



**University of
Zurich^{UZH}**

Physik-Institut

Machine Learning Techniques in Gamma-ray Astrophysics

UZH ML Workshop, 16/11/20

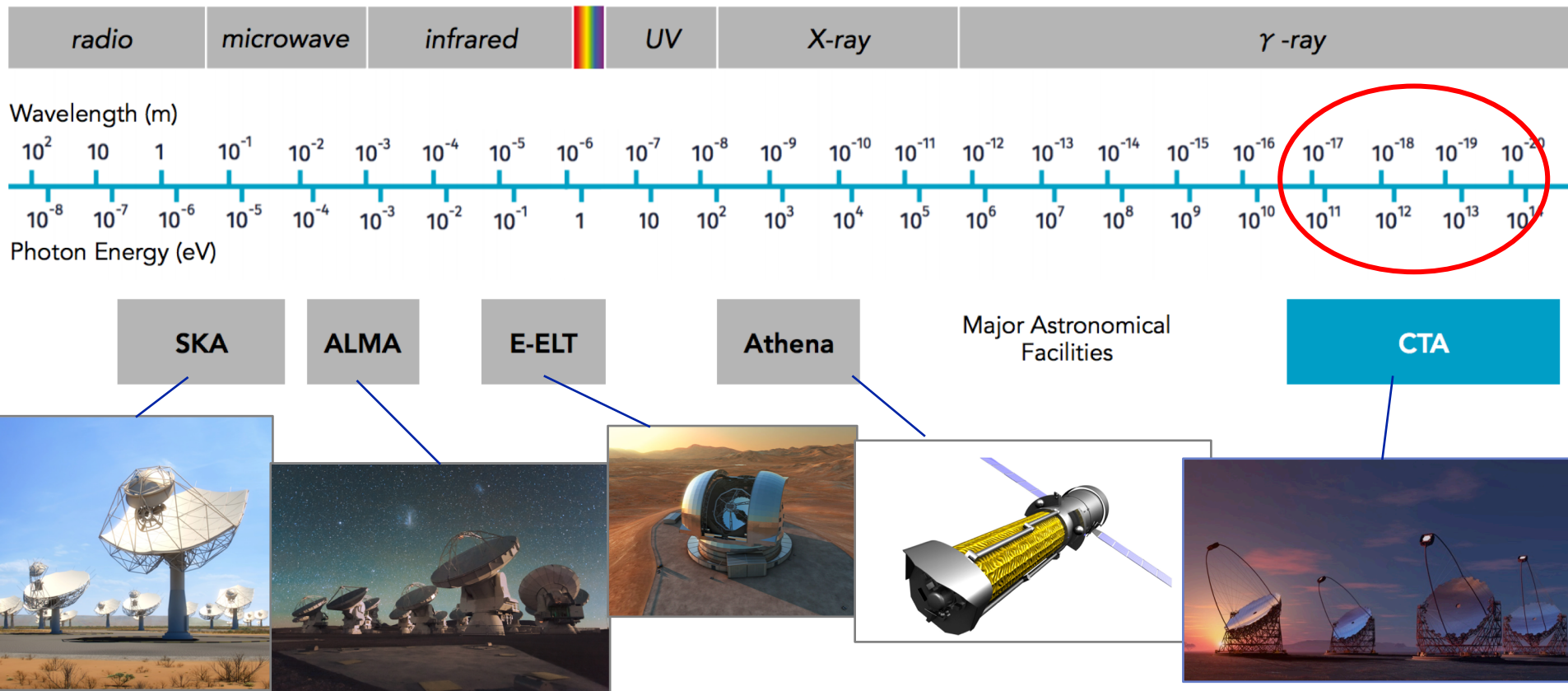
Dr. A. Mitchell

Very High Energy (VHE) γ -ray Astronomy

VHE ≈ 30 GeV – 300 TeV

“particle astrophysics”/“astroparticle physics”: study the most energetic astrophysical objects in our universe,

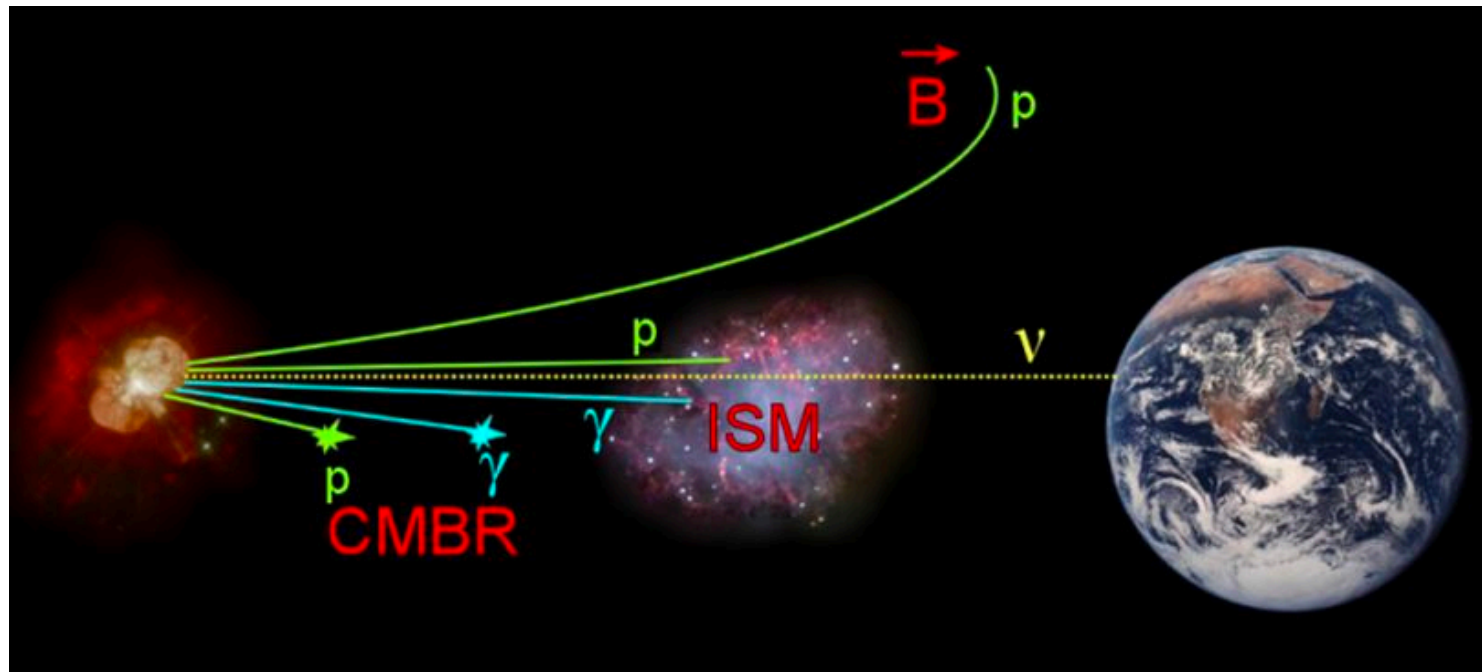
Identify sources of cosmic rays: astrophysical particle accelerators



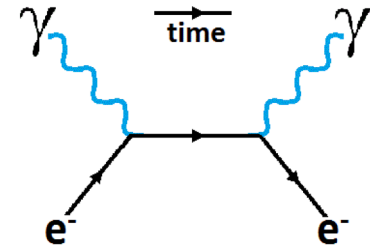
Introduction to Gamma-Ray Astronomy

What kinds of sources accelerate cosmic rays?

- Cosmic rays are scattered by magnetic fields
- Cosmic rays interact within the source environment producing gamma-rays
- Gamma-rays travel without deflection from source to observer



VHE Emission Mechanisms

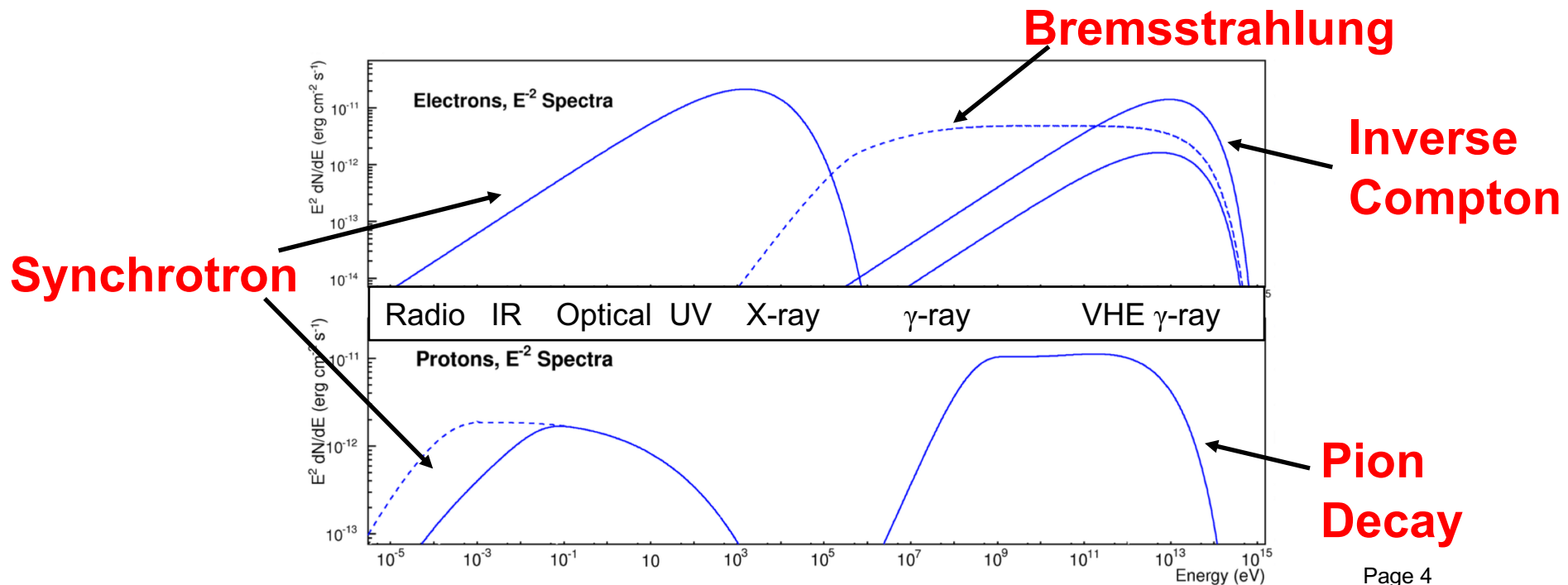


Inverse Compton Scattering:

scattering of energetic particles on background low energy photons (e.g. CMB, starlight...) – energy transfer: photons accelerated to TeV energies

Pion decay $\pi^0 \rightarrow \gamma + \gamma$:

signature for hadronic emission and the presence of highly energetic charged particles; potential cosmic ray source



Ground-based gamma-ray telescopes

Earth's atmosphere is opaque to gamma-rays:

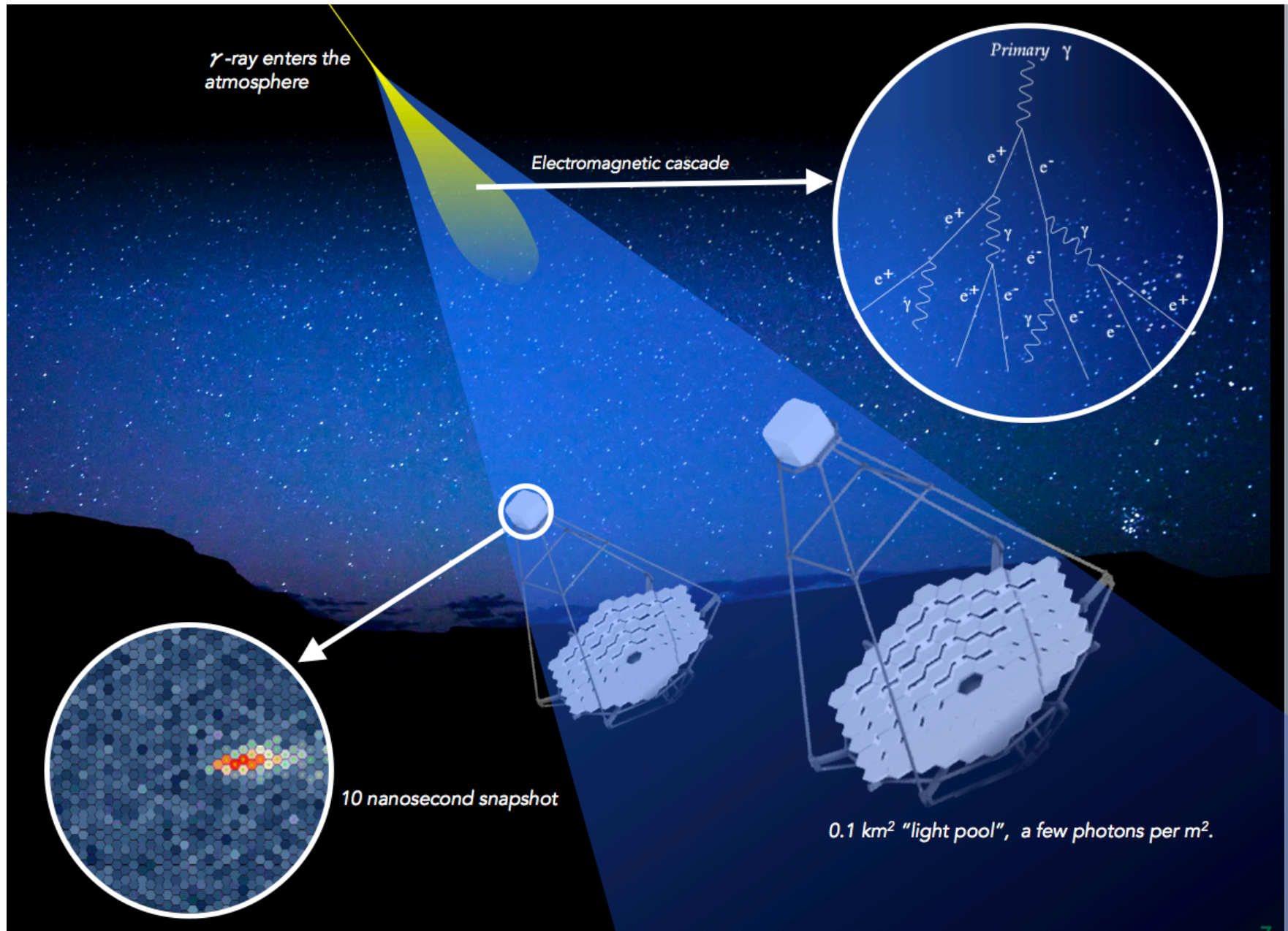
Solution – build a satellite? → Fermi-LAT

→ Only works up to energies ~ 2 TeV

Lower rate, need larger area → use atmosphere as part of the detector



Cherenkov Detection Technique



Ground-based gamma-ray telescopes

Earth is opaque to gamma-rays:

Solution – build a satellite?

→ Only works up to energies ~ 2 TeV

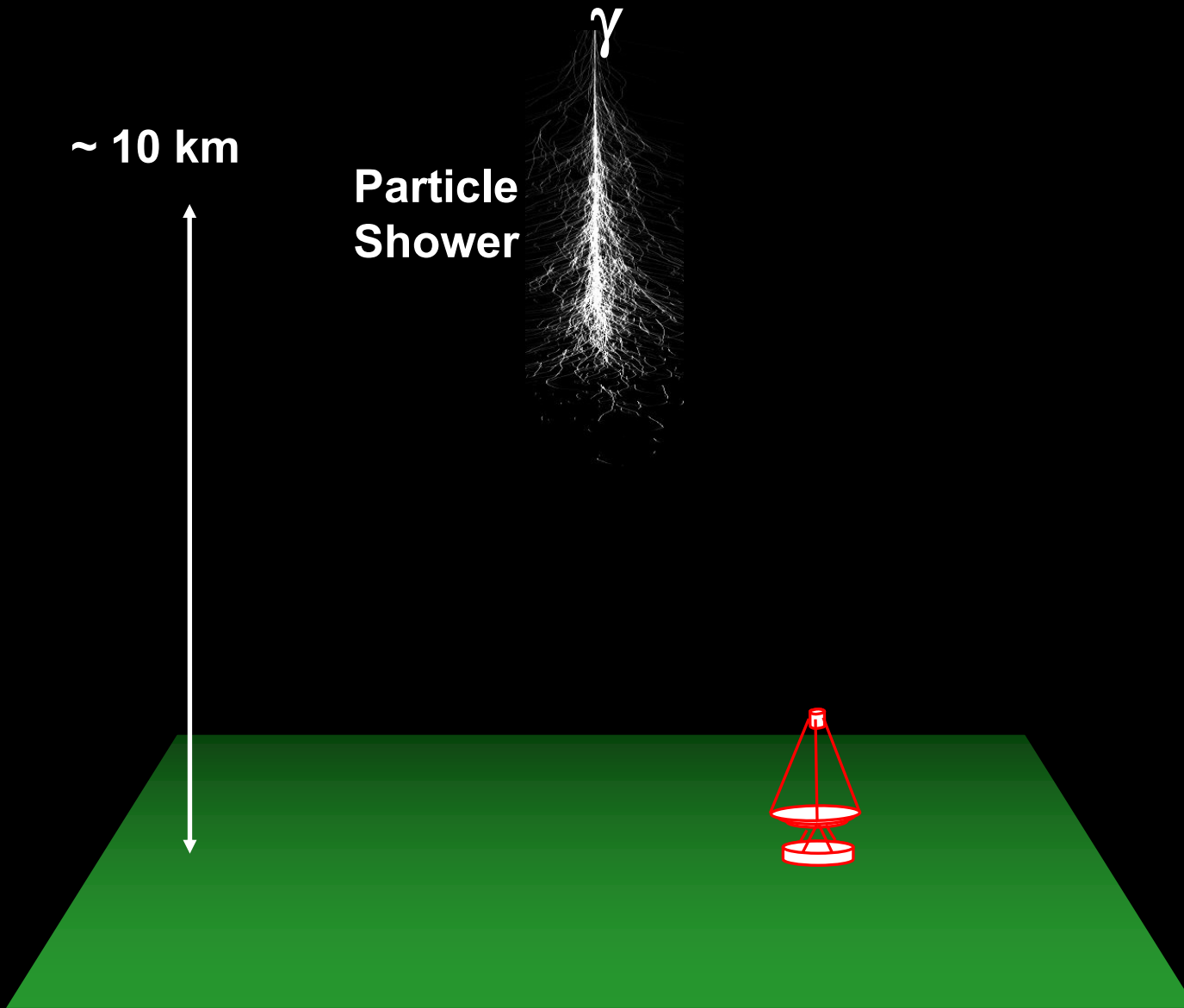
Lower rate, need larger area → use atmosphere as part of the detector

→ Charged particles travelling faster than the **local** speed of light produce Cherenkov radiation

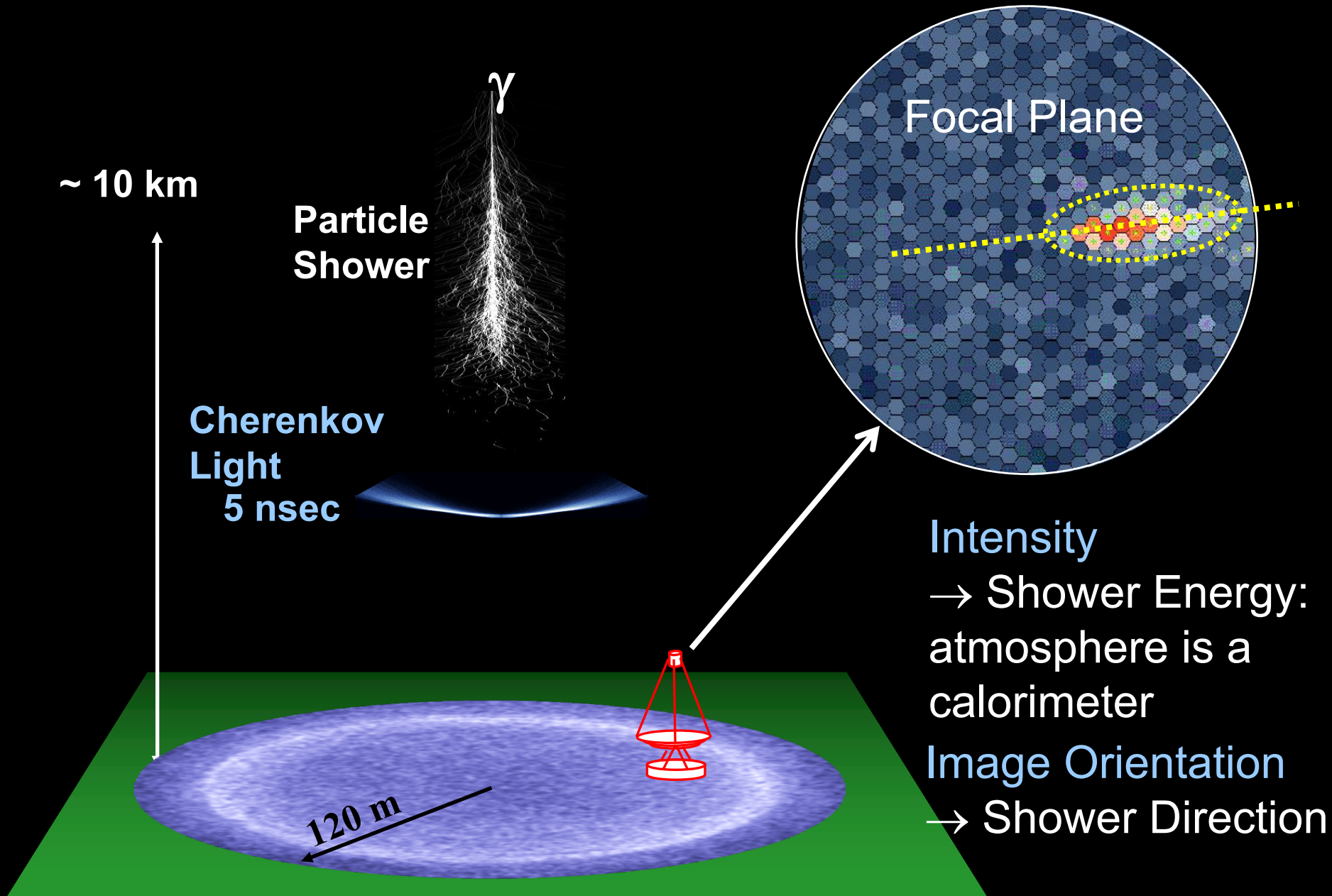
→ Illuminates a light pool on the ground



