IN2P3/IRFU Machine Learning workshop 2025

STEREOGRAPH

Advanced stereoscopy applied to Cherenkov Telescope Array (CTAO)

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CONTEXT

- **Gamma Learn:** launched in 2017 through a collaboration between LAPP and LISTIC.
- **Goal :** to improve CTAO monoscopic event reconstruction using AI methods, deep learning
- **Stereograph**
- **Objective:** to explore stereoscopic reconstruction of gamma events using graph neural networks

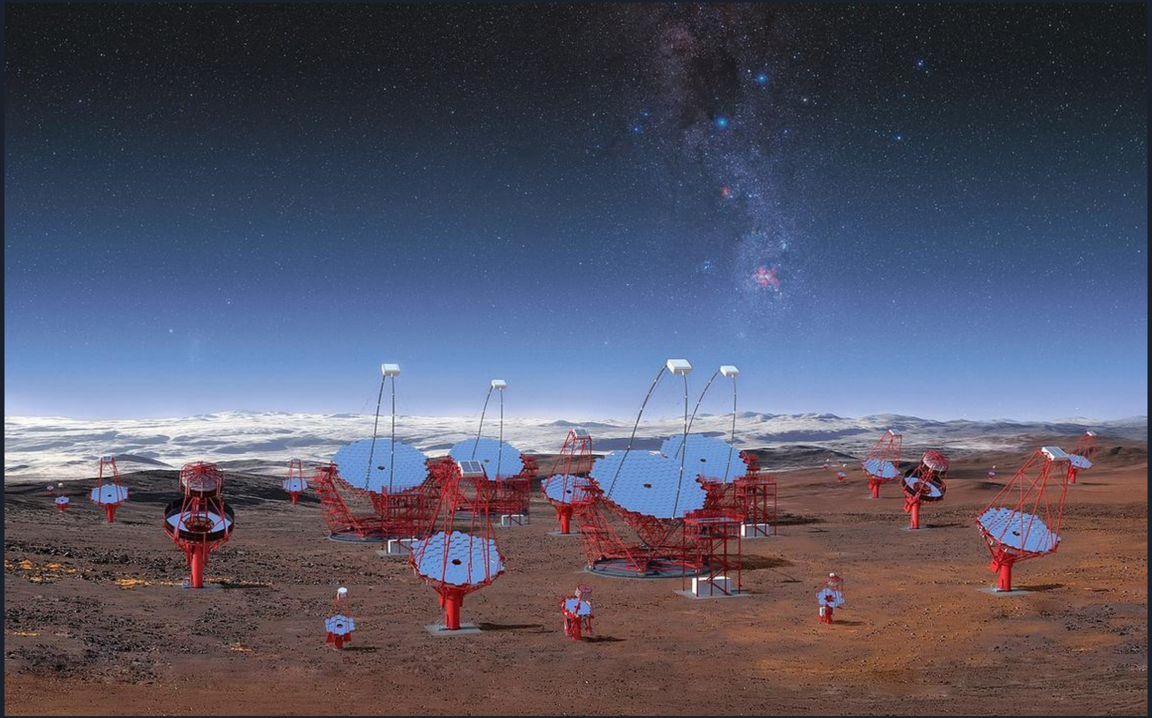
Contents

Introduction

The Cherenkov Telescope Array Observatory

CTAO
Cherenkov Telescope Array Observatory

- The project : about sixty telescopes of various sizes.
- Installed in the Northern Hemisphere on the island of La Palma and in the Southern Hemisphere in Chile.
- **Energy range** : [20 , 300] TeV.



Artist's view of the three types of telescopes that will be deployed in Chile

3 TYPES OF TELESCOPES

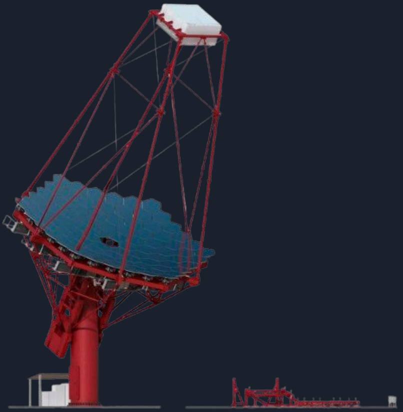
- Ongoing project under construction
- Currently, only one telescope is in operation (LST-1).

