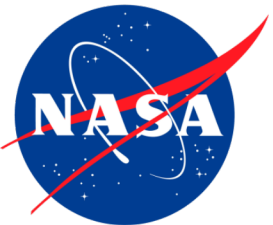


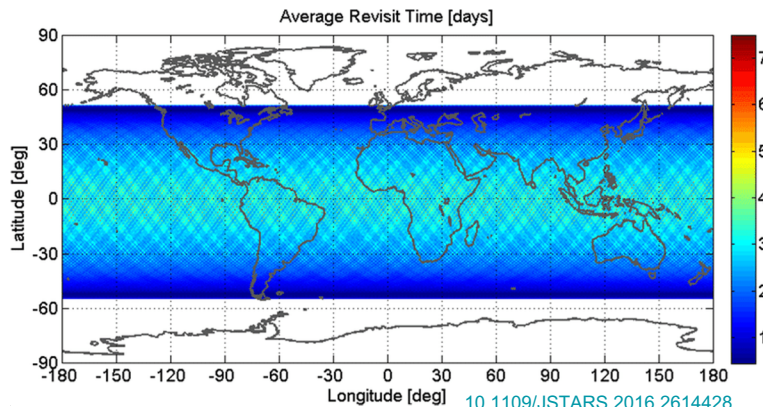
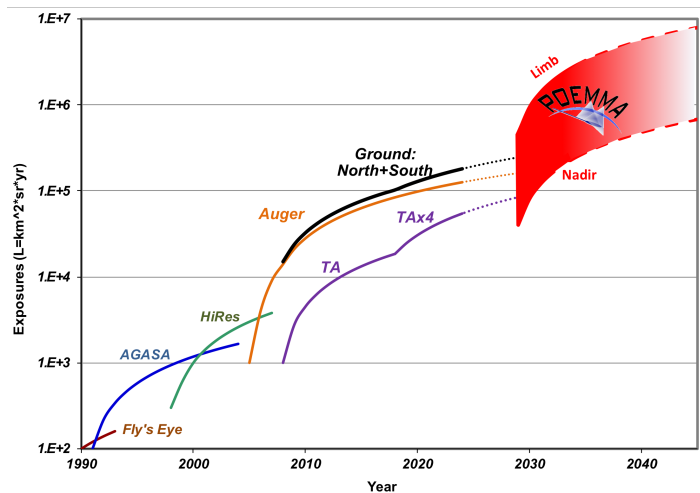


# Neural Network Approaches for Event Classification Onboard EUSO-SPB2

G. Filippatos

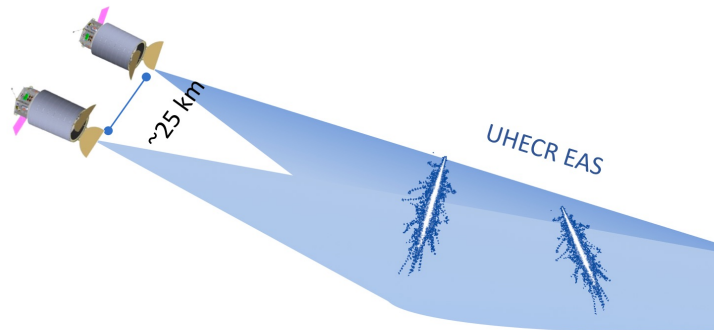


# Space Based Observations of UHECRS: Why?



[10.1109/JSTARS.2016.2614428](https://arxiv.org/abs/10.1109/JSTARS.2016.2614428)

- Large aperture
- Full sky coverage
- X-Max  $\rightarrow$  composition dependent anisotropy possible



[arXiv:2012.07945](https://arxiv.org/abs/2012.07945)

# The story so far . . .



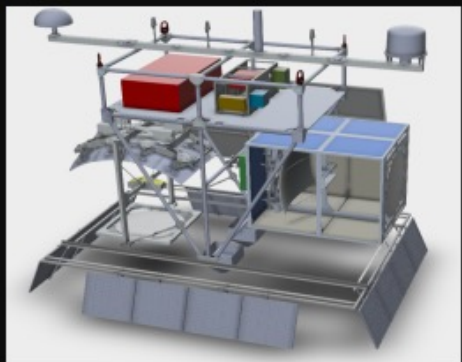
EUSO-Balloon

2014 Timmins



EUSO-SPB1

2017 Wanaka



EUSO-SPB2

👉 (2023) Wanaka 👈



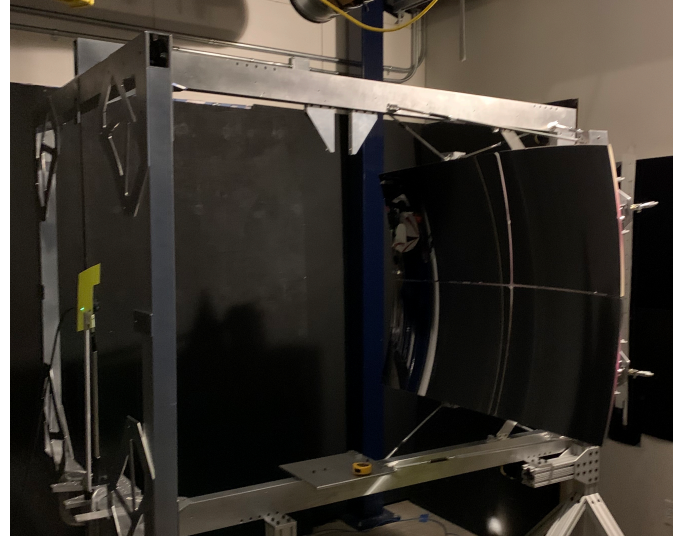
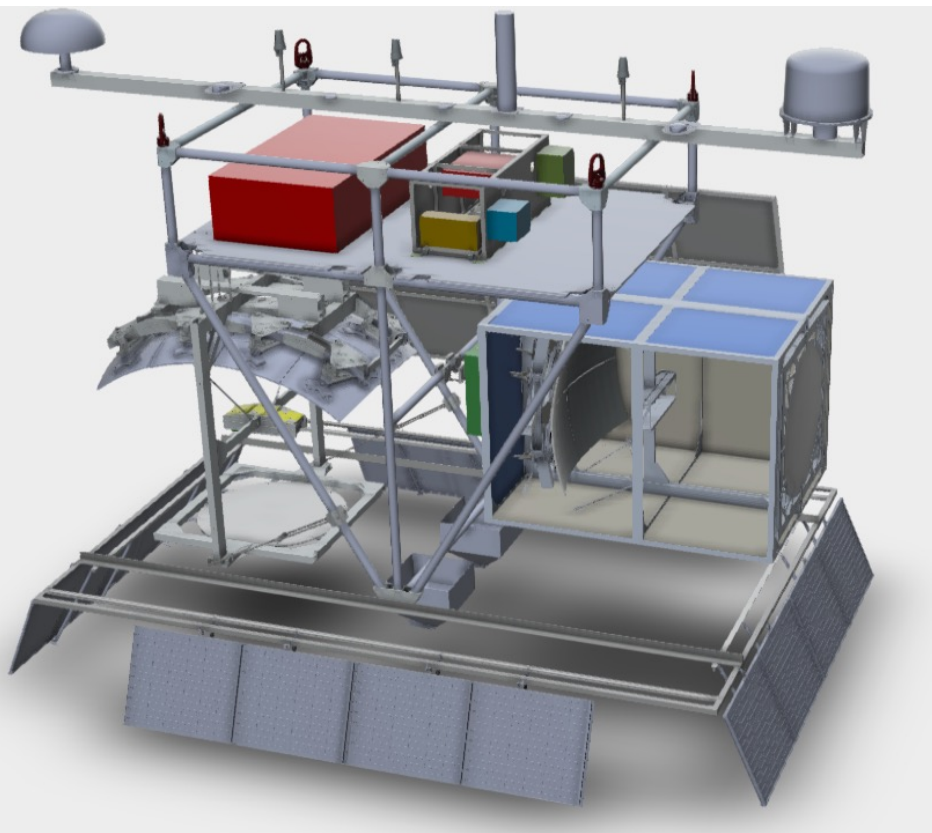
POEMMA

