Time-domain astronomy with the COMCUBE-S gamma-ray mission

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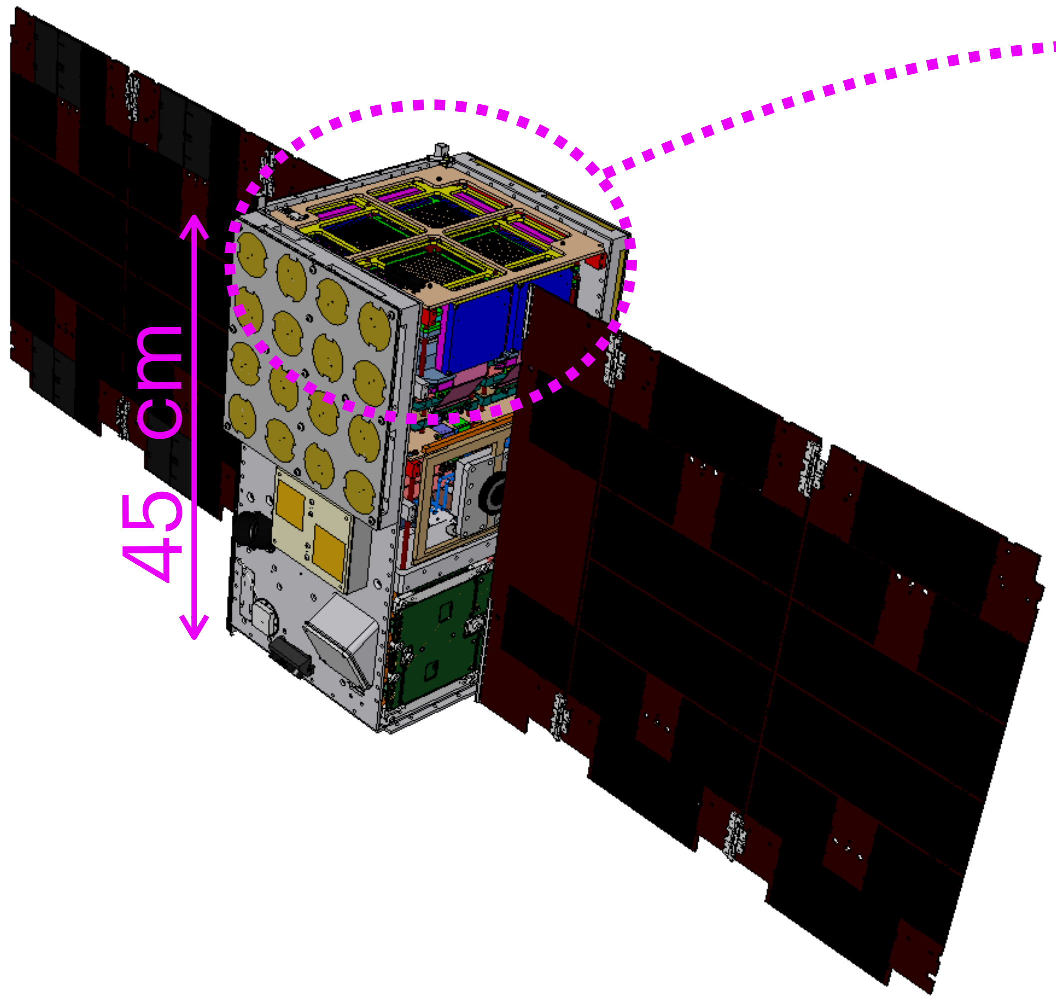
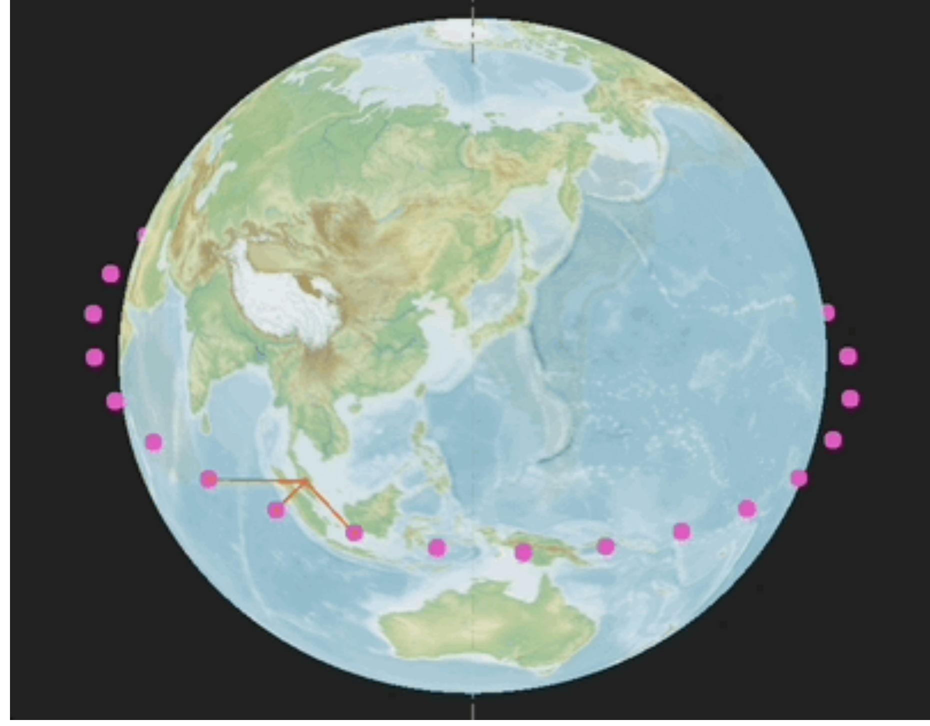
Laboratory : IJCLab

The space mission COMCUBE-S



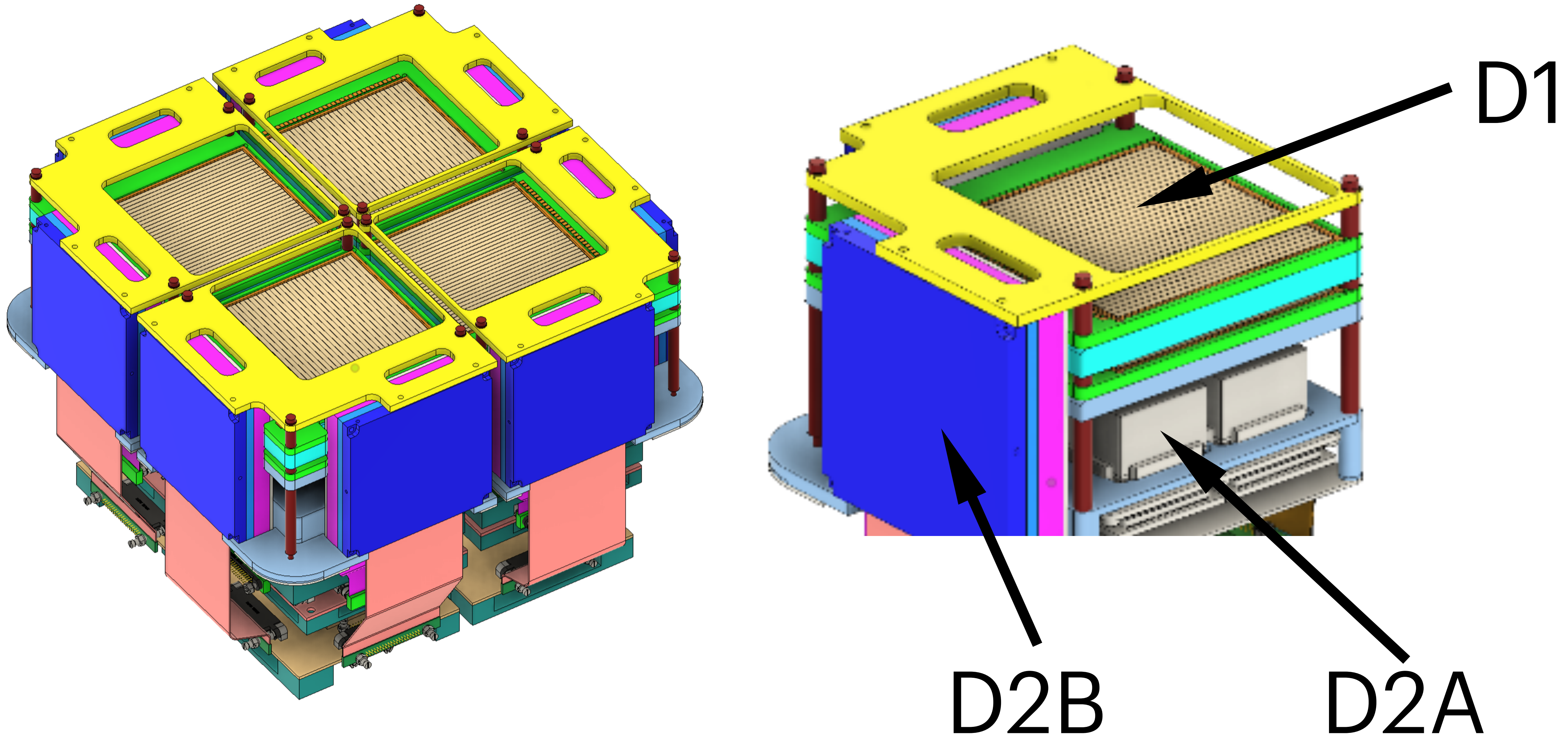


- Main target: Gamma Ray Bursts, to do:
  - Imaging
  - Spectroscopy
  - Polarimetry

- 27 CubeSats in equatorial LEO
- All sky view at all times
- Compton telescope: 30 keV to 2 MeV

- Main science goals:
  - Better understand the physics of GRB jets
  - Gamma-ray sky monitoring for time-domain and multimessenger astrophysics

- Requirements
  - Rapid localisation of transient gamma ray sources
  - Automated source classification ⟶ sending alerts (GCN)



D1: Double-sided Silicon Strip Detector — **8 detectors**

D2A: cerium-doped Gadolinium Aluminium Gallium Garnet — **16 detectors**

D2B: Cerium Bromide — **8 detectors**

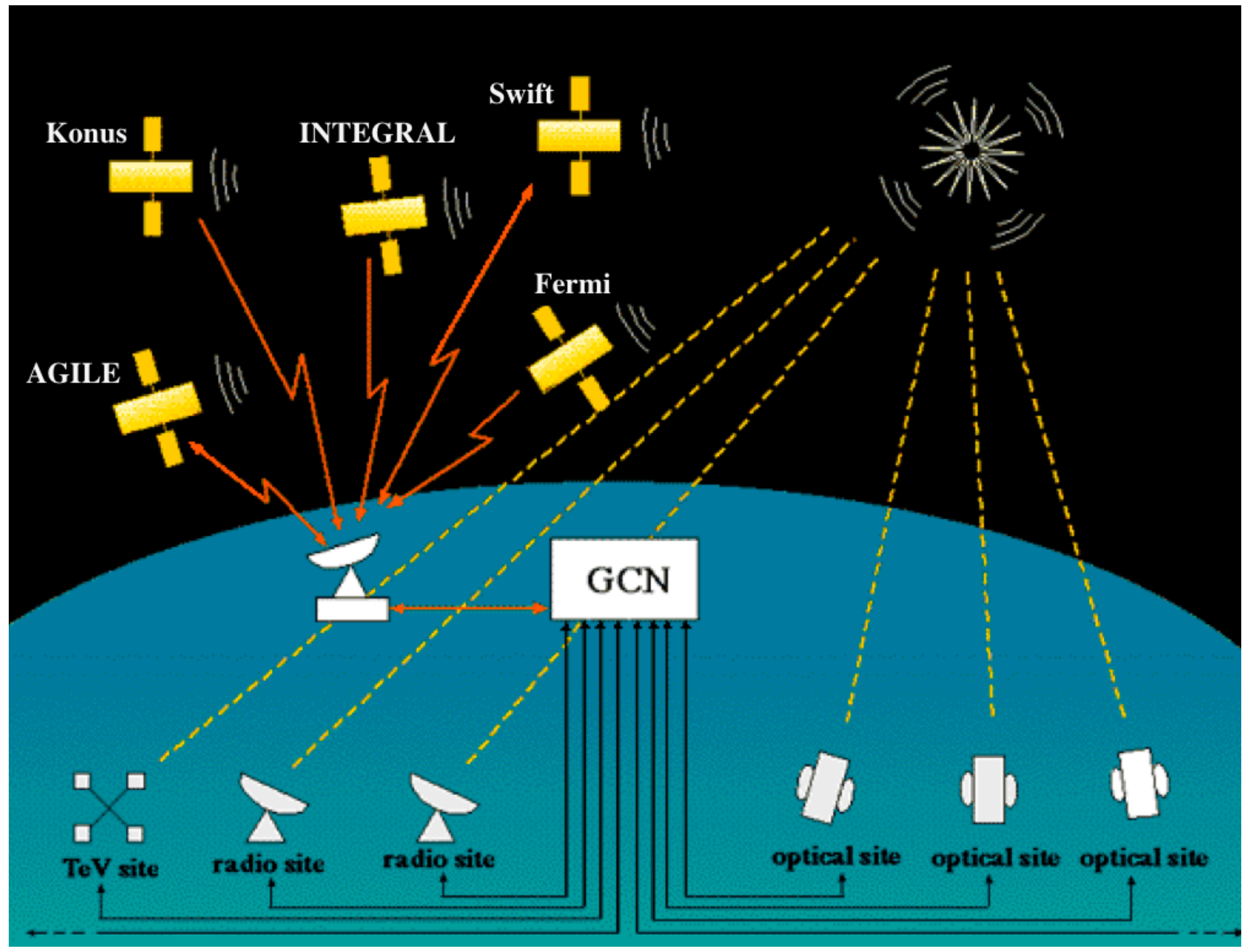
Total : 32 detectors

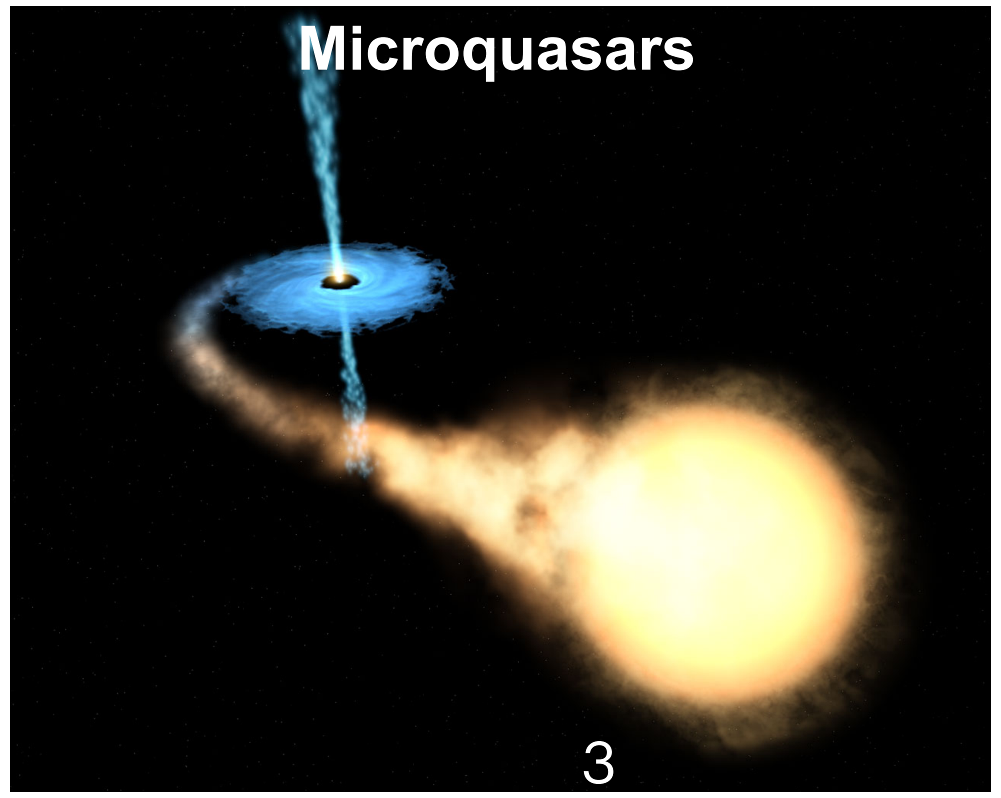
Thesis (2025-2028) :
alert system for COMCUBE-S

