

# Реконструкция ШАЛ, зарегистрированных флуоресцентными телескопами, с помощью нейронных сетей

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The 8th International Conference on Deep Learning in Computational Physics, Moscow, June 2024

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<sup>а</sup>Моделирование и анализ для EUSO-TA поддержаны грантом РФФ 22-62-00010;  
разработка нейронных сетей для EUSO-SPB2 была выполнена при поддержке гранта РФФ 22-22-0367.

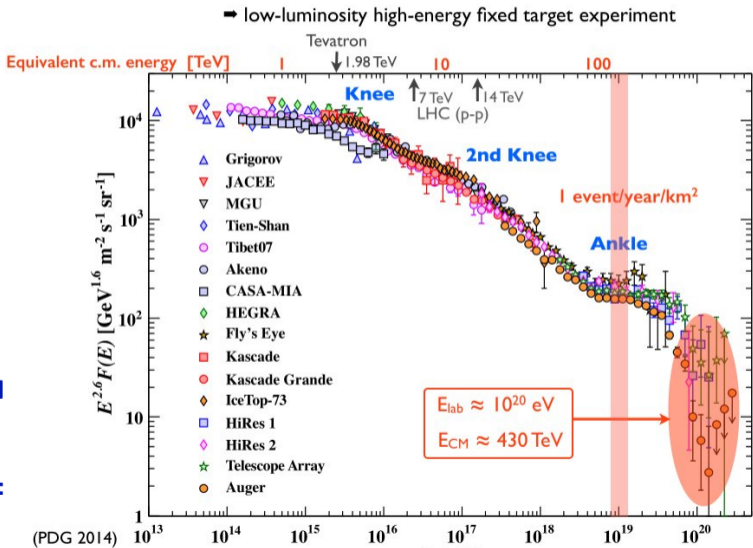
# Глобальный предмет исследований: космические лучи предельно высоких энергий

**КЛ ПВЭ:**  $E \gtrsim 5 \times 10^{19}$  эВ  
(начиная с предела ГЗК)

- 1961: **50 ЭэВ** (Volcano Ranch)
- 1962: **100 ЭэВ** (Volcano Ranch)
- 1991: **320 ЭэВ** (Fly's Eye)
- 1993: **213 ЭэВ** (Agasa)
- 2021: **244 ЭэВ** (Telescope Array)

**Природа и происхождение КЛ ПВЭ остаются загадкой!**

**Одна из ключевых проблем: крайне низкий поток**



# Изучение КЛ ПВЭ из космоса и с земли

1980: Linsley, Benson:

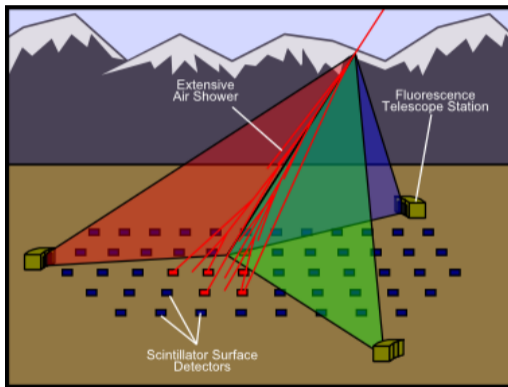
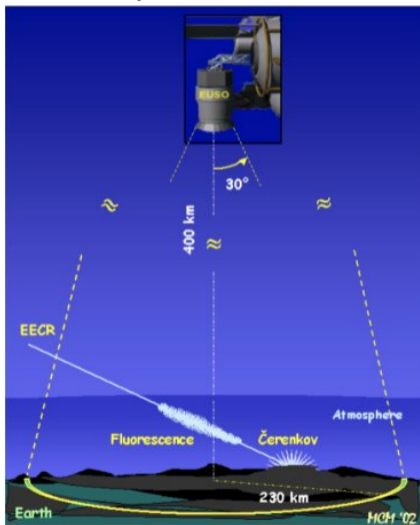
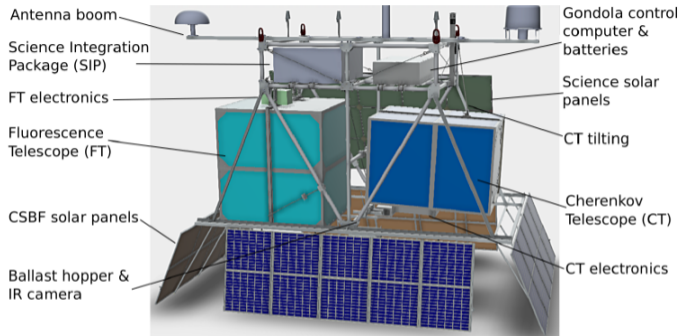