(2029) Earth Orbit

K-EUSO

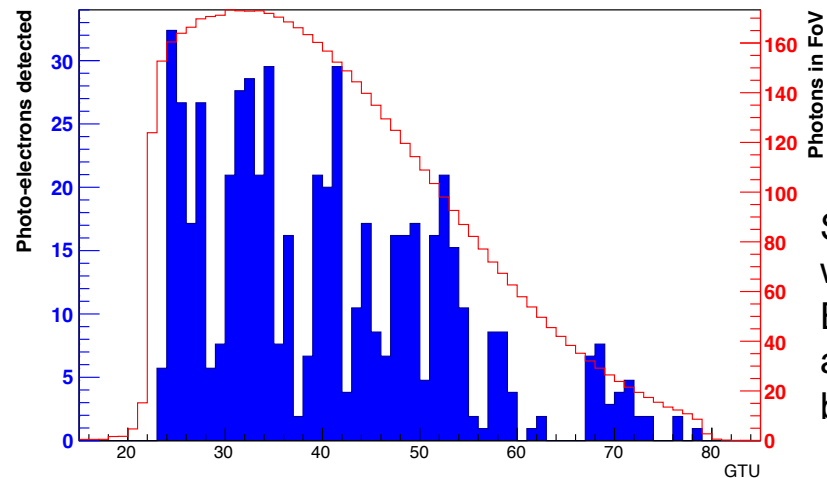


# EUSO-SPB2

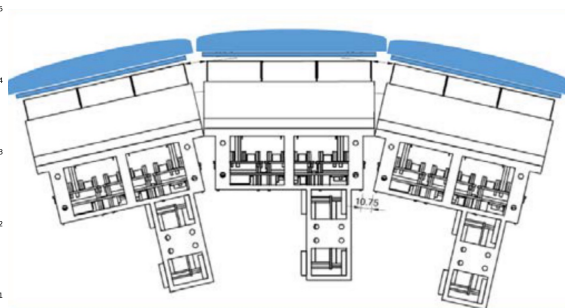
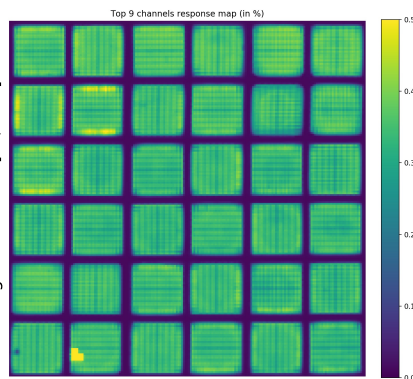
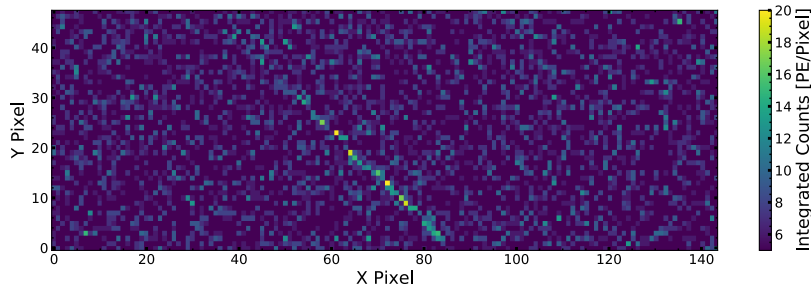
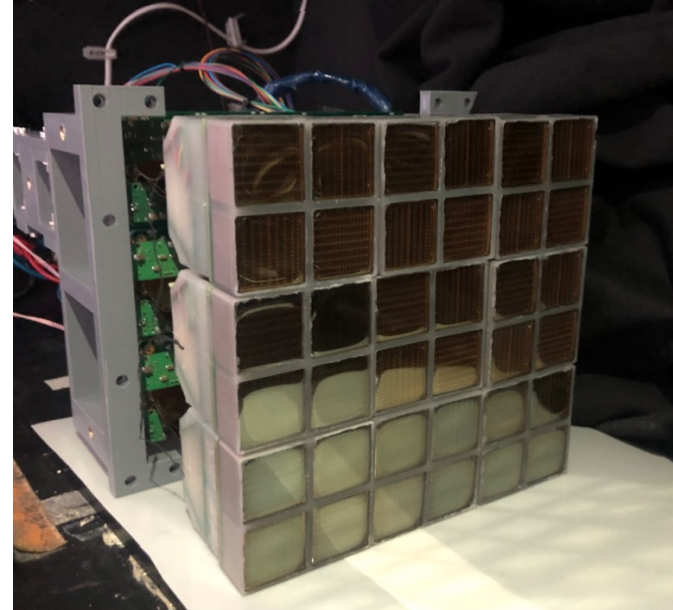


# The Fluorescence Camera

Example Event



Simulated shower with Energy  $E = 3 E_eV$ ,  $\theta = 57^\circ$ , and ideally placed below detector