Small-Sized Telescope

9m

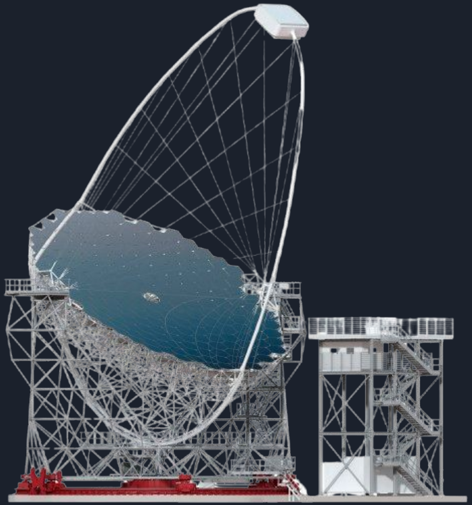
Medium-Sized Telescope

27m



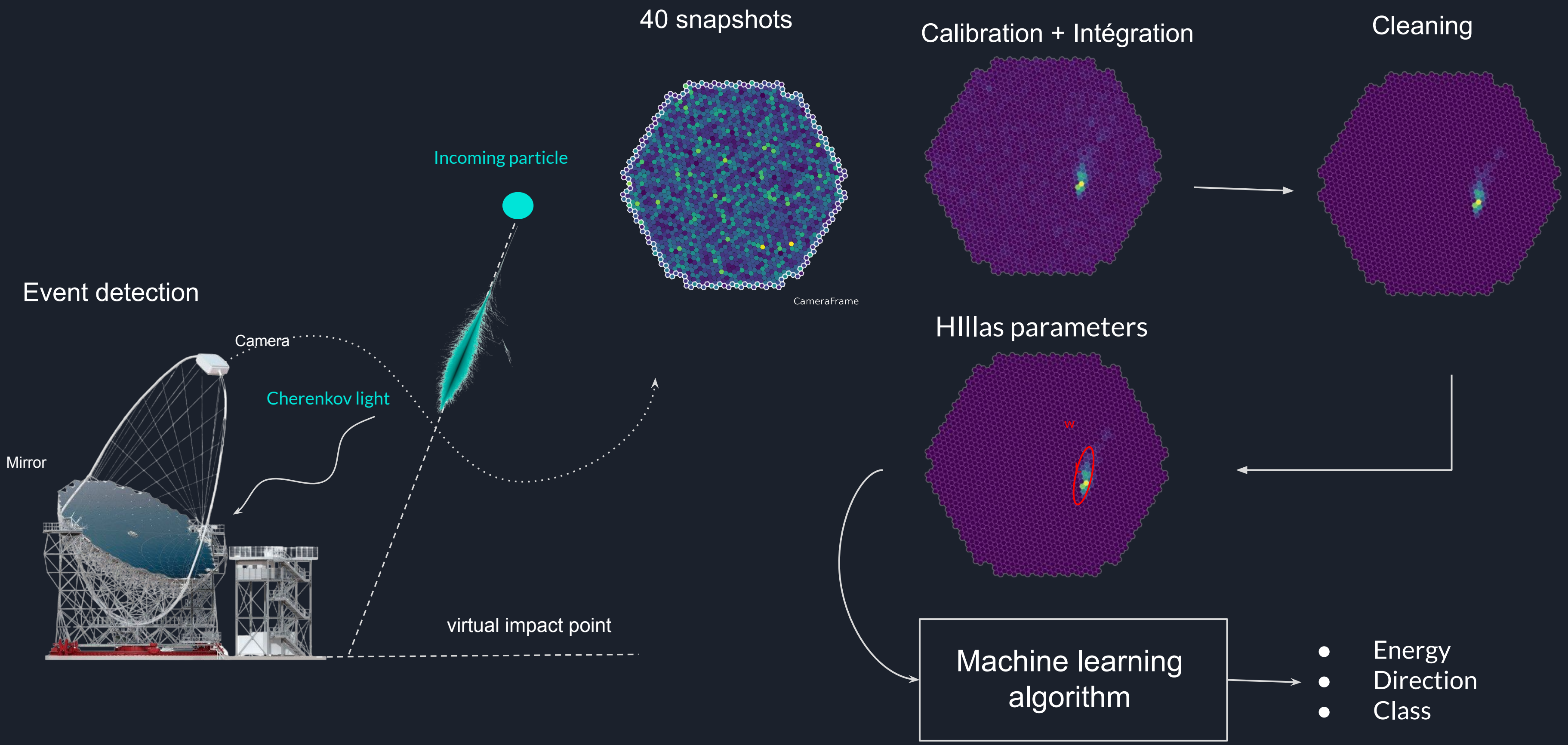
Large-Sized Telescope

45m

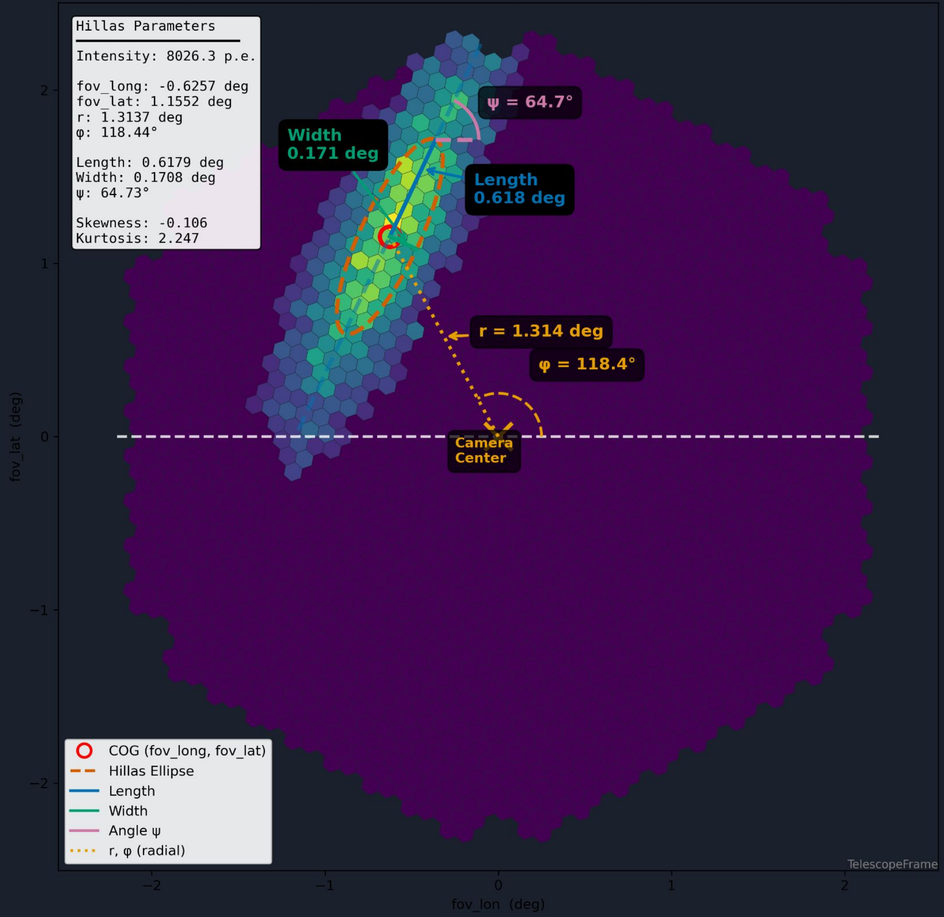


https://www.ctao.org/emission-to-discovery/telescopes/

Event reconstruction



Hillas parameters



Standard Method :

Random Forests + Hillas

Step 1 – Monoscopic Reconstruction

