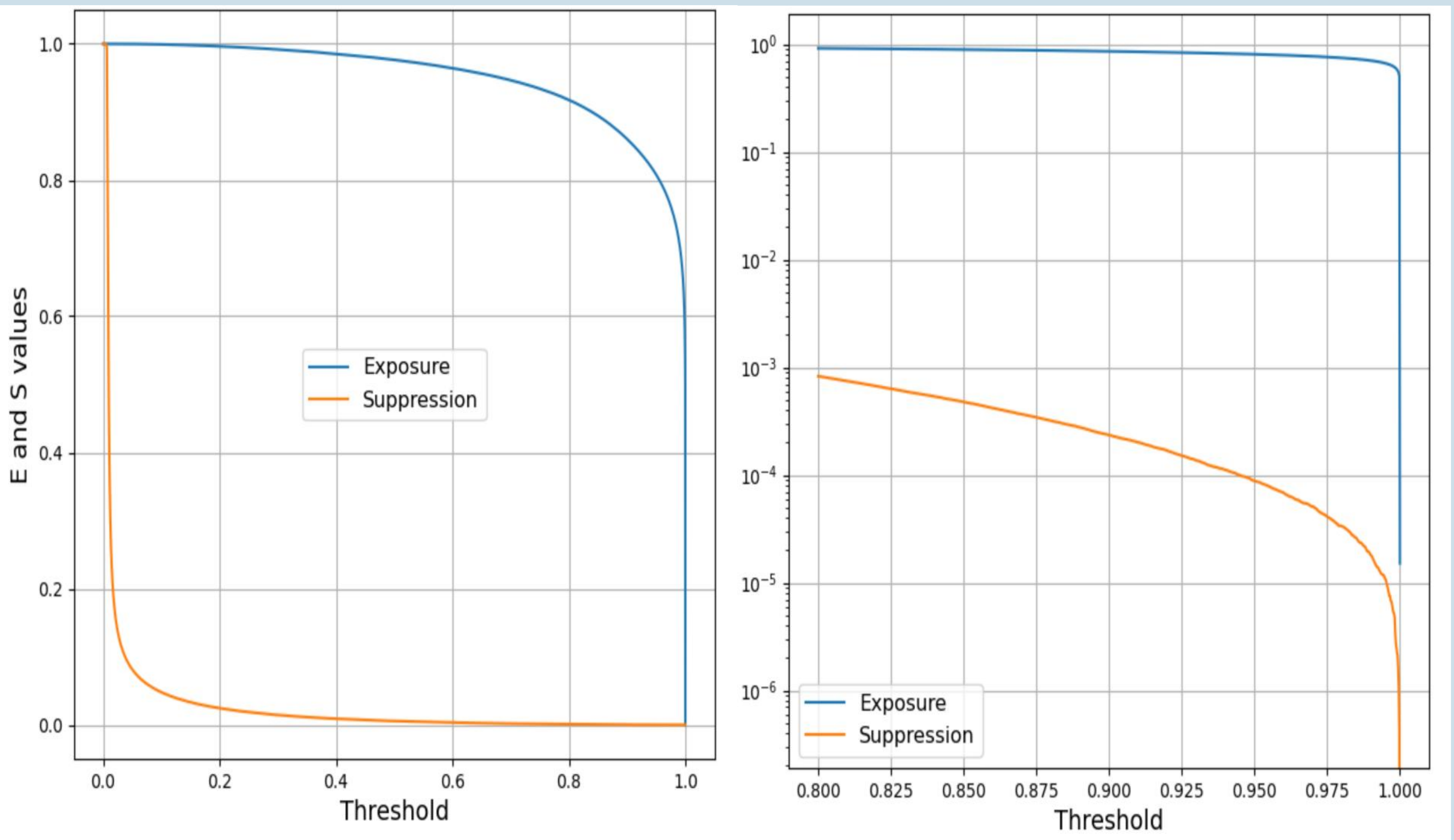


Fig.4. Exposure (blue) and Suppression (orange) vs classification threshold.

Conclusion 1

The desired suppression level is achived with saving 50% of neutrino events!