# Technical Challenges

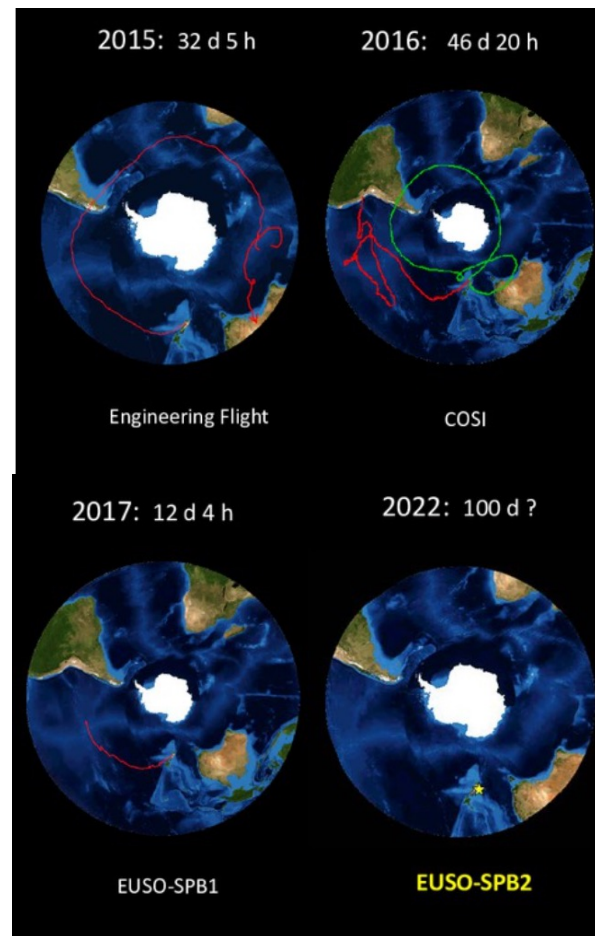
No guarantee of recovery

Limited telemetry to be shared with two telescopes + housekeeping/operations

**~1-5% of recorded FT events will be downloaded**

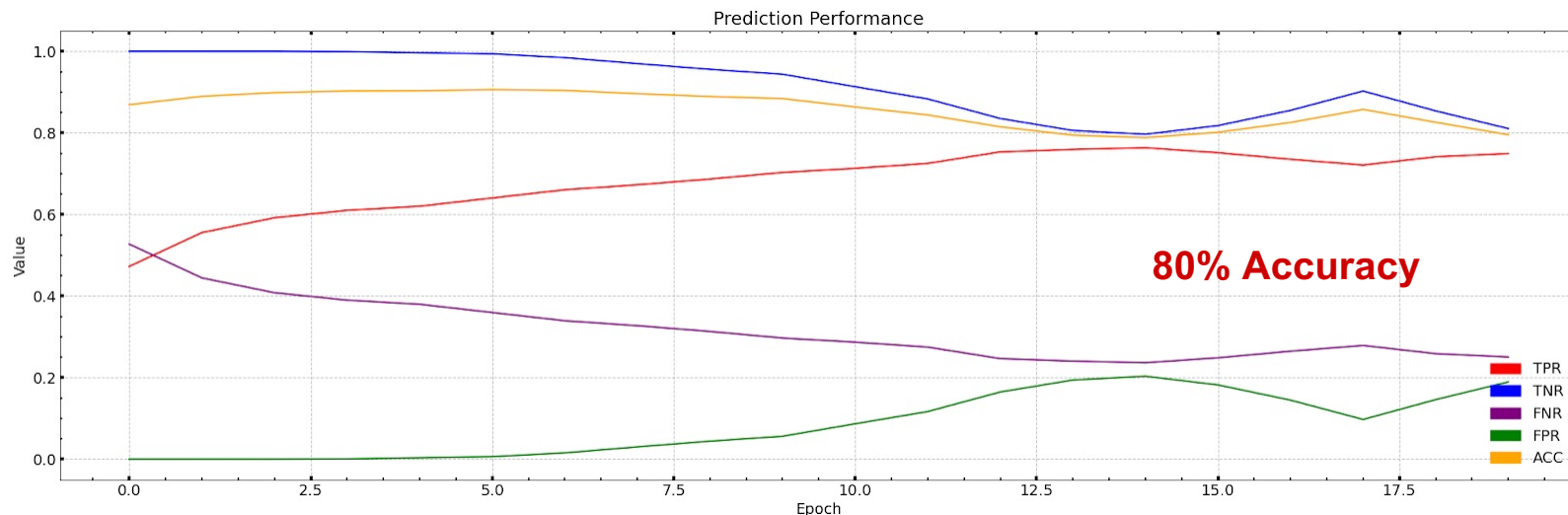
<<1% of recorded events will be EAS

Want a robust, computationally efficient way to identify events for high priority download.

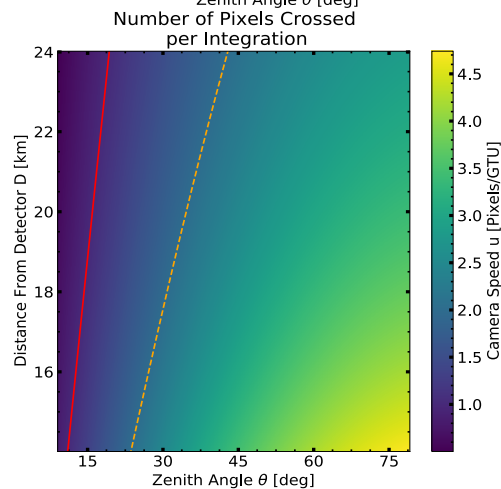
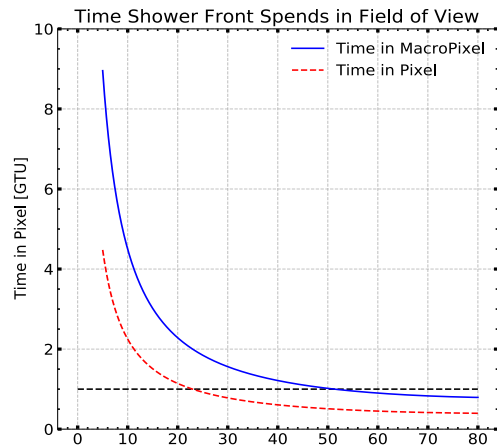


# Convolutional Neural Network

- Binary classifier trained on simulated EAS and simulated noise,  $\sim 10^4$  of each
- First attempt trained on entire event, averaging prediction of each frame to assign a prediction label