- Predicts energy and particle class with a Random Forest algorithm

- We use observations from a single telescope.

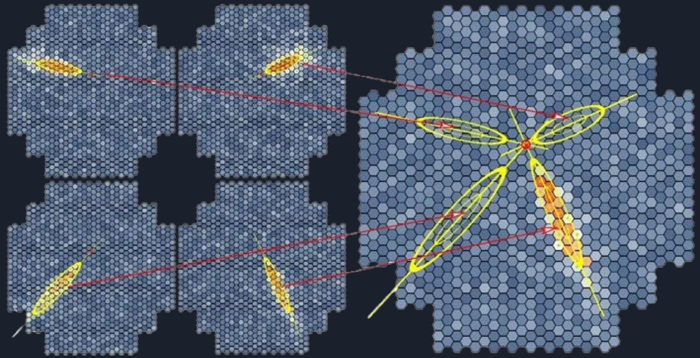
➔ We train one RF per telescope and per task (energy, class)

Step 2 – Stereoscopic Reconstruction

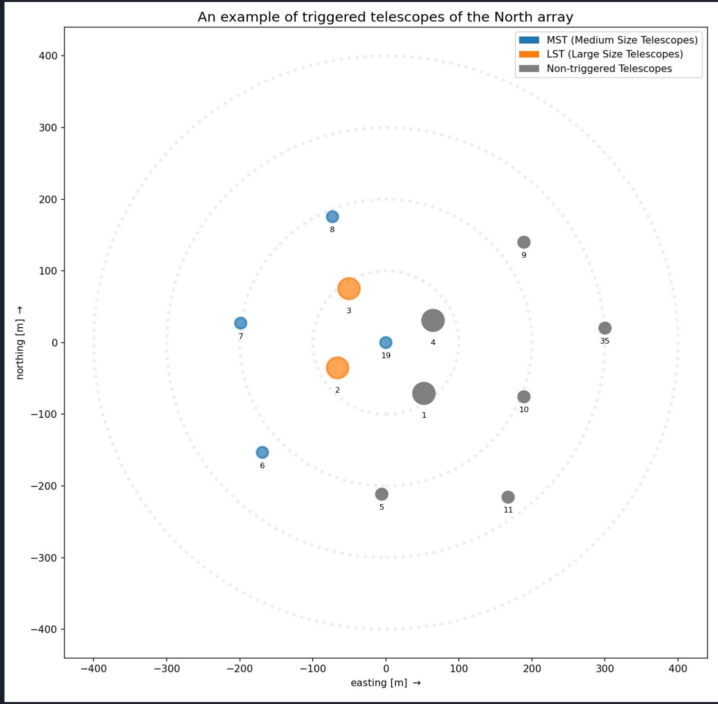
- Energy and gammaness: Weighted average across telescopes weight=Intensity*(length/width)