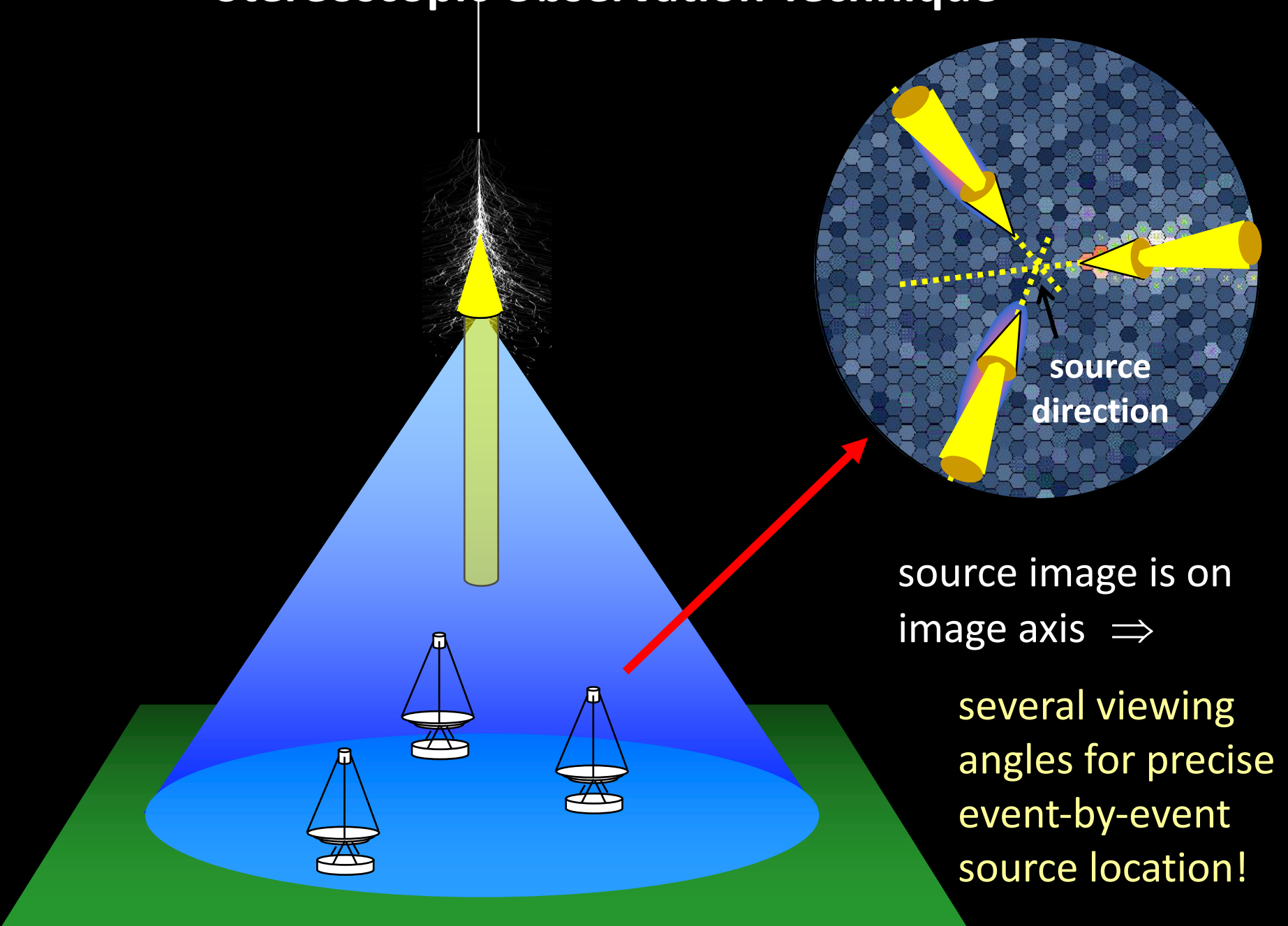
Detection of Cosmic Rays and Gamma Rays



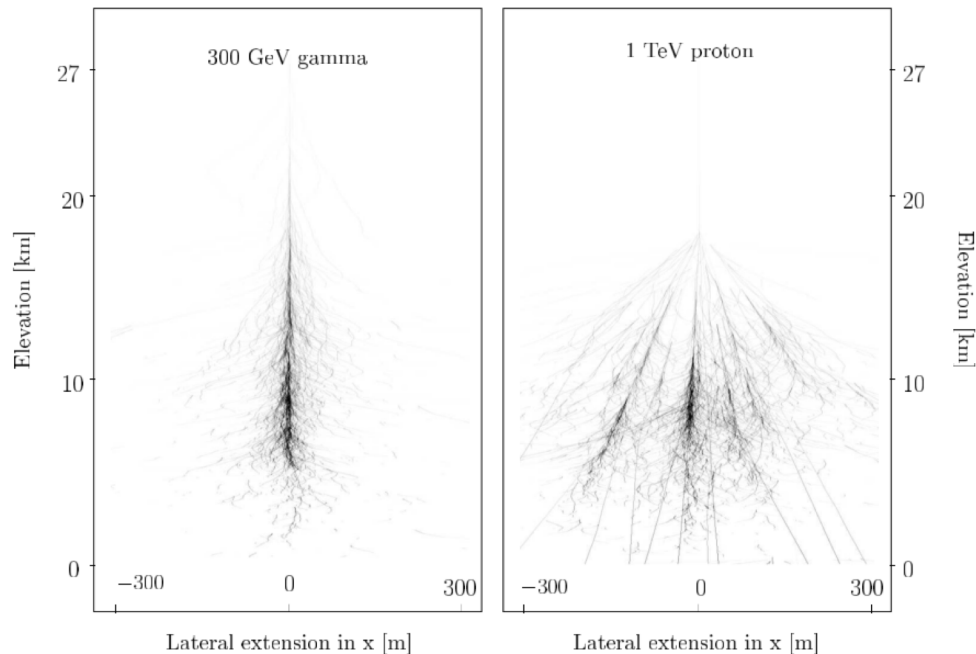
Detection of Cosmic Rays and Gamma Rays



Stereoscopic Observation Technique



Imaging Atmospheric Cherenkov Technique

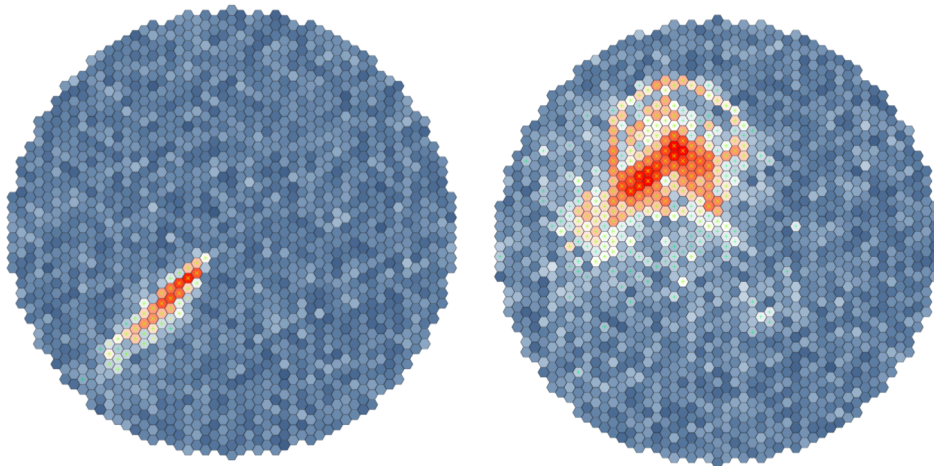


γ -ray images have a characteristic elliptical shape

Background: Cosmic Ray triggered air showers

γ -hadron separation is key

Current state-of-the-art:
machine learning approaches

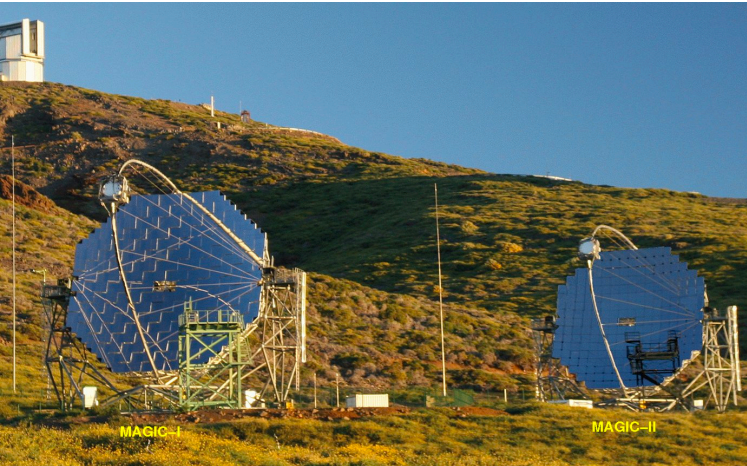


Current IACT Arrays

VERITAS,
Arizona, USA



MAGIC,
La Palma, Spain



H.E.S.S.
Namibia



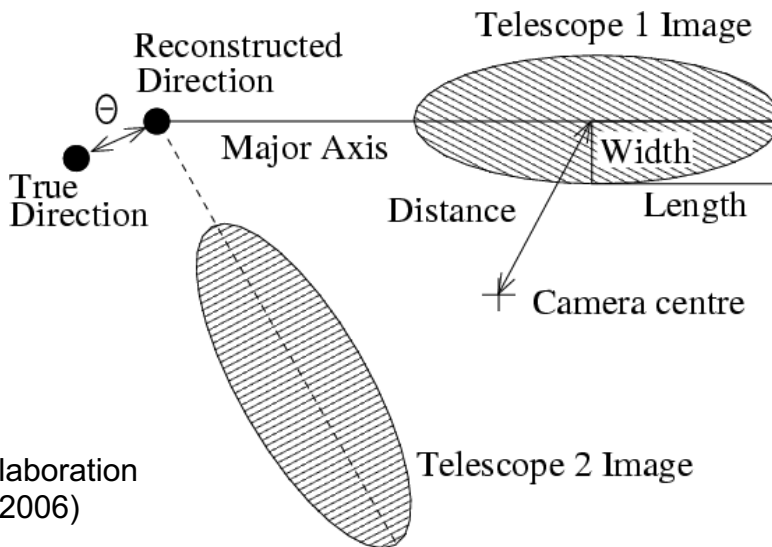
Extensive Air Showers

Simulation of Extensive Air Showers as seen from the ground [here](#)

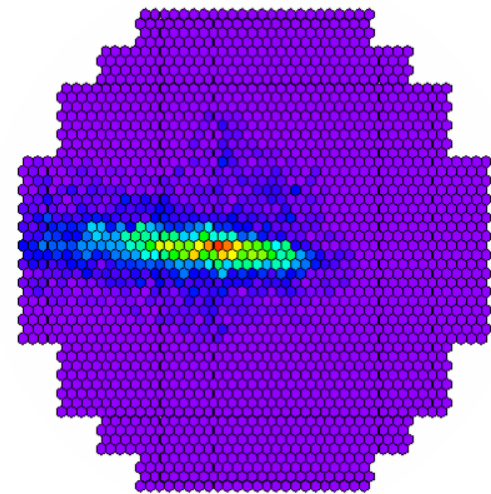
Hadronic EAS can look very similar to gamma-rays

→ Parameterise images to distinguish between gamma and hadron initiated EAS

→ "Hillas Parameters"



HESS Collaboration
A&A 457 (2006)
899-915



Mitchell et al Astropart. Phys.
111 (2019) 23-34

Gamma-hadron Separation

Hadronic air showers – major source of background in gamma-ray astronomy.

