



Analysis of IACTs data in the Machine Learning era

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with inputs from R. Terrier (APC), Q. Remy (IRAP), R. Lang (ECAP),
A. Moralejo (IFAE), F. Acero (CEA), M. Fueßling (CTAO),

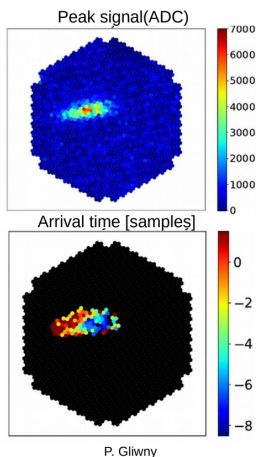
From 9 to 14: The SST telescopes and Gamma-ray Science with ASTRI and CTAO
(Sexten, Italy)

Indirect detection of gamma rays

Detection of Cherenkov light

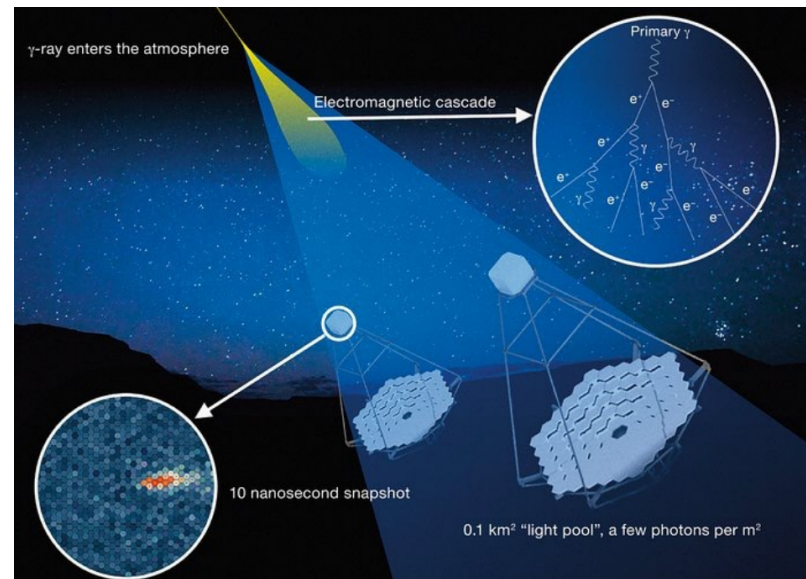
Complex data processing of telescopes data

- From calibration to gamma-ray observables



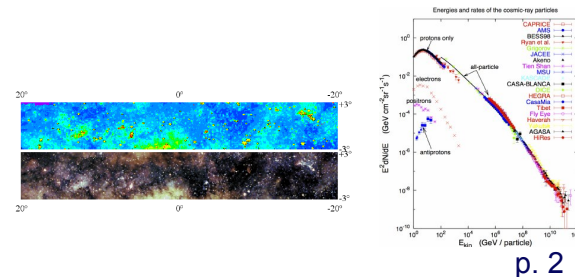
0(1000) pixels
per camera

- Arrival Time (MJD)
- Arrival Direction (ICRS)
- Reconstructed Energy (eV)



Signal purification

- Night Sky Background and atmospheric Cosmic Rays



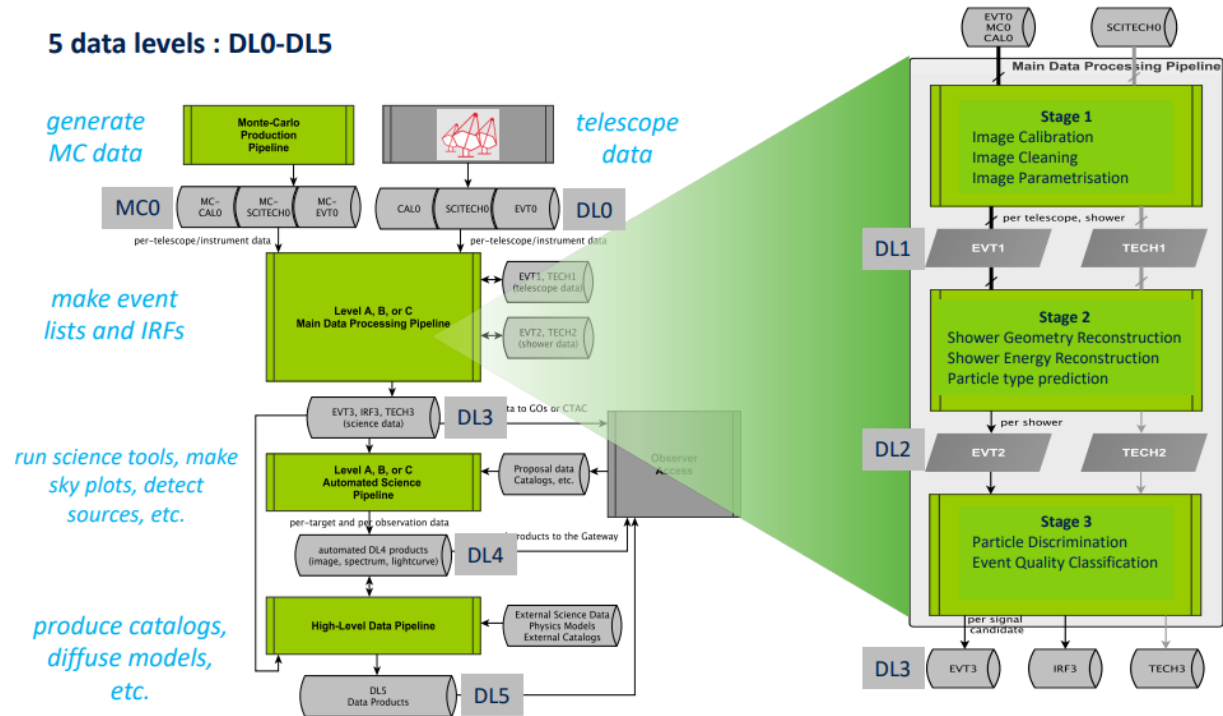
Indirect detection of gamma rays (2)

Complex workflow

- Different data levels
- For the real data
- And the simulations...

Determination of the Instrument Response Functions (IRFs)

Low-Level Analysis



From events to γ -ray sources

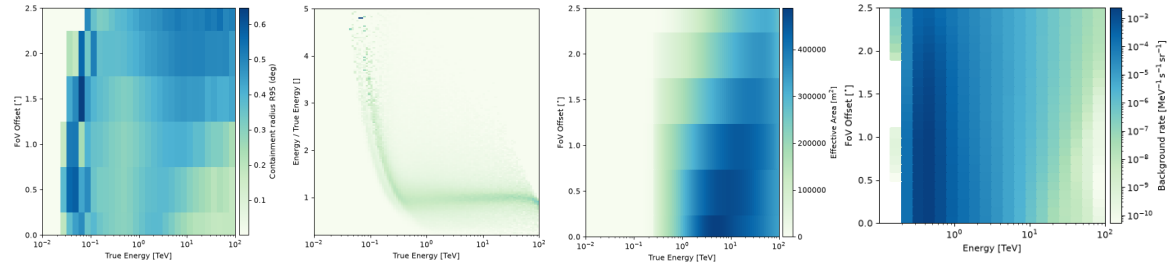
Counting experiments

Non-invertible IRFs

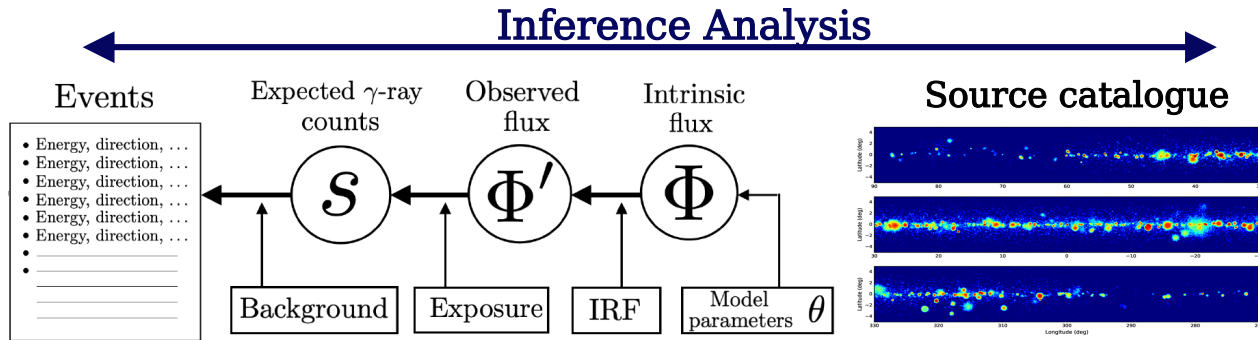
γ -rays IRFs

PSF, En dispersion, Effective Area

Cosmic-Ray IRF



Complex statistical analysis



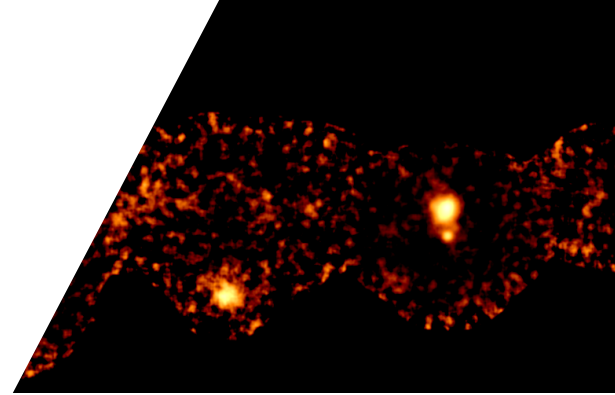
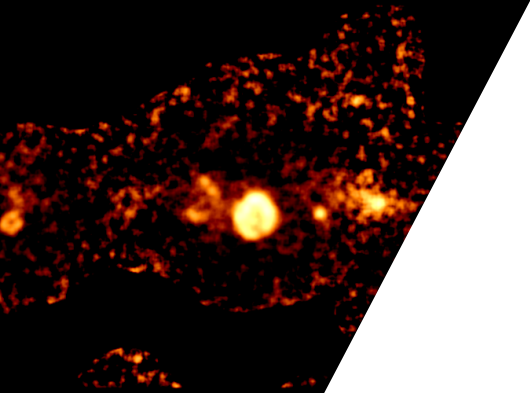
High-Level Analysis