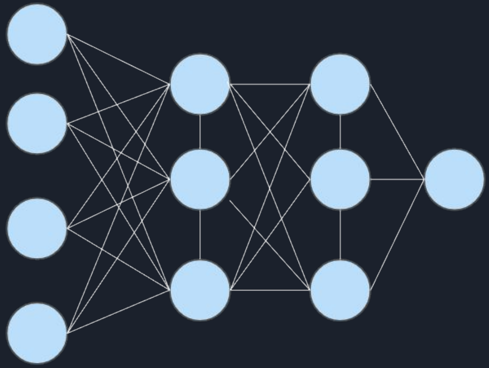
- Direction: We combine the observations of all telescopes to give a common estimation of the recorded shower

➔ The intersection of the major-axis of the ellipses gives the position of the source.



Fully connected network





Output :

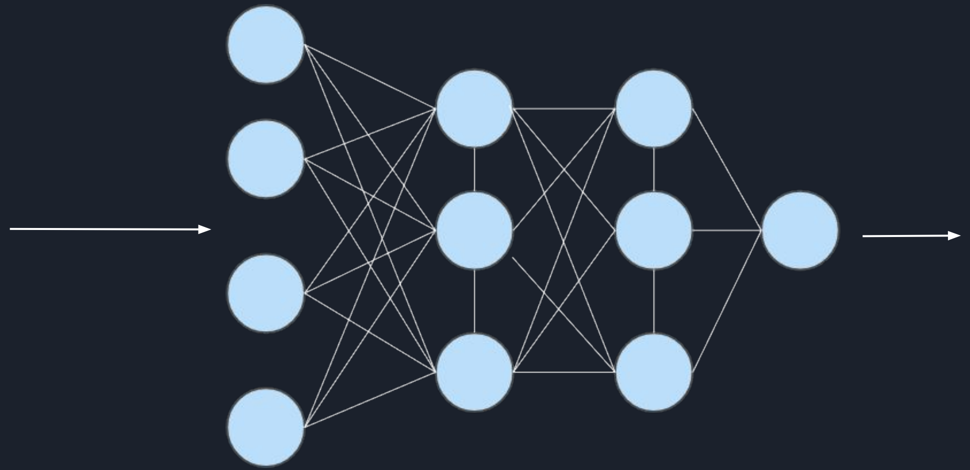
Energy

Array display (North site-La Palma):
An example of triggered telescopes

Fully connected network

Input : A sparse feature vector
➔ contains all hillas parameters

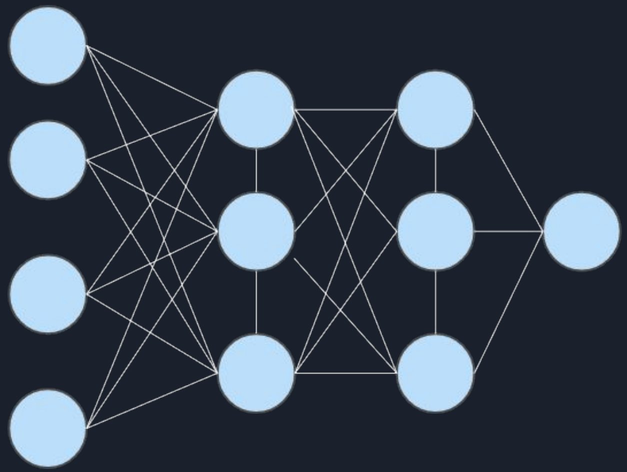
tel_id	intensity	time	width	length	...
1	0	0	0	0	...
2	12.3	5.6	1.2	3.4	...
3	8.9	4.5	0.8	2.1	...
4	0	0	0	0	...
5	0	0	0	0	...
6	10.5	6.2	1.1	3.0	...
7	7.8	3.9	0.9	2.3	...
8	9.2	5.1	1.0	2.8	...
9	0	0	0	0	...
10	0	0	0	0	...
11	0	0	0	0	...
19	11.0	5.8	1.3	3.2	...
35	0	0	0	0	...