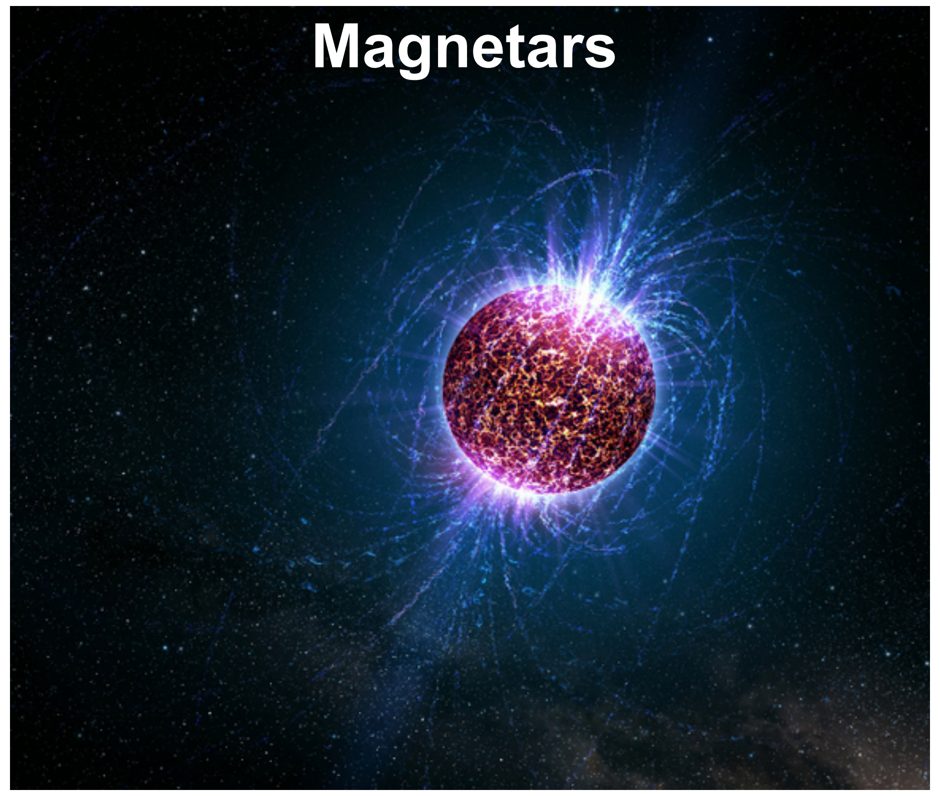
- **Localizing the sources**
- Classification of the trigger types
- Using the broker system FINK developped for Vera Rubin Observatory

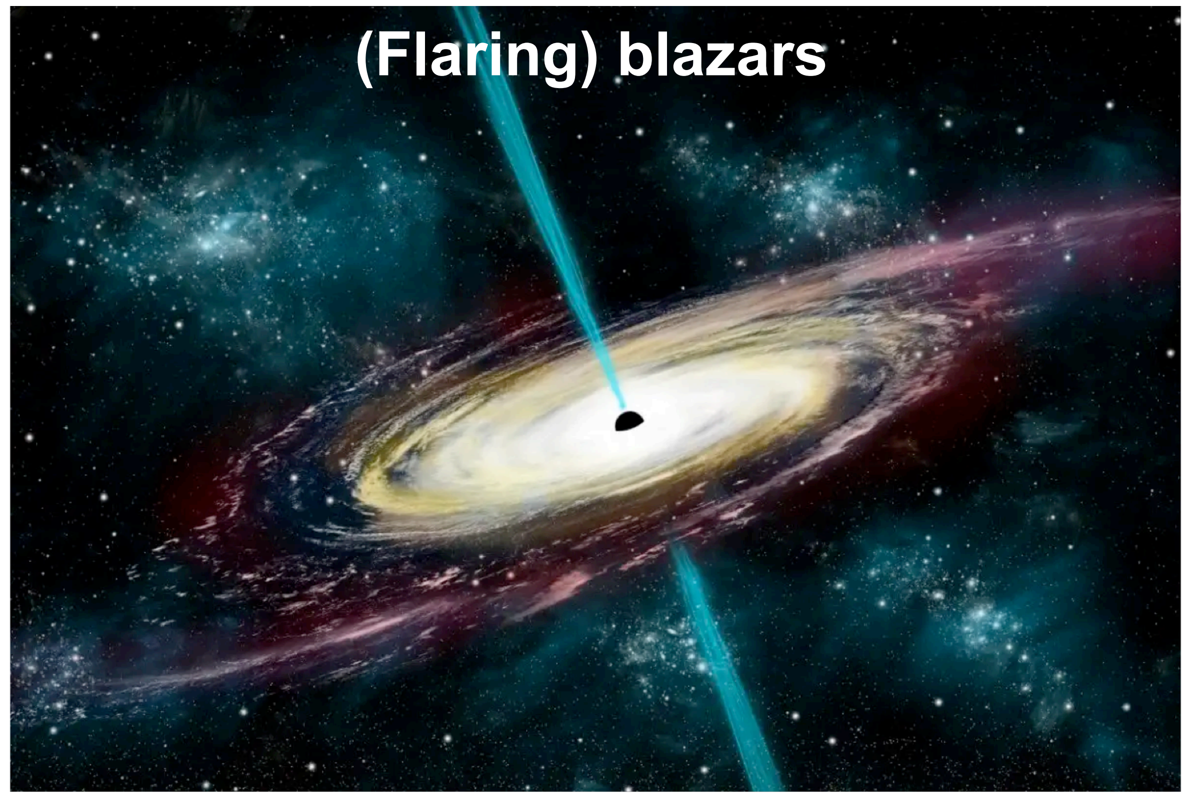
Type	Number	Percentage
Gamma-Ray Burst	3982	34.89%
Solar Flare	2436	21.35%
Local Particles	1561	13.68%
Terrestrial Gamma-Ray Flash	1515	13.28%
Soft Gamma Repeater	662	5.80%
Uncertain	585	5.13%
Generic Transient	448	3.93%
Distance particle event	119	1.04%
Unrelocated	81	0.71%
Below Horizon	20	0.18%
Galactic binary	3	0.03%
Total	11412	

FERMI: GBM trigger catalogue





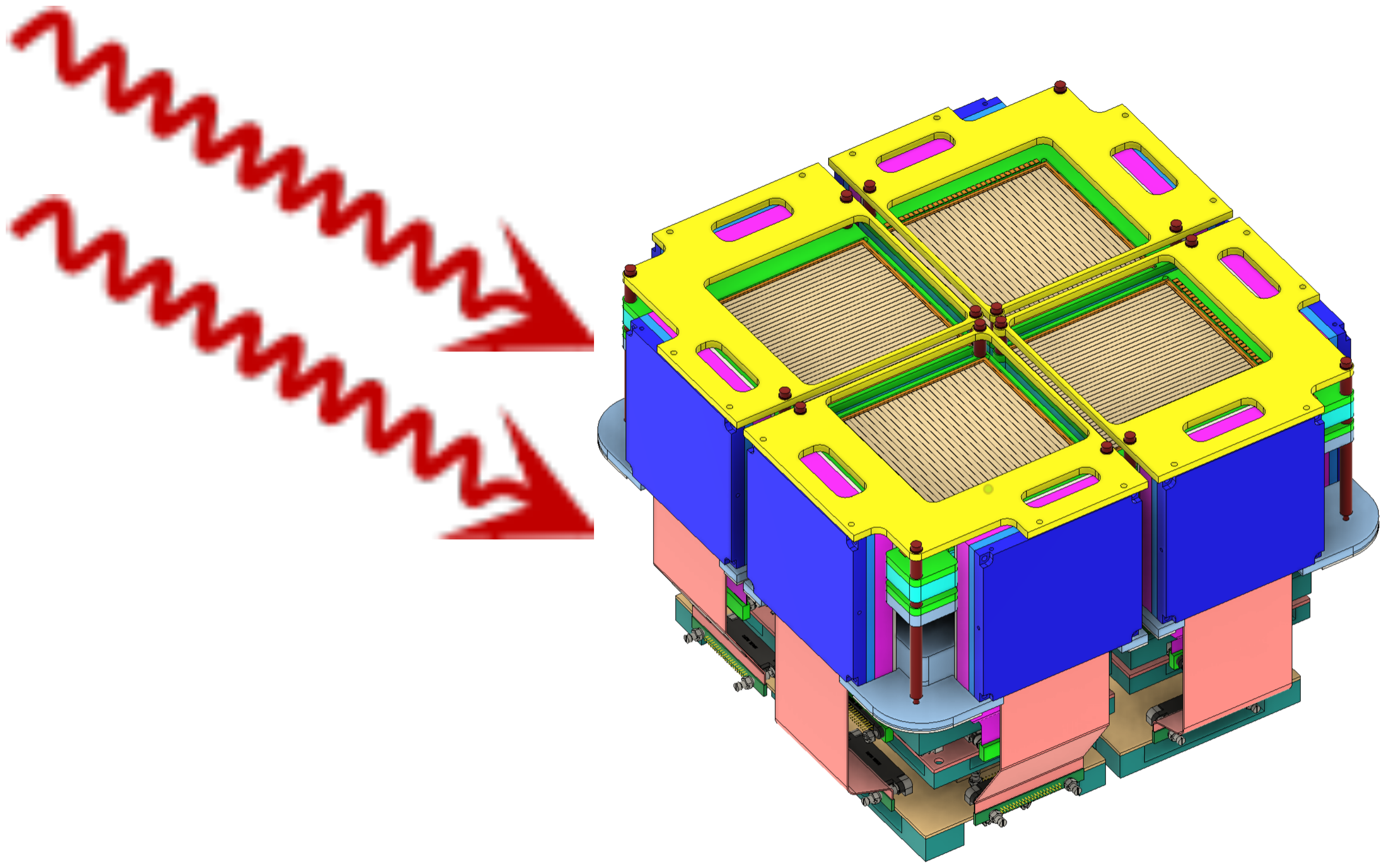




Localizing Sources

Methods

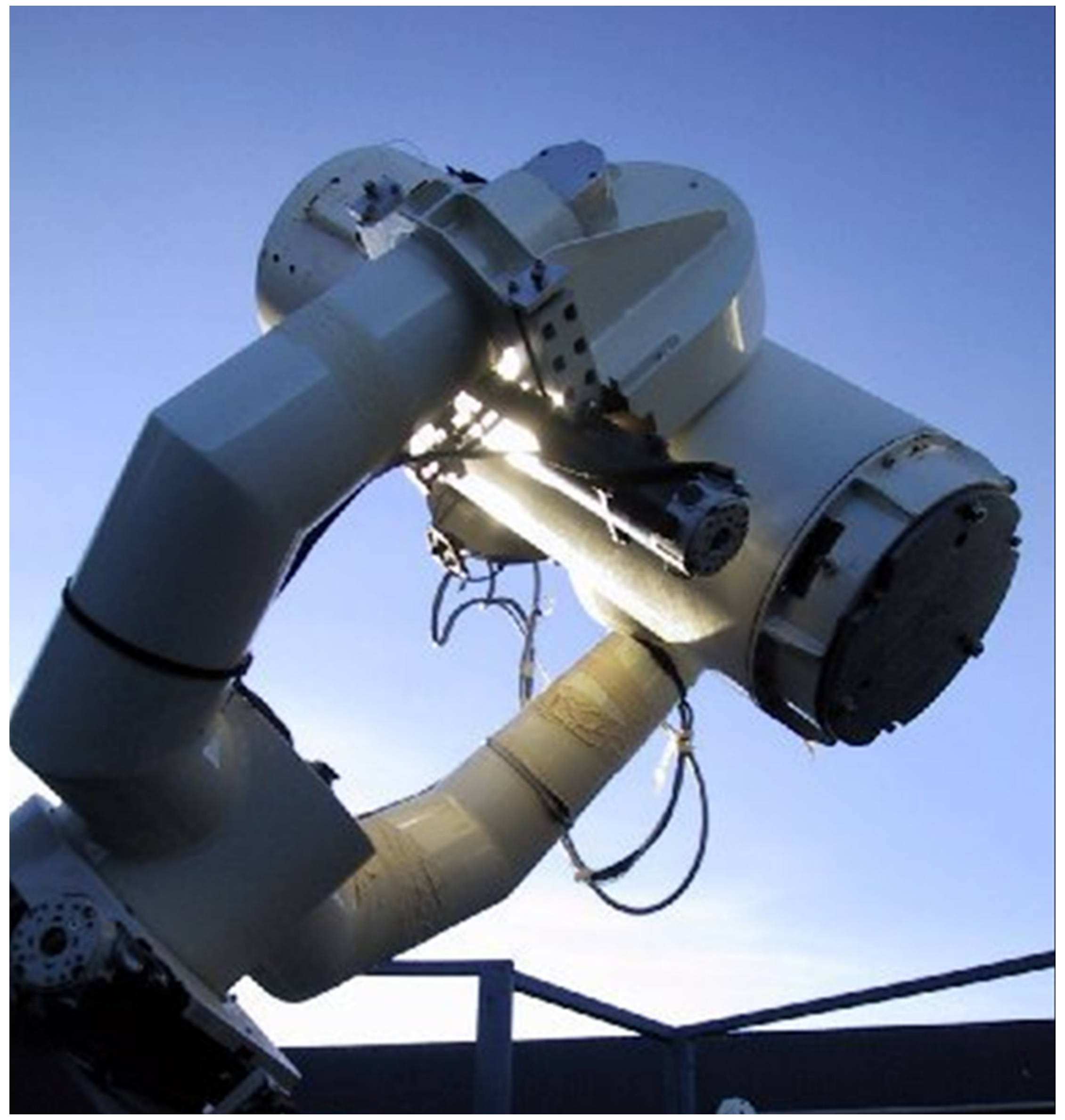
- COMCUBE-S will implement **3 GRB localisation methods** using :
    - (i) Pseudo-range multilateration (time triangulation)
    - (ii) Compton imaging
    - (iii) Relative detector count rates