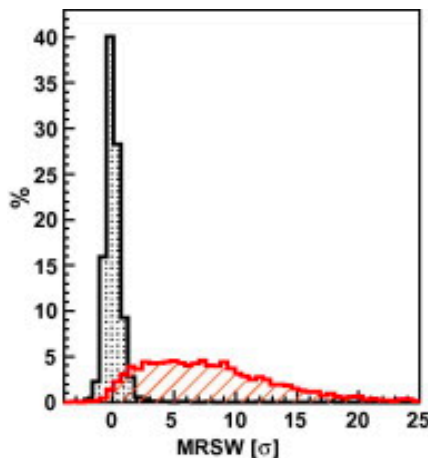
A lot of effort goes into reducing the background – identifying gamma-rays.

Hillas parameters help:

e.g. “Mean Reduced Scaled Width”

→ for a given image size and distance (from shower to telescope on the ground), the expected width from lookup tables $\langle w_i \rangle$ is compared to the measured width W_i

→ Scaled width per telescope i is given by $SCW_i = (W_i - \langle W_i \rangle) / \sigma_i$ and the mean $MRSW = \frac{1}{\sum_{i \in N} w_i} \cdot \sum_{i \in N} (SCW_i \cdot w_i)$ → key discriminating variable

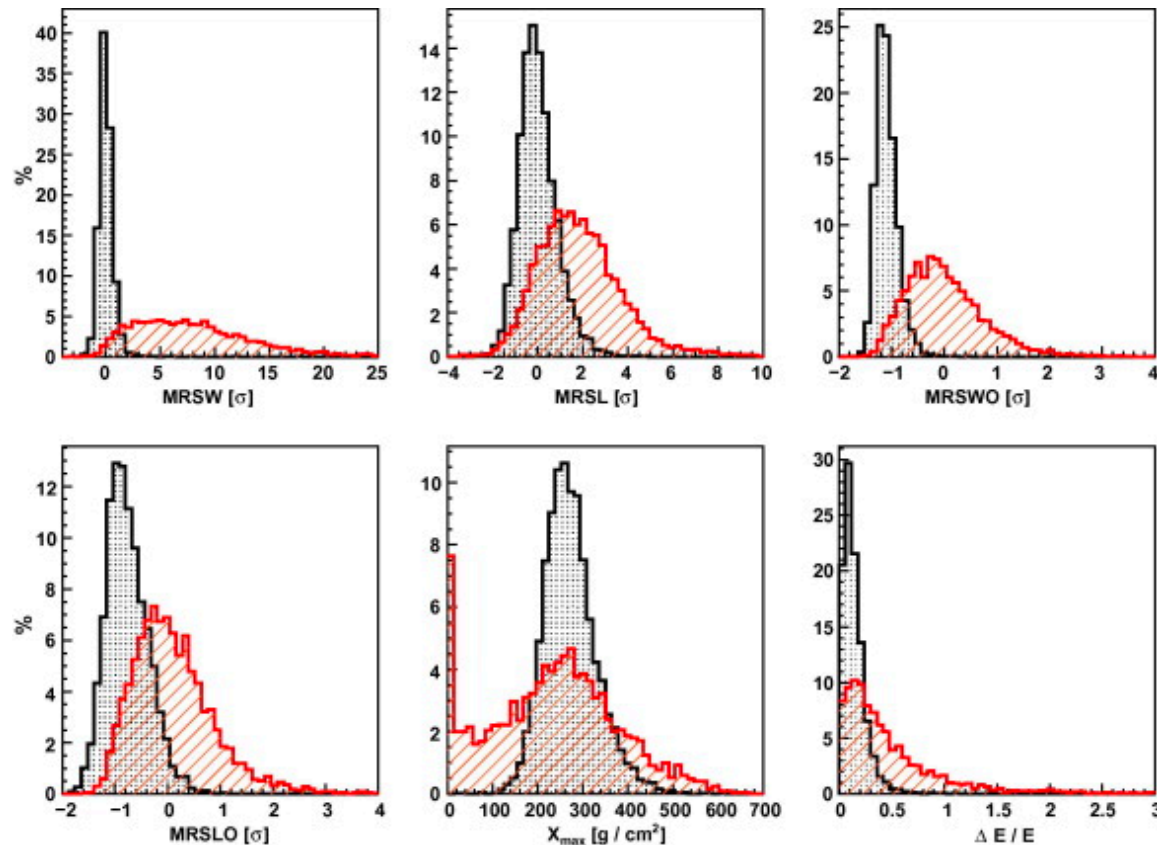


Gamma-hadron Separation

There are also other parameters of the image reconstruction

Each show some variation between gammas (black) and protons (red)

→ **Multivariate Analysis!**



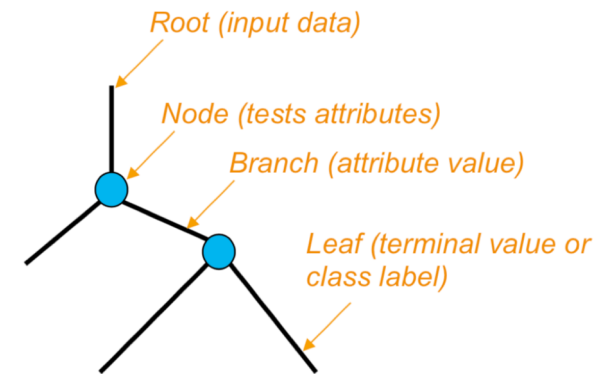
Decision Trees

Tree structure represents decision paths

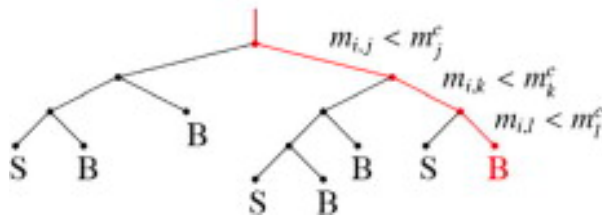
Classification trees → predict a class (discrete options)

Regression trees → predict a real number (continuous)

Decision trees → map n-dimensional input to 1d output.



Event with set of parameters $M_i = (m_{i,1}, \dots, m_{i,6})$



Tree needs to learn how to make a decision – in this case signal S or background B.

→ Provide list of variables with classification potential

→ Provide representative training data

Monte Carlo and training data

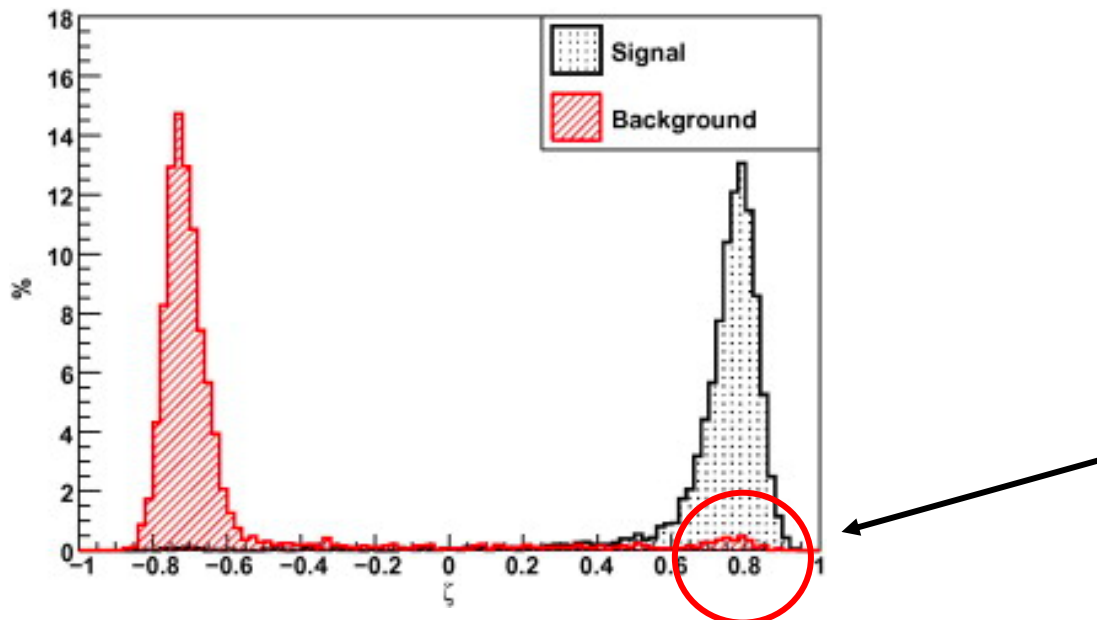
Training data can be either:

→ Simulations of how EAS appear in a telescope camera (known input)

→ "OFF" data – i.e. background from real data

In practise, to train a BDT:

1. Split training data into subsets based on attributes
2. Repeat process iteratively to grow the decision tree
3. Stop when leaves (terminal nodes) reach a certain level of purity



Gamma-ray data analysis

Notice the “irreducible” background.

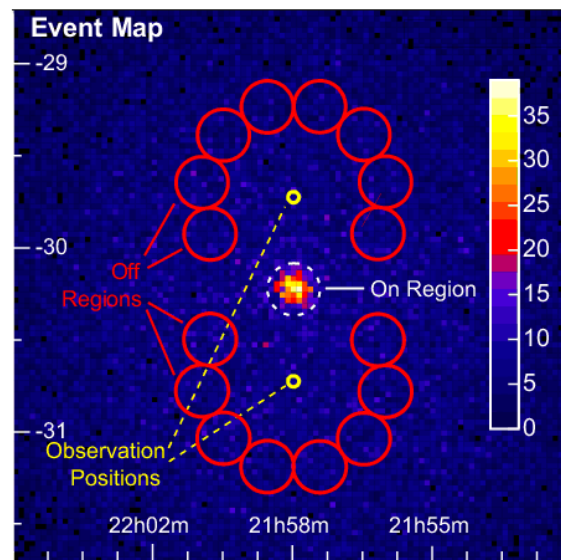
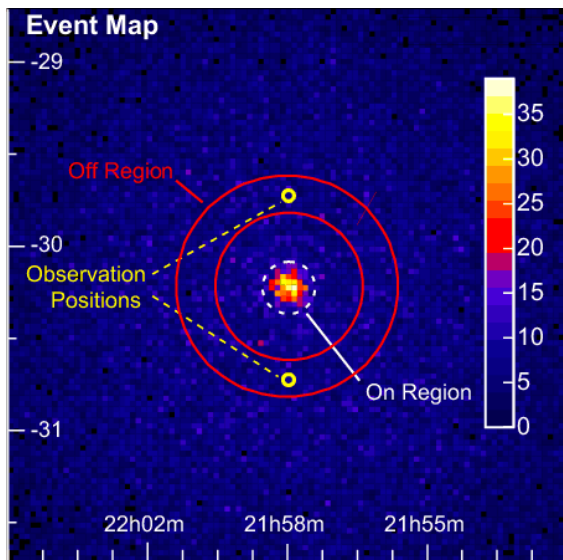
If a proton transfers most energy to a neutral pion π^0 early in the EAS development, this decays $\pi^0 \rightarrow \gamma + \gamma$...and looks like a gamma-ray shower.