Figure: Telescope Array

# EUSO-SPB2 (2023)



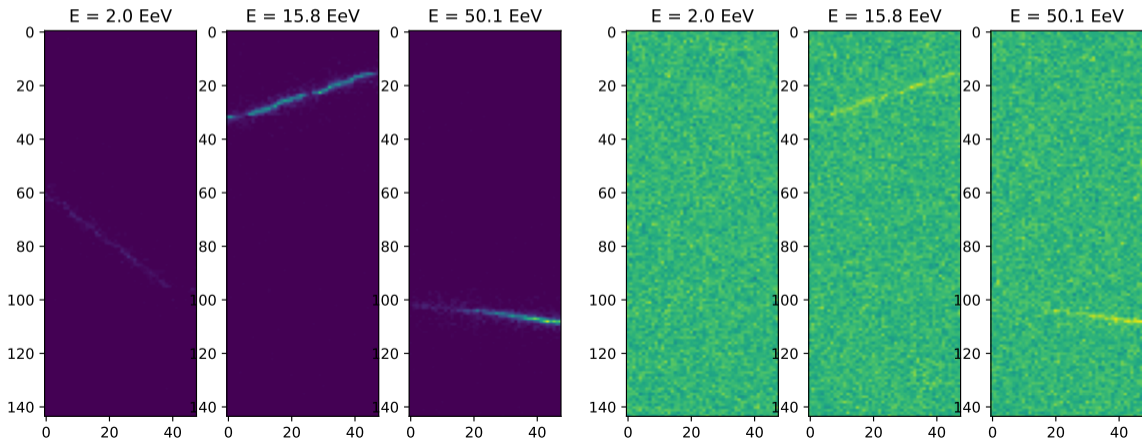
Стратосферный эксперимент: черенковский и флуоресцентный телескопы.

FT: входное окно  $\varnothing 1$  м, поле зрения  $12^\circ \times 36^\circ$ , фокальная поверхность  $48 \times 144$ .

# The datasets, integral tracks w/o & with background

Two datasets simulated with Offline: energies  $10^{18.1}$  eV,  $10^{18.2}$  eV, ...,  $10^{19.7}$  eV (1.26...50.12 EeV)

- 1 Set created with Geant4-based optics: 8,123 tracks; 5,527 of them with  $E \geq 10^{19}$  eV
- 2 Set created with parametric optics: 141,425 tracks; 102,086 of them with  $E \geq 10^{19}$  eV



# 1. Track Recognition via Semantic Segmentation

For Mini-EUSO, we developed a 2-step method of meteor track recognition employing a CNN for the signal localization in a 3D chunk of data and an MLP identifying hit pixels within the chunk [Algorithms, 2023]. It can be applied here, too.

Completely different approaches are possible. One of them is **semantic segmentation**, which means predicting, for each pixel of an image, the class of the object to which it belongs.