Output :

Energy

Fully connected network



Pros:

- Simple and easy to implement

Cons:

- Sparse and very long feature vector
- Memory greedy
- Longer to train
- Loss of spatial correlations between telescopes

Graphs

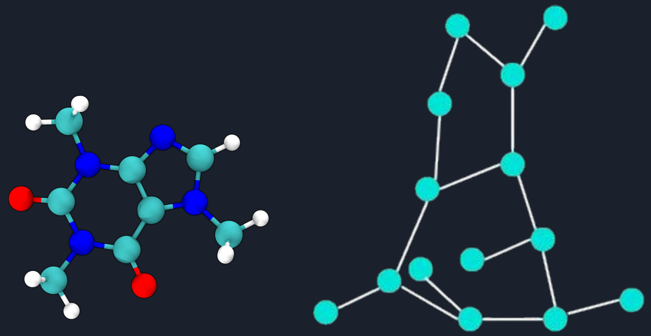
- **G=(V,E)** : A pair consisting of two sets
- **V :** vertices (also called nodes)
- **E :** edges, each associated with a pair {u, v} of vertices, where (u, v) $\in$ V
- Graphs are everywhere around us, and they can be found in various fields and applications, such as

Social networks

Images

Pixels

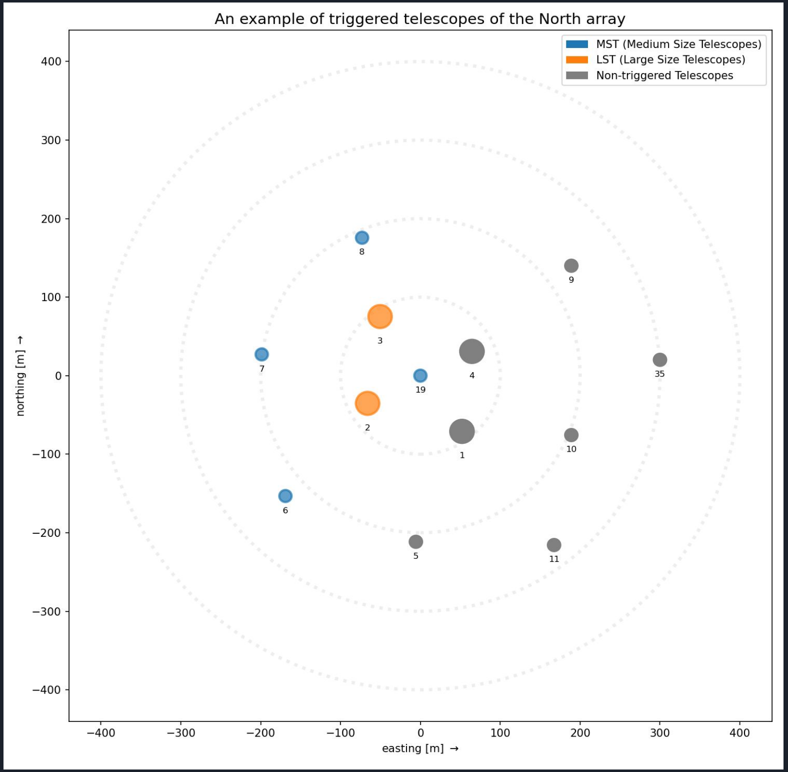
Text



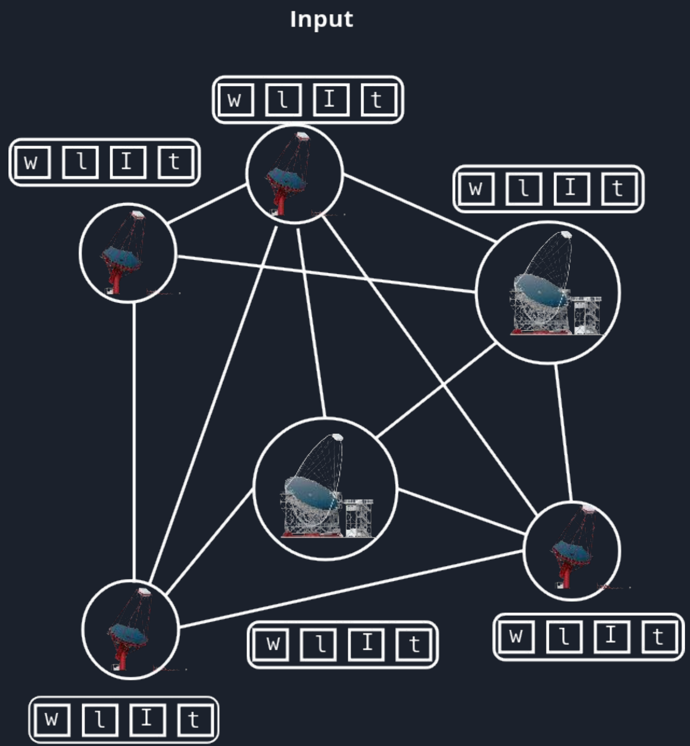
Molecule structures

Caffeine

• *Why graphs?*



Array display (North site-La Palma): An example of triggered telescopes

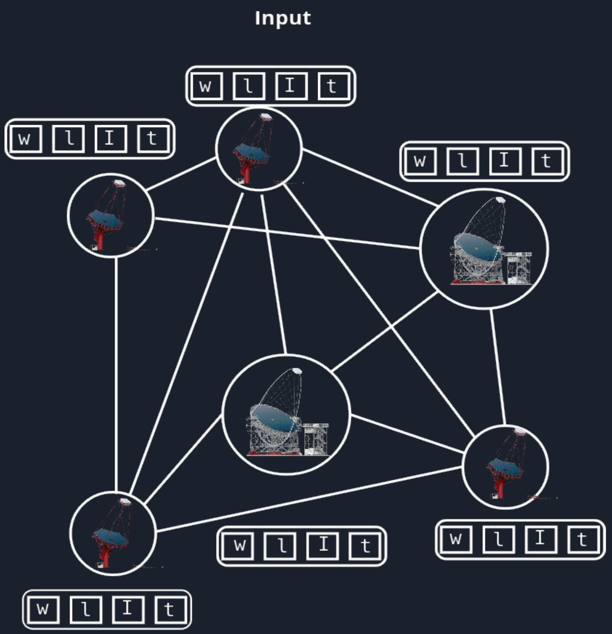


Schematic representation of a graph. Each node of the graph is a telescope of the array.

The application of GNN's to the Stereoscopic Reconstruction of gamma events

PRODUCING GRAPHS

- Each event will be represented by one graph.
- 42 features per node
- Hillas parameters on nodes
- Monte Carlo (MC) simulations from ctapipe v19 (prod5_ctapipe_v0.19).
- One network per task