Adapted from G. D'Amico, 2022

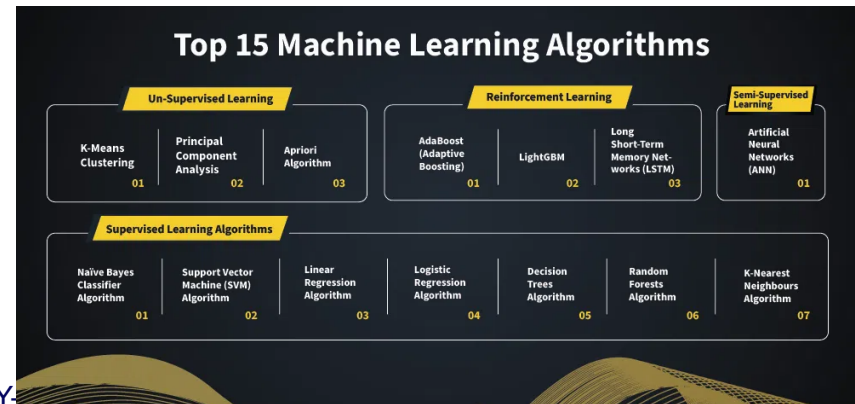
Summary

- 1- The era of Machine Learning**
- 2- Low-Level analysis**
- 3- High-Level analysis**

The era of Machine Learning



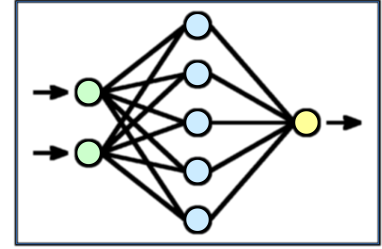
B. Khélifi | July, 23th 2026 | CC BY-



ANN and Learning

Artificial Neural Network

Model that stacks simple "neurons" with an activation function in layers and learns pattern-recognizing weights and biases from data to map inputs to outputs.



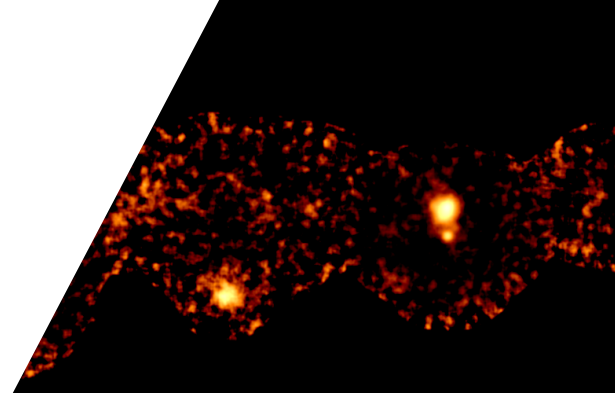
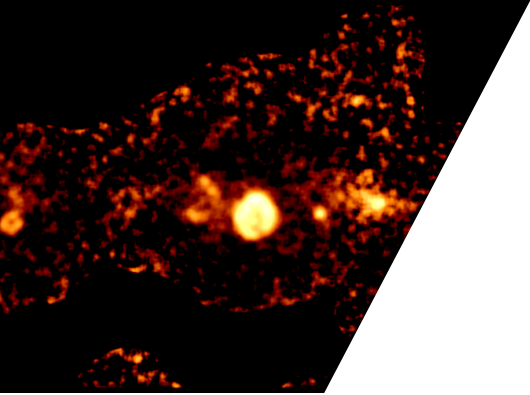
Machine Learning vs Deep Learning

ML used for prediction, classification and clustering.
DL is for more complex tasks like image/voice recognition, or complex images recognition

Supervised vs unsupervised Learning

Supervised learning uses labelled training dataset, which is not the case for the unsupervised learning

Low-Level Analysis



Generation of calibrated images

Calibration Processes

Many steps are required to calibrate images, using dedicated data from specific observations, standard scientific data or specific devices

Up to now, there are only few usage of ML for the calibration workflow

- In contrary to Particle or Nuclear Physics

Telescope Optical Efficiency

- Measured with muon rings on standard observations
- VERITAS: use of **Convolutional Neural Network** (Feng et al., 2016, [arXiv:1611.09832](https://arxiv.org/abs/1611.09832)) → successful
- Identification of muons from raw data

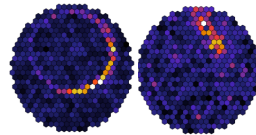
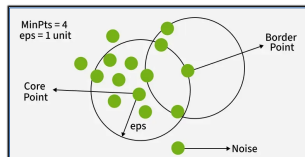


Image Cleaning

- Many reconstruction algorithms use Hillas parameters A.M. Hillas, 1985 ([link](#))
 - Rejection of the main noise source: the Night Sky Background
- H.E.S.S.: use of **DBScan** (Ćelić et al., 2025, [arXiv:2503.22361](https://arxiv.org/abs/2503.22361))
 - Hierarchical density-based clustering algorithm (Ester et al. 1996) in Scikit-Learn
 - Use of both pixel intensities and their timing
 - Can be used for Data Volume Reduction: Nieves et al., 2025, [arXiv:2411.14852](https://arxiv.org/abs/2411.14852)



Insights

CNN

ANN made with numerous hidden layers, and millions of parameters.

It uses Convolution and pooling processes sub-sample the given input before applying an activation function.

The convolutional layer applies a set of filters to the input image, each filter producing a feature map that highlights a specific aspect of the input image. The pooling layer then downsamples the feature map to reduce its size, while retaining the most important information.

Event reconstruction: the first major ML usage

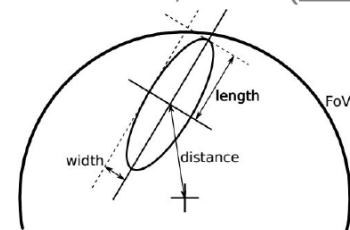
ROOT/TMVA

Open library that offers many tools:

- Unsupervised learning (e.g. Principal Component Analysis)
- Supervised learning (e.g. BDT)



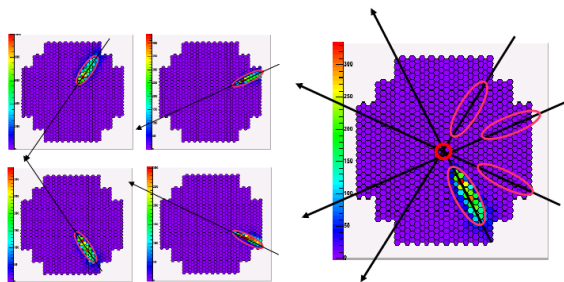
A.M. Hillas, 1985 ([link](#))



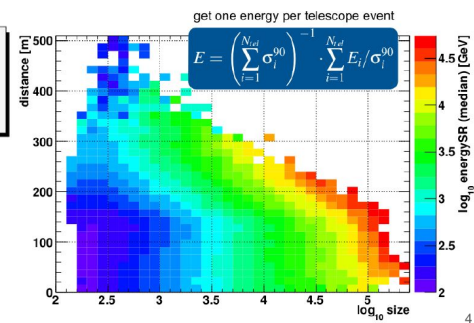
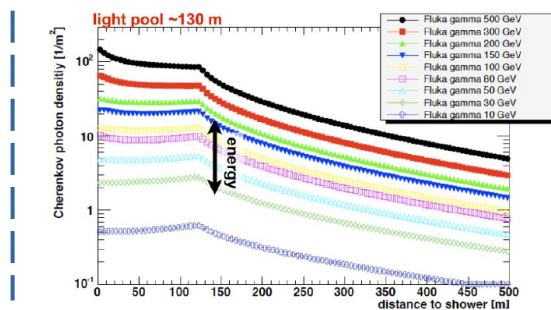
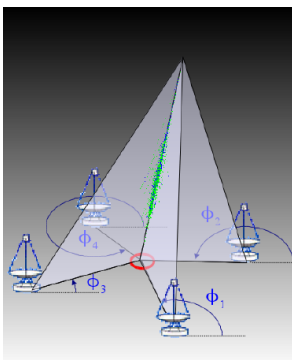
Main inputs: image parametrisation (Hillas)

Energy and direction reconstruction

Initially, using standard techniques w/o ML



M. de Naurois, 2012 ([link](#))



A. Petrashyk, 2016 ([link](#))

Event reconstruction: the first major ML usage (2)

Gamma/Hadron Discrimination

Classification problem

- **Random Forest** : e.g. Albert et al., 2008, [arXiv:0705.3244](#)
- **Boosted Decision Trees** : e.g. Ohm et al., 2009, [arXiv:0904.1136v1](#); Becherini et al., 2011 [arXiv:1104.5359](#); Krause et al., 2017, [arXiv:1701.06928](#)

Performances

- M. Sharma et al. (2014, [link](#)) claim that RF is better performing
- *But*, BDT show its high performance and stability, and using different inputs than image parametrisation – **The physicist's choices are crucial !**

Challenges

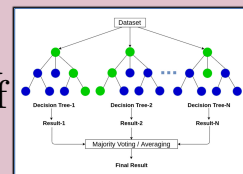
- Stability: sensitive to input data when badly chosen input variables
- Statistics: require a LOT of OFF data for EACH instrument configuration
- Resources: computing power and manpower (long to set up)



Insights

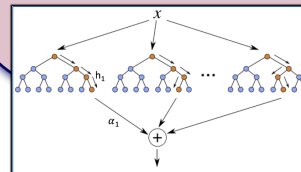
RF

Decision trees can be visualized as a flow chart of conditions that can be used to most accurately classify or predict outcomes.



BDT

An ensemble model by combining several weak decision trees sequentially. It assigns weights to the output of individual trees. Then it gives incorrect classifications from the first decision tree a higher weight and input to the next tree.