- The Detector Count Rate method enables **near-real-time localisation** with minimal data transfer via **intersatellite links**
- On-ground calculation from all detector count rates

⇒**Follow-up with robotic optical telescopes** and other facilities

⇒ Requirement to enable prompt follow up : alert **within 60 s** from the trigger time, with **localisation < 2°** **(**95% CL)



TAROT telescope
(Observatoire de la Côte d'Azur)

Localizing Sources

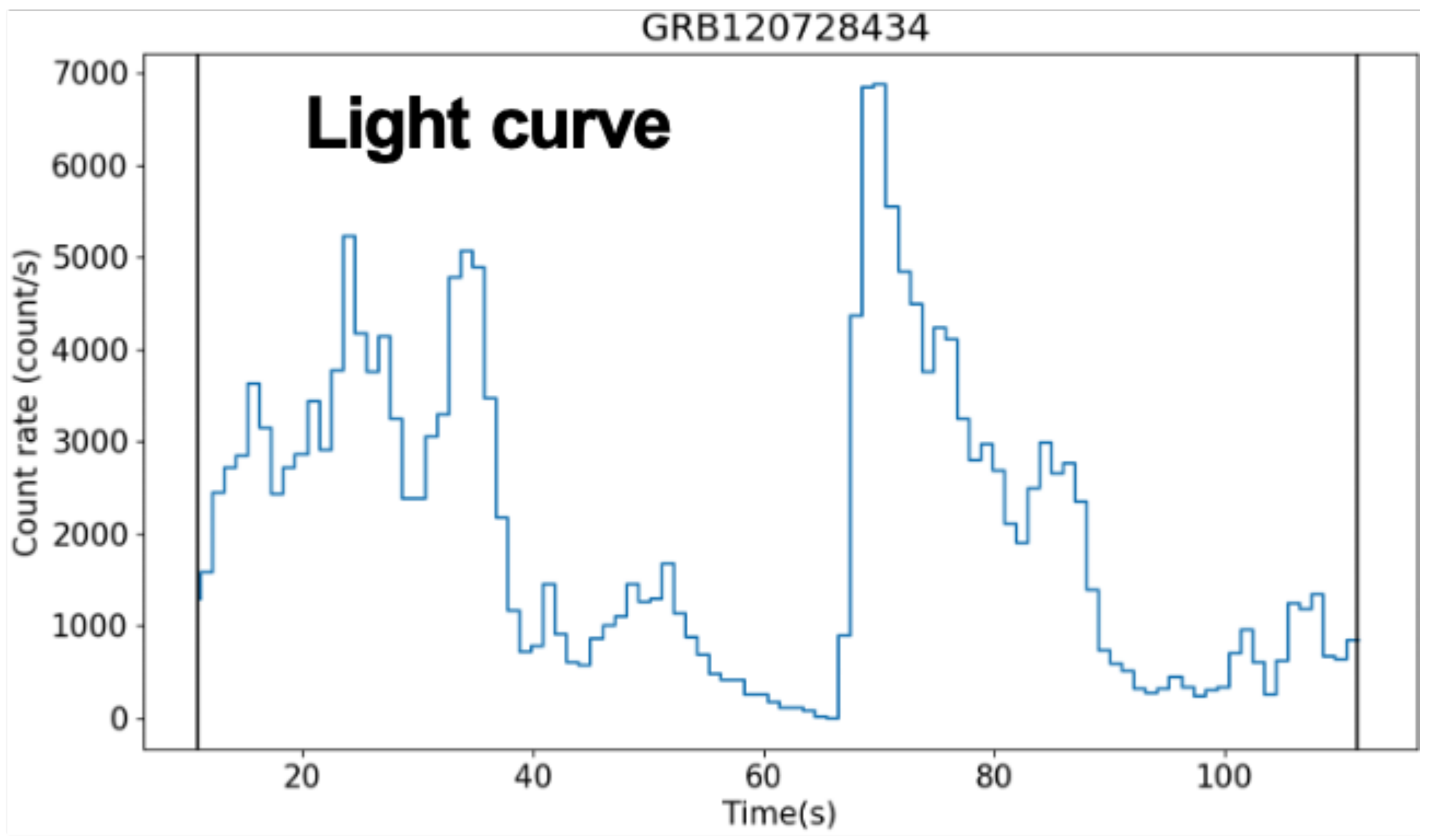
Simulations

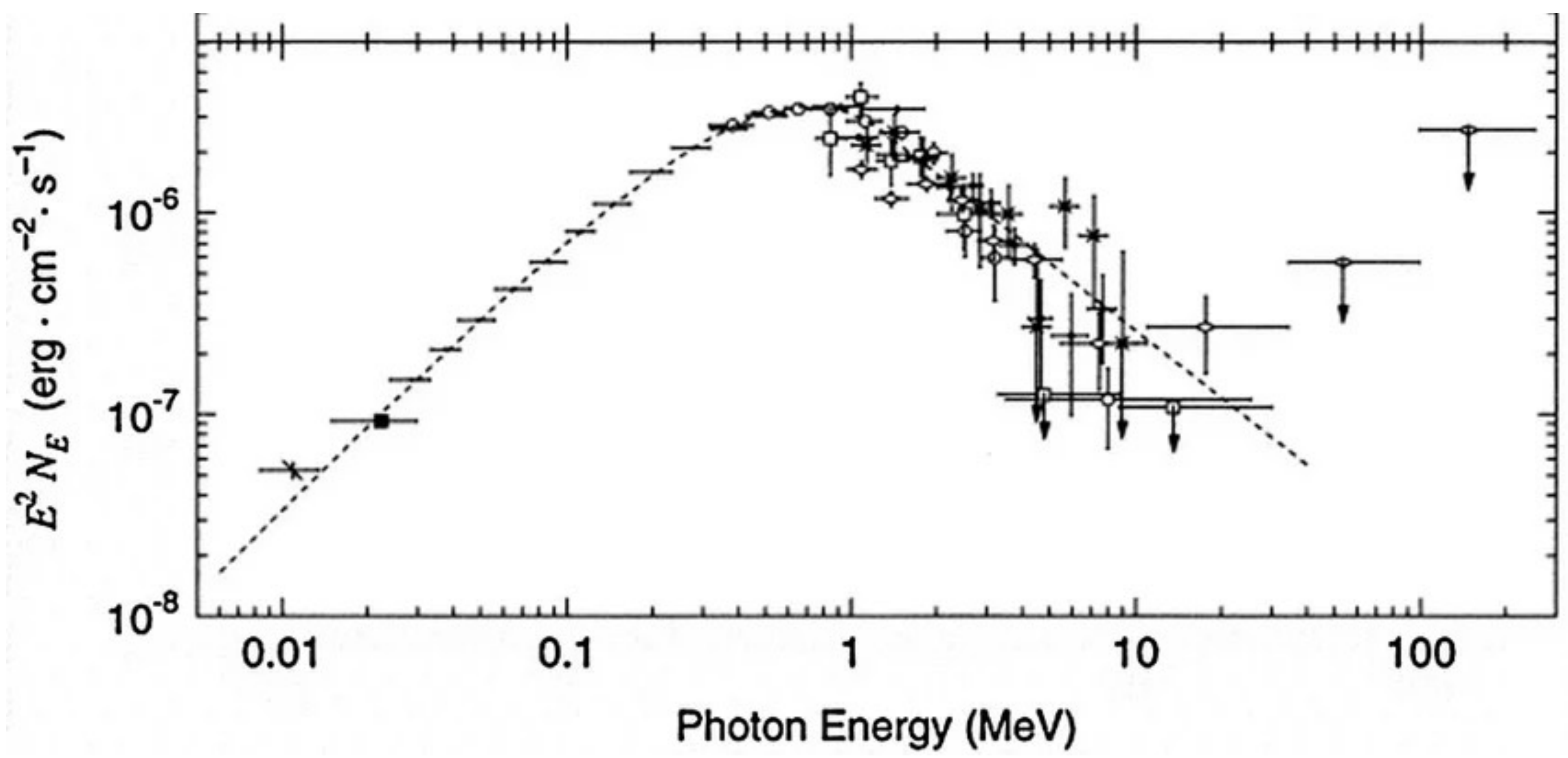
MEGAlib

The Medium-Energy Gamma-ray Astronomy library

https://megalibtoolkit.com/home.html

- **CubeSat response simulation** using the description of the geometry of the instrument
- **Simulated GRB properties:** duration, light curve, flux, energy spectrum
- **GRB sky position**: relative position of the source to the satellite





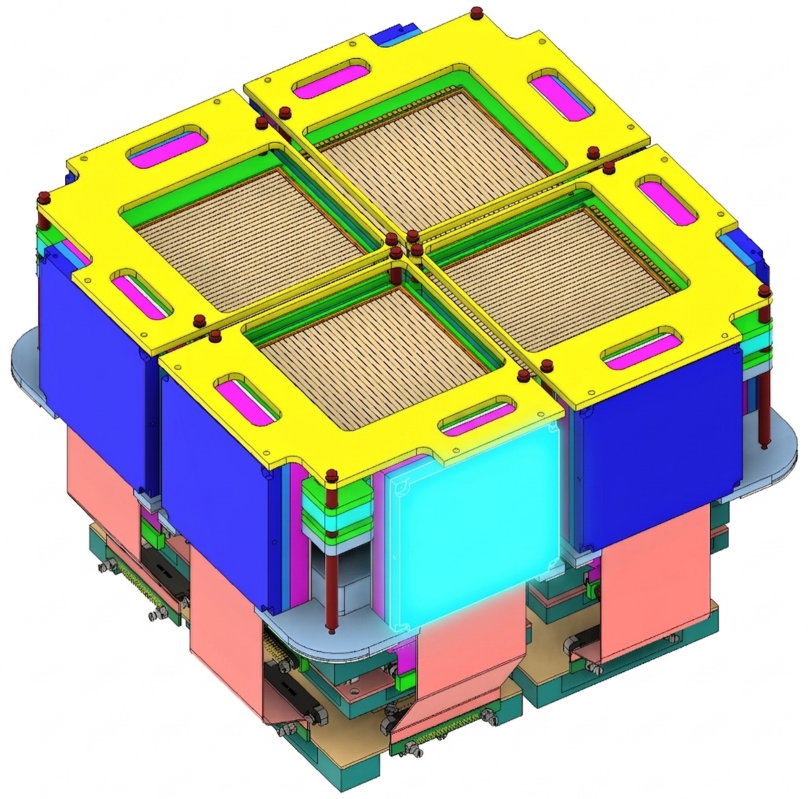
Band function : $N(E) = \begin{cases} E^{\alpha} \exp\left(-\frac{E}{E_0}\right), & \text{if } E \leq (\alpha-\beta)E_0 \\ [(\alpha-\beta)\,E_0]^{(\alpha-\beta)} E^{\beta} \exp(\beta-\alpha), & \text{if } E > (\alpha-\beta)E_0 \end{cases}$

Monte Carlo event simulation

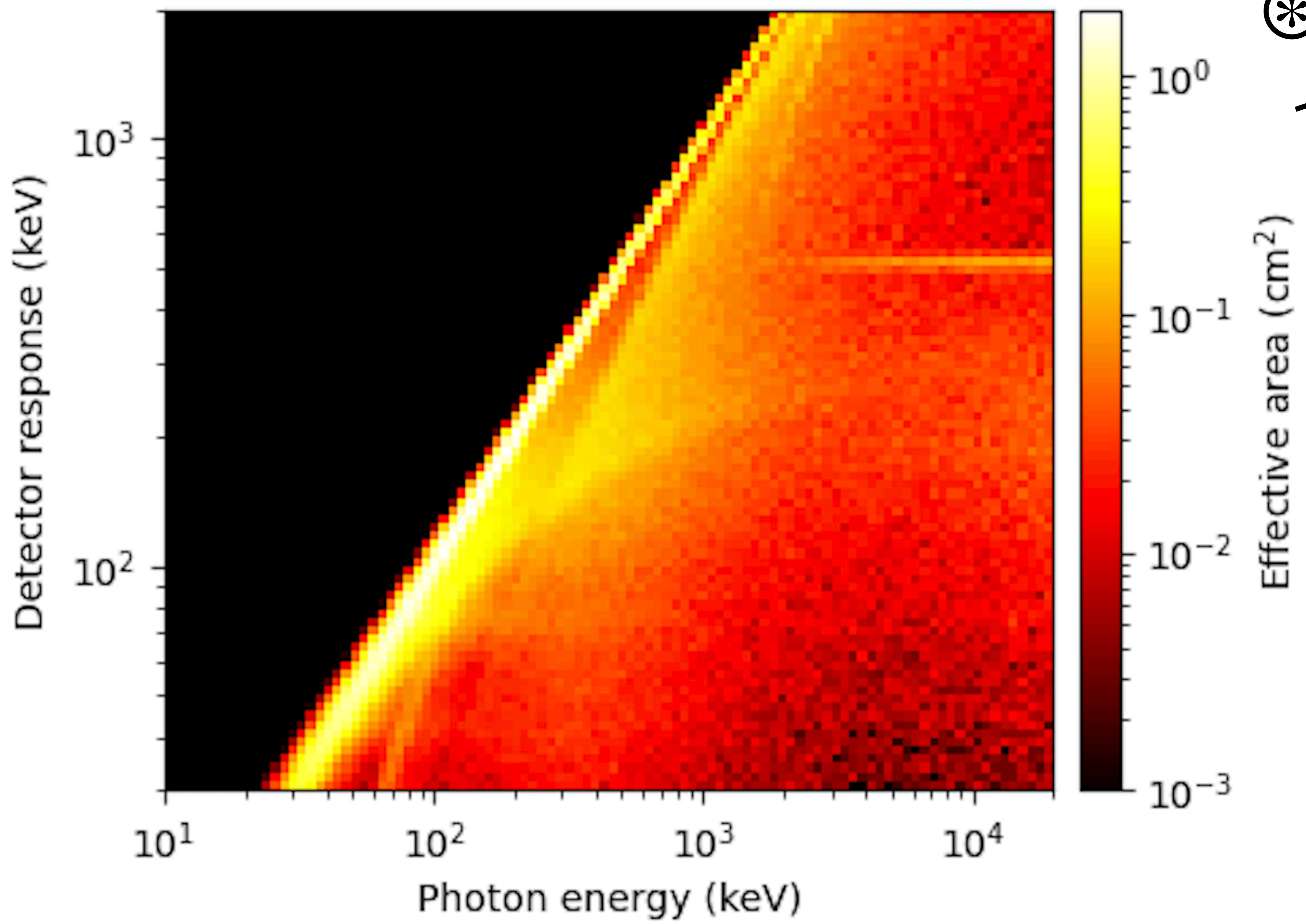
- Interactions in detectors
- Effective Area (detection sensitivity)
- Count Rates