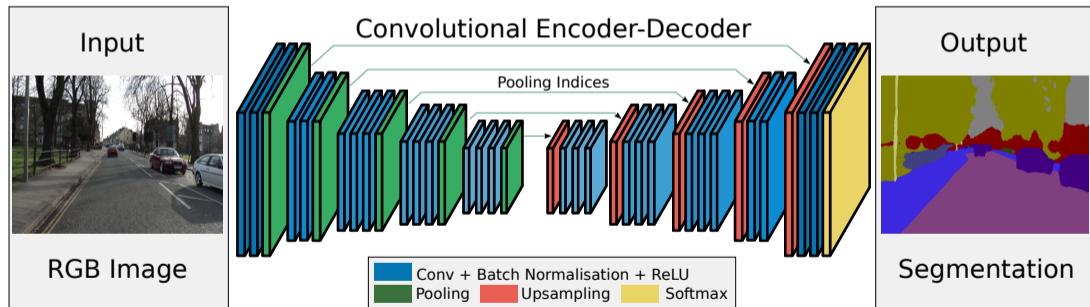
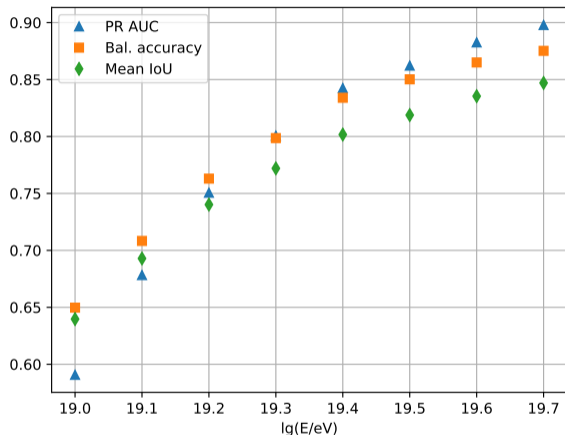
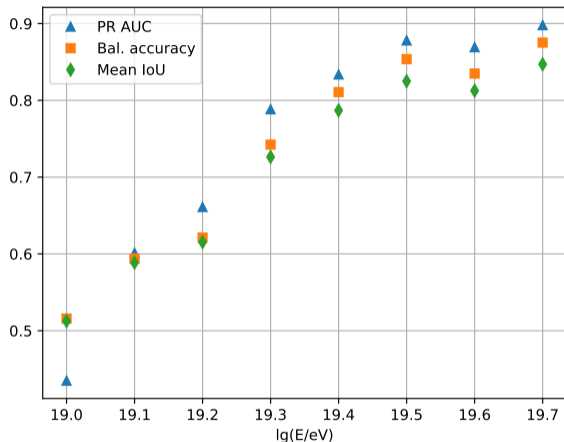


Figure: <https://arxiv.org/abs/1511.00561>

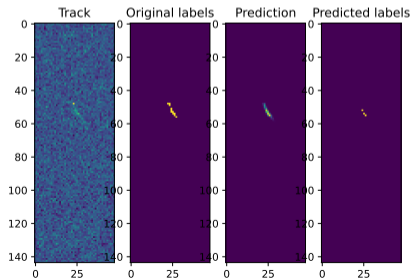
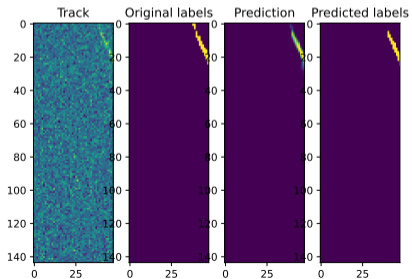
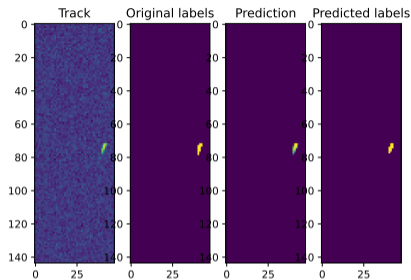
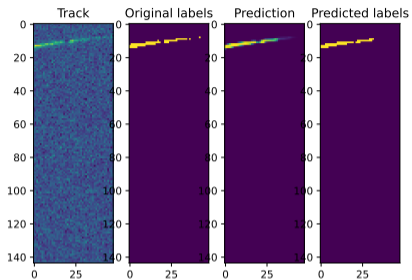
# Performance metrics for tests (integral tracks)