Outcome of Open Science

Python ecosystem

Explosion of freely accessible algorithms via many libraries:

- PyTorch, Scikit-Learn, Keras, TensorFlow, Networkx
- With in background Numpy, Scipy and Pandas / Matplotlib, Seaborn
- Usage of GPUs

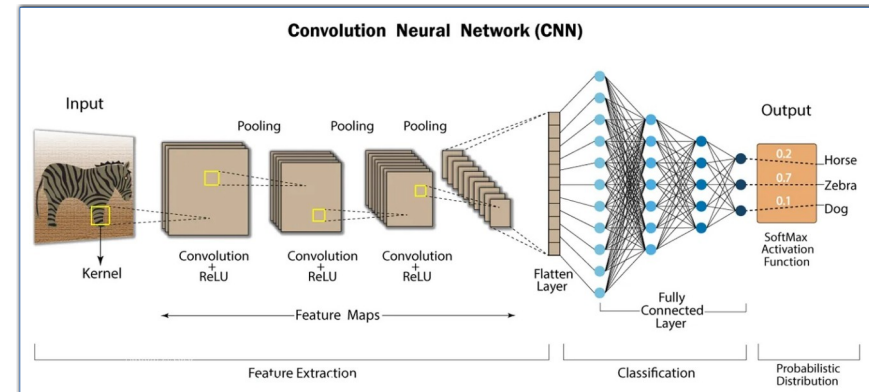
Opening towards Deep Learning

Convolutional Neural Networks (CNNs)

Made with an input layer, an output layer, numerous hidden layers, and millions of parameters.

It uses Convolution and pooling processes sub-sample the given input before applying an activation function.

The convolutional layer applies a set of filters to the input image, each filter producing a feature map that highlights a specific aspect of the input image. The pooling layer then downsamples the feature map to reduce its size, while retaining the most important information.



Outcome of Open Science (2)

Python ecosystem

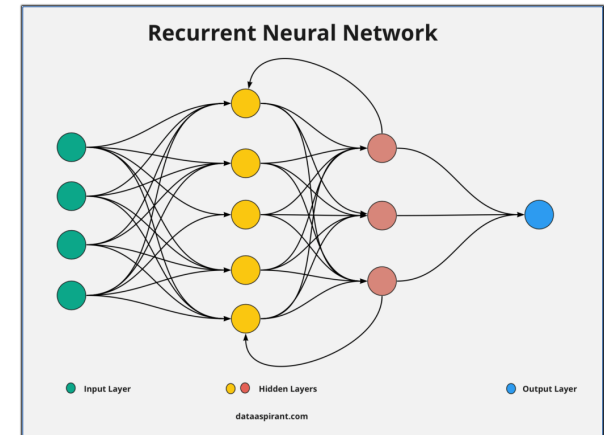
Explosion of freely accessible algorithms via many libraries:

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Opening towards Deep Learning

Recurrent Neural Networks (RNNs)

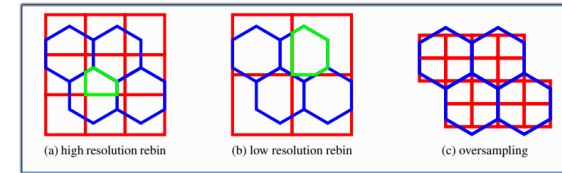
Deep neural network trained on sequential or time series data to create a machine learning model that can make sequential predictions or conclusions based on sequential inputs.



Deep Learning

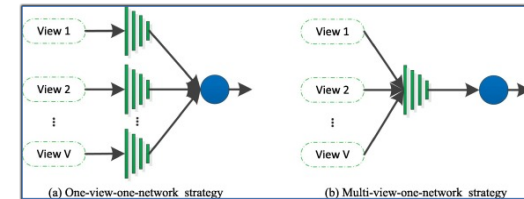
CNN

- Studies to transform hexagonal grids of pixels to a Cartesian grid
 - H.E.S.S. – MC data (Holch et al., 2017, [arXiv:1711.06298](#))
 - CTAO full-array – MC data (Nieto et al., 2019, [arXiv:1912.09898](#))
- CTAO 4 LSTs – MC data (Mangano et al., 2018, [arXiv:1810.00592](#))
 - Fusion of all images into one grid with squared pixels
 - “No need of physics in input”, ... but worse performances for discrimination (+ energy and direction)
- H.E.S.S. – MC data (Warnhofer et al., 2024, [arXiv:2403.18516](#))
 - “Earlier view fusion strategies work best”



CRNN (combination of CNN and RNN)

- H.E.S.S. (Shilton et al., 2018, [arXiv:1803.10698](#)): **improved discrimination**
 - Pure CNN: MC/real data discrepancy
 - 1/ Image pre-processing: hexagonal pixels within camera shape → squared pixels within a grid
 - 2/ RNN: sequence of telescope images ordered by size → CNN
- Toy IACT – MC data (Parsons et al., 2022, [arXiv:2203.05315](#))
 - **Strong dependence of predictions on the noise level, dead pixels**
 - Jacquemont et al., 2021 ([hal-03241475](#)) confirmed that on real data of LST-1



Deep Learning (2)

Graph Convolutional Neuronal Network

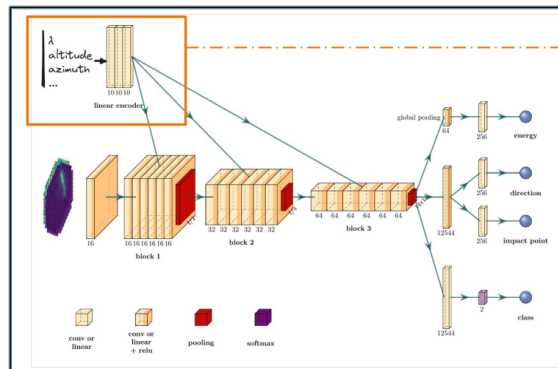
- H.E.S.S. (Glombitza et al., 2023, [arXiv:2305.08674](https://arxiv.org/abs/2305.08674))
 - On mono and stereo real data
 - **Improved discrimination** compared to BDT, even with no cleaning (in stereo)

MultiLayer Perceptron

- HAWC (Alfaro et al., 2025, [arXiv:2506.18277](https://arxiv.org/abs/2506.18277))
 - ⚠ Not an IACT
- **Improved discrimination (20%) on real data** (compared to BDT, CNN)

Add Transformers to CNN

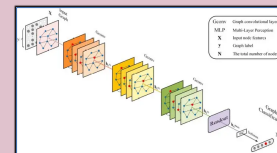
- LST-1 (Dell'Aiera et al., 2024, [DOI:10.2139/ssrn.6675118](https://doi.org/10.2139/ssrn.6675118))
 - Normalisation of parameters conditional to some external parameters (e.g. NSB): uses an additional MLP



Insights

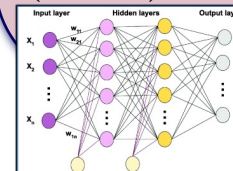
GCNN

Decision trees designed for whose inputs are graphs (permutation invariant). Inputs of the CNN are from the graph analysis using the Adjacency and Degree matrices.



MLP

NN with nonlinear activation functions. Permits to distinguish data that is not linearly separable. Neurons not with a sigmoid function, but a Rectified Linear Unit (ReLU): $\max(0, x)$.



Deep Learning (3)

CNN

- Still

And many more R&Ds...

- CT

- Mangano et al., 2018, [arXiv:1810.00592](https://arxiv.org/abs/1810.00592): CNN on CTAO full-array, pure MC

- I

- Aschersleben et al., 2021, [DOI:10.22323/1.395.0697](https://doi.org/10.22323/1.395.0697): CNN on CTAO full-array, pure MC → Energy reconstruction

- H.

- Lyard et al., 2019, [arXiv:1907.02428](https://arxiv.org/abs/1907.02428): CNN on CTAO full-array, pure MC

CRNN

- H.

- Spencer et al., 2019, [arXiv:1907.04566](https://arxiv.org/abs/1907.04566): CRNN 4 2M-SSTs, pure MC

- Using pixel waveforms improve performance

- I

- De et al., 2022, [arXiv:2206.05296](https://arxiv.org/abs/2206.05296): CNN + autoencoder on H.E.S.S., pure MC

- To

- discrimination, CR identification, anomaly detection (BSM)

- S

- Unbehau et al., 2025, [arXiv:2501.08671](https://arxiv.org/abs/2501.08671): NN for energy, BDT for direction and discrimination for H.E.S.S. CT5 real data → reduced analysis energy threshold

MLP

- H/

- etc



Towards open ML libraries for IACTs

Open packages under development

Event reconstruction and ML are areas of experts

- Very complex and rich algorithmics
- Very technical implementation on CPU or/and GPU
- Require stable and reproducible performances

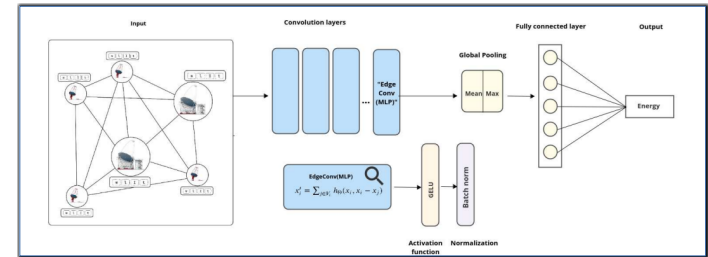
Movement to build high-level, open-source Python packages

- In line with Open Science
- Permits the consolidation of the community of experts

Still in development and R&D phase, but **already interoperable with the CTAO pipeline**

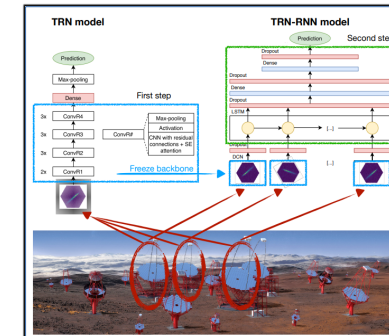
GammaLearn – Jacquemont et al., 2021, [hal-03043188](https://arxiv.org/abs/2103.03043)

- Relies on PyTorch (Meta)
- Based on the γ -PhysNet architecture:
 - Multi-task learning (MTL) with hard parameter sharing architectures
 - Uses Attention mechanism (Transformer) that helps deep learning model focus on relevant features through trainable weights between all tasks
- Permits full-event reconstruction



CTLearn – Nieto et al., 2019, [arXiv:1912.09877](https://arxiv.org/abs/1912.09877)

- Relies on TensorFlow (Google)
- Based on a shallow residual NN inspired from Thin-ResNet (TRN) – Xie et al., 2017, [arXiv:1902.10107](https://arxiv.org/abs/1902.10107)
- Permits full-event reconstruction reconstruct (better than CTAO standard analysis <1TeV with 4 LSTs)



ML use for model templates

Event Reconstruction

Adjustment of image templates to the data

- Templates generated from γ -rays MC simulations; EAS parameters derived with a Likelihood fit
- Initially developed by the CAT collaboration (Le Bohec et al., 1998, [arXiv:2406.17502](https://arxiv.org/abs/2406.17502))

Modern implementations for H.E.S.S.