Particle identification is done on a statistical basis.

To calculate a significance, we compare a signal “ON” region to a background “OFF” region to find the excess gamma-ray counts.

$N_\gamma = N_{ON} - \alpha N_{OFF}$ where α is a normalisation factor

(...among other methods...)



Berge et al A&A 466
(2007) 1219-1229

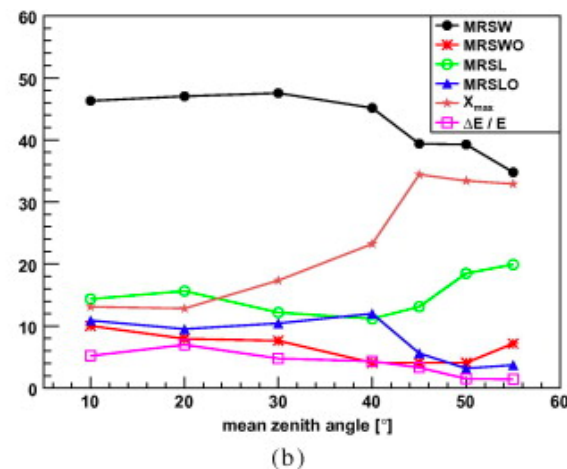
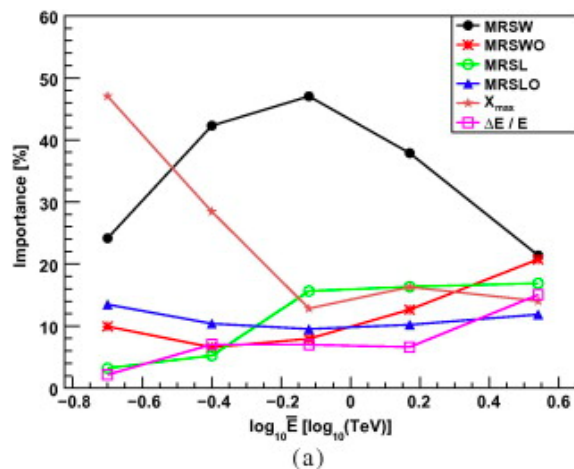
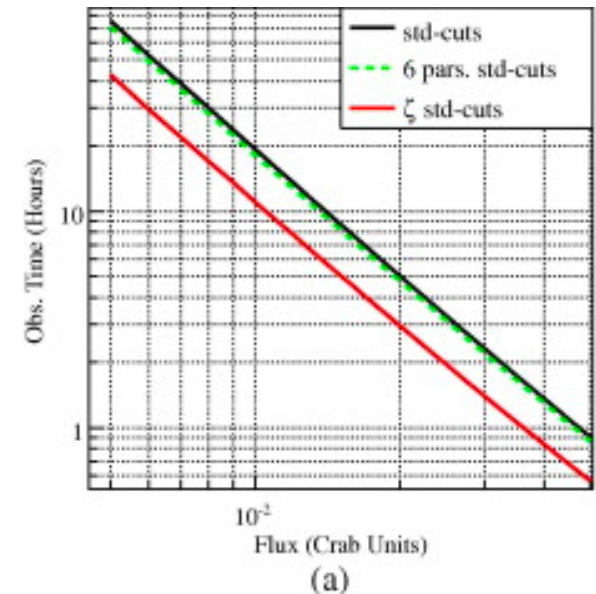
Gamma-ray data analysis – performance

A more sensitive analysis enhances the difference between ON and OFF counts.

Therefore also saves observing time

Note: parameter importance changes with:

- gamma-ray energy
- observing direction



Artificial Neural Networks

Mapping N-dimensional input to M-dimensional output

Each neuron returns a response to input signals

Numeric weights determine importance of inputs

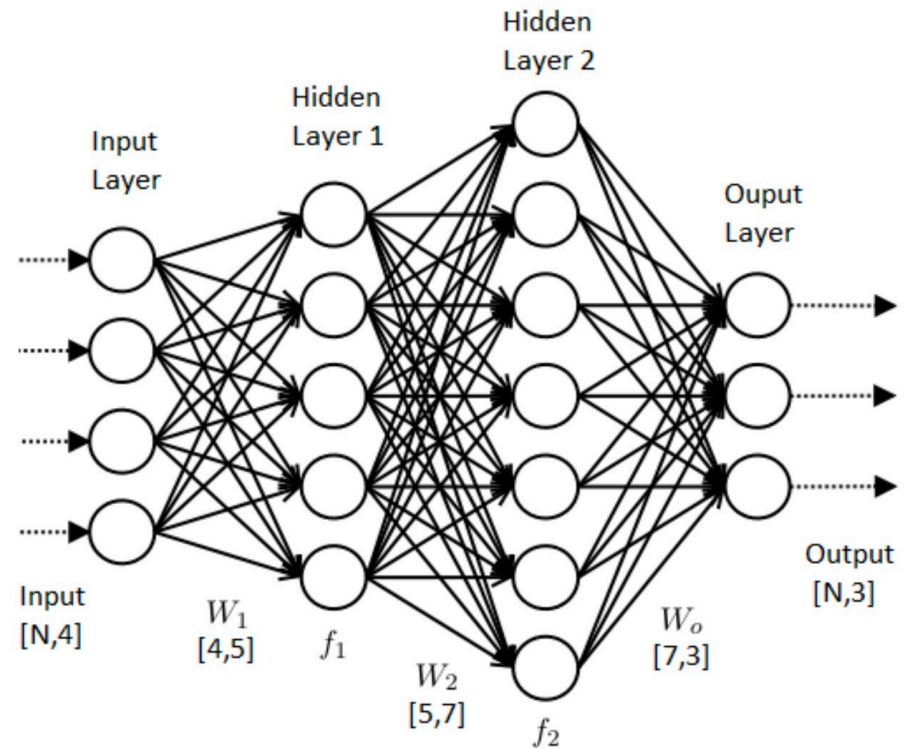
RNN = "Recurrent
Neural Network"
CNN = "Convolutional
Neural Network"

Back-propagation:

→ provide N training events & input
parameters

→ Let ANN classify and compare
output to expectation

→ Adjust weights and repeat



Convolutional Neural Networks

Convolutions for feature extraction

→ account for input often rotated / translated

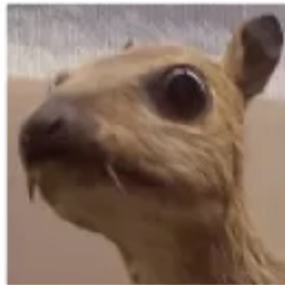
1	1	1	0	0
0	1	1	1	0
0	0	1 _{x1}	1 _{x0}	1 _{x1}
0	0	1 _{x0}	1 _{x1}	0 _{x0}
0	1	1 _{x1}	0 _{x0}	0 _{x1}

Image

4	3	4
2	4	3
2	3	4

Convolved
Feature

Input image



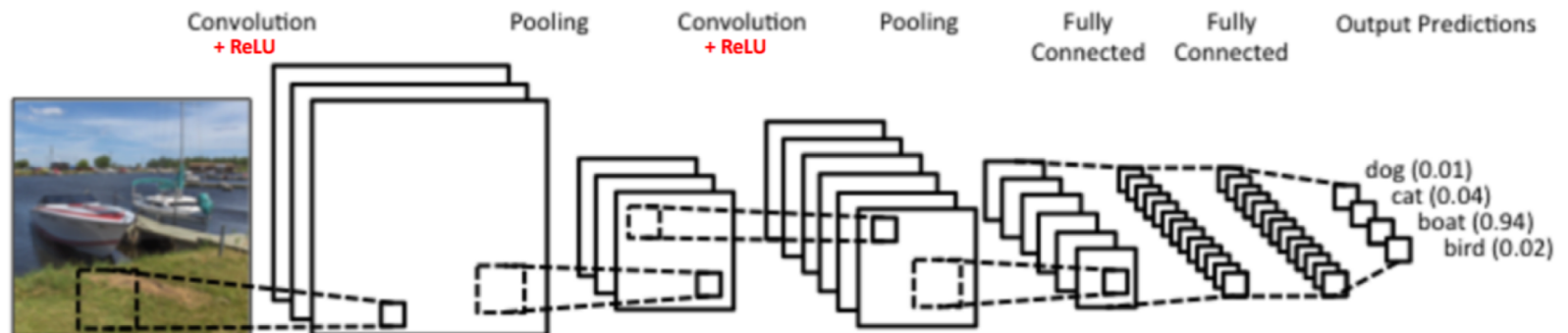
Convolution
Kernel

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Feature map



Stack successive convolutions, use as input to Neural Network



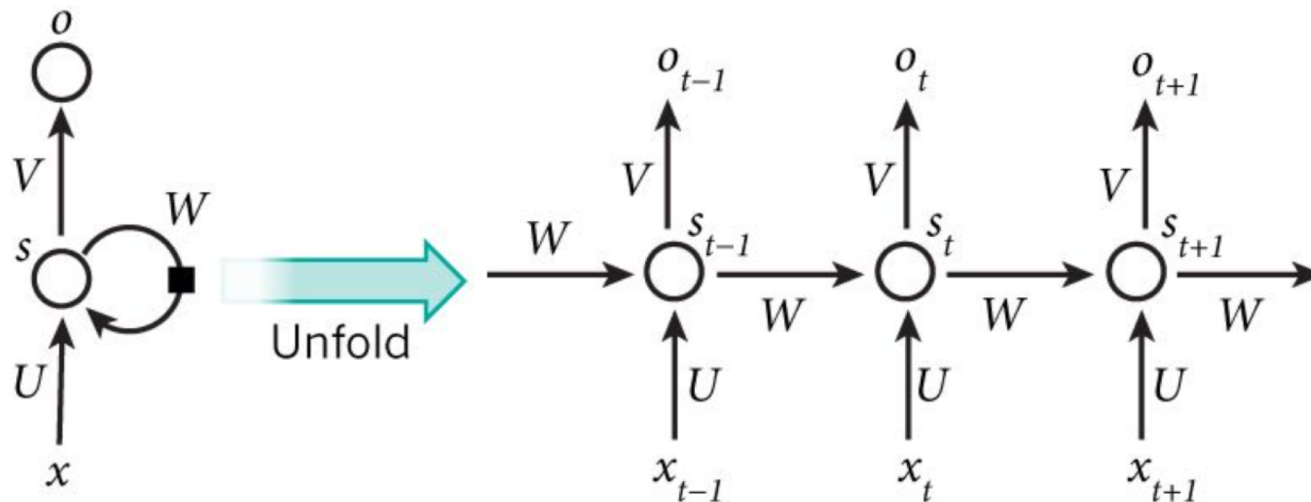
<https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/>