# The “Macro-Pixel”



1	4	1	1	2	3	3	2	4	1	3	2	2	1	0	1
0	2	1	2	1	3	5	5	2	2	1	0	2	0	3	1
3	2	1	2	5	7	2	3	0	2	0	3	1	1	0	4
5	0	3	2	1	4	2	4	5	2	1	2	0	0	2	1
0	1	2	6	3	3	2	3	2	1	1	4	2	1	1	0
3	1	3	4	1	1	0	1	1	1	0	2	1	2	1	2
1	5	2	1	2	3	1	1	1	5	2	1	2	0	3	2
0	1	1	2	4	1	0	2	0	1	1	2	4	1	2	6
0	3	2	0	0	0	1	0	2	3	2	1	1	1	1	1
1	2	4	2	1	1	1	2	1	4	1	2	2	0	3	1
1	3	2	1	2	0	3	4	3	3	1	4	0	1	2	3
5	2	2	3	0	1	2	1	1	1	2	1	0	3	3	2
1	1	0	1	3	1	3	1	1	0	1	1	2	1	1	1
3	1	3	4	1	0	0	2	0	2	1	1	2	0	0	2
1	5	2	1	3	1	3	1	1	1	2	1	1	2	1	1
0	1	1	2	1	0	2	0	0	1	1	2	1	1	2	1

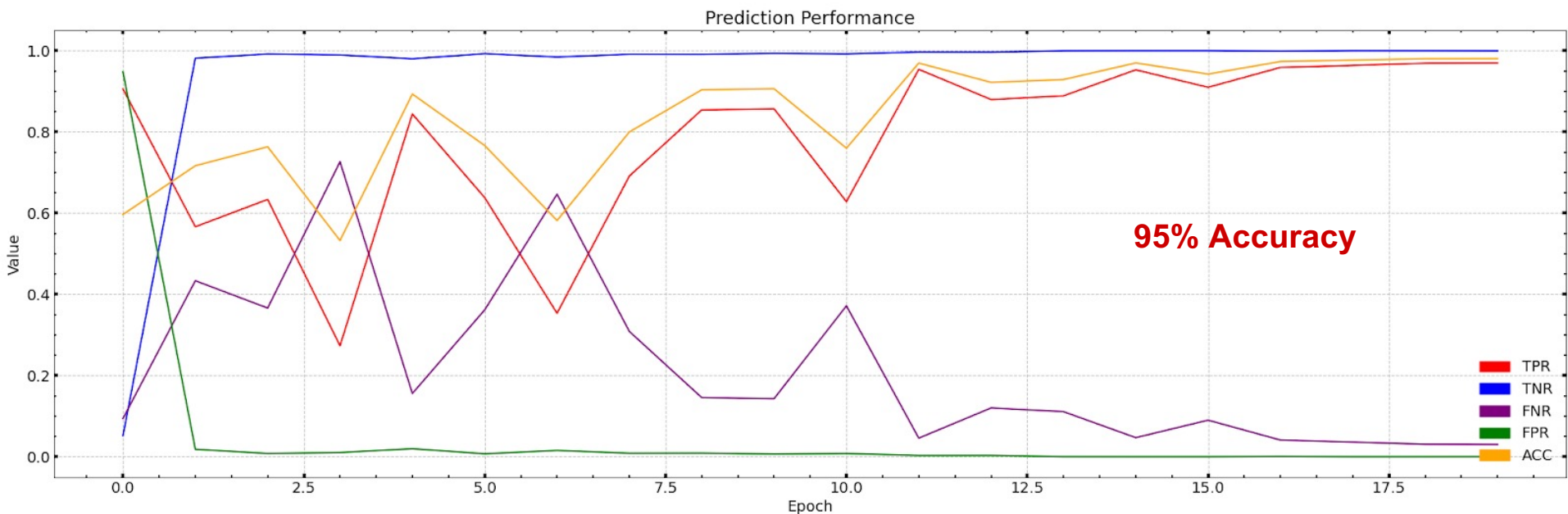
4 MAPMTs at pixel level

7	5	9	15	9	6	5	5
10	8	17	11	9	6	2	7
5	15	8	6	5	7	6	4
7	6	10	4	7	6	7	13
6	8	2	4	10	6	4	6
11	8	3	10	8	8	4	10
6	8	5	6	3	4	5	4
7	6	5	6	3	6	5	5

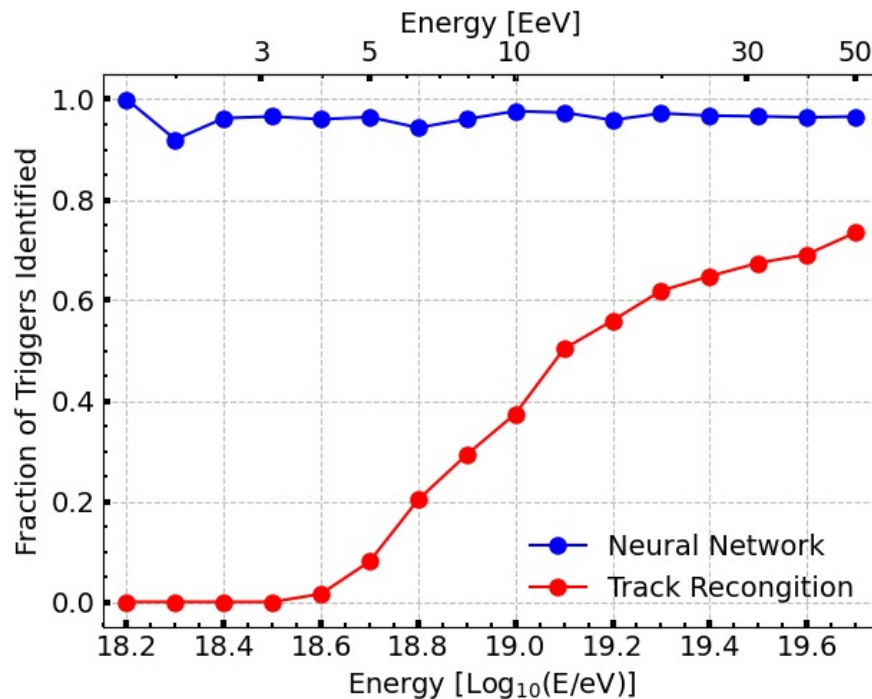
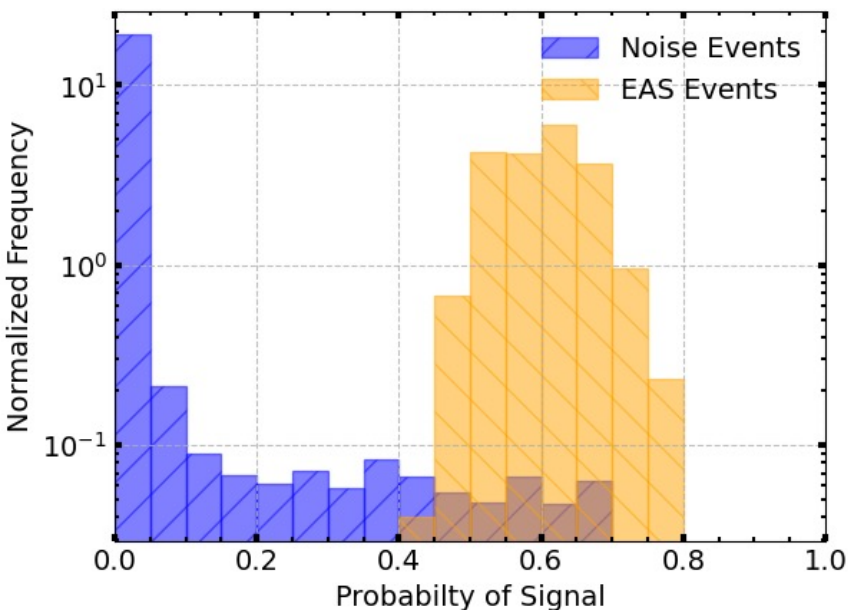
The same 4 MAPMTs at MacroPixel level