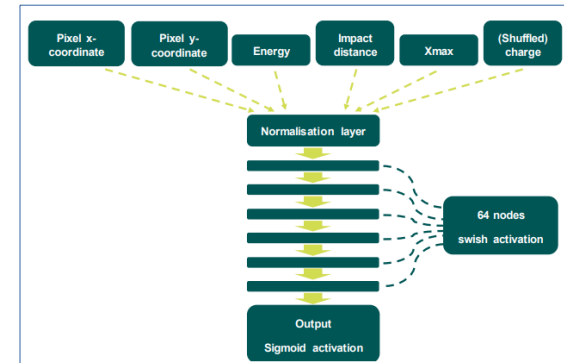
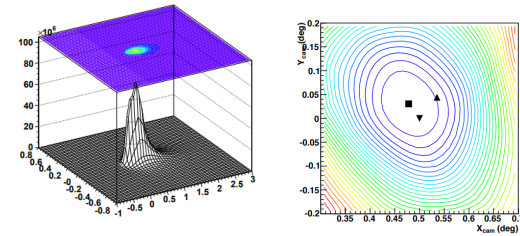
- Model++ : de Naurois et al., 2009, [arXiv:0907.2610](https://arxiv.org/abs/0907.2610)
- ImPACT : Parsons et al., 2014, [arXiv:1403.2993](https://arxiv.org/abs/1403.2993)

Performance

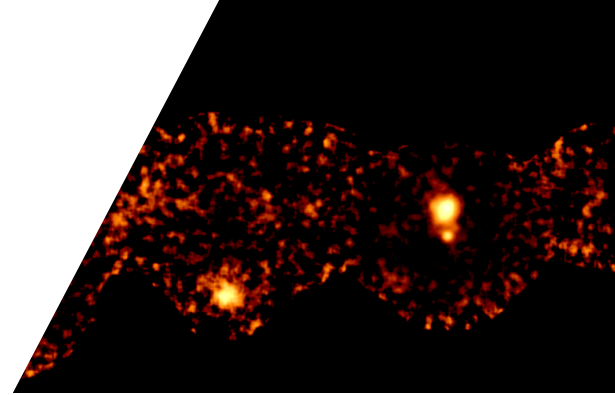
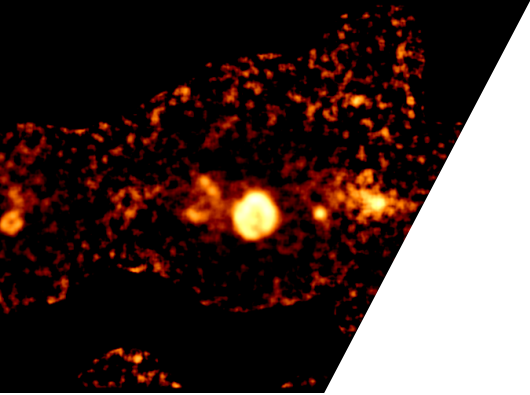
- Excellent results on event reconstruction
- But discrimination sensitive to instrumental artefact and long processing

Modern Improvement

- FreePACT : Schwefer et al., 2024, [arXiv:2406.17502](https://arxiv.org/abs/2406.17502)
- Instead of using a huge image template, use a likelihood-free inference of the pixel charge PDF using **NN**



High-Level Analysis



Source modelling and fitting

From the event list to source characterisation and catalogues

Low-Level analysis provide only γ -ray candidates

→ One should infer γ -ray sources properties

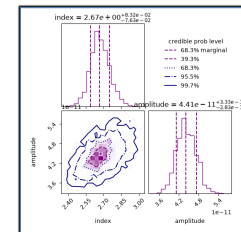
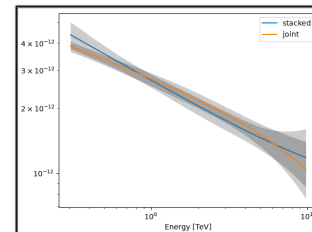
Hard task because IRFs are not invertible

- Standard analyses based on Likelihood inference of sources parameters
- Initially set up for IACTs by Piron et al., 2001, [arXiv:astro-ph/0106196](https://arxiv.org/abs/astro-ph/0106196)
- For CTAO, implemented into the [Gammapy](https://gamma-irf.github.io/) open package

Extremely powerful tools permitting now 3D analysis

Could we go further?

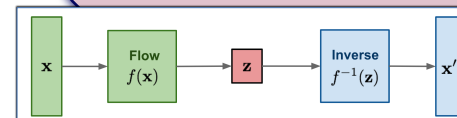
- Nested sampling
 - Because of the large number of overlapping sources and astrophysical foreground/background, the number of fitted parameters is expected to grow significantly
 - Stochastic algorithm for Bayesian Inference using **Normalising Flows** (in gravitation: Williams et al., Phys. Rev. D 2021, [link](#))



Insights

NF

Generative models that transform a simple base probability distribution into a complex, multi-modal data distribution through a series of invertible, differentiable mathematical operations.



Real astrophysical modelling

Going away from simple parametric γ -ray properties

The VHE modelling of data is very poor compared to other astrophysics domains

With our next generation of instruments, one should change of modelling scale

The Multi-Wavelength and Multi-Messenger astrophysics is exploding with the advent of VHE Open Science

Challenge

- For a set of 0(10) parameters, astrophysical models are long to compute
- For advanced astrophysics, OPEN event list + IRFs should be used
- For advanced astrophysics, OPEN astrophysics codes should be used



Insights

BAN χ^2 FIT on “flux” points

SEDs assume a model shape and astrophysical models never match this assumed shape:

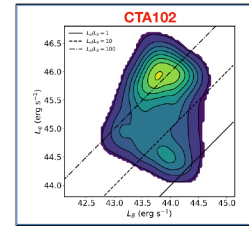
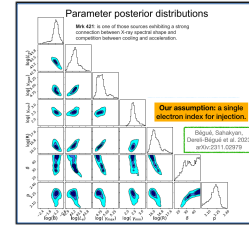
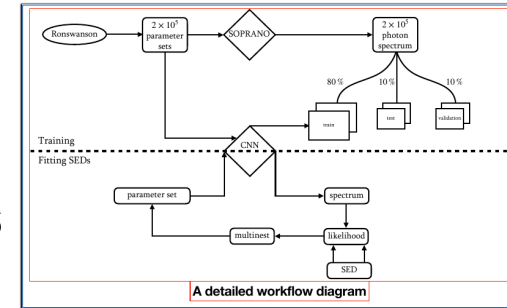
- biased fitted parameters
- totally wrong parameters errors

Surrogate astrophysical models

CNN simulation-based inference

Computation of accurate spectra after training

- Bégué et al., 2023, [arXiv:2311.02979](https://arxiv.org/abs/2311.02979)
- Capture the relationship between input parameters and spectra in few ms
- Can be plugged into Science Tools



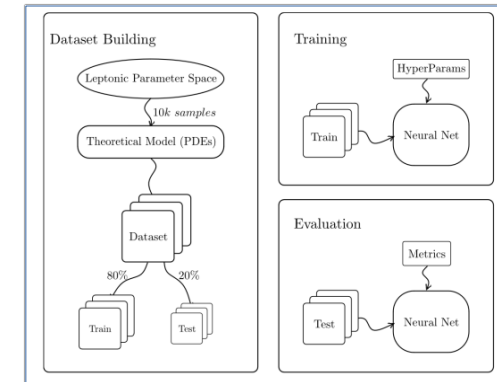
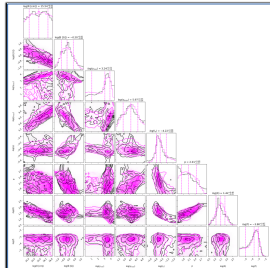
See also: Deistler et al., 2025, [arXiv:2508.12939](https://arxiv.org/abs/2508.12939)

RNN simulation-based inference

Computation of spectra in a few ms with a

Gated Recurrent Unit

- Tzavellas et al., 2023, [arXiv:2311.06181](https://arxiv.org/abs/2311.06181)
- Capture the relationship between input parameters and spectra



Catalogue Generation

A very complex pipeline

Uniform data treatment of large datasets

- No space for human tuning

Challenge of sources confusion and weak extended emission

- Which component(s) should be attached to a “source” ?
- What is coming from the astrophysical background ?