Recurrent Neural Networks

Deal with sequences of data

→ Use these to combine information from multiple telescopes

→ Network weights are modified based on information already seen

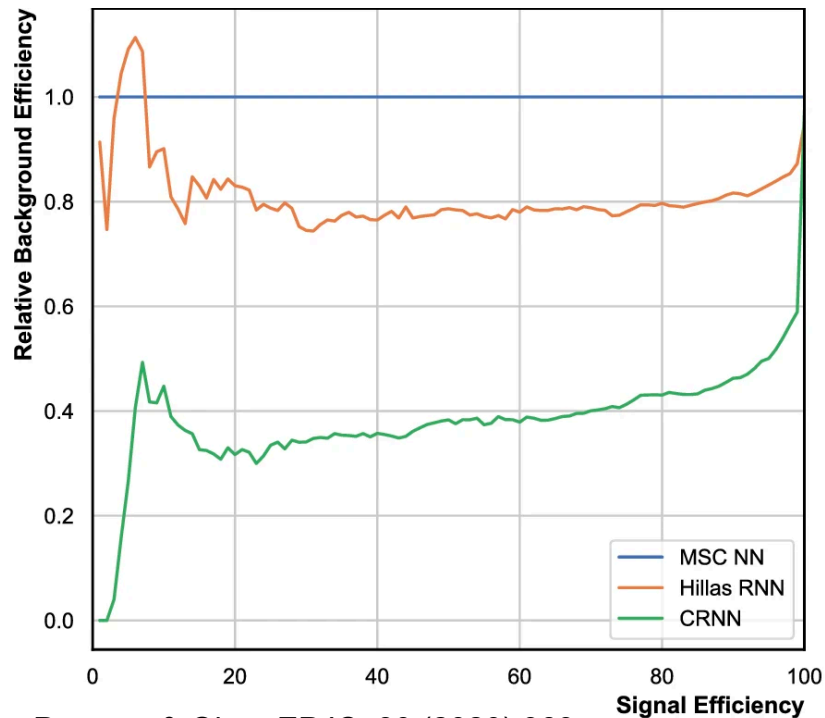


Neural Networks for gamma-hadron separation

Hexagonal pixels = headaches!

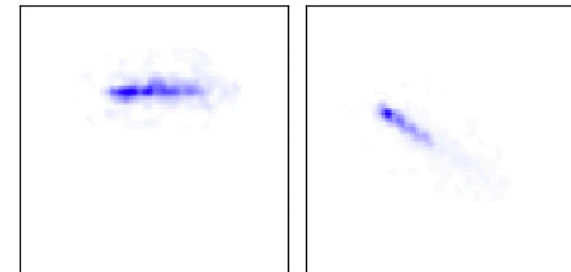
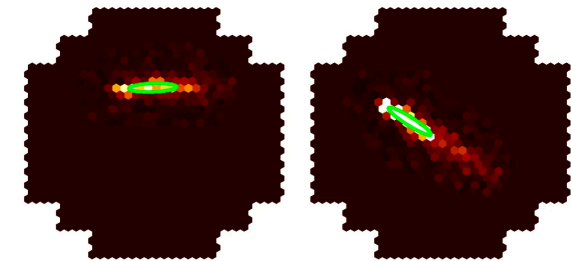
Deep NNs – map each pixel to input layer

Much better relative performance predicted on simulations

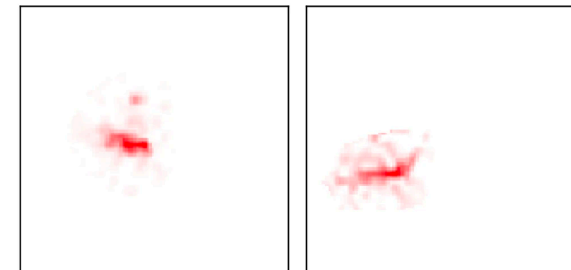
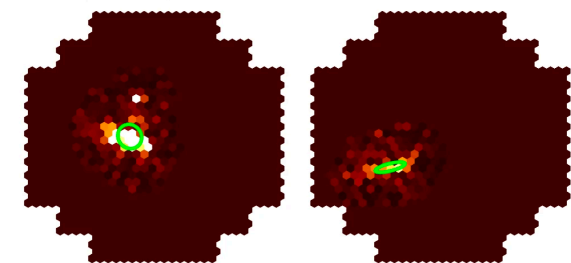


Parsons & Ohm, EPJC, 80 (2020) 363

Gamma-ray (2.39 TeV)



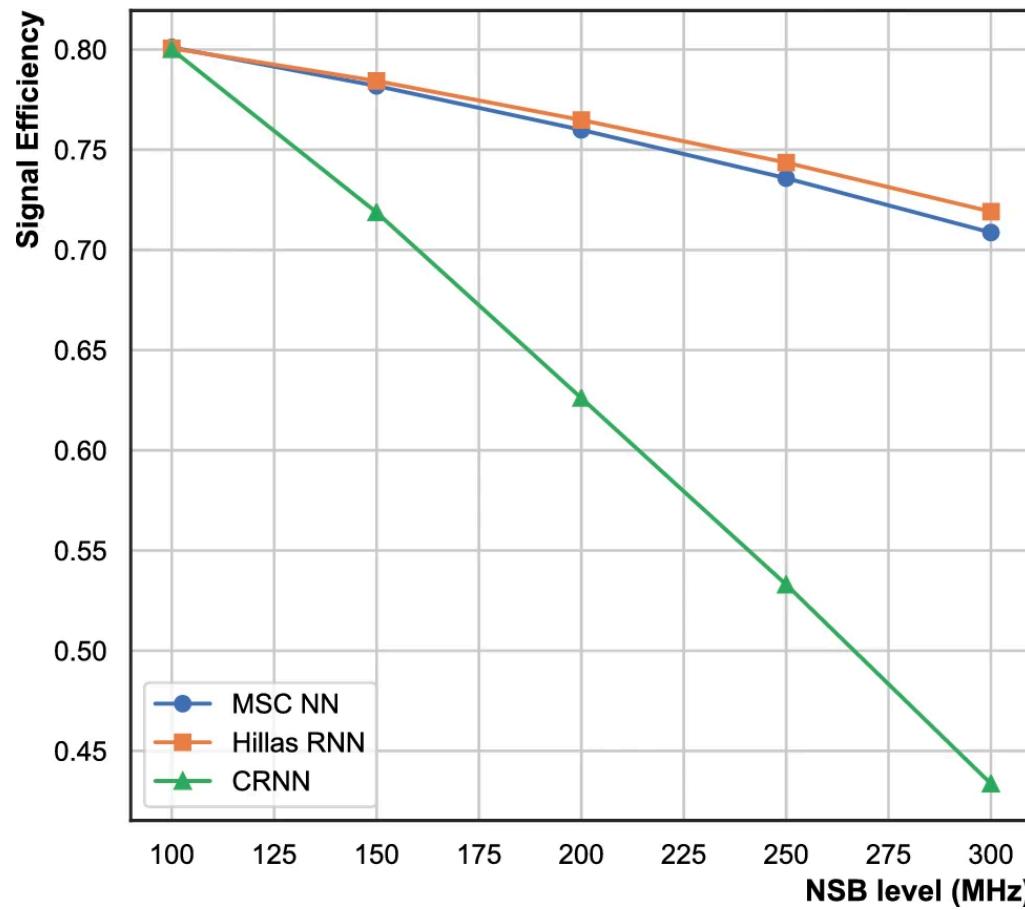
Proton (6.06 TeV)



Neural Networks for gamma-hadron separation

However....highly sensitive to Night Sky Background
(i.e. ambient starlight, scattered moonlight etc.)

→CRNN must be trained to well-matched conditions. → Is it worth it?

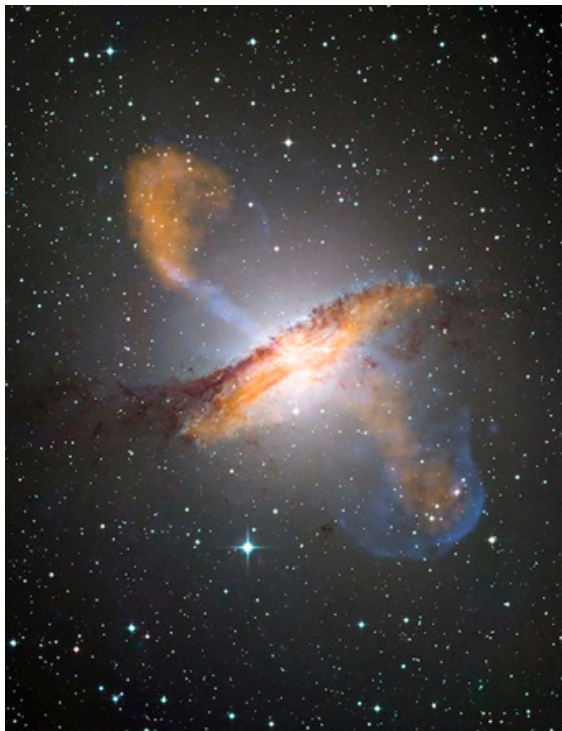


Machine Learning for Source Classification

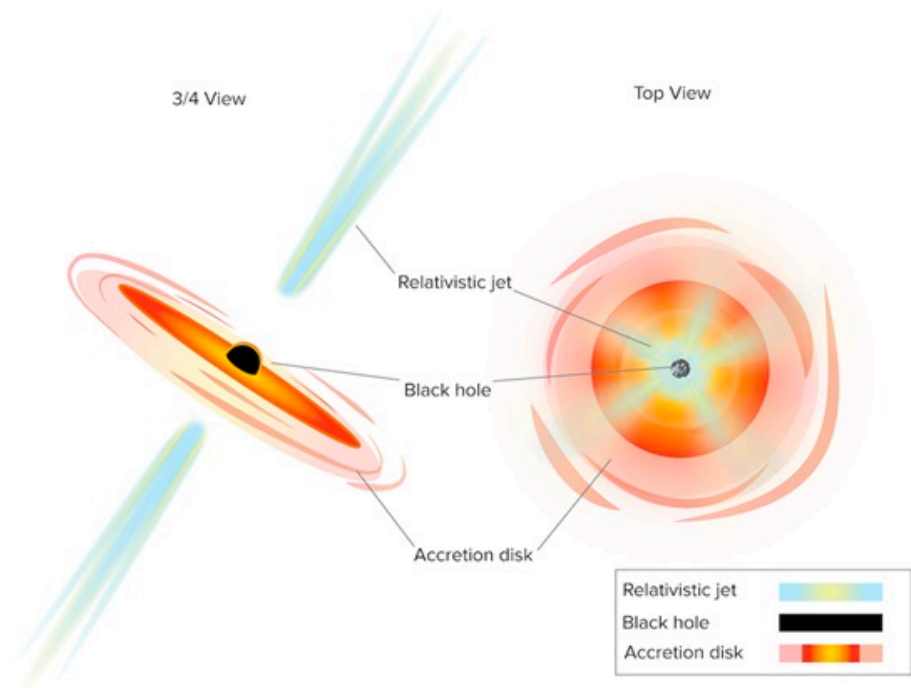
Gamma-ray sources = cosmic ray accelerators