# Convolutional Neural Network – Macro-Pixels

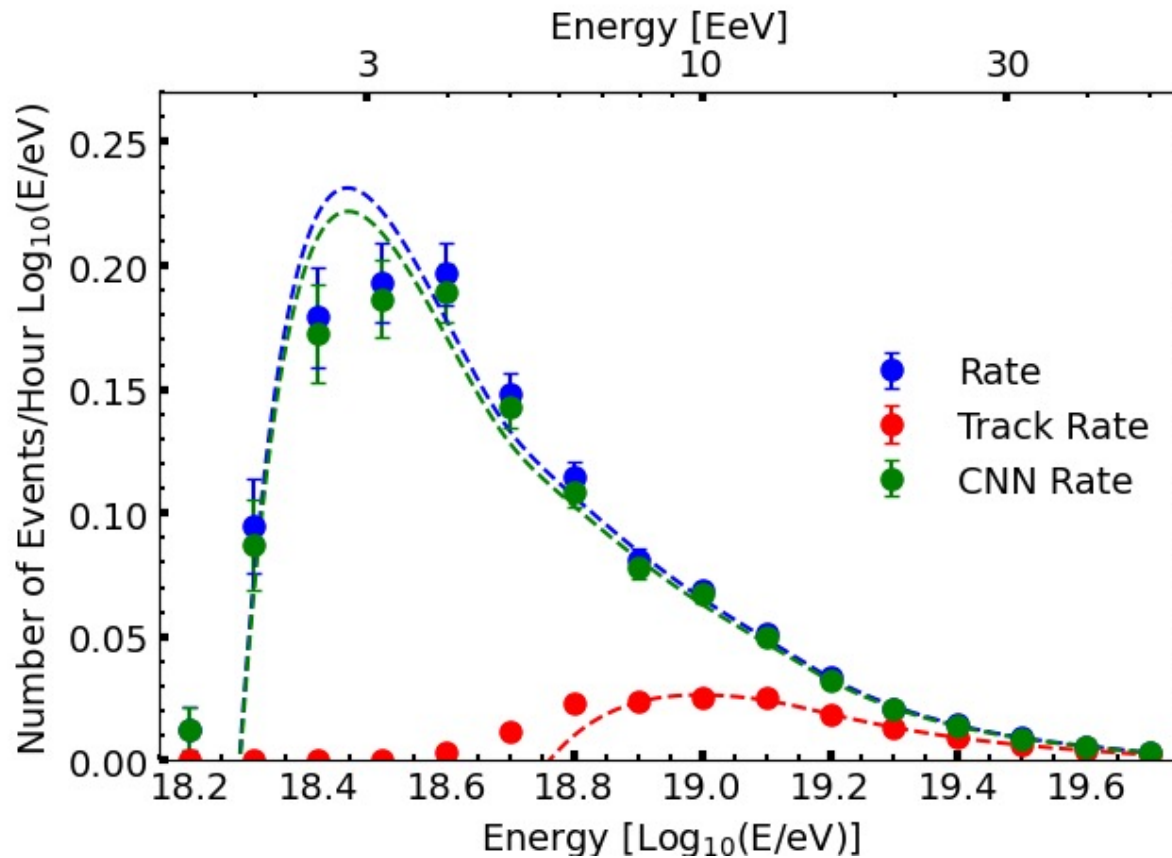


# Convolutional Neural Network – Macro-Pixels



- Specifics: 5-layer CNN, Adam's optimizer, LR 0.001, L2 penalty of 0.01, 20 epochs, 20% dropout rate

# Impact on recorded event rate



# Using NN to classify Mini-EUSO Data

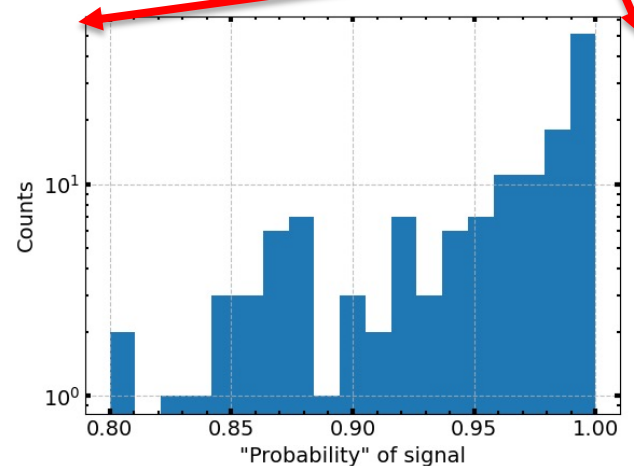
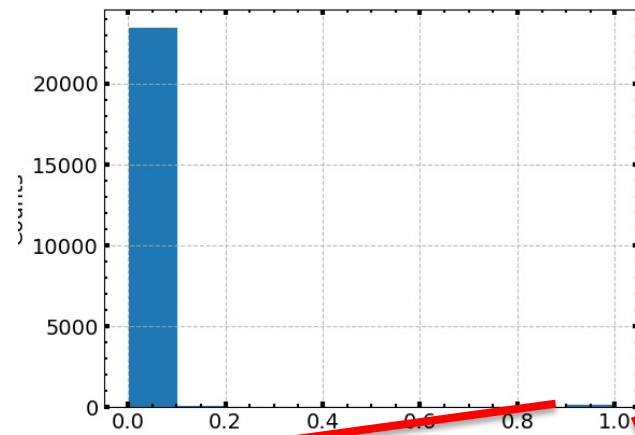
ISS