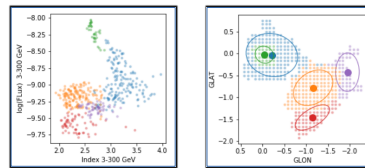
Association with other MWL catalogues

- Many information of different nature and accuracy to cross-match

H.E.S.S./CTAO - Q. Remy, CTAO: [arXiv:2310.02828](https://arxiv.org/abs/2310.02828), H.E.S.S. [arXiv:2308.08969](https://arxiv.org/abs/2308.08969)

Iterative 3D modelling leads to a long list of fitted components

- Grouping to form a source
- Outlier detection using the **Isolation Forest** algorithm (Hariri et al., 2018, [arXiv:1811.02141](https://arxiv.org/abs/1811.02141))



Identification of “false” component (systematic effects, like from the Interstellar Emission Models)

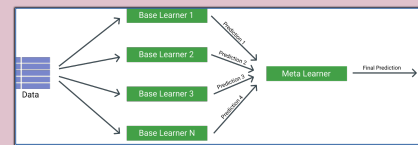
- Outlier detection using Isolation Forest algorithm with different criteria, then used as input of a **Stacked Classifier** (Wolpert, 1992, [link](#))



Insights

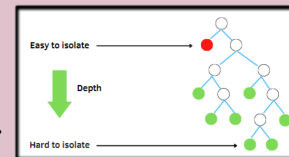
SC

Learning technique similar to random forest where the quality of prediction is improved by combining weak models.

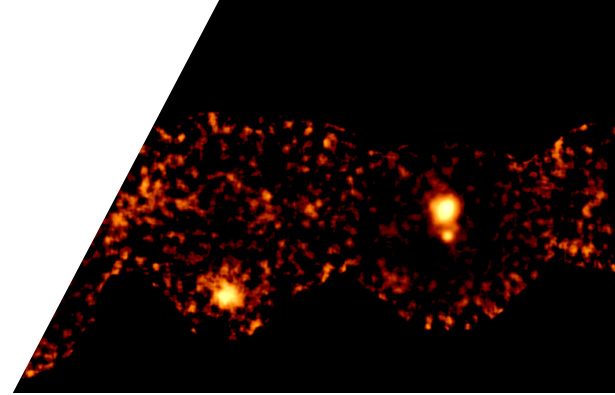
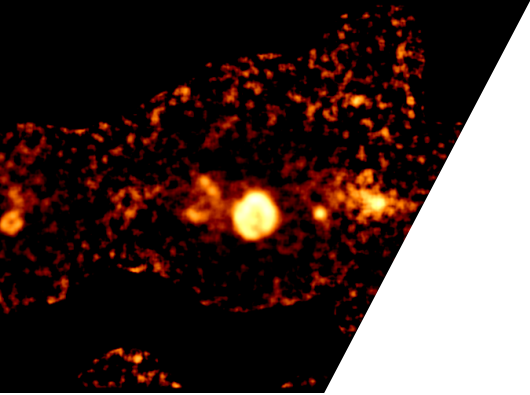


IF

A type of Random Forest: unsupervised ML algorithm specially designed for anomaly detection. It is a type of Random Forest.



Conclusions



ML-based analysis

Being possible with open research software

From ROOT/TMVA to the Python eco-system, the number of accessible algorithms explode

Triggering many R&Ds and the building of interoperable packages

Still require an high level of expertise in data science

Support data scientists
for our numerical
instrumentation

Event reconstruction

Many efforts on simulation and real data

- Still on-going, issues of robustness w.r.t observation conditions
- Lacking of error estimation for the energy and direction → Use of Deep Bayesian Active Learning (Gal et al., 2017, [arXiv:1703.02910](#)), Deep Convolutional Mixed Density Network (D'Isanto et al., 2017, [link](#)) or Mixture Density Network (Bishop, 1994, [link](#))

Still many space for improvements

- Ingest array configuration and EAS physics (+ geomagnetic field)!
- And don't forget to report non-working configurations!
- Understand the ANN behaviours → Use **SHAP** (SHapley Additive exPlanations) and **LIME** (Local Interpretable Model-Agnostic Explanations) !

ML-based analysis (2)

Very low-level analysis

Quite unexplored field for the ML use

- Instrument design, calibration, DAQ, real-time trigger

High-level analysis reconstruction

Tools starting to be used, for the source parameter inference or catalog pipelines

- Much to learn from the cosmology domain

Theoretical modelling has so much to gain by opening the tools and plugging to the current statistical science tools

And don't forget ... the AI

Operations: some possible use

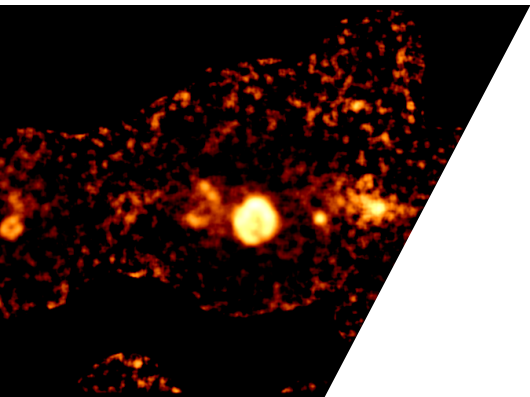
- Analysing logs, monitoring data, to detect trends and support preventive maintenance
- Shift support (operator tool)
- User support (helpdesk)
- Scheduling
 - For CTAO, using Swarm Intelligence Algorithms (Hadasch and al., 2025, [link](#))
- Proposal evaluation (as tested in ESO)
- Software dev, quality (unit tests, code analysis, vulnerability analysis)
- Interface design (GUI, web-based)

Thank you for your attention

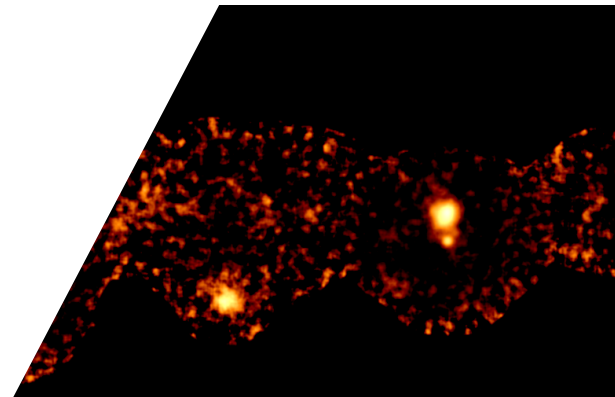
From 9 to 14:
The SST telescopes and Gamma-ray Science
with ASTRI and CTAO

Sexten, Italy





Annexes



Some great reviews...

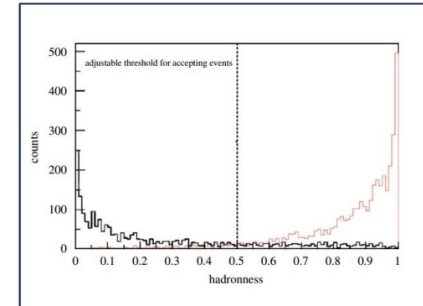
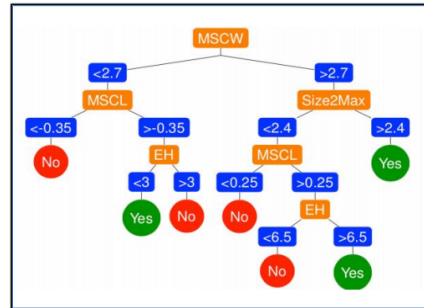
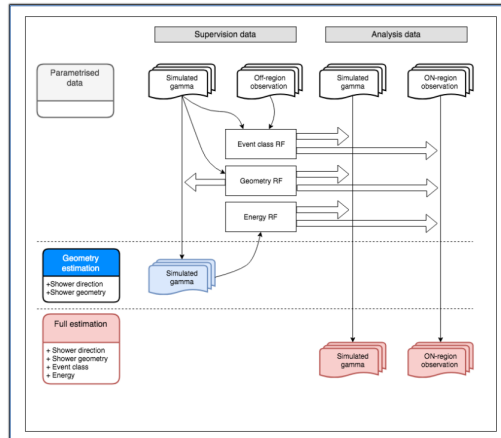
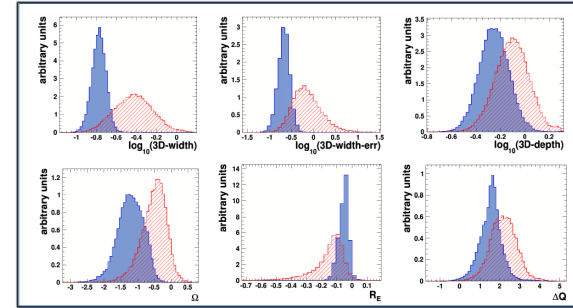
Reviews and references

- M. Lieu, “A Comprehensive Guide to Interpretable AI-Powered Discoveries in Astronomy”, 2025, Universe ([link](#))
- Y. Lecun et al., “Deep Learning”, 2015, Nature ([link](#))
- A. Di Piano, “Deep Learning Models for the Real-Time Scientific Analysis of the Cherenkov Telescope Array Observatory”, PhD thesis, 2025 ([link](#))
- M. Dell’aiera, “From simulations to real data, on the relevance of deep learning models and domain adaptation : Application to astrophysics with CTAO and LST-1”, PhD thesis, 2016 ([link](#))
- K. Ishio, “Improvement in the γ -ray energy reconstruction of MAGIC and impact on the spectral analysis of the first Gamma Ray Burst detected at TeV energies”, 2020 ([link](#))

RF and BDT

Concept

- Train on a MC sample of gammas and hadronic events from OFF data
- Inputs: standards Hillas parameters or advanced discrimination variable as tree nodes
- Output: a single parameter to classify events



Convolutional Neural Network

Concept

A typical architecture of a CNN includes numerous Convolutional Layers (CLs), followed by a number of dense layers (usually ≤ 3). A CL typically comprises three stages: a convolution stage, an activation stage and a pooling stage. It should be noted that variations of this structure

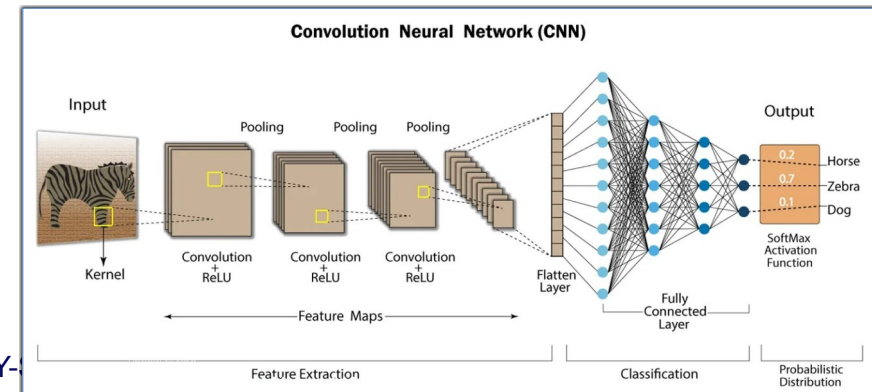
Convolution

- The convolution stage relies on a set of learnable filters with a fixed size, which is spatially smaller than the 2D input. Each of the filters is convolved across the entire width and height dimensions of the 2D image matrix to produce linear outputs. The small spatial size of the filters allows the CNN to detect meaningful features (e.g. edges of a shape) which occupy only a small portion of the image.
- The convolution operation involves an element-wise multiplication between the filter and local patches of the image of the same size as the kernel. This local (or sparse) connectivity significantly reduces the number of free parameters and memory requirements of the model.
- Moreover, each parameter of the filter is “shared” across the image, in the sense that it is applied at every position of the image (disregarding boundary effects). Parameter sharing through patches of the image introduces translational equivariance, meaning that a shift in the input leads to the same shift in the output.