Localizing Sources

Detector Count Rate



For a detector and a direction (coordinates relative to the satellite)

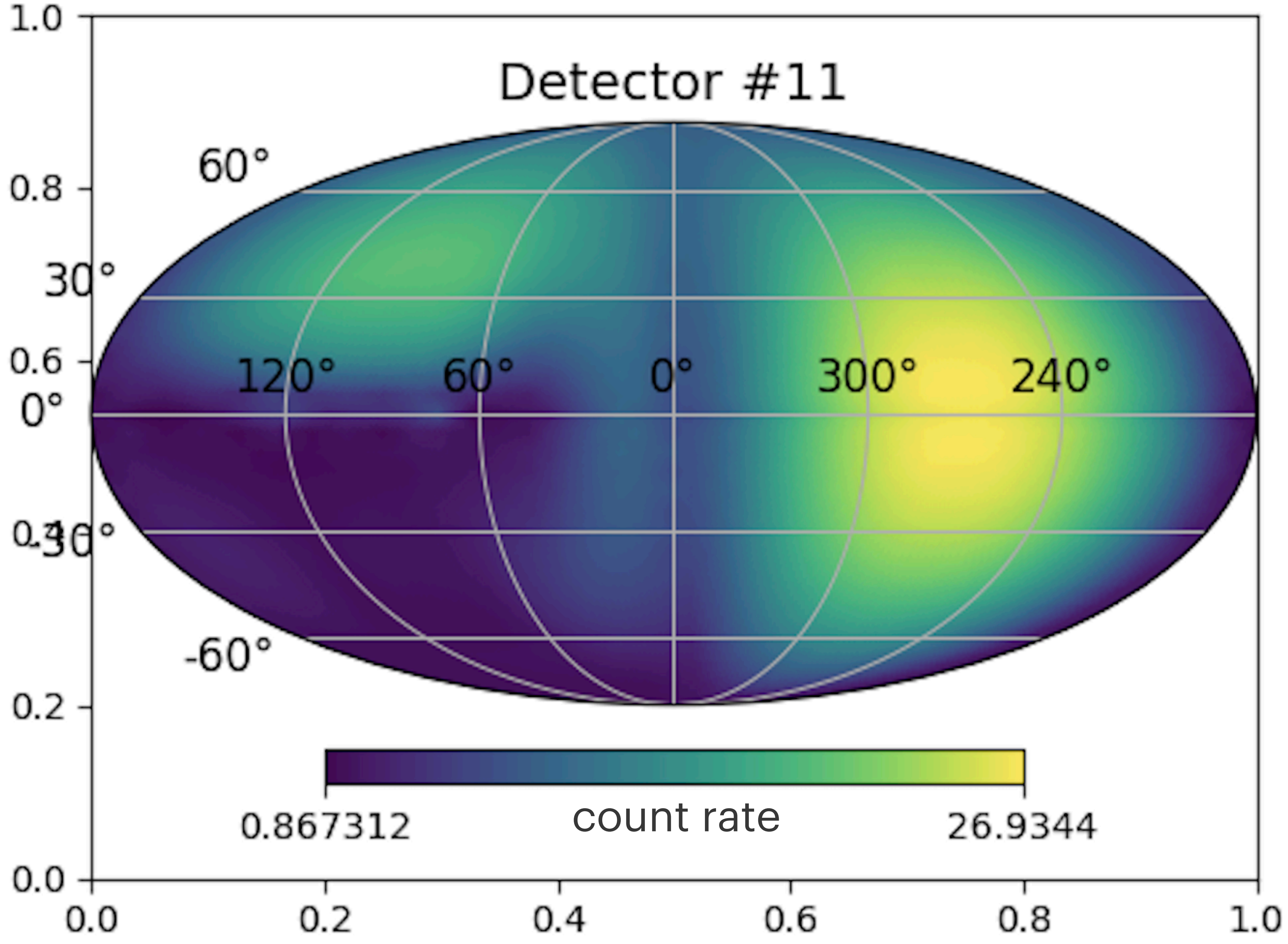


⊛ spectrum

Count rate

200k sky positions

For a detector and a flux spectrum

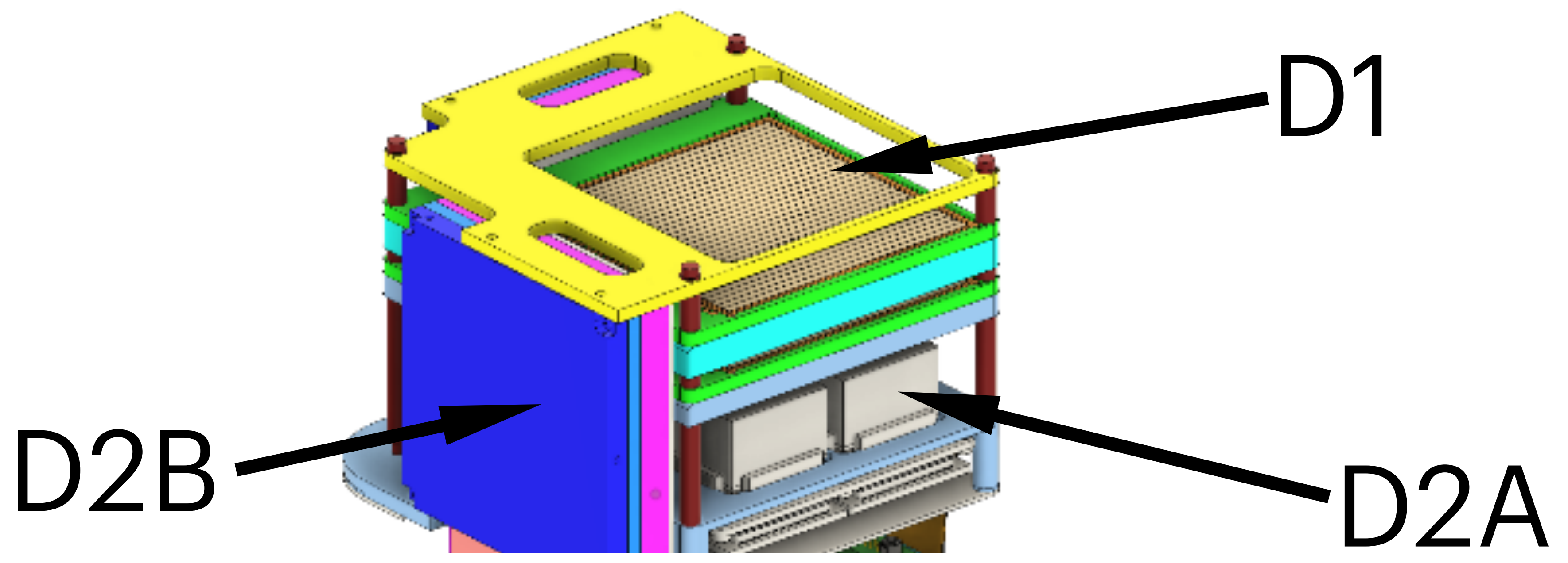


Detector Response Matrix

Count Rate Map

Localizing Sources

Count Rate Maps for 32 detectors



Localizing Sources

χ^2 Method

- Already used for GRB localisation with BATSE (CGRO) and GBM (Fermi) instruments for 1 satellite with several detectors
- For 27 satellites with 32 detectors:

$$\chi^2 = \sum_{d=1}^{27\times 32} \frac{\left(S_d - \left(B_d + f(s) \circledast R_d(i)\right)\right)^2}{B_d + f(s) \circledast R_d(i)}$$

Signal

Background

Fluence and spectrum

Detector response matrices

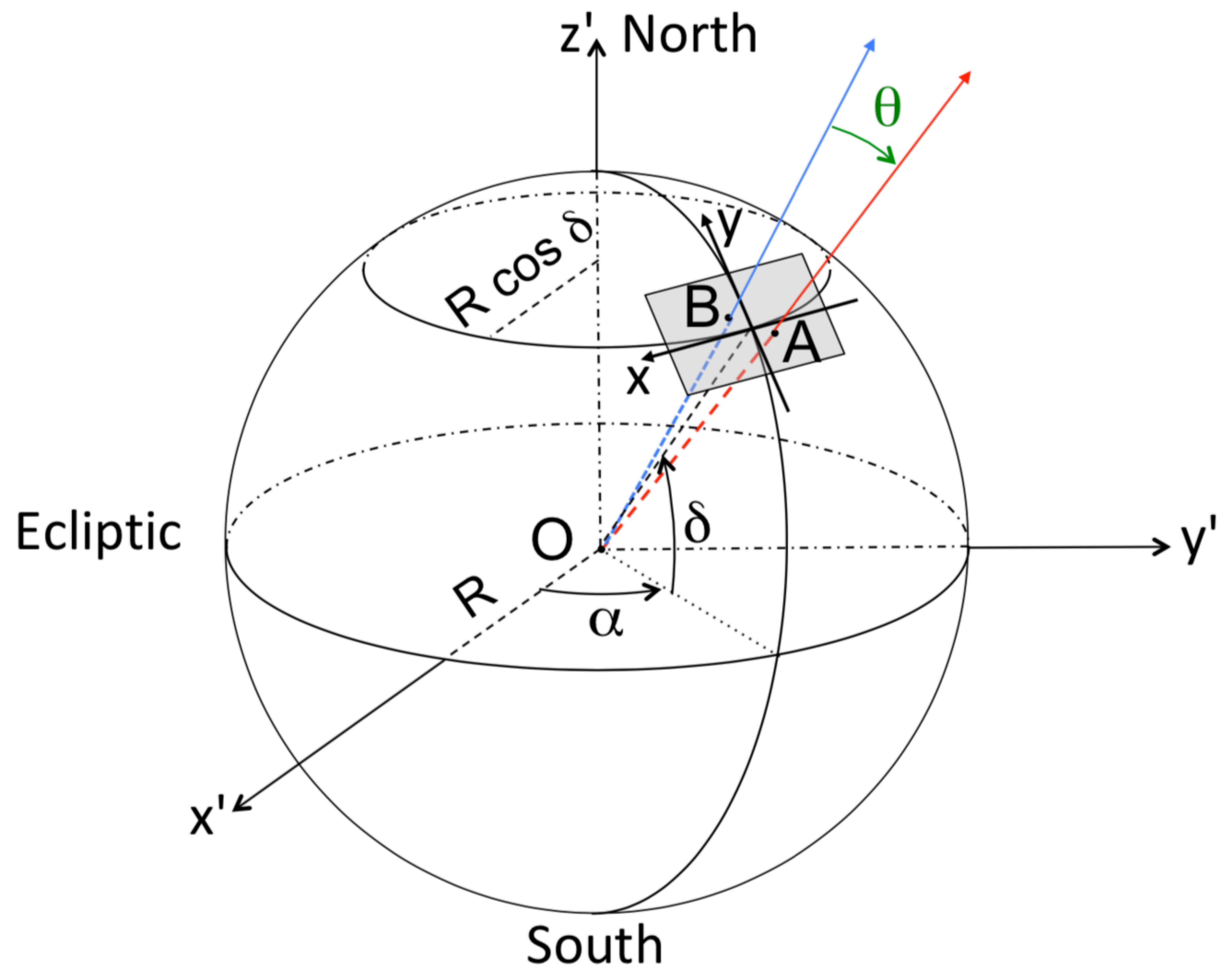
Coordinates

Other parameters

- Fluence
- Spectra parameters:
  for Band function: α, β, E_{peak}
- Inability to localise and estimate the spectrum at the same time
- Heavy, time-consuming calculations
- Possible degeneracies