Mini-EUSO

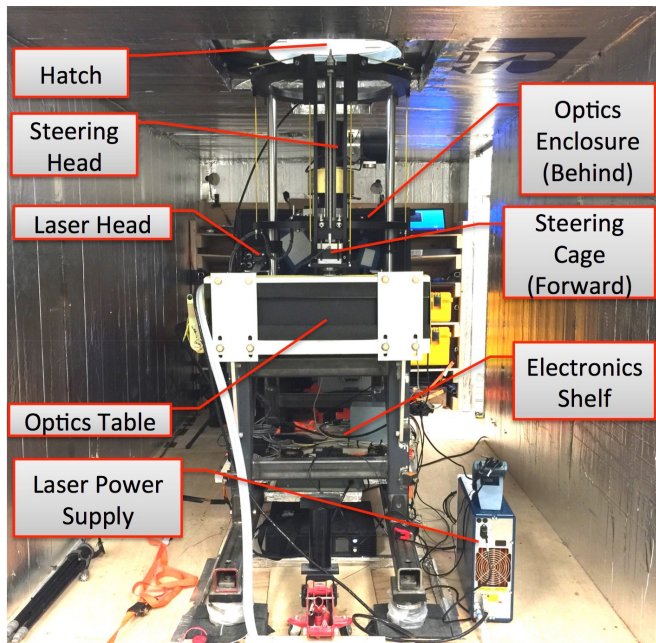
UV-transparent window

<https://twitter.com/KudSverchkov/status/1342023781854961665?s=20>

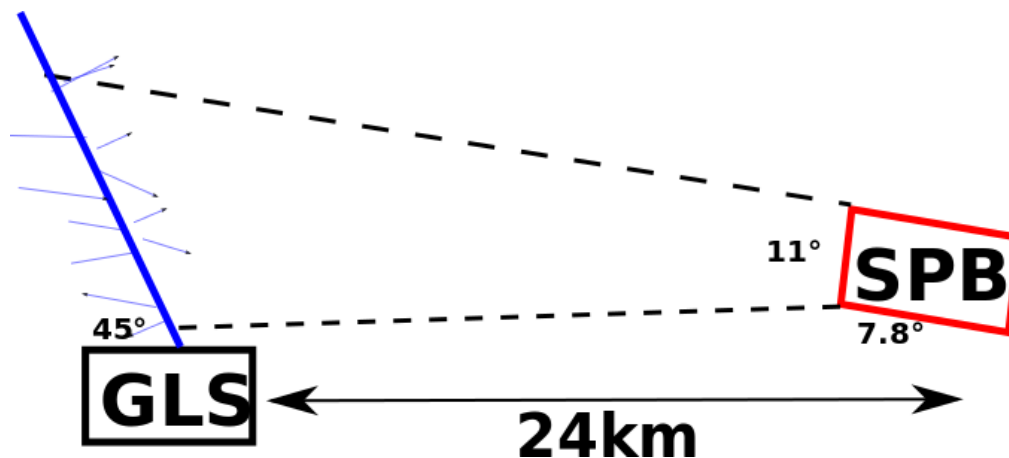


# Field Tests

[10.22323/1.236.0626](#)



Steerable laser:  
355 nm  
0.25-80 mJ (5% acc.)  
Pointing acc.  $0.2^\circ$





# Convolutional-Recurrent NN

Input shape: [-1, 2, 20, 48, 48]

-1 denotes batch size

2 represents the two records of the same angle (should be described similarly)

Convolutional module processes every frame in each record

Output shape: [-1, 2, 20, 784]

One 784-dimension vector to describe each frame of input

RNN module processes frame vectors sequentially

Output shape: [-1, 2, 784]

One 784-dimension vector to describe each sequence in the input

Obtain sequence *projections* for each record

Output shape: [-1, 2, 36]

Calculate contrastive loss using projections

**\* Load pre-trained model weights \***

Input shape: [-1, 20, 48, 48]

-1 denotes batch size

Convolutional module processes every frame in each record

Output shape: [-1, 20, 784]