Activation: where each linear activation is fed into a nonlinear activation function.

Pooling

A pooling function replaces the output of the layer at a certain location with a summary statistic of the nearby outputs, such as the maximum output in the neighbourhood of that location. The pooling operation makes the output of the convolution become approximately invariant to small translations in the input.

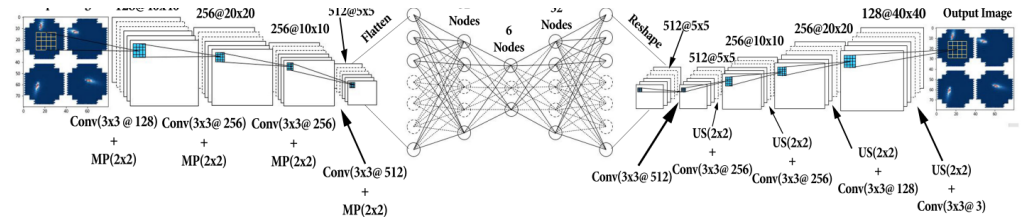
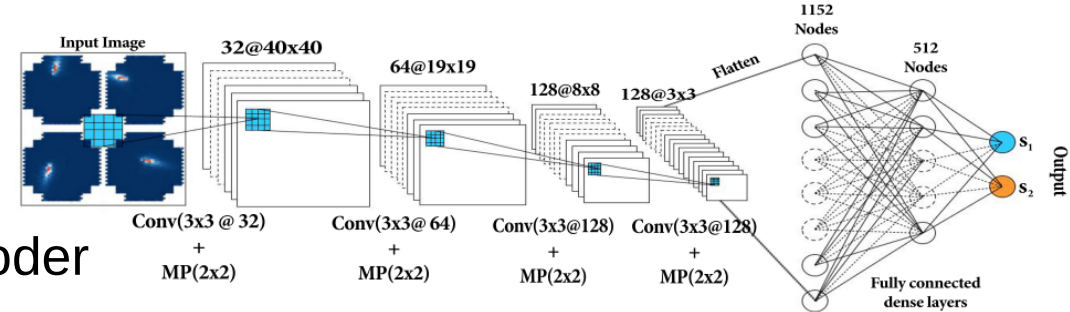
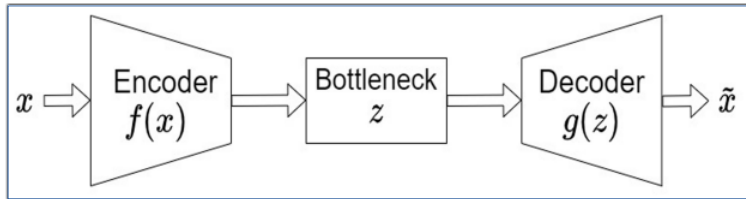


Auto-encoder

Auto-encoder to detect anomalies

De et al., 2022, [arXiv:2206.05296](https://arxiv.org/abs/2206.05296)

- Typical architecture of a CNN
- Feed the output into an auto-encoder

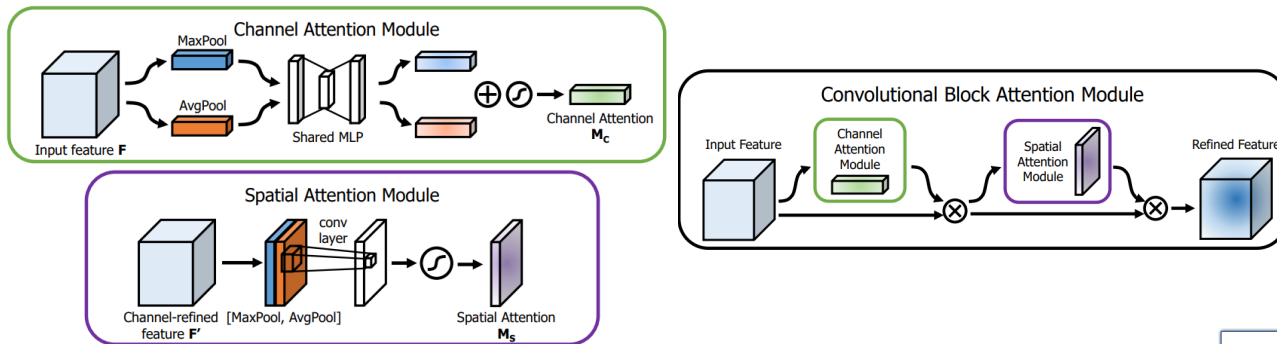


- Then compare to find anomalies

$$\mathcal{L}(x, \tilde{x}) = MSE = \frac{1}{m} \sum_{i=1}^{i=m} (x_i - \tilde{x}_i)^2.$$

CTLearn and Attention mechanism

Cerviño et al., IPARCOS conf 2025 ([link](#))



Convolutional Block Attention Module (CBAM)

- Woo et al., 2018, [arXiv:1807.06521](#)
- Avoid to make cleaning:
spatial attention (pixels) + channel attention (time, image)

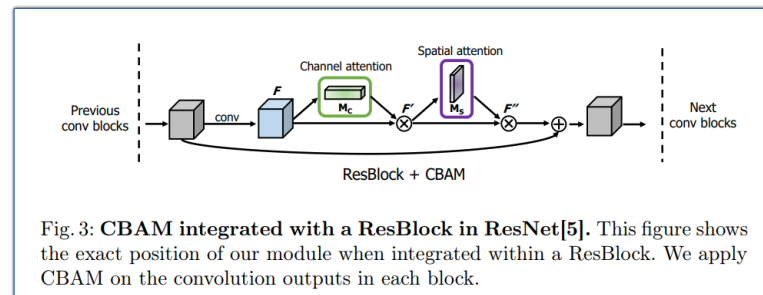
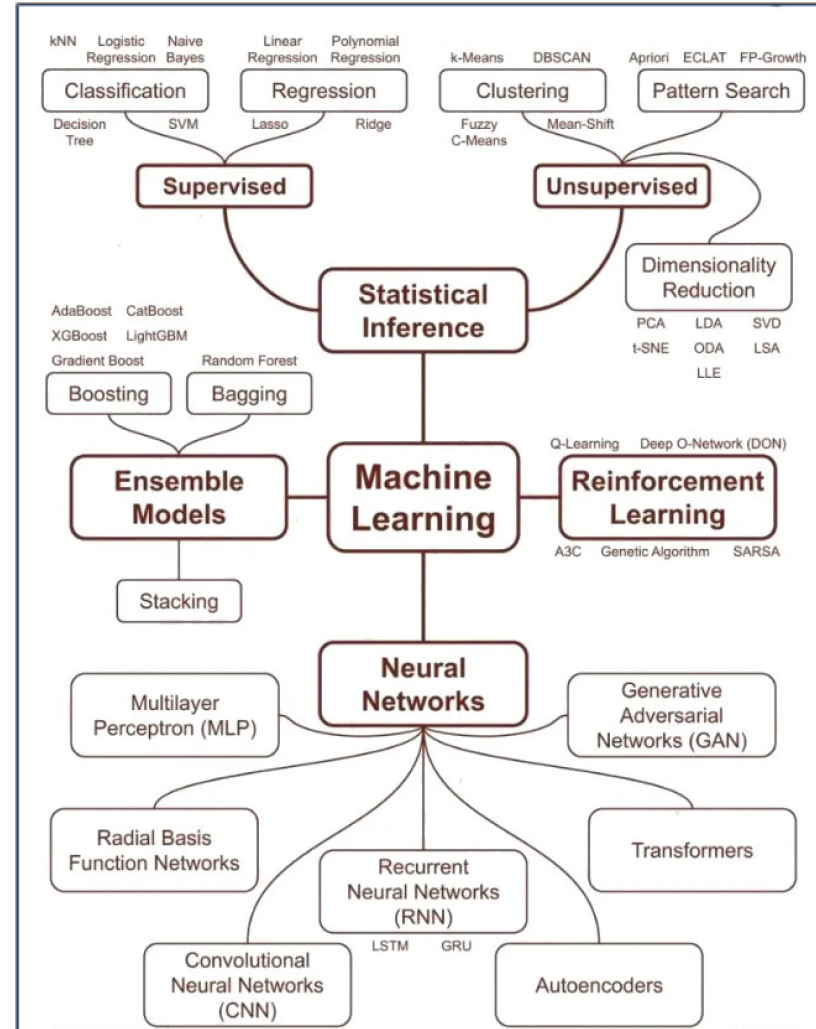


Fig. 3: CBAM integrated with a ResBlock in ResNet[5]. This figure shows the exact position of our module when integrated within a ResBlock. We apply CBAM on the convolution outputs in each block.