**Left:** each test was run on samples with the same energy as used for training.

**Right:** ANN trained on  $E = 10^{19.7}$  eV samples.

# Track recognition for photon count sums, $E = 10^{19.7}$ eV





## Another approach: Image Filtering

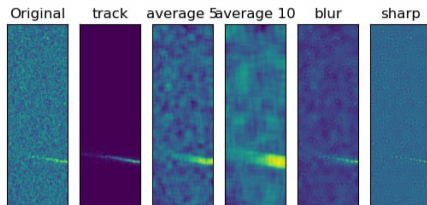
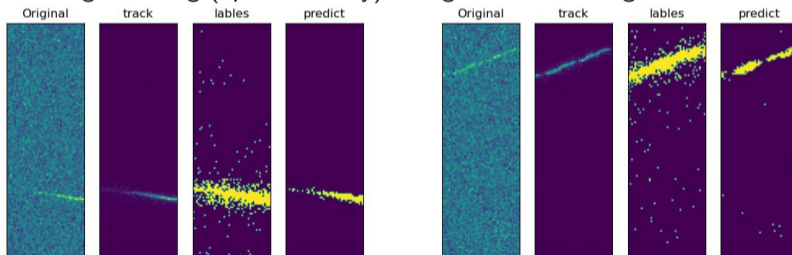
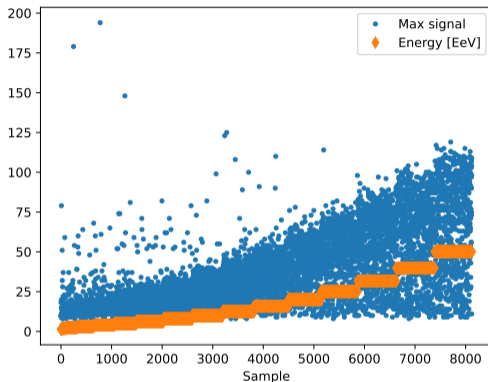


Image filtering (opencv library) and gradient boosting classifier.



Left: training sample. Right: test sample.

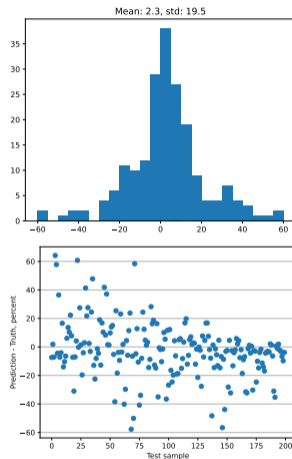
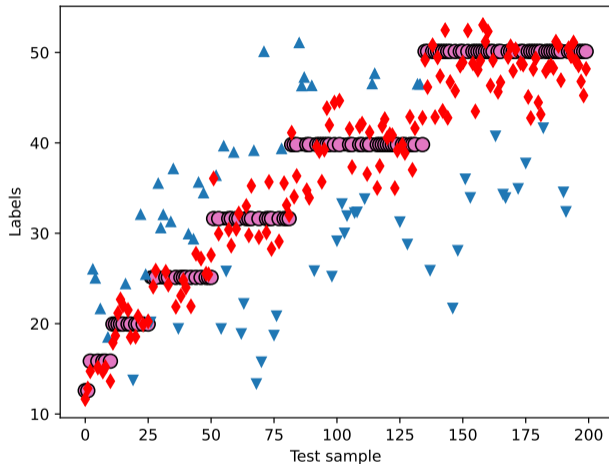
## 2. Energy Reconstruction via Regression



Dependence of the maximum photon count vs. energy in samples in dataset 1.

One can employ a CNN similar to those used for image classification with the linear activation function in the final FC layer instead of sigmoid. Currently: 6 convolutional and 3 FC layers.

## Data set 2 (parametric optics) with “realistic” track recognition



$E \geq 10$  EeV, tracks recognized with Mean IoU  $\geq 0.89$ . MAPE  $\approx 14\%$ . MAPE  $\sim 16\%$  for MIoU  $\geq 0.8$

# EUSO-TA: наземный ФТ на сайте эксперимента Telescope Array (USA)



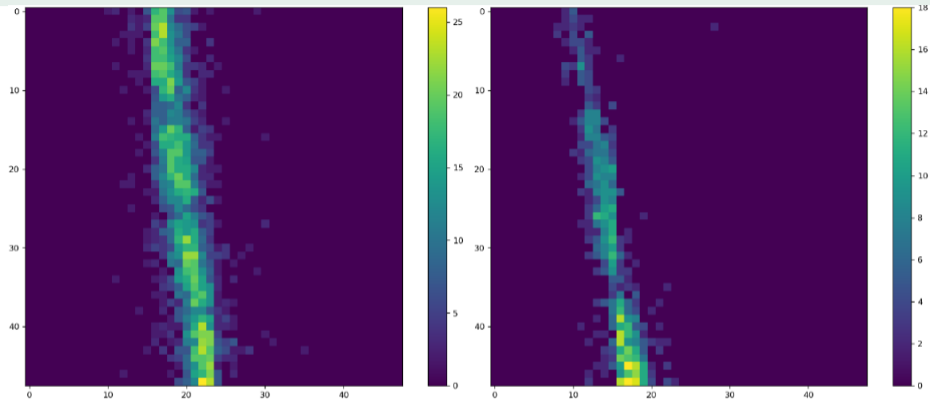
Телескоп-рефрактор: две линзы Френеля  $\varnothing 1$  м, фокальная поверхность  $48 \times 48$ .