Introducing: Blazars → active galactic nuclei with jet pointing towards Earth

Strong gamma-ray emitters, time variable



ESO/WFI (visible); MPIfR/ESO/APEX/A.Weiss et al. (microwave); NASA/CXC/CfA/R.Kraft et al. (X-ray)



Sophia Dagnello, NRAO/AUI/NSF

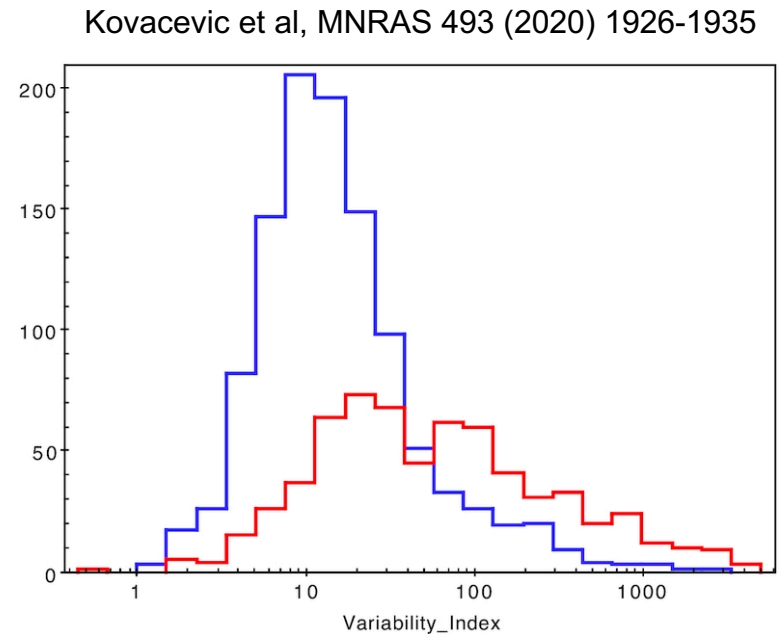
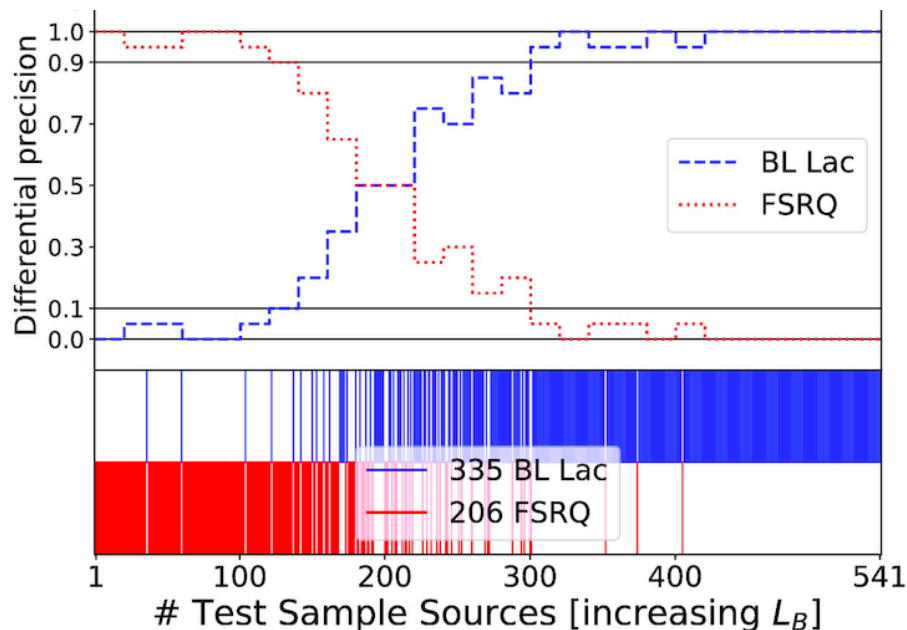
Machine Learning for Source Classification

Gamma-ray sources = cosmic ray accelerators

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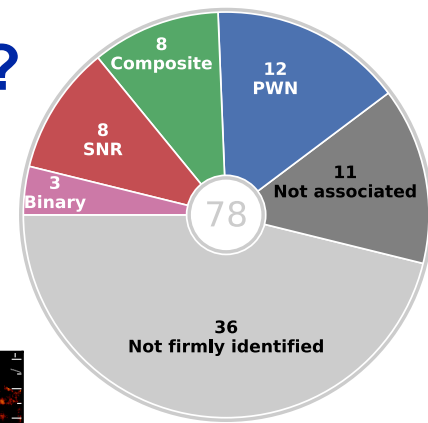
Strong gamma-ray emitters, time variable

Recent paper: classifying gamma-ray blazars according to sub-type (BL Lac vs FSRQ) with an ANN (data from Fermi-LAT satellite)

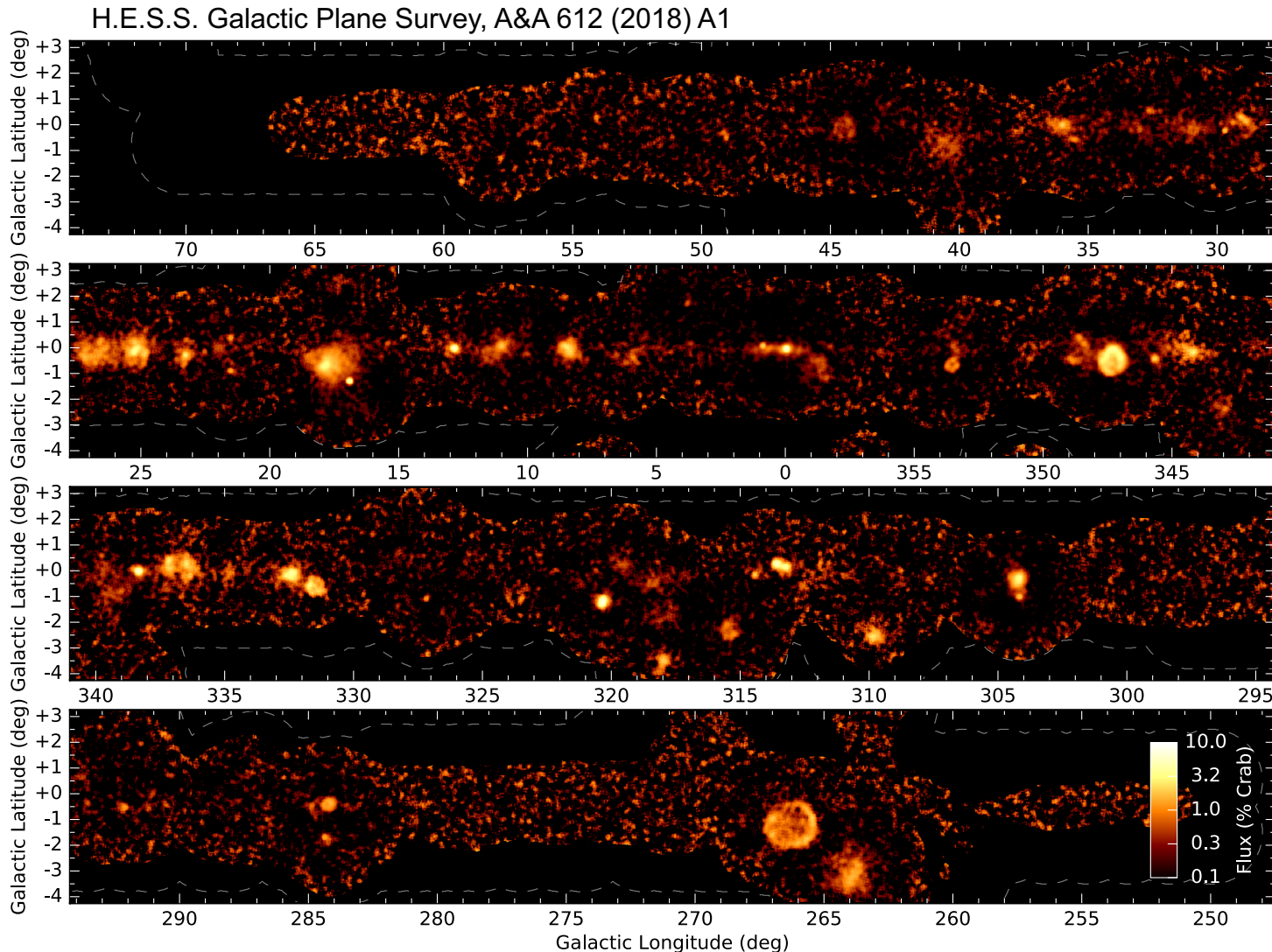


Machine Learning for Source Classification?