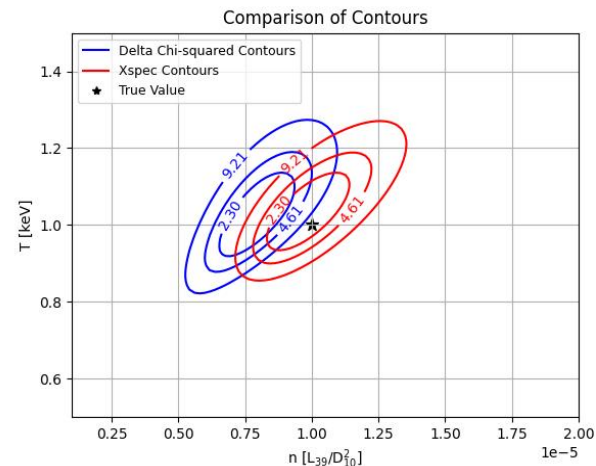
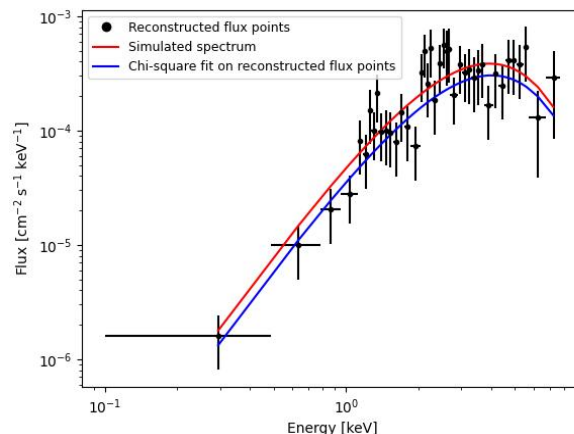
Classification of the ML algorithms



Ban χ^2 fits on flux 'points'

A simple Black Body spectrum

Simulation for Swift
XSPEC



From M. Cerruti (2023)

Bias of 20%
with the χ^2 !!

- Statistical behaviour known since the 90's in X-ray
 - See also Humphrey *et al.*, 2009 **ApJ** 693 822
- In addition, uses of priors to deal with possible systematics between instruments

SHAP and LIME

Concept

Tools that are model agnostic allowing to interpret model predictions

- Which model feature explains the outcome?

SHapley Additive exPlanations

Framework for interpreting model predictions by quantifying the contribution of each input feature to the final output.

SHAP values : explains individual predictions by calculating how much each feature contributes to pushing the model's prediction from the base value to the actual prediction.

Key advantage: ability to provide both local explanations for individual predictions and global insights into overall model behaviour.

Local Interpretable Model-Agnostic Explanations

Versatile frameworks for explaining predictions across a wide range of model types
aims at explaining only a small part of the ML function.

Figure 3. SHAP applied to a CNN model trained to classify galaxy morphologies. The example shows the explanation of a correctly predicted smooth-cigar-shaped galaxy. Here, superpixels with positive SHAP values (red) contribute positively towards the prediction. Blue contribute negatively. We use the partition explainer, which does not assume that features are independent from each other. The SHAP explanation suggests that the focus is on the center of the image, with the disk contributing negatively towards the spiral or round classes.

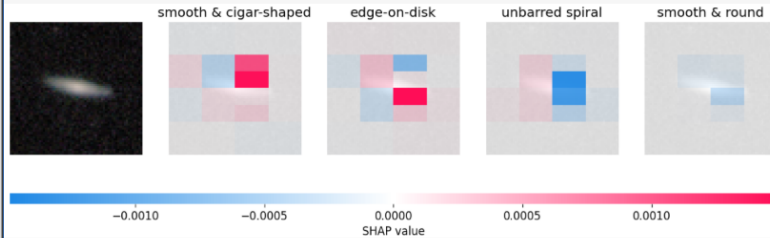
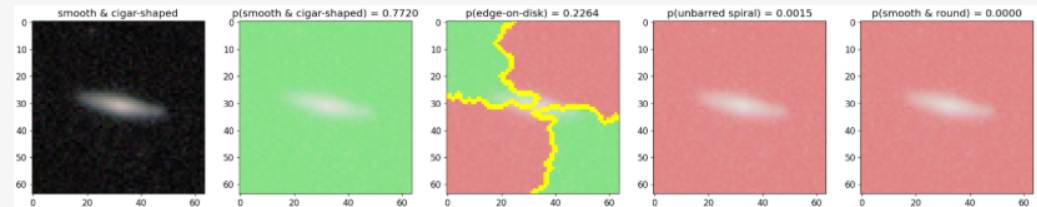


Figure 4. LIME explanation of a correctly predicted smooth-cigar-shaped galaxy by a CNN classifier model. Green corresponds to superpixels that positively contribute to the prediction, and red corresponds to superpixels that negatively contribute. This highlights that the LIME interpretation is that the classification focuses on the image as a whole rather than any particular region.



Poisson Log-Likelihood

Common algorithms for the libraries: Poisson Log-Likelihood

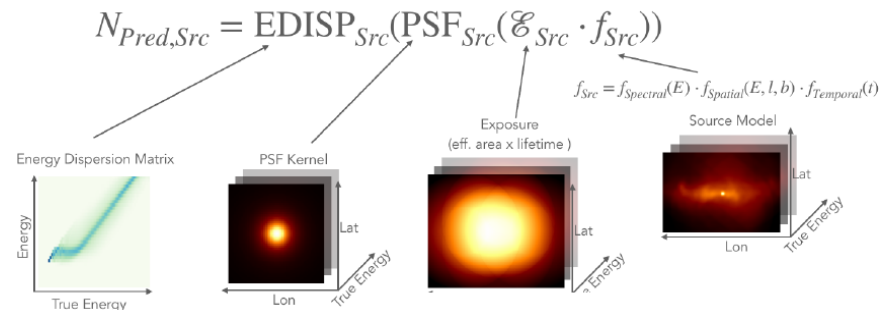
"Cash statistics": summed over all "bins"

$$\mathcal{C} = 2 \sum_i N_{Pred}^i - N_{Obs}^i \cdot \log N_{Pred}^i$$

i: spectral channels or 3D voxels

$$N_{Pred} = N_{Bkg} + \sum_{Src} N_{Pred,Src}$$

- Bins in the spectral, spatial, temporal domain
- Need of a "global" background model template with "correction parameters"



→ Need of the "signal" IRFs and

Most of the time,
Identical factorization of the IRFs
 for X-rays → UHE & neutrino exp.

Cherenkov Telescope Array

Gamma-ray observatory

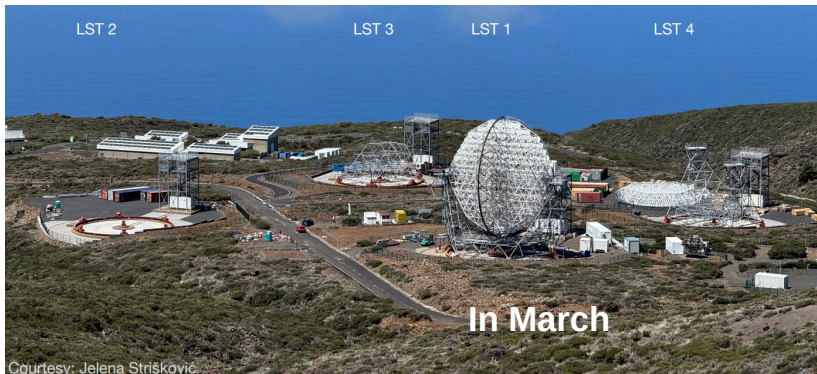
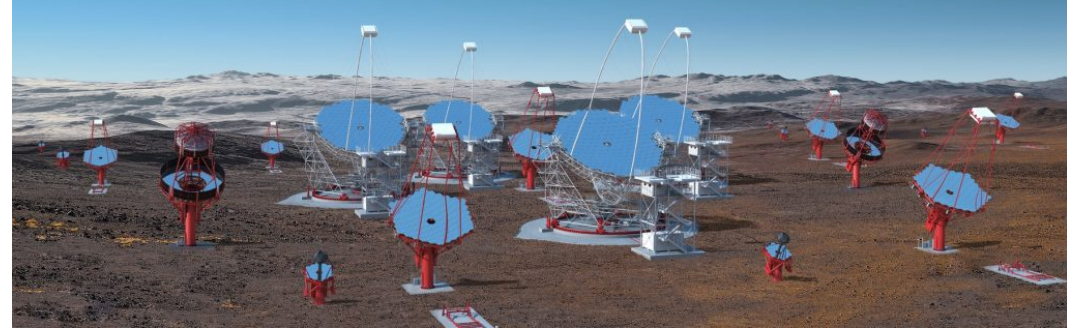
- First Open VHE observatory
- $O(10)\text{GeV} \rightarrow 200\text{TeV}$
- PSF: $0.3^\circ \rightarrow 0.02^\circ$
- Observations with FoV of 3° - 10° during dark nights

Full sky observations

Under construction



CTAO



Courtesy: Jelena Strišćević

Array of the Northern site (La Palma)

- 9 MSTs (88 m²), 4 LSTs (400 m²)

Array of the Southern site (Paranal)

- 2/3 LSTs (400 m²), 14 MSTs (88 m²),
42 SSTs (5 m²)