# Ingredients

- CONEX (QGSJet-II)
- Offline (eyeCentric).  
The core of EASs is within the projection of the EUSO-TA FoV on the ground.
- Two sets of events with energies in the range 5...100 EeV (one log-uniform, another quasi uniform)
- Elevation angle  $10^\circ$ .
- Data selection:
  - `HasTrigger = True`
  - In the pure signal, the number of GTUs with non-zero signal is  $> 1$ .
  - In `IntTrack`, the distance between pixels with  $> 2$  photon counts is  $\geq 24$  (to exclude dim “clouds”)
- The number of events used for training: 40–50 thousand. Test: 200 events.
- The convolutional network is almost the same as used for EUSO-SPB2.
- The background was simulated but not used yet.

At the moment, I omit the stage of track recognition because it is clear how to implement it, and work only with pure signals. According to the SPB2 experience, this isn't crucial.

## Наземный телескоп: сигнал зависит от расстояния до оси ливня



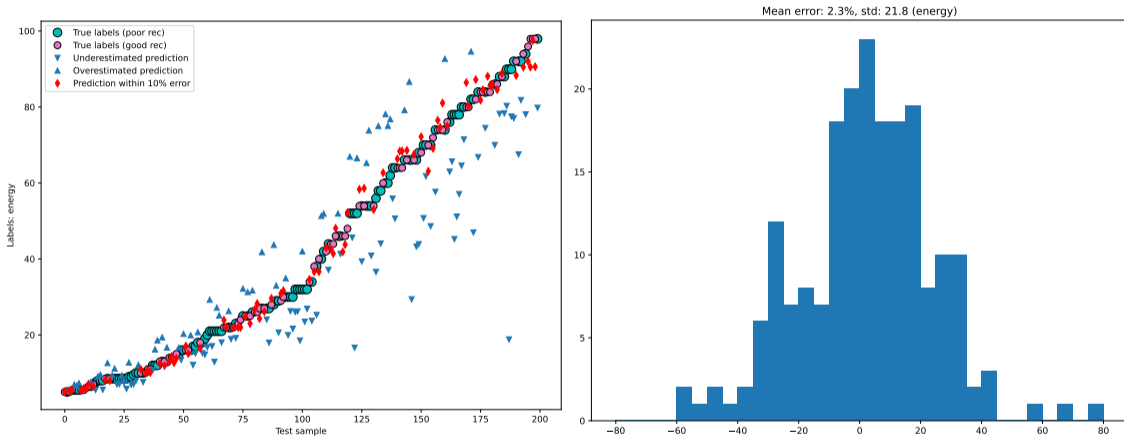
Пример интегральных треков

Слева:  $E = 38 \text{ EeV}$  ( $D = 10.6 \text{ km}$ ),  $\theta = 33^\circ$ ,  $\phi = 173^\circ$

Справа:  $E = 92 \text{ EeV}$  ( $D = 18 \text{ km}$ ),  $\theta = 42^\circ$ ,  $\phi = 15^\circ$