Neutrino flux measuring

Considering the neural network as a black box, that classifies neutrino- (EAS-) induced events correctly with probability *p* = ***E*** (*q* = *1*-***S***), one can derive a formula for evaluating the number of neutrino-induced events in a sample of size *n*:

$$n_\nu \approx \frac{n(\xi) - S^0(\xi)\ n}{E^0(\xi) - S^0(\xi)} \qquad (1)$$

Here, *n(ξ)* is a number of events, that the network put right to the treshold *ξ*. ***E^0*** and ***S^0*** are estimations of ***E*** and ***S***, which are measured on Monte-Carlo events. The confidence intervals for ***E^0*** and ***S^0*** can be calculated, allowing the error in evaluation (1) to be estimated. The formula has been tested on Monte-Carlo data, consisting of 30 neutrino- and $3*10^7$ EAS- induced events. The result one can see **in Fig.5.**
To measure the Poisson parameter of the neutrino flux, total number of events *n* should be considered as a random variable, that also contributes to the error.

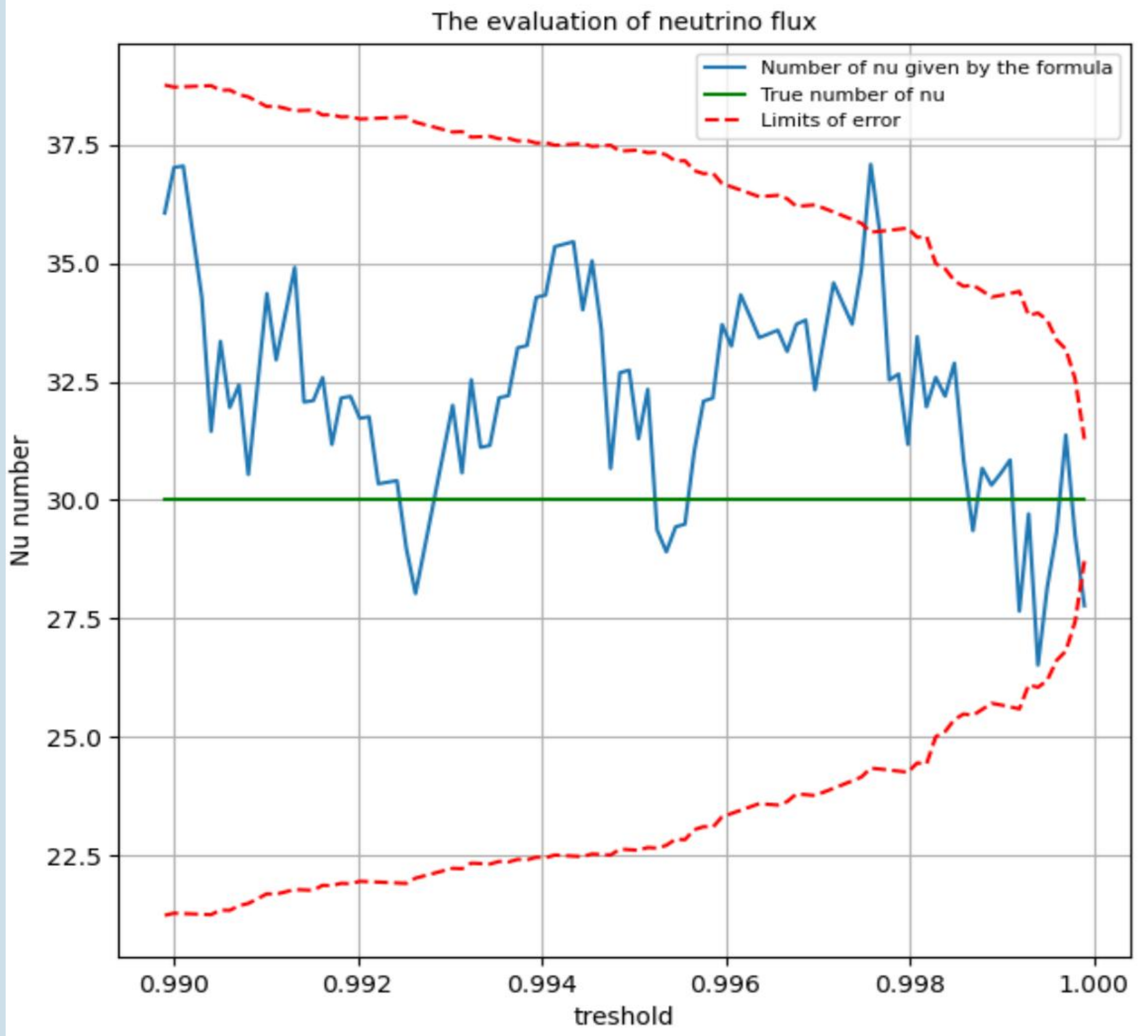


**Fig.5.
Predicted by (1) number of neutrino-induced events (blue line) with its error (red line)
vs
classification treshold.
Green line represents the true number of the events in the data.**

Conclusion 2

One can predict the number of neutrino in data with the smallest possibe error!