→ Open Problems

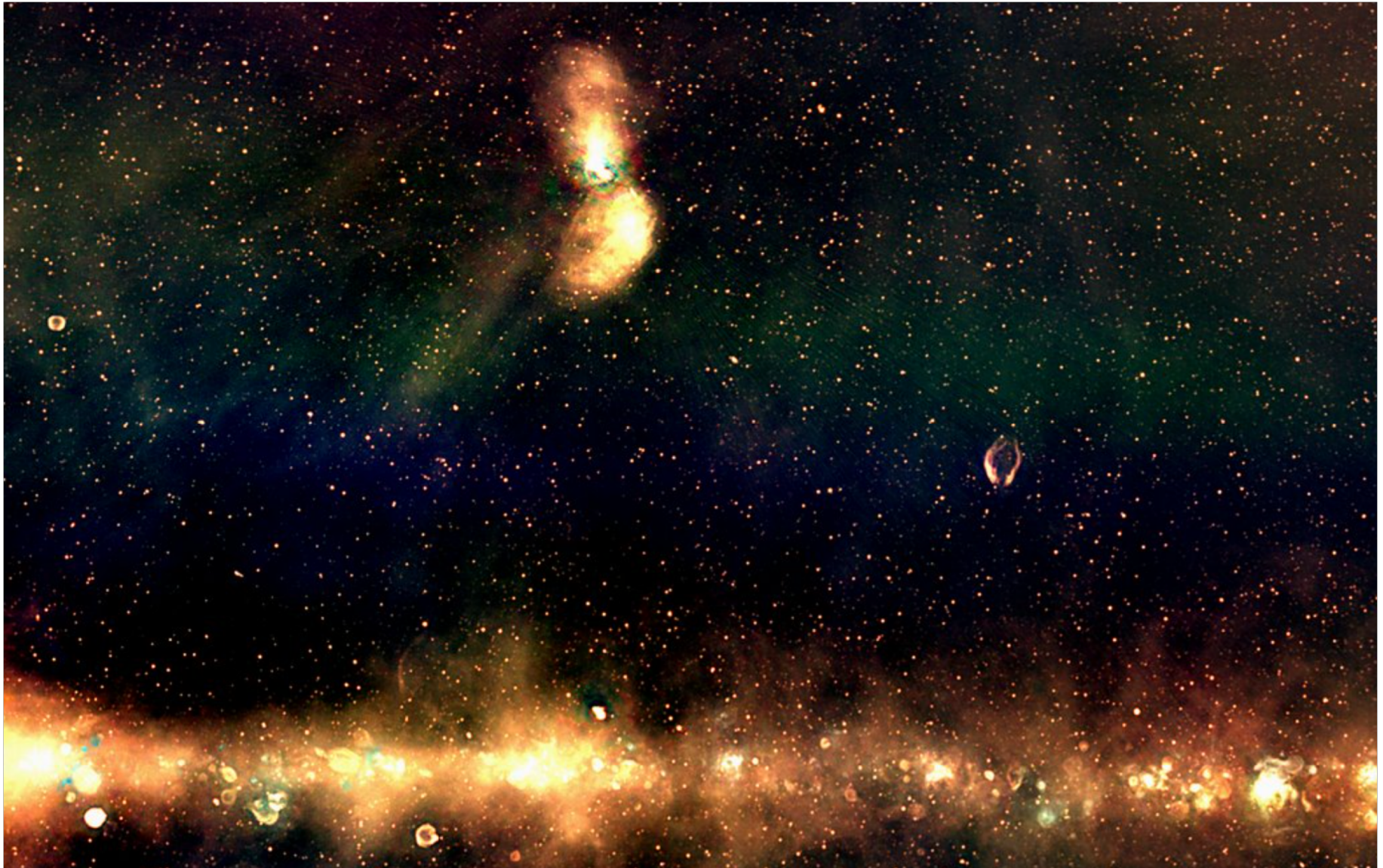


SNR =
Supernova
Remnant



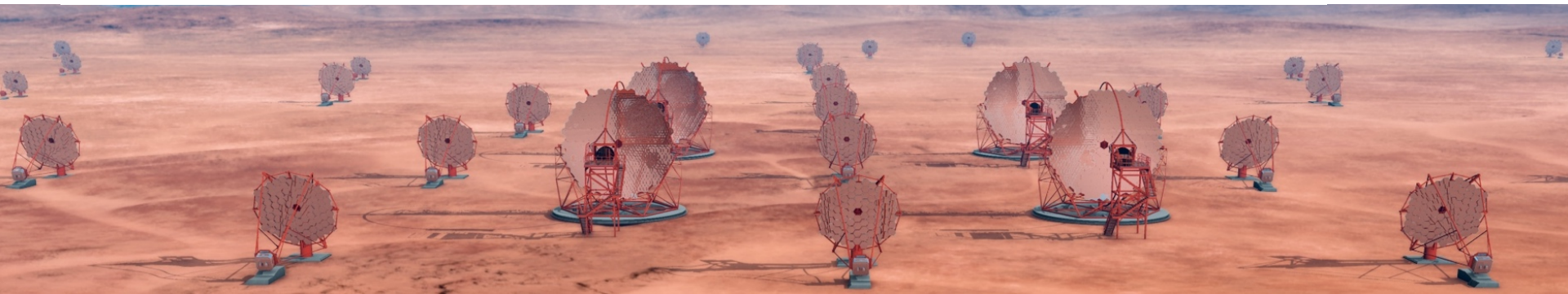
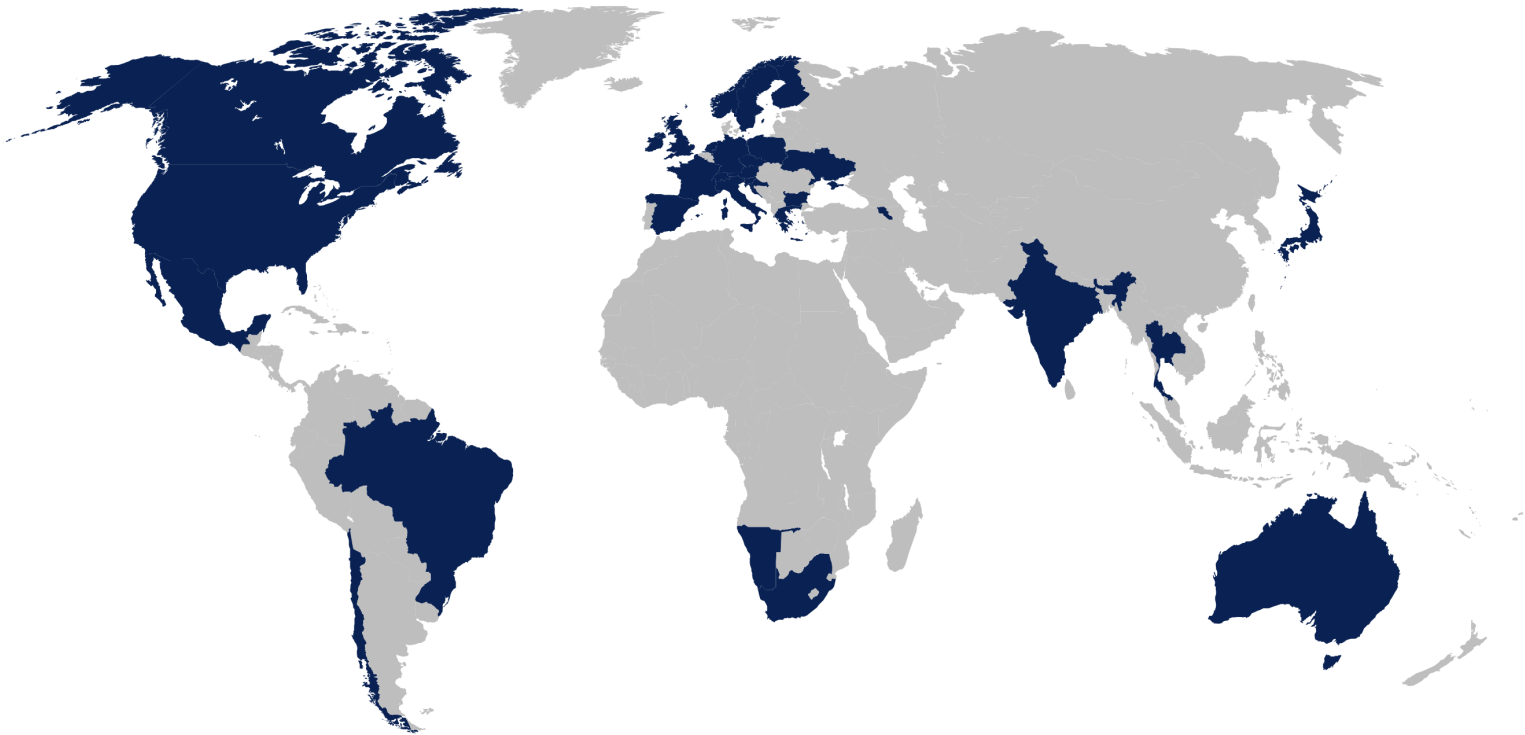
Potential Application: Supernova Remnants – radio data

Credit: Dr Natasha Hurley-Walker (ICRAR/Curtin) and the GLEAM Team

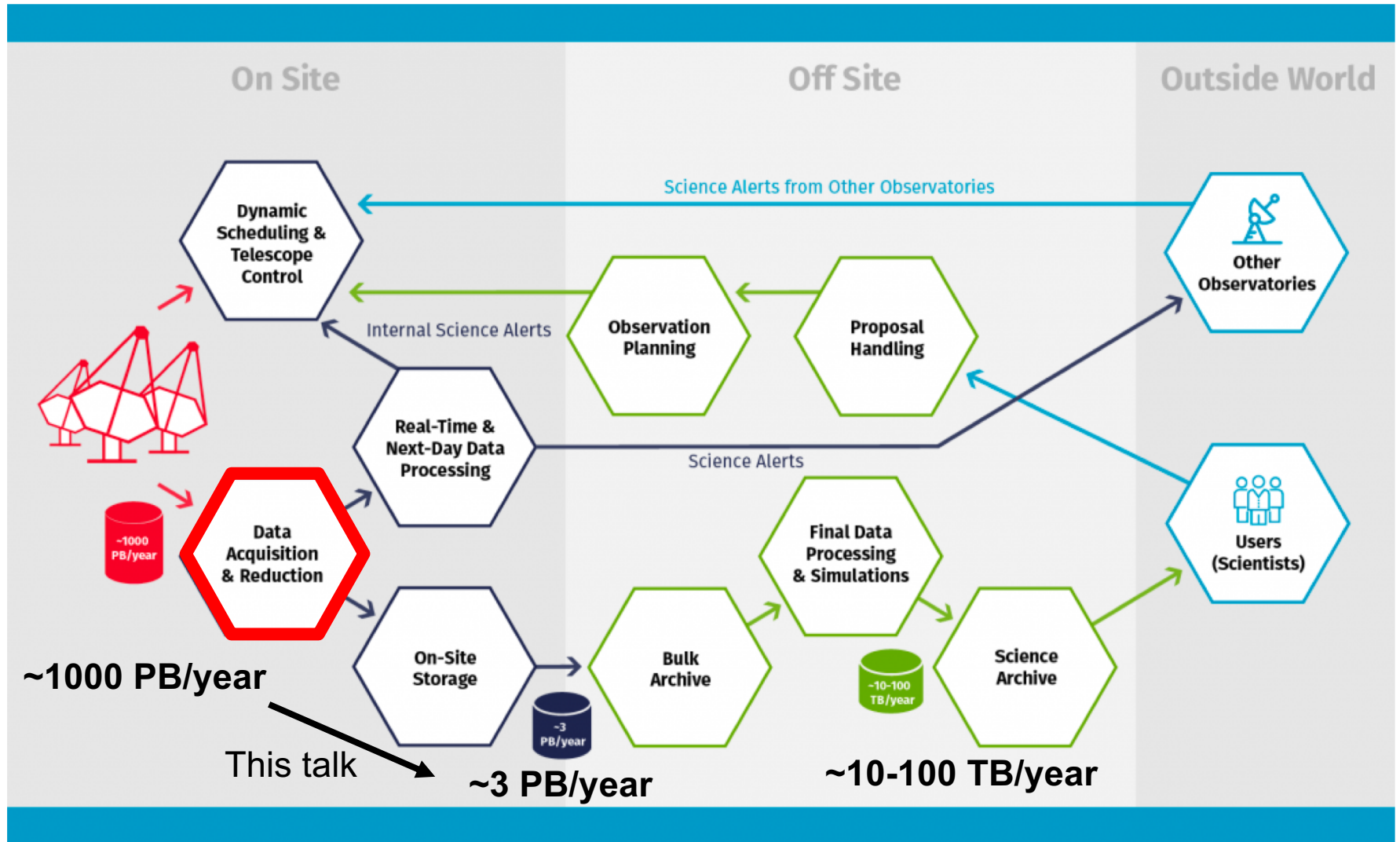


The future: Cherenkov Telescope Array

31 countries, >200 institutes, > 1500 members, 2 sites, up to 100 telescopes



Big Data in the future of astronomy



www.cta-observatory.org

Thank you for your attention

Any questions?