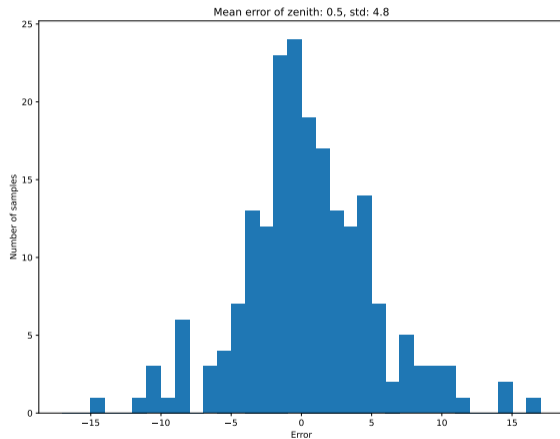
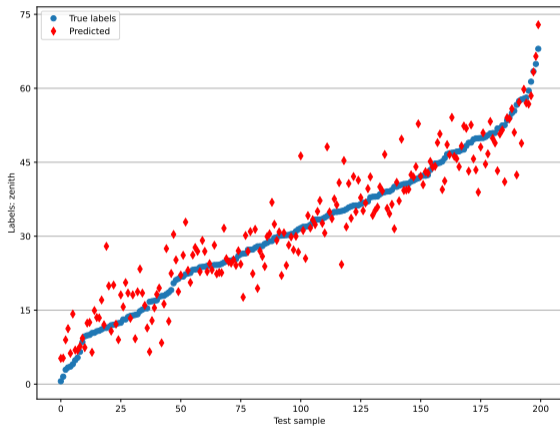
Маленькое поле зрения  $10.5^\circ \times 10.5^\circ$ . Практически нет полных треков.

# Reconstruction of energy. Metric: MAPE = 17%



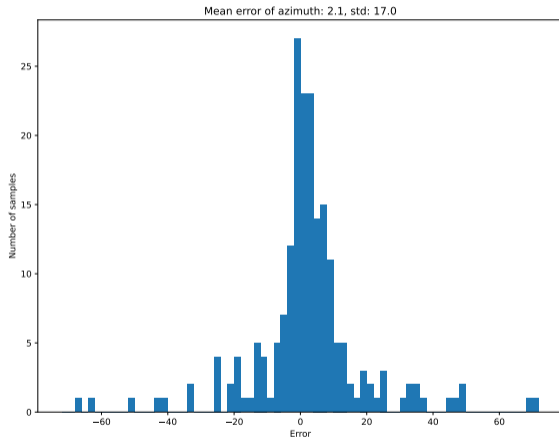
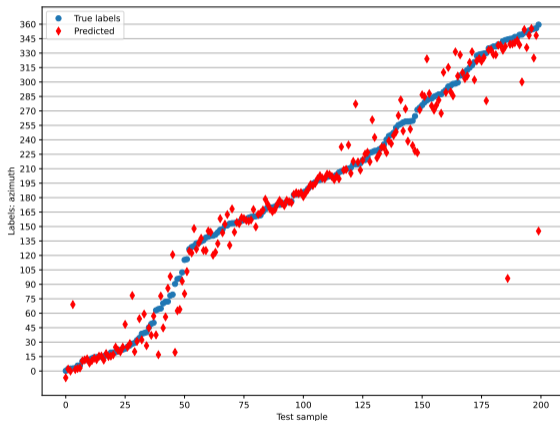
Left: true labels vs. predicted ones (units: EeV).  
Right: histogram for percentage error  $100(\text{true}-\text{predicted})/\text{true}$