Localizing Sources

χ^2 Method Results

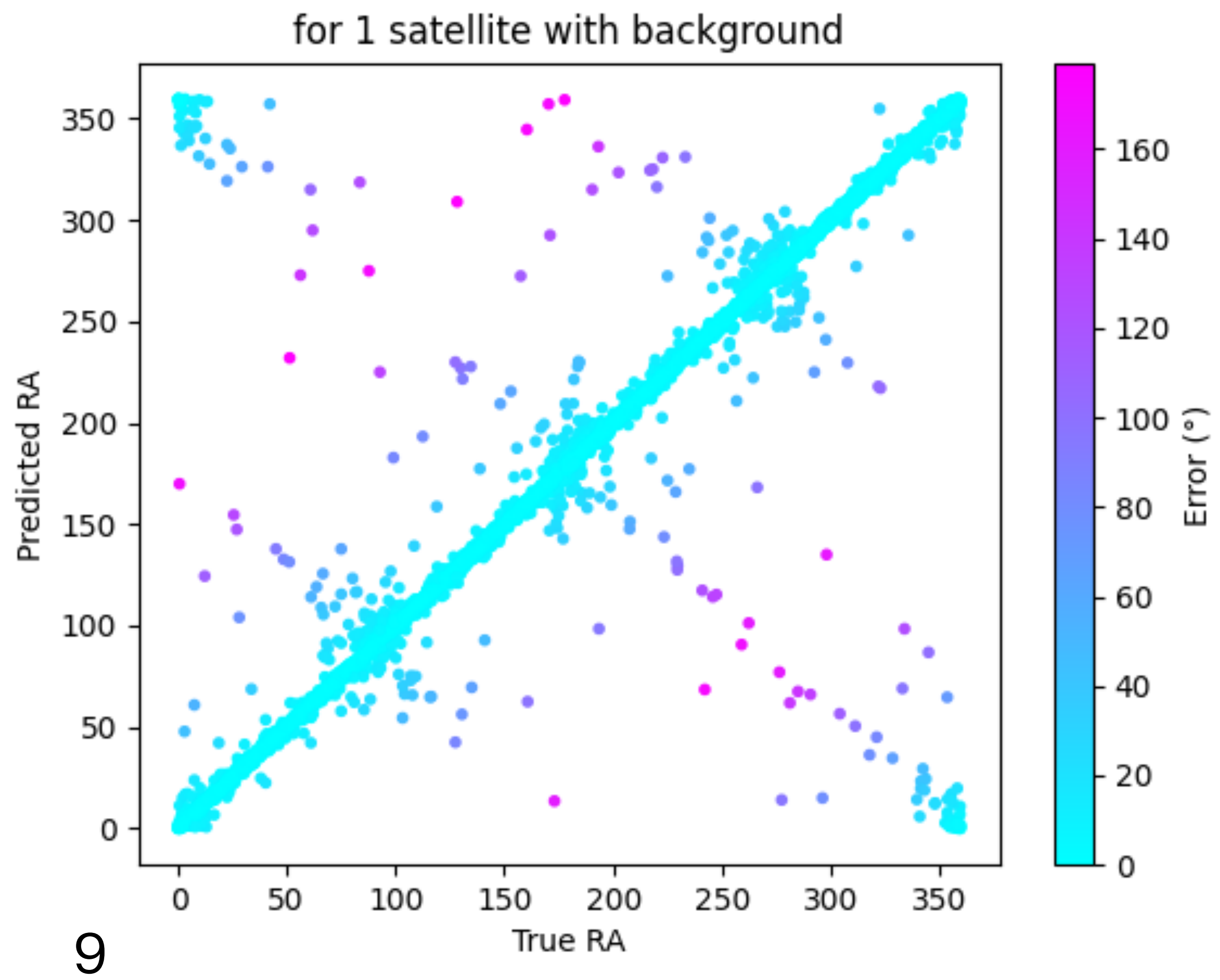


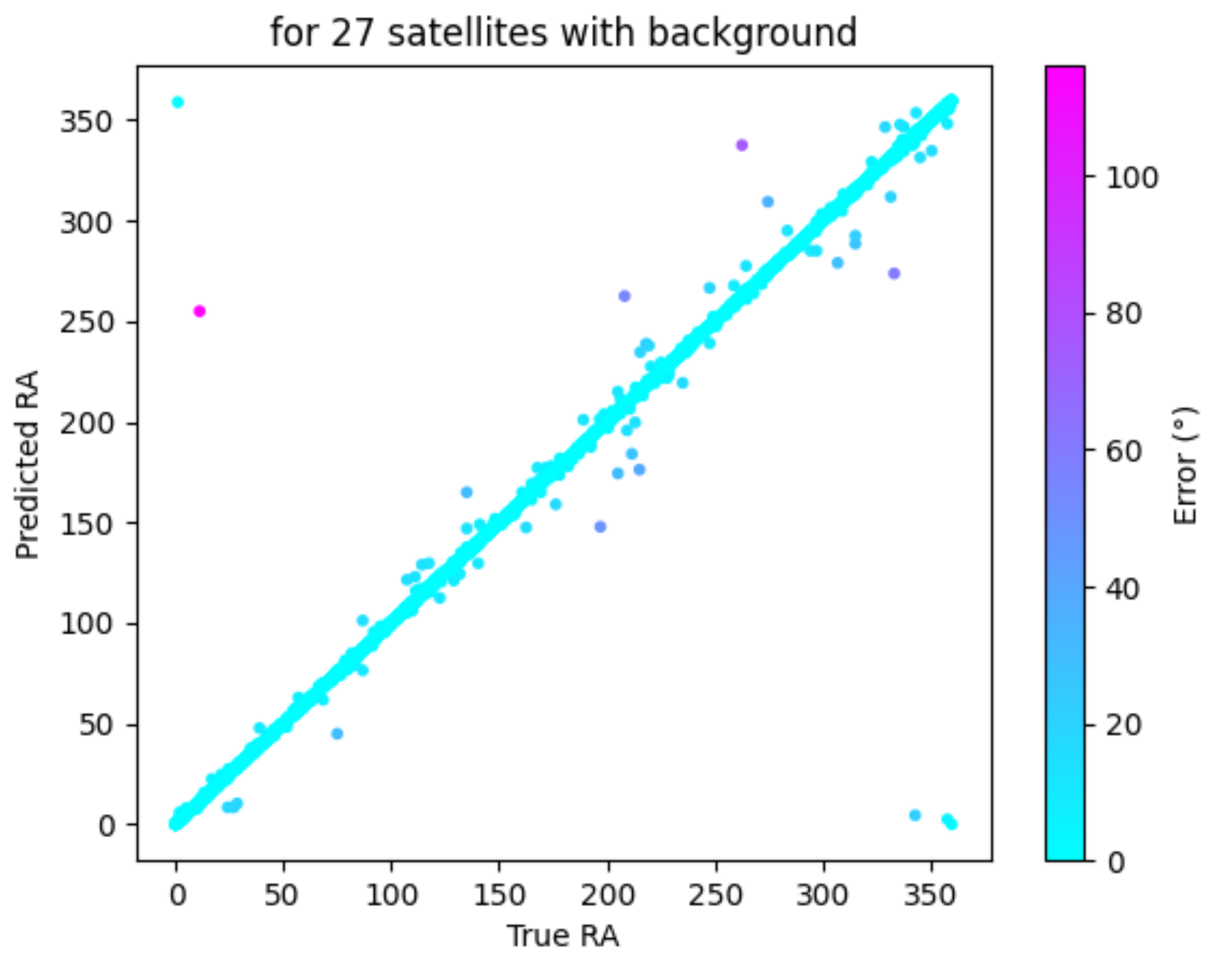
$$\mathbf{n_A} = \begin{pmatrix} \cos\delta_A \cos\alpha_A \\ \cos\delta_A \sin\alpha_A \\ \sin\delta_A \end{pmatrix} \qquad \mathbf{n_B} = \begin{pmatrix} \cos\delta_B \cos\alpha_B \\ \cos\delta_B \sin\alpha_B \\ \sin\delta_B \end{pmatrix}$$

Angular distance : $\mathbf{n_A} \cdot \mathbf{n_B} = \cos\theta$

	1 sat with no bkg	1 sat with bkg	27 sats with no bkg	27 sats with bkg
angular error	0.73±1.68	**1.16±2.66**	0.02±0.13	**0.18±0.28**

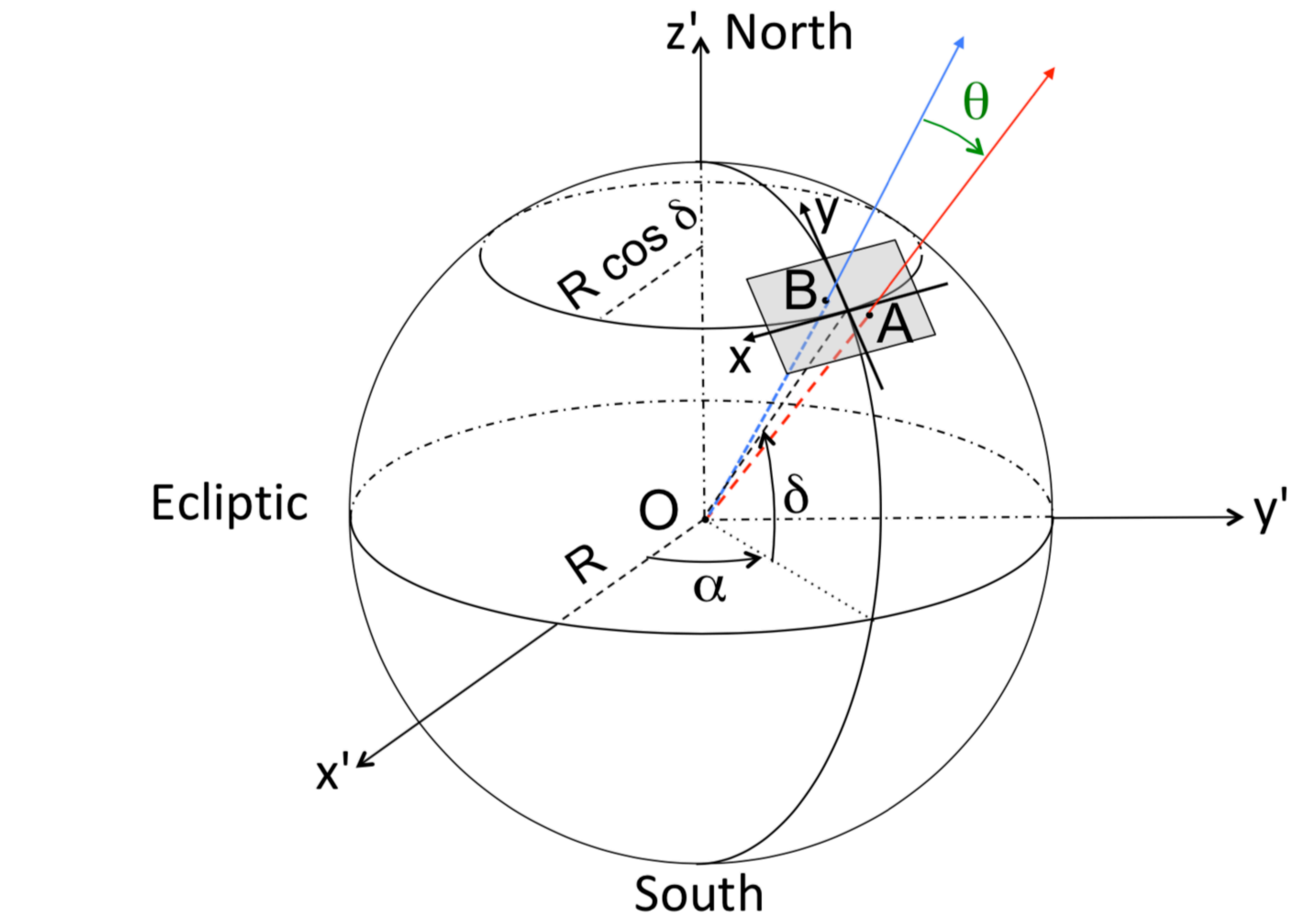
Results





Localizing Sources

χ^2 Method Results



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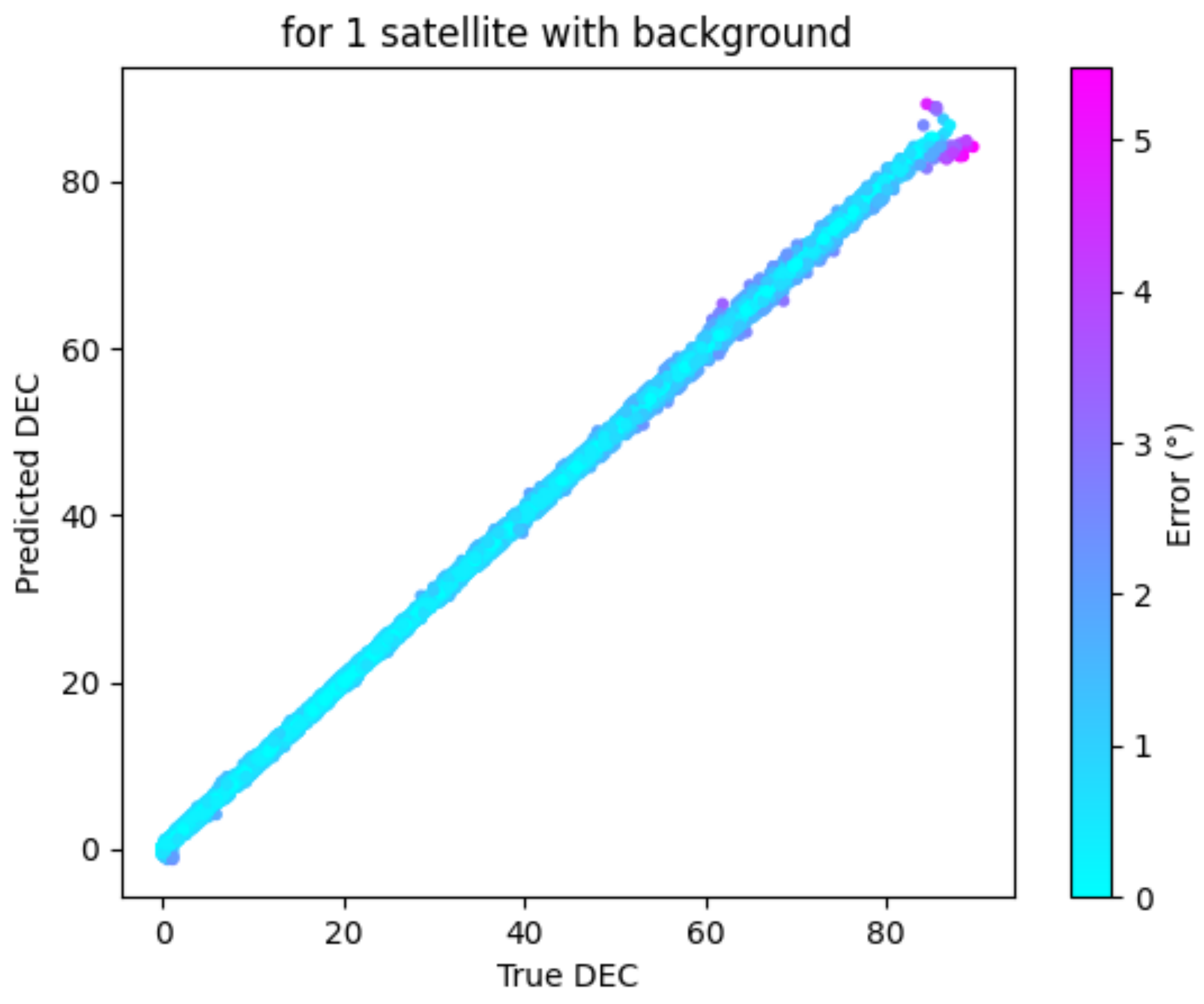
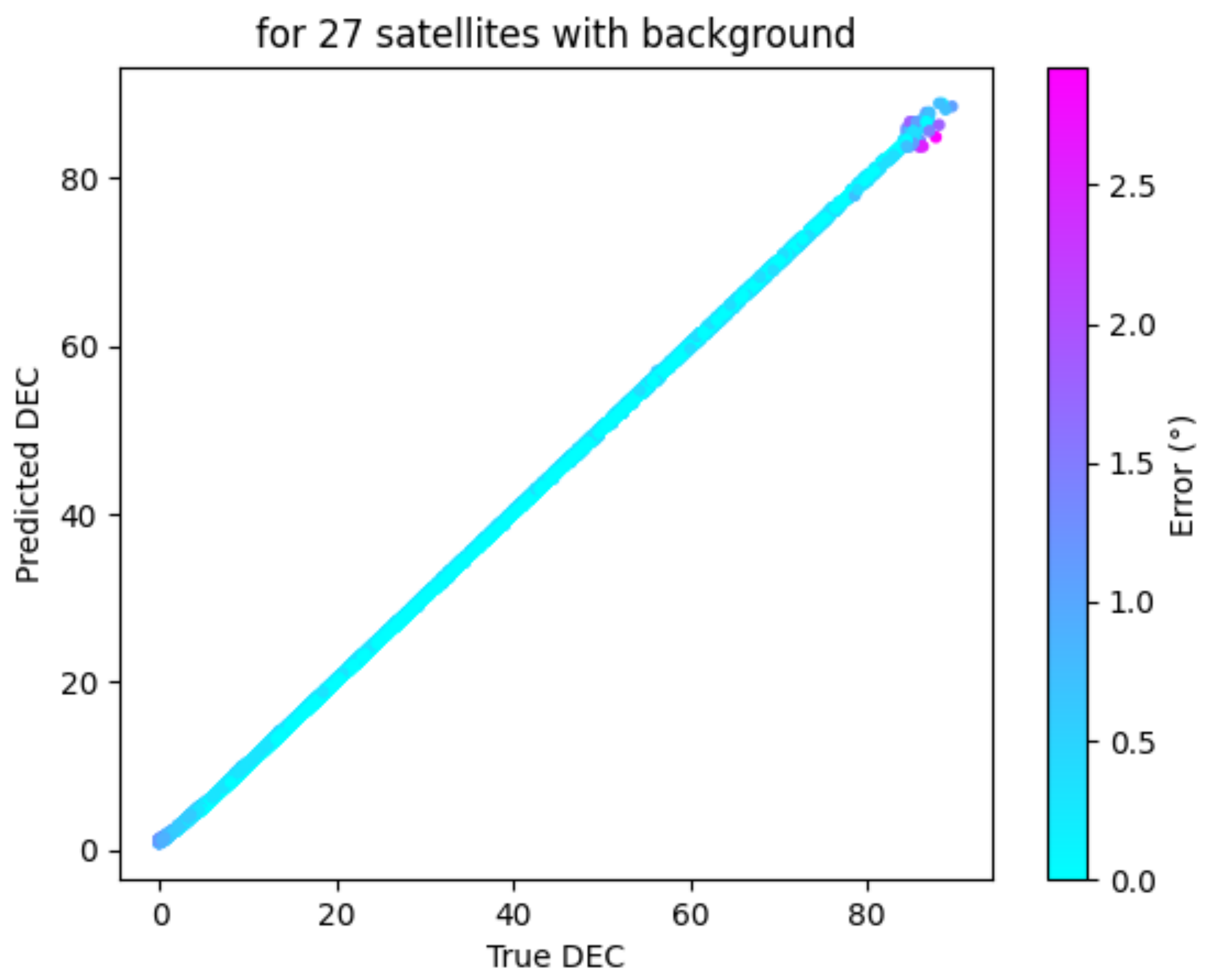