One 784-dimension vector to describe each frame of input

RNN module processes frame vectors sequentially

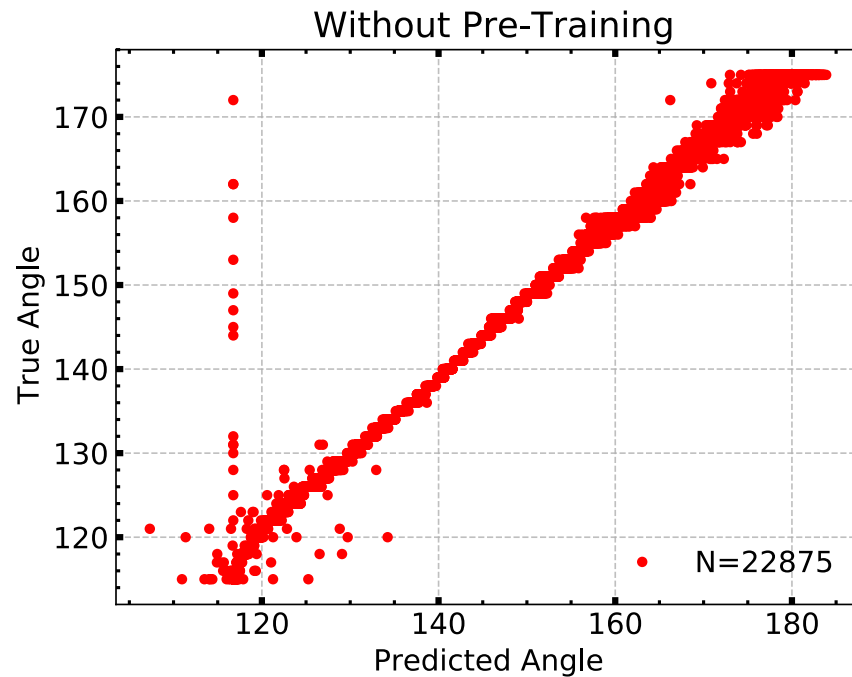
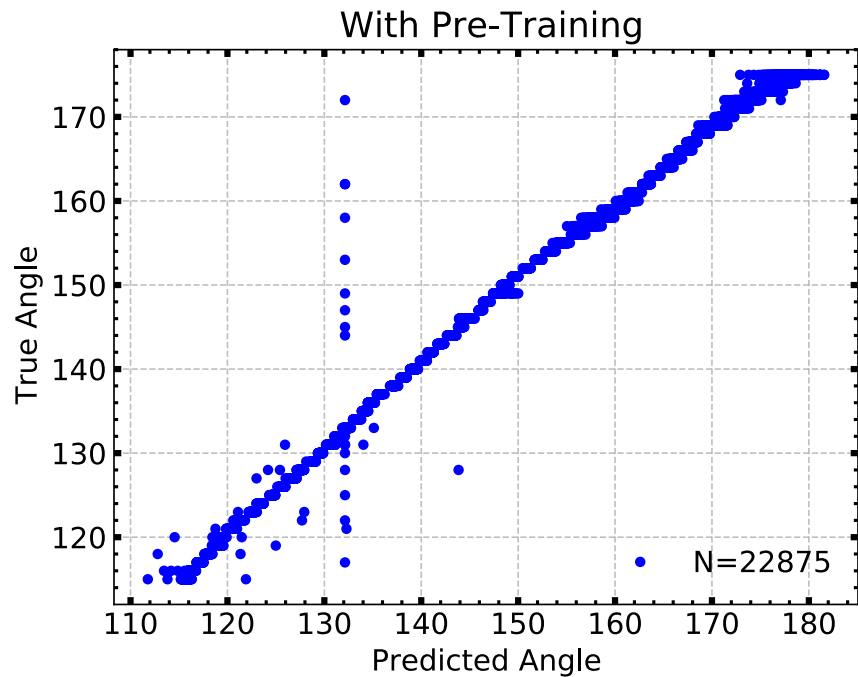
Output shape: [-1, 784]

One 784-dimension vector to describe each sequence in the input

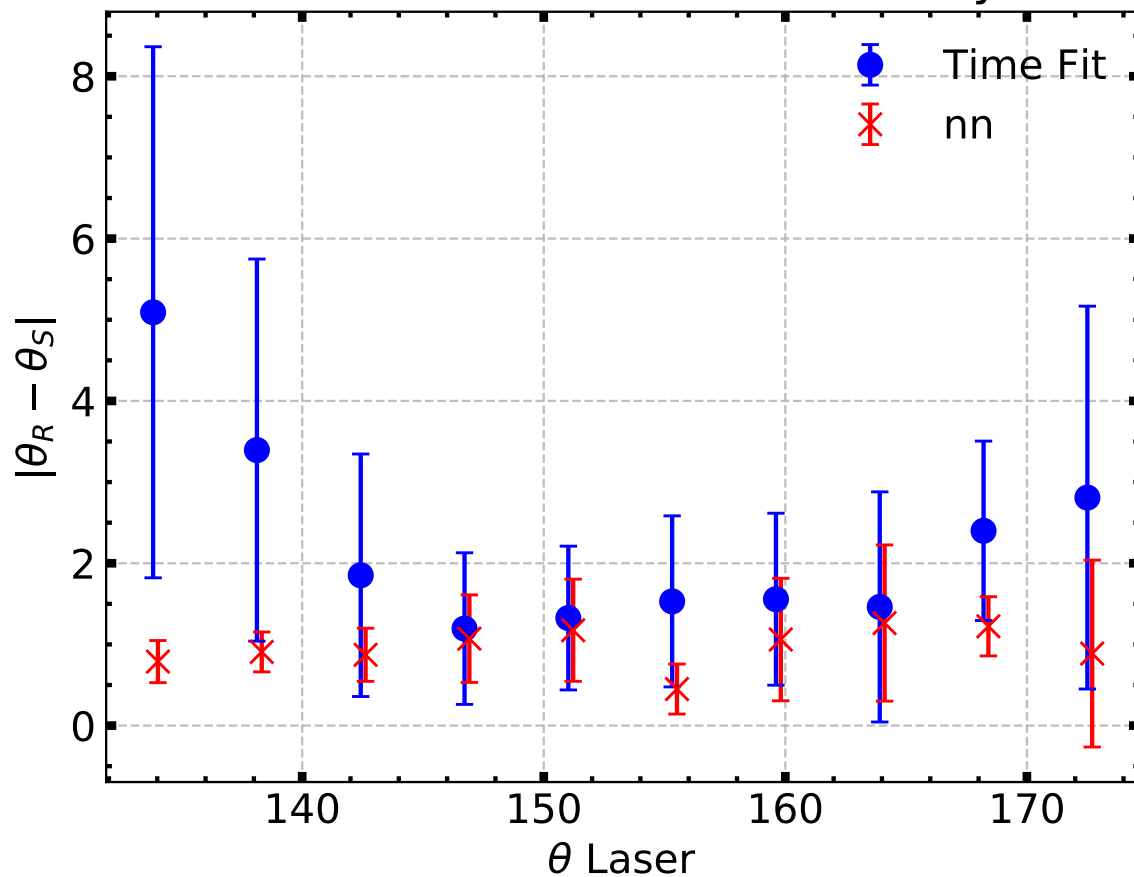
Use sequence embeddings to predict the angle of the record

Minimize MSE(predictions, labels)

# Impact of Pre-Training



# Comparison with standard reconstruction







# Conclusions

- CNN shows promise for onboard classification of EAS events for EUSO-SPB2
- More complex models show promise for offline analysis/event reconstruction
- Both techniques can be validated prior to flight during field tests using controlled laser shots

This research used resources of the National Energy Research Scientific Computing Center (NERSC), a U.S. Department of Energy Office of Science User Facility operated under Contract No. DE-AC02-05CH11231.