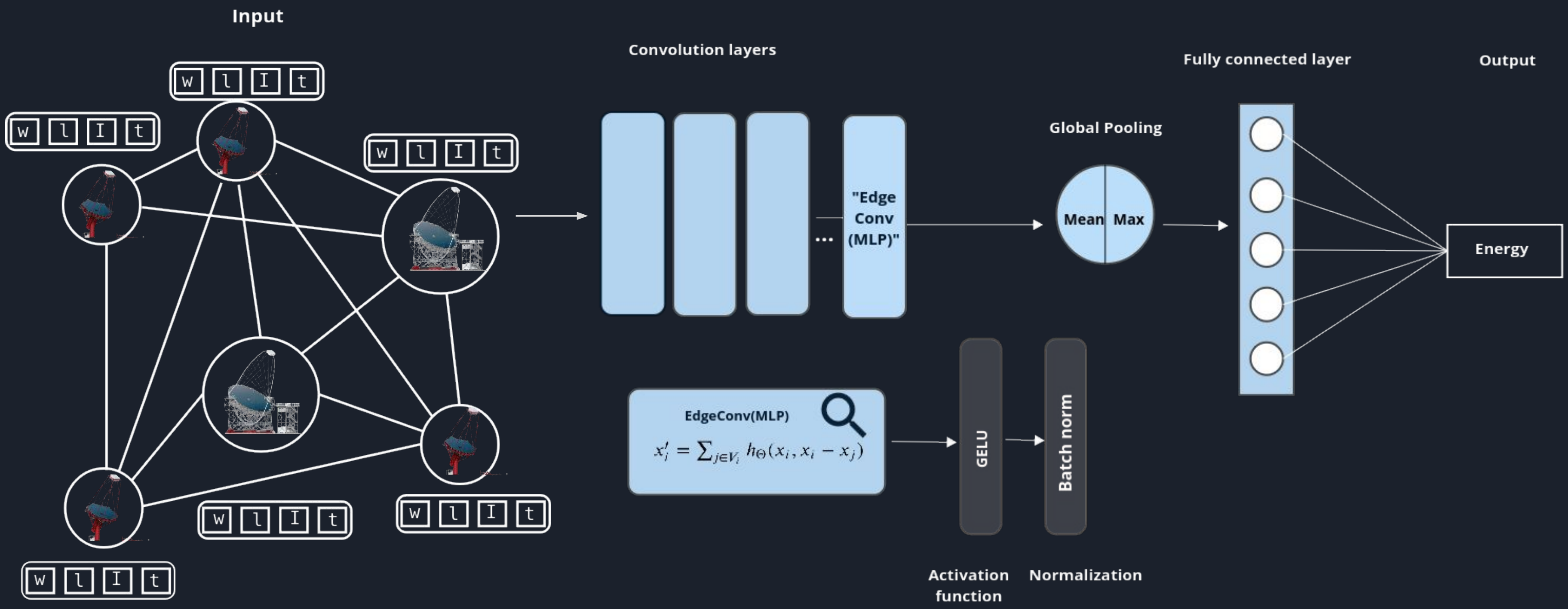


- Energy
- Direction
- Class

Each node has the Hillas parameters as node features.
For each graph, we predict a global graph reconstruction:
the direction, energy, and class probability.

The **stereoscopic** event reconstruction

MODEL ARCHITECTURE



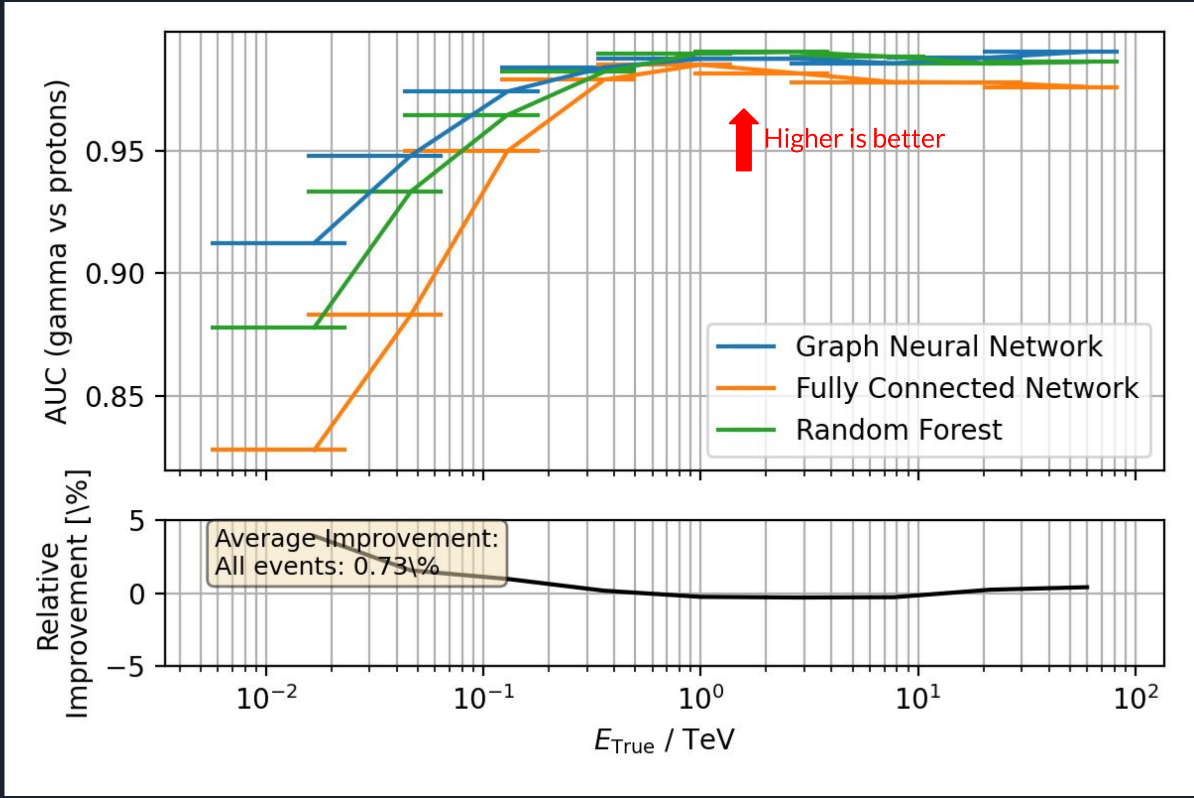
RESULTS

Metrics

Task	Metric	Definition	Goal
Classification	AUC	Area Under the Curve, measures the classifier performance	Higher is better
Energy reconstruction	Energy resolution	A measure of error across energy bins.	Lower is better
Direction reconstruction	Angular resolution (PSF)	A measure of directional error across energy bins.	Lower is better
	Sensitivity	Evaluates the overall performances of the telescopes.	Lower is better