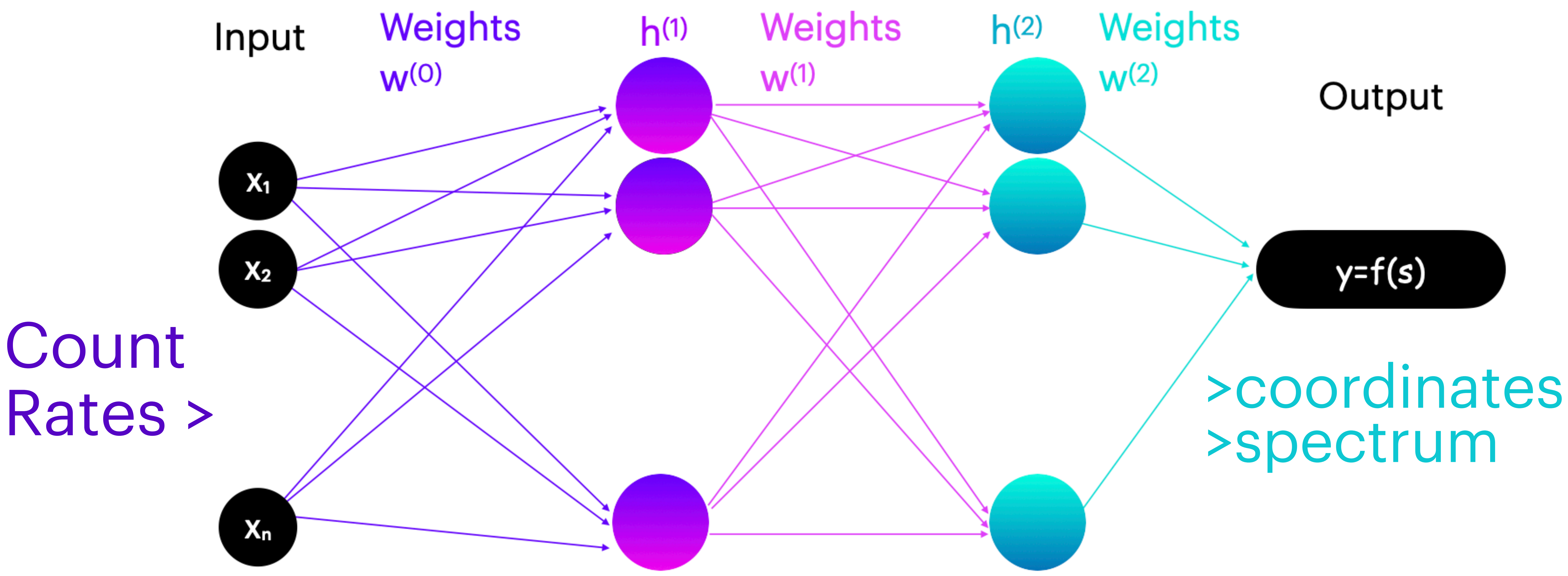


Neural Networks

Multi Layer Perceptron (MLP),

Convolutive Neural Network (CNN),

Recurrent Neural Network (RNN)



- Very quick computation:
  after training the model, we get the weight matrices, which are used to get a location out of the count rates
- Matrix calculations are very quick
- Can do localisation and determination of the spectra simultaneously
- Better robustness than χ^2
- Better handling of degeneracies

Localizing Sources

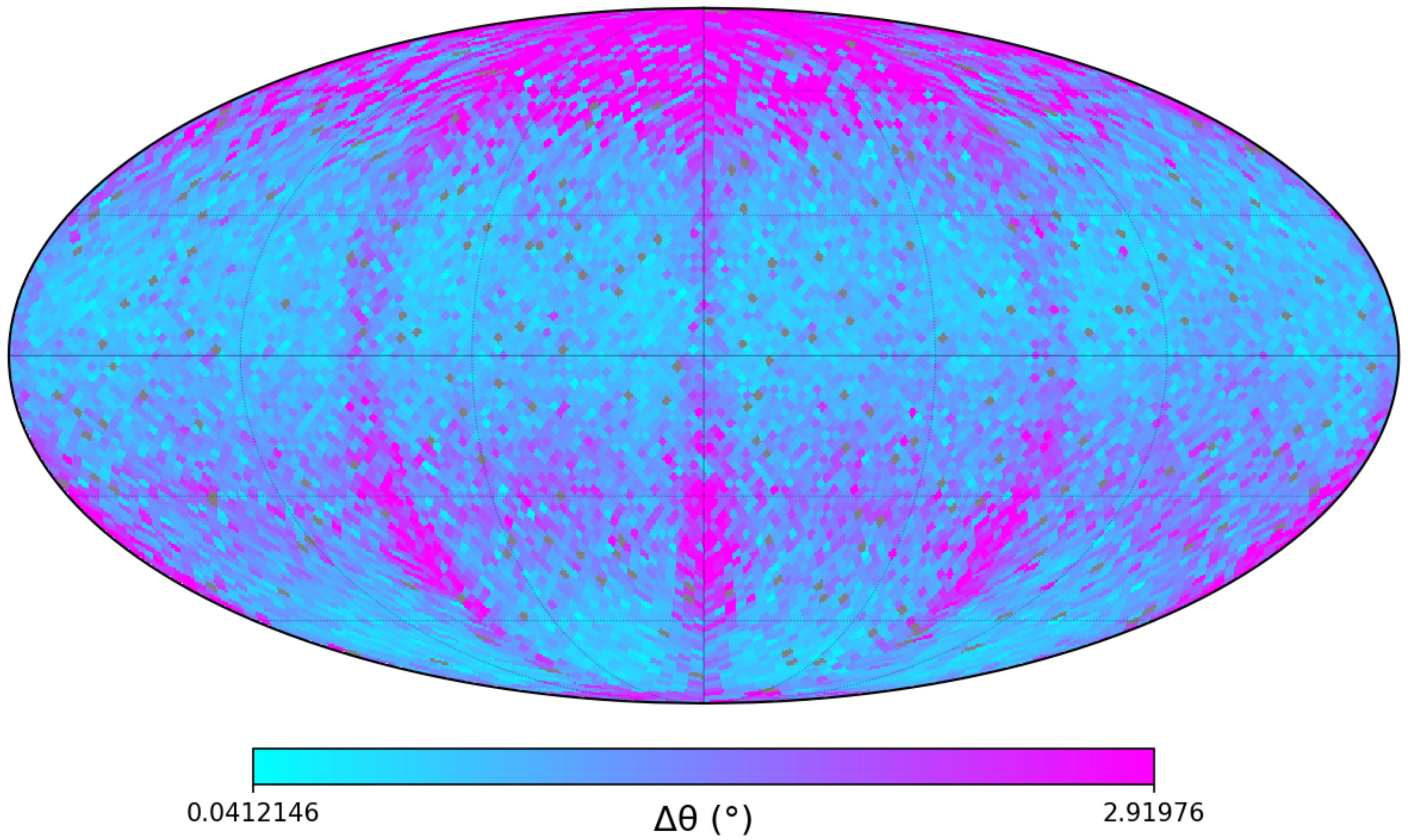
MLP Results

Different models have been tested with different :

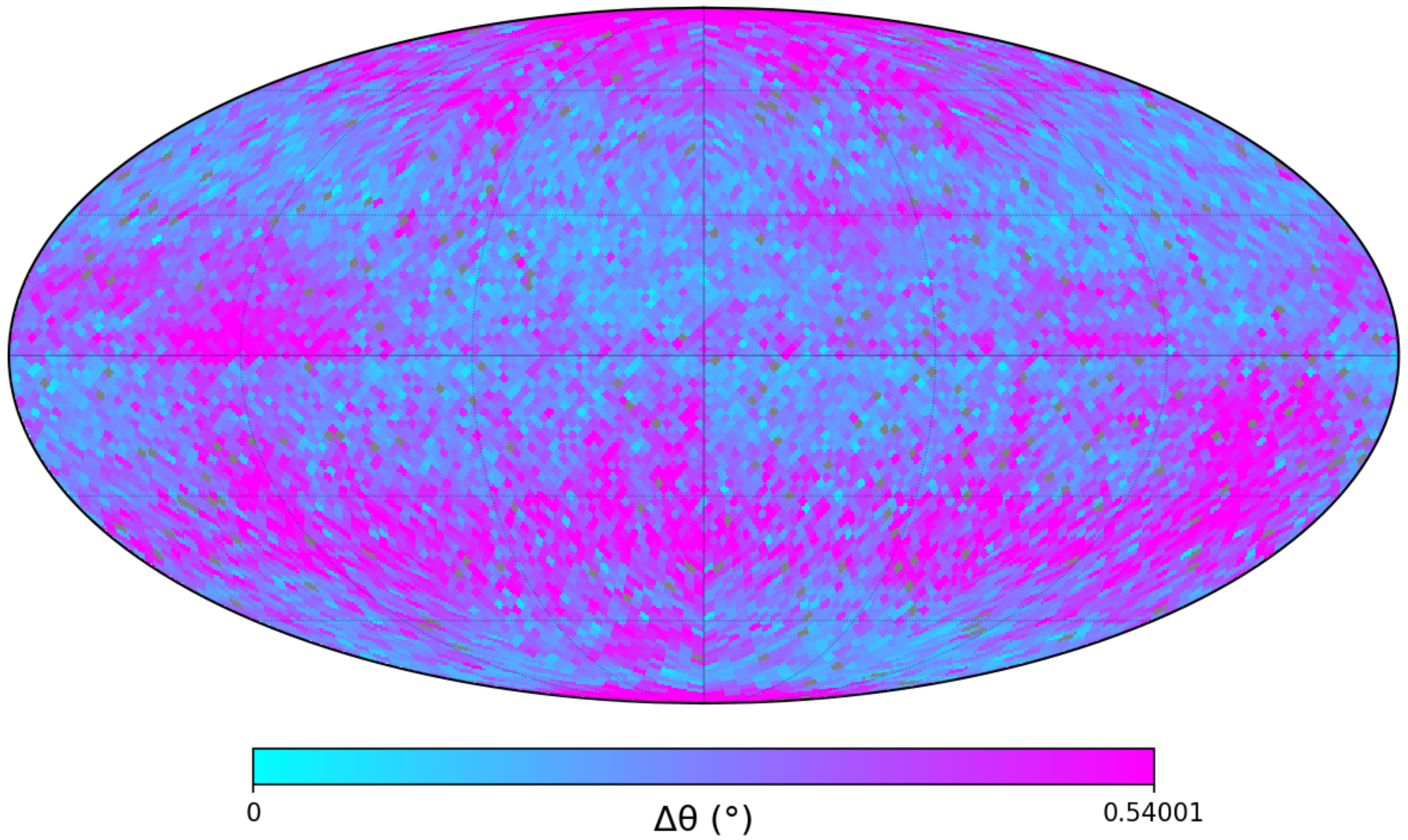
- activation functions
- optimizers
- learning rates
- Batch size and epochs
- depth (number of layers)
- width (number of neurons per layer)

	1 sat with no bkg	1 sat with bkg	27 sats with no bkg	27 sats with bkg
angular error	1.29±1.64	**1.92±2.42**	0.26±0.17	**0.31±0.23**

Results: MLP



Sky error map: for 1 satellite



Sky error map: for 27 satellites

Localizing Sources

CNN Results

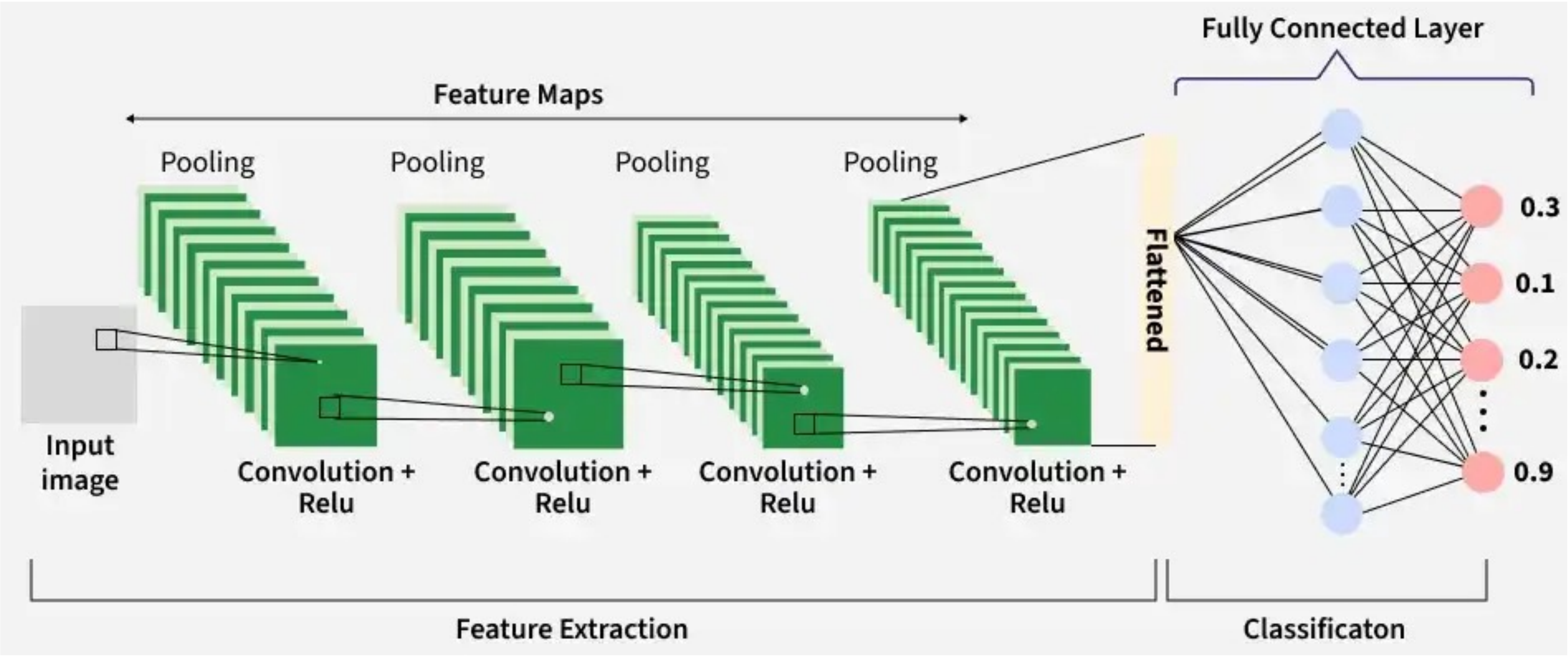
- Recognises spatial patterns in structured data (takes into account the geometry of the telescope and relative detector responses)