# Extras



# Hardware Trigger

- Works at MacroPixel level (i.e. sum of a 2x2 square grid of pixels)
  - residence time in a pixel for medium to high inclined shower is less than  $1\mu\text{s}$ . MacroPixels fully contain the signal.
- Adaptive threshold independent for each MacroPixel
  - Background estimated by the integral of 16ms of data ( $AVG_i$ )
  - Background values saved for exposure estimation
  - Threshold set  $n_\sigma$  [5] above the background level of each MacroPixel
  - Threshold updated every 500ms

$$AVG_i = \frac{1}{16384} \sum_{GTU=0}^{16383} \sum_{PXL=0}^4 PXL_i(GTU)$$

$$THR_i = AVG_i + n_\sigma \sqrt{AVG_i}$$

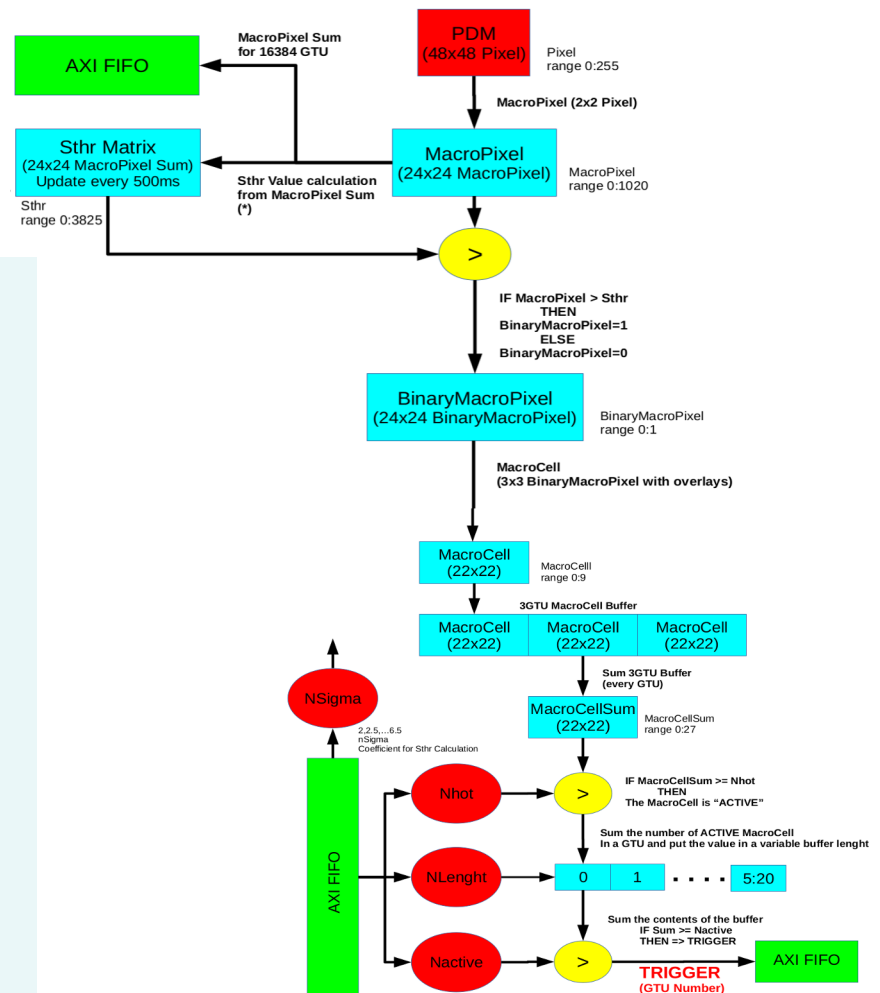
# Hardware Trigger

The following operations are performed every GTU [1 $\mu$ s]:

1. Create a boolean matrix (**BinaryMacroPixel**) with "1" if the MacroPixel is above threshold, "0" otherwise
2. Count all the **MacroPixels above threshold** in a 3x3 grid over 3 consecutive GTUs. This 3x3x3 cell is called **MacroCell**.  
If the value of a MacroCell is  $\geq n_{Hot}$  [2], the **Macrocell** is considered **active**
3. Count how many **Active MacroCells** there are in the entire PDM in **TriggerLength** [20] **consecutive GTUs**. If  $\geq n_{Active}$ , a **trigger** is issued

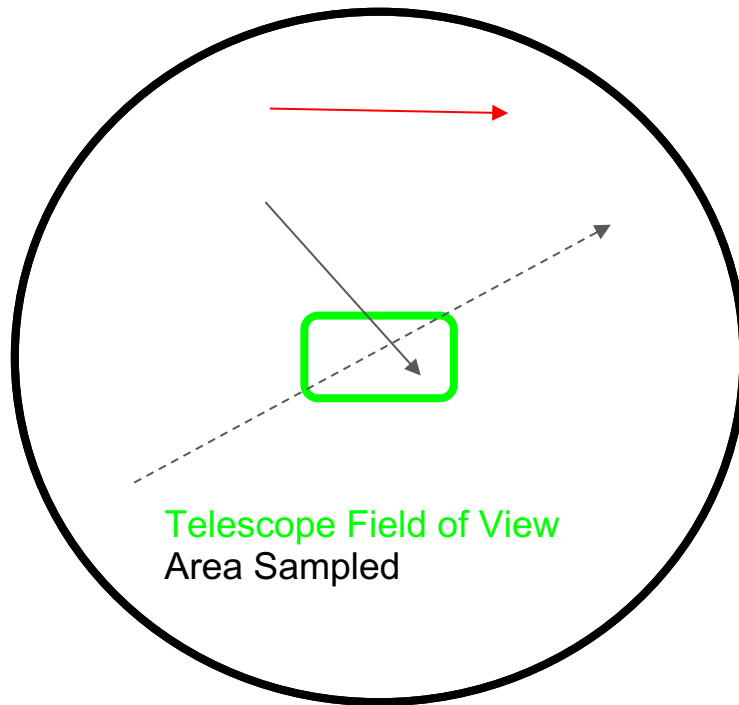
4 parameters to be set from outside:  $n_{\sigma}$ ,  $n_{Hot}$ ,  $n_{Active}$  and **TriggerLength**. The values in square brackets are the best.

Upon the issue of a trigger, **128 $\mu$ s of data** are stored for all the 3 PDMs, 64 before and 64 after the trigger time.



# Event Rate Calculation

- Showers simulated in Conex using EPOS-LHC
- Showers thrown isotropically over a 100 km disk
  - Zenith angles 0°- 80°
  - Energies from 10<sup>17.8</sup>-10<sup>19.7</sup> eV
  - 80k showers per energy
- Converted to event rate using the energy spectrum measured by Auger [\*].
- Geant4 simulation of optics, parametric simulation of electronics in the JEM-EUSO OffLine framework



$$\text{Rate} = \left( \frac{\text{Showers Triggered}}{\text{Showers Thrown}} \right) A\Omega \int J(E)dE$$

[\*] Pierre Auger Collaboration arXiv:2008.06486

# Event Rate Calculation