# Reconstruction of zenith angles

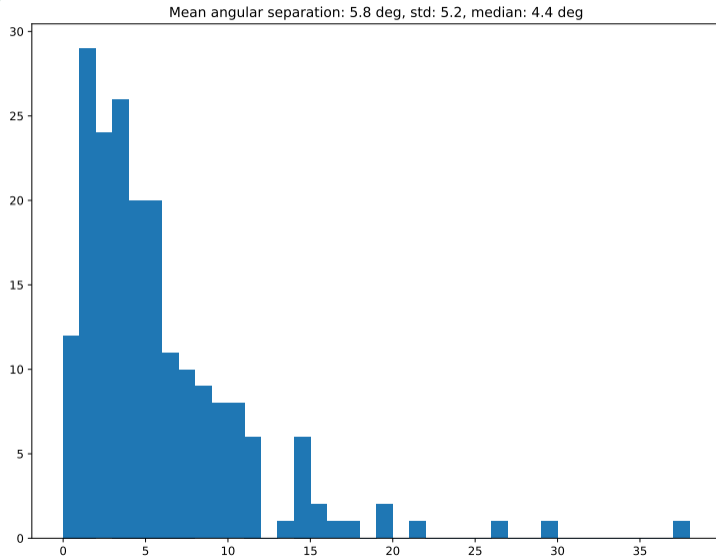




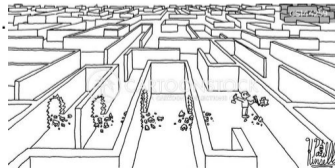
# Reconstruction of azimuth angles



# Angular separation between true and predicted arrival directions



- We have developed a pair of simple ANNs aimed at recognition of EAS tracks and reconstruction of CR energy and arrival directions using simulated data for the EUSO-SPB2 and EUSO-TA fluorescence telescopes. (Very) preliminary results for EUSO-SPB2 are available in the [ICRC-2023 proceedings](#).
- To the best of our knowledge, this is the first work of this kind for FTs. Neither TA, nor Auger have published works on ML-based energy/AD reconstruction with FT data.
- The approach is generic and can be applied to other FTs, both in space and on the ground.
- The first results aren't groundbreaking but... Work in progress.



# Backup slides

# Performance Metrics (intrinsically imbalanced data!)

**PR AUC:** area under the precision-recall curve

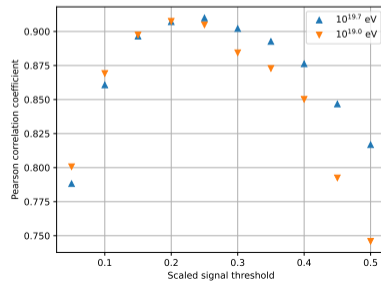
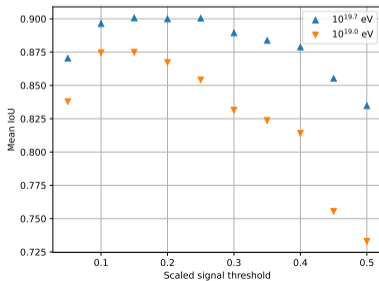
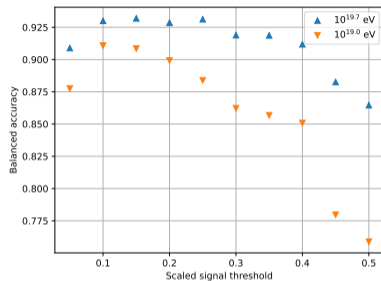
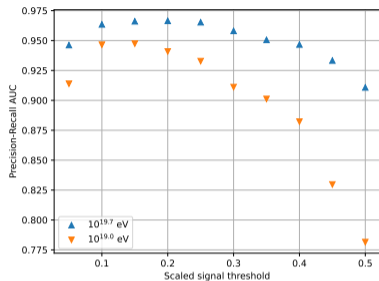
$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \text{Recall} = \text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

**Mean IoU** (a common evaluation metric for semantic image segmentation):

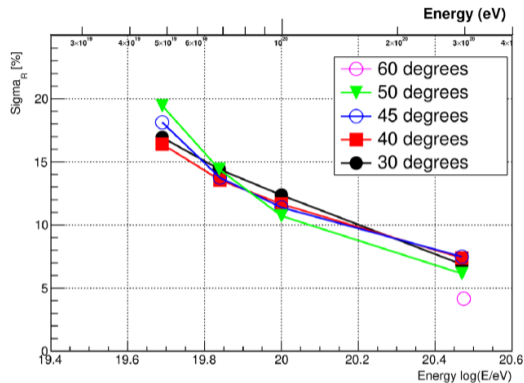
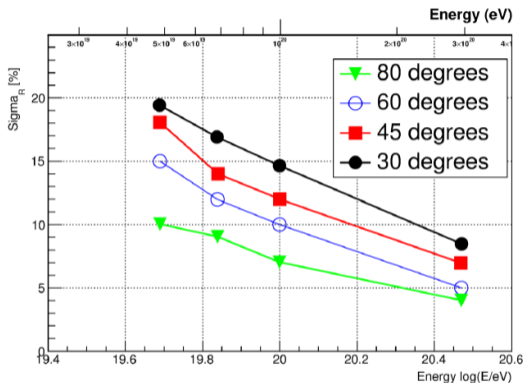
$$\text{Intersection-Over-Union} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}}$$

**Balanced accuracy** (useful when  $\#$  positives  $\ll$   $\#$  negatives):  $(\text{TPR} + \text{TNR})/2$

# Train/test with IntTracks: Test metrics for different cuts at two energies



# Реконструкция энергии для орбитального телескопа JEM-EUSO



Два метода реконструкции энергии КЛ ПВЭ, см. Exp. Astronomy (2015) 40:153.