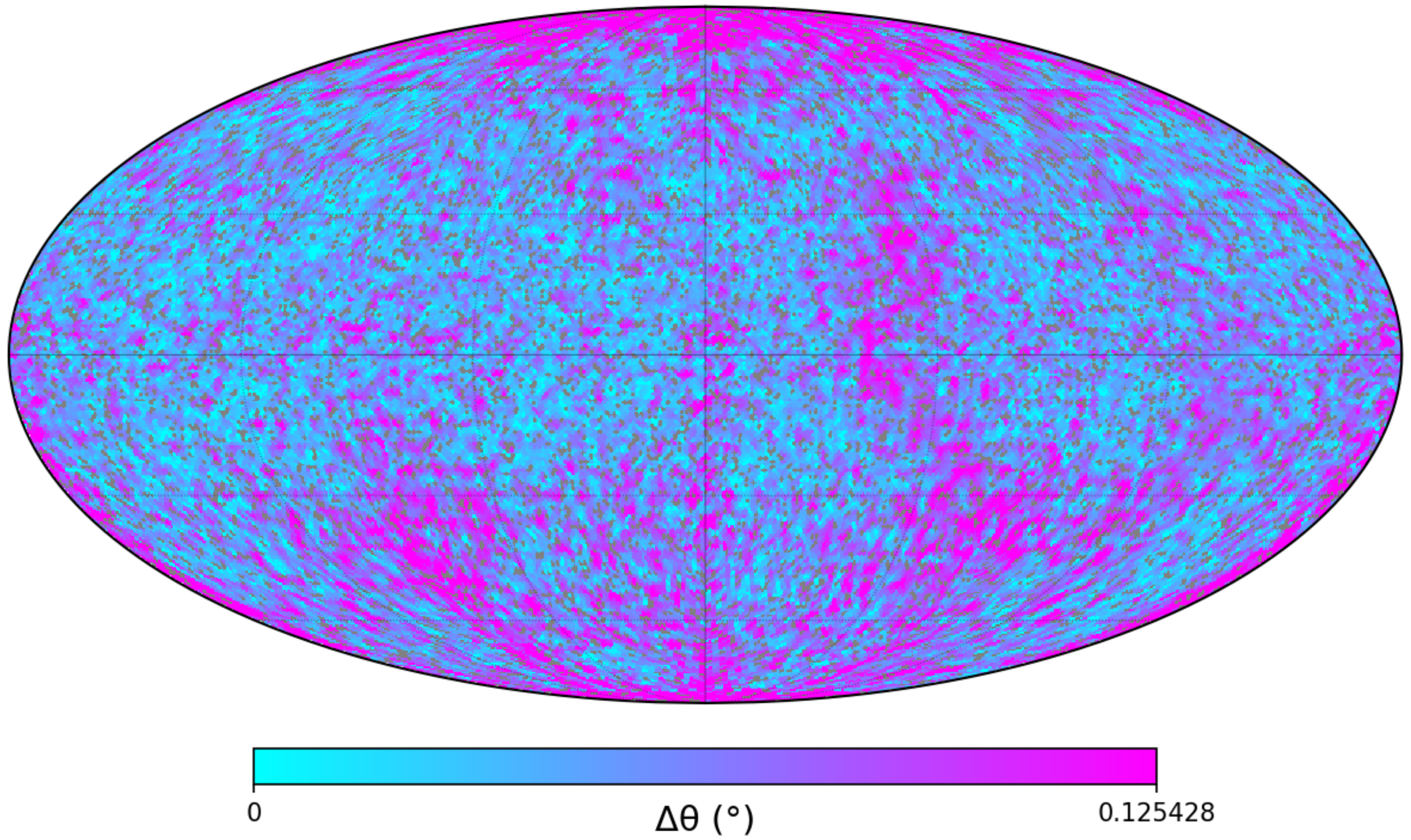
- Parameter reduction (enhanced efficiency)

- More robust

	1 sat with no bkg	1 sat with bkg
angular error	0.05±0.03	**0.05±0.03**

Preliminary Results: CNN





Sky error map

Conclusion

- Development of an alert system for COMCUBE-S

  -Validation of the χ^2 count-rate method

  -Implementation of machine-learning approaches (MLP, CNN)

  -Significant improvement in localization throught the use of CNNs

  -Establishment of a baseline framework for future developments (CNN, RNN, spectral parameter estimation,...)

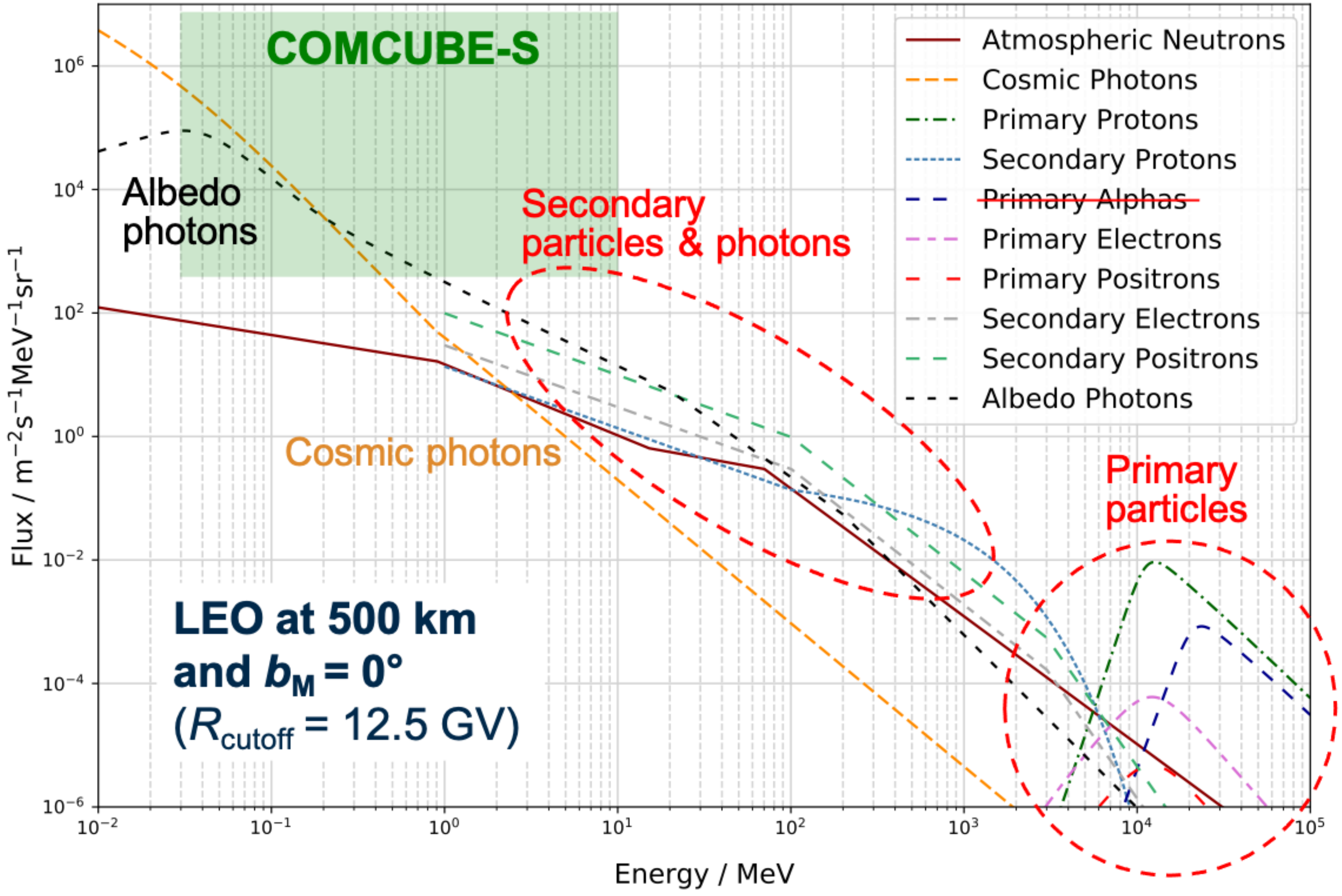
- Contribution to time-domain and multi-messenger astronomy
- Participation in a space mission and development of a system to better understand GRBs and other transient sources