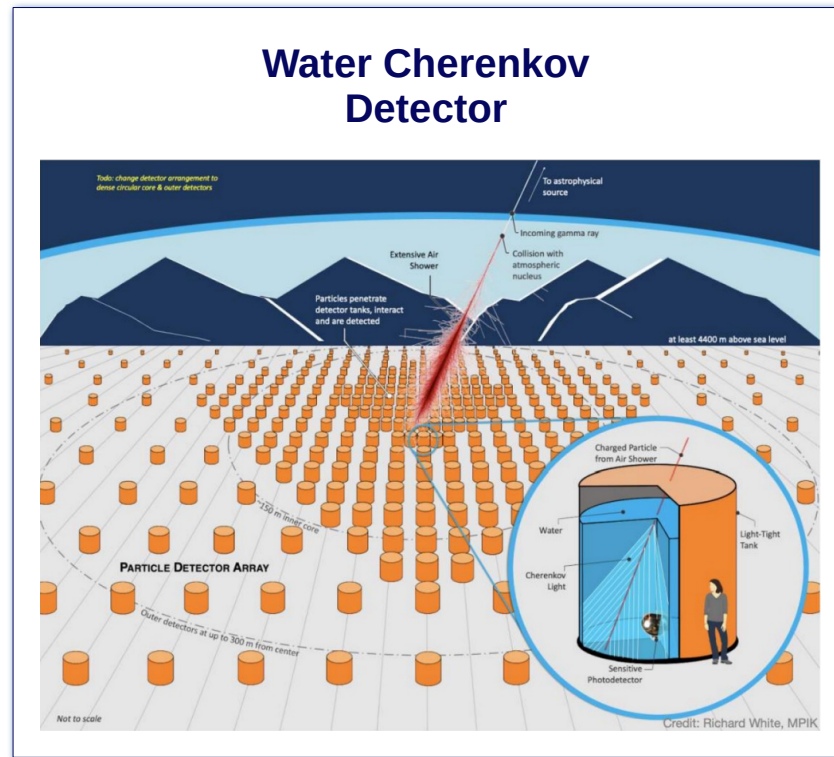
Southern Wide-field Gamma-ray Observatory

Project of new UHE observatory

- $O(100)\text{GeV} \rightarrow \text{PeV}$
- PSF: $1^\circ\text{-}2^\circ \rightarrow 0.04^\circ$
- FoV of 60° during day and nights

Under Design Study

-
- | | |
|-----------|---|
| M1 | R&D Phase Plan Established |
| M2 | Science Benchmarks Defined |
| M3 | Reference Configuration & Options Defined |
| M4 | Site Shortlist Complete |
| M5 | Candidate Configurations Defined |
| M6 | Performance of Candidate Configurations Evaluated |
| M7 | Preferred Site Identified |
| M8 | Design Finalised |
| M9 | Conceptual Design Report Complete |
-



Selected site (Aug. 24):
Atacama Astronomical Park,
Chili

The project Gammapy

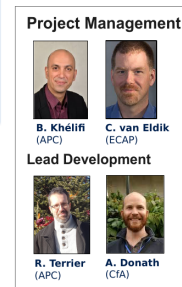
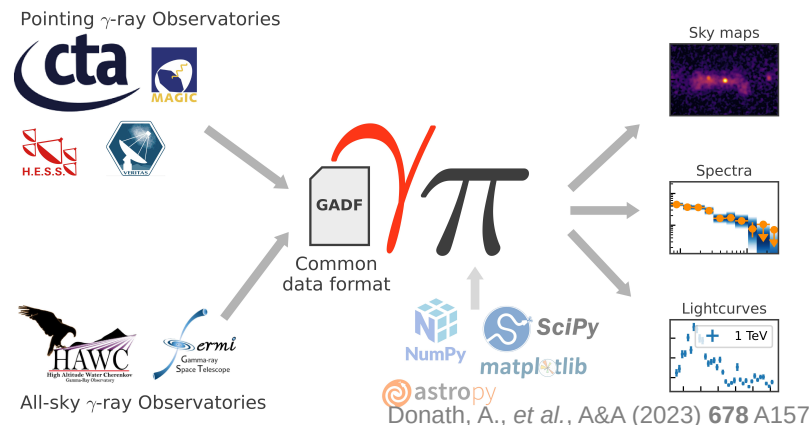
 π A Python package for
gamma-ray astronomy

Open Python analysis library

- Uses data written in the GADF format
- Inserted into the Python ecosystem
- Respecting the FAIR4RS principles
- Making multi-instrument joint analyses

Open Research Software

- Open contributions within an open organisation with an open governance
- Reference library for the VHE gamma-ray astronomy
 - Selected as core library of the open Science Analysis Tool of CTAO
- Well recognized : jury's prize of the CoSO (2022)



FAIR4RS principles

As with the FAIR Guiding Principles, the [FAIR4RS Principles](#) (2022) are intended to be aspirational. The application of the FAIR4RS Principles is the responsibility of the owners (who are often the creators) of the software, not the users.

- F** Software, and its associated metadata, is easy for both humans and machines to find
- A** Software, and its metadata, is retrievable via standardized protocols
- I** Software interoperates with other software by exchanging data and/or metadata, and/or through interaction via application programming interfaces (APIs), described through standards.
- R** Software is both usable (can be executed) and reusable (can be understood, modified, built upon, or incorporated into other software)



H.E.S.S. and XMM-Newton



Multi-instrument analysis examples

Joint X-ray and γ -ray fits

First approach:

- Read OGIP spectra (1D DL4) produced by X-ray telescopes and fit

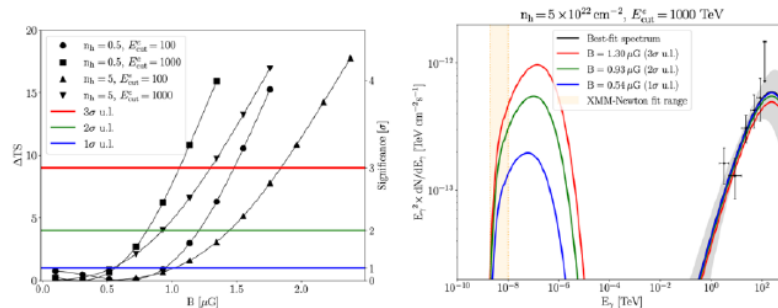
gammapyXray package

DOI [10.5281/zenodo.7092736](https://doi.org/10.5281/zenodo.7092736)

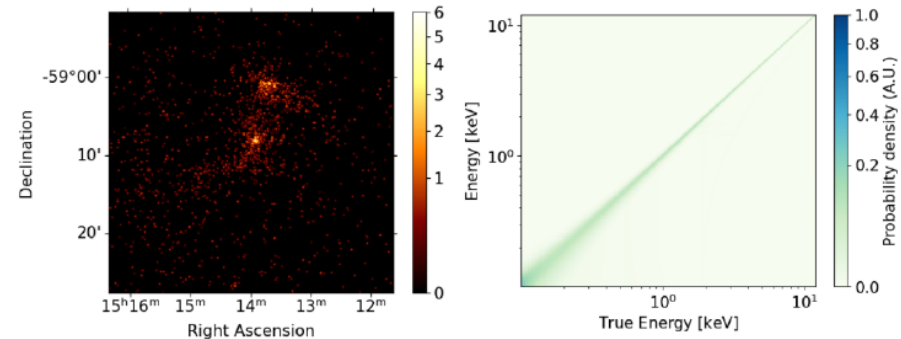
Second approach:

- Read X-ray events, IRFs and create 3D DL4 dataset

See e-ROSITA converter in [K. Egg poster](#)



[Giunti et al \(2022\)](#)



19

From R. Terrier,
Gamma2024

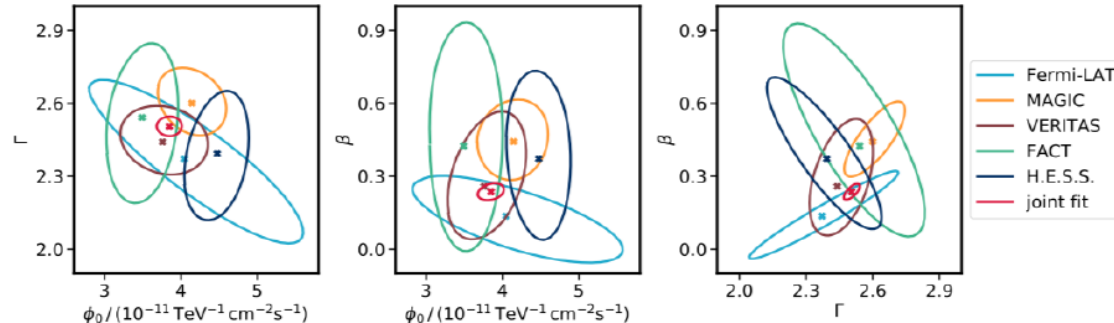
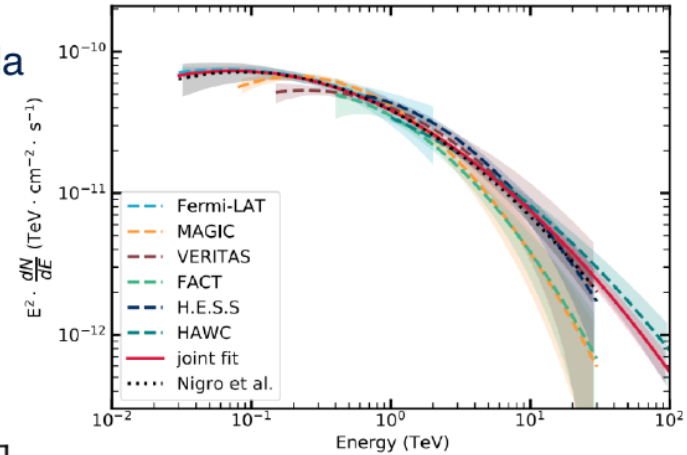
Crab nebula: HE $\rightarrow$ UHE

An example of multi-instrument analysis

Combining Crab observations



- Joint point-like 1D spectral analysis of the Crab nebula
- 5 different instruments over 3 decades in energy
 - Simple log-parabola & physical inverse Compton model
 - Modeling of some systematic uncertainties
- Fully reproducible analysis



+HAWC data [Albert et al \(2022\)](#)

[Nigro et al. 2019](#)

From R. Terrier,
Gamma2024

17

MWL extension of the Crab



Multi-instrument analysis examples

Spectrum and extension of the inverse-Compton emission of the Crab Nebula from a combined *Fermi*-LAT and H.E.S.S. analysis

[HESS Collab. 2024](#)

GAMMAPY has the advantage that it enables a combination of the *Fermi*-LAT data with that of H.E.S.S., and it offers the possibility to include customised physical models in the analysis.