Thank you

Back up slides

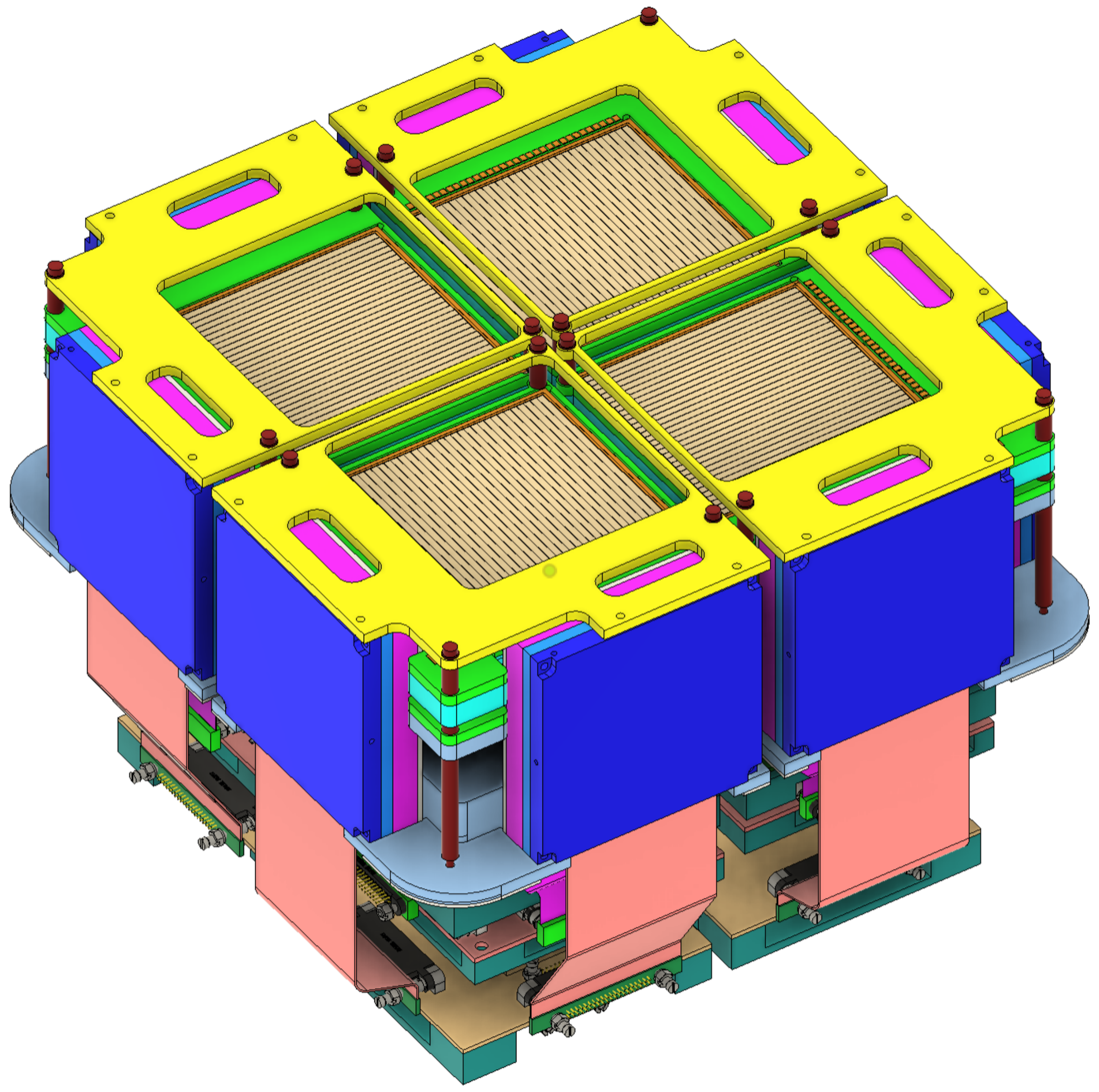
Background

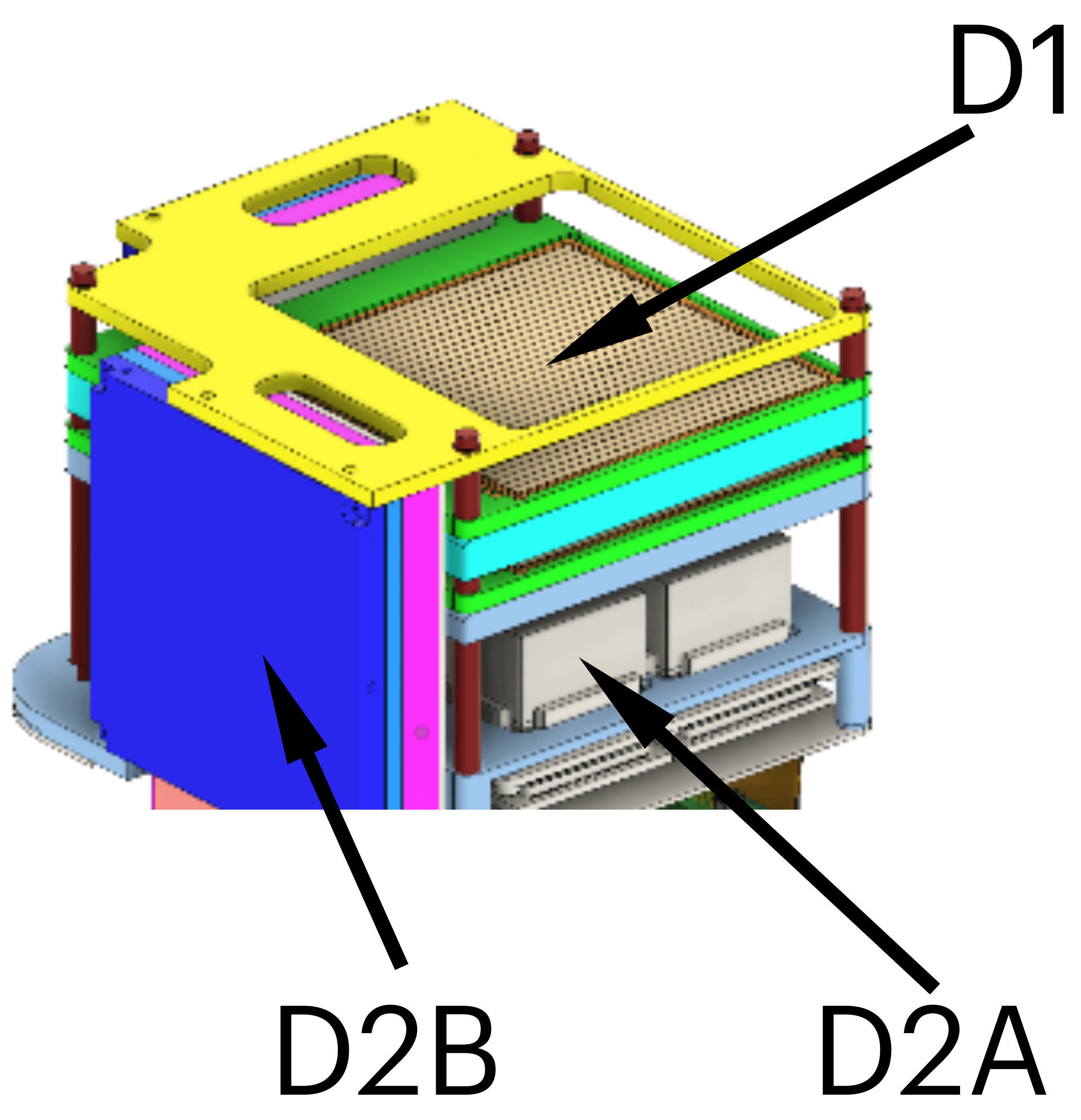
- **Detailed background model** for a gamma-ray satellite on a Low-Earth orbit (extension of the model by Cumani et al. 2019)
- **MeV electrons**: (i) soft gamma-ray background by **bremsstrahlung** in the spacecraft and (ii) increase the **leakage current** of detectors
- **GeV protons**: (i) **damage** to on-board electronics and sensors, (ii) build up instrument background from spacecraft material **activation**



Context

The Compton telescope COMCUBE-S





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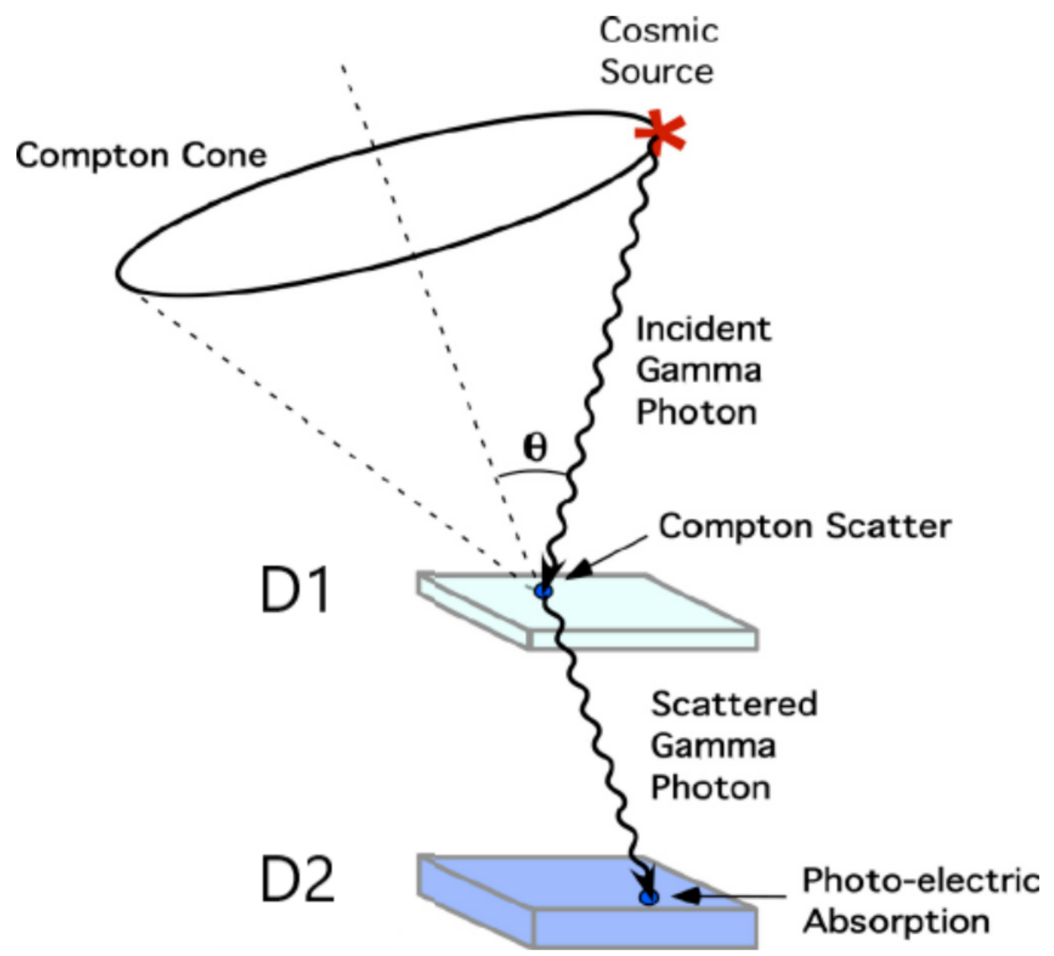
D2A: cerium-doped Gadolinium Aluminium Gallium Garnet — **16 detectors**

D2B: Cerium Bromide — **8 detectors**

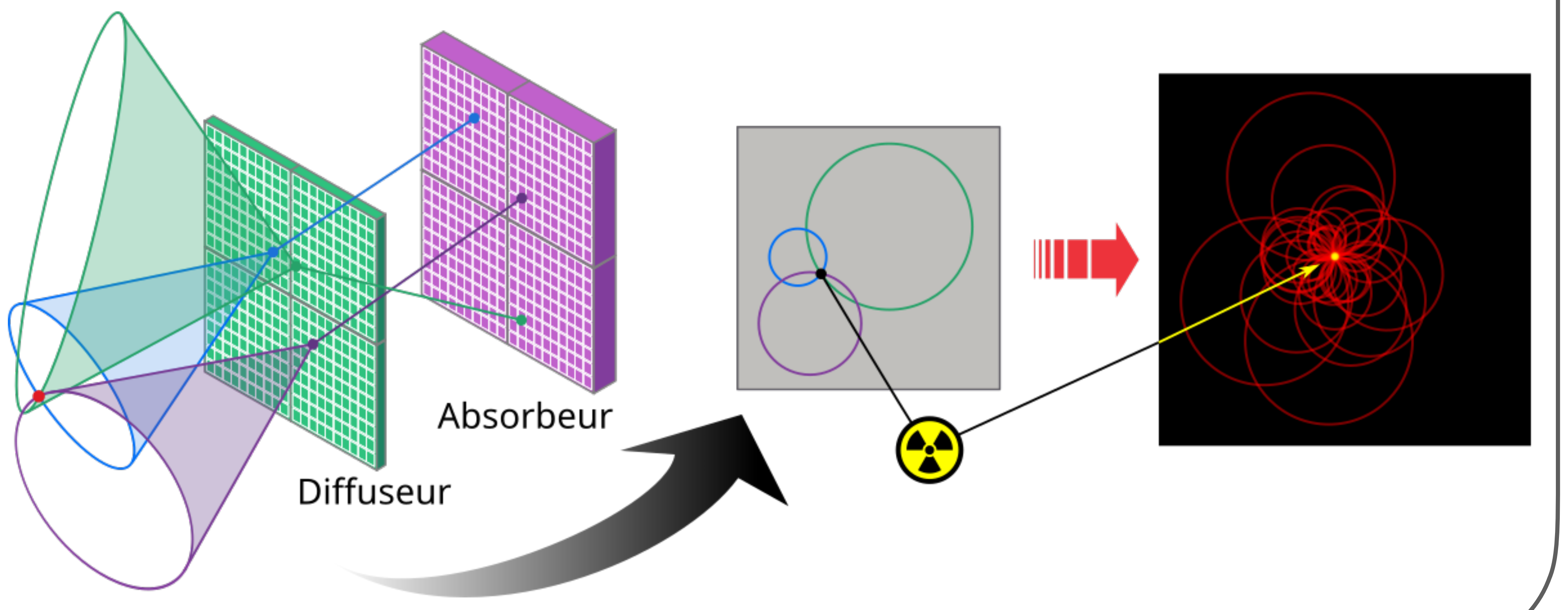
Total : 32 detectors



Energy conservation

Momentum conservation

$$\theta_{measured} = \arccos[1 - m_e c^2 (\frac{1}{E_2} - \frac{1}{E_1 + E_2})]$$

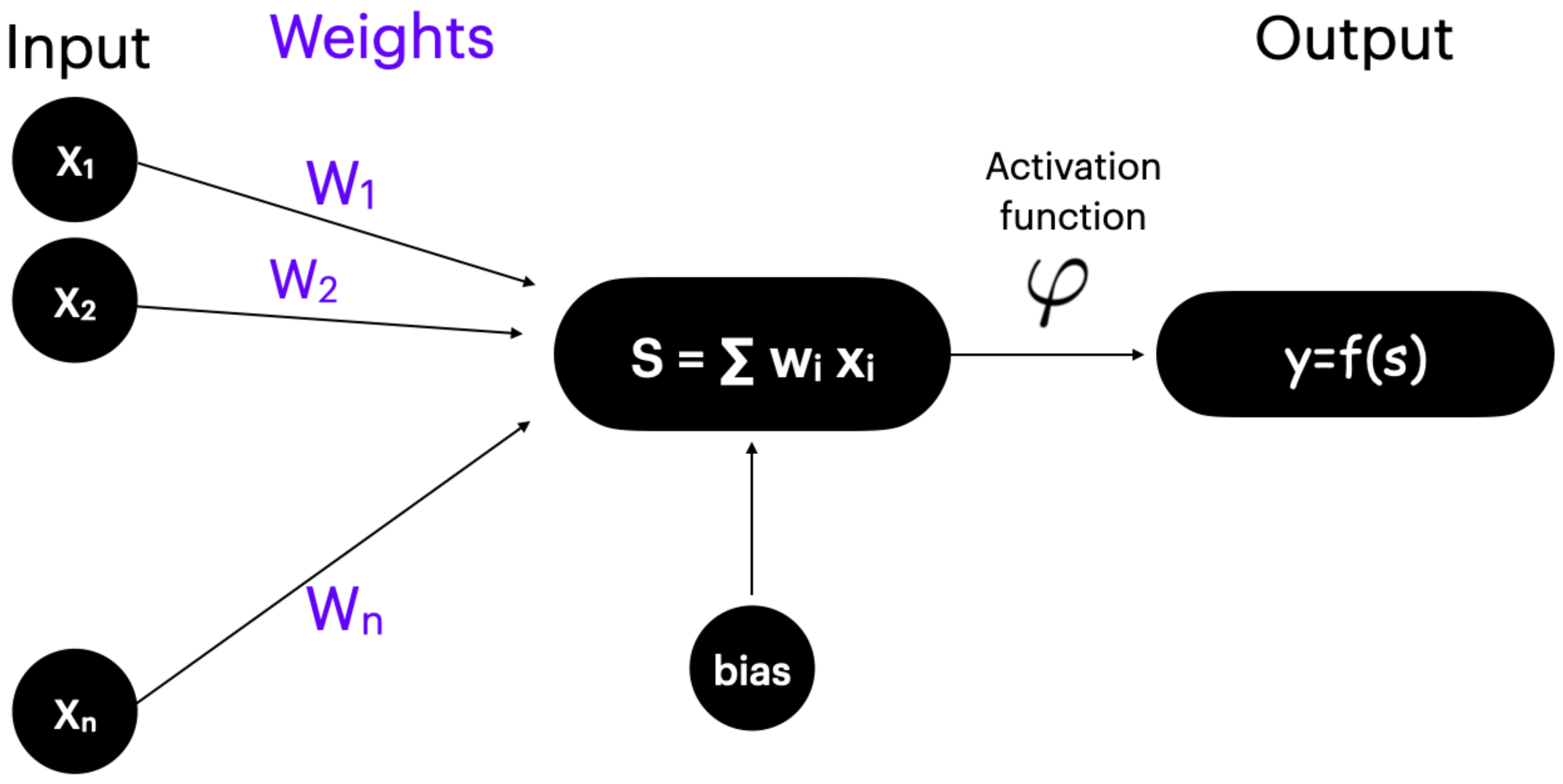


Neural Network

Artificial Neuron

A neuron is the following parameterised function that takes a vector x and gives a single value a

$$a = \varphi(\mathbf{wx} + b)$$

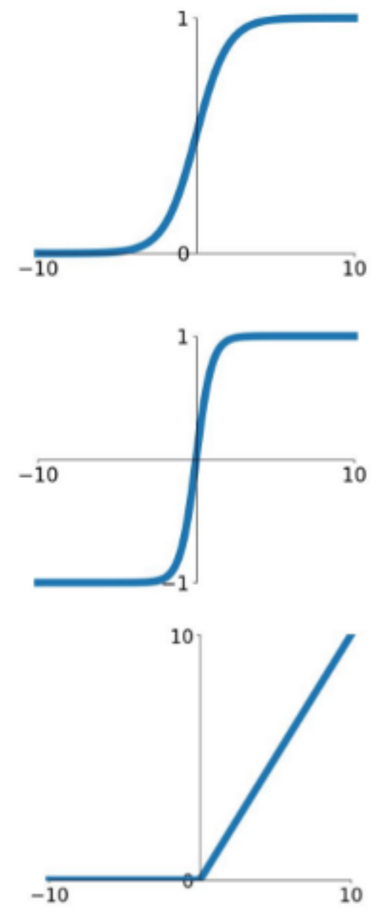


Activation Functions

Sigmoid
$\sigma(x) = \frac{1}{1+e^{-x}}$

tanh
$\tanh(x)$

ReLU
$\max(0, x)$



Optimization :
The goal is to find the parameters for which the model's results are closest to observed data, and the strategy is the **gradient descent**

The quantity to minimize is the « **loss** »: $\mathcal{L}(w) = \sum_i (\hat{y}_i - y_i)^2$

with $\hat{y}_i = wx_i$

Neural Networks: Recurrent RNN

Processes sequences over time

Advantages :

Best for temporal analysis (uses time information)

Can help distinguish signal vs background