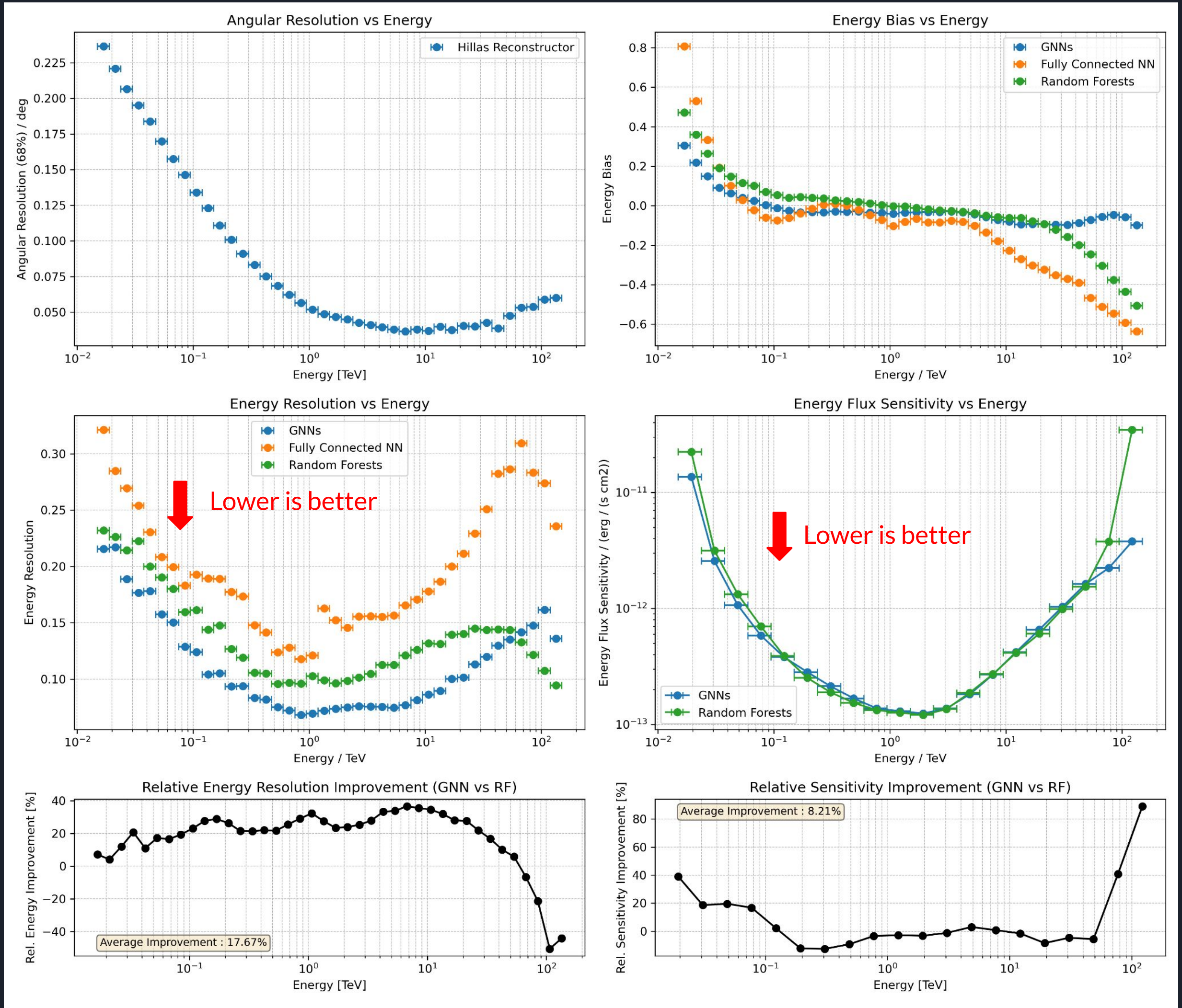
Results

Gamma/hadron separation



Results

- Gamma/hadron cuts
- Cuts on the origin direction



Conclusion

- Graphs : **A promising approach** for the stereoscopic reconstruction of gamma events.
- Significant improvement observed in the reconstruction, with better energy resolution and energy biais, as well as improved separation between gamma photons and protons.
- Not more complicated than RFs (same inputs, restructured as node features).
- Relatively fast to train (a few hours on a small GPU, or CPU)

Perspectives

- Combining CNNs and GNNs : potential integration into the GammaLearn project, which is currently focused on monoscopic reconstruction.
- Working on graph explainability

- Reproducible analysis (Open data)
- Gitlab repository (Open source) :

  Stereograph: https://gitlab.in2p3.fr/gammalearn/stereograph/stereograph

  Documentation: https://gammalearn.pages.in2p3.fr/stereograph/stereograph

Bibliography

[1] CORSIKA: A Monte Carlo code to simulate extensive air showers
[2] https://doi.org/10.1016/j.astropartphys.2008.07.009
[3] https://doi.org/10.22323/1.444.0703
[4] https://doi.org/10.5281/zenodo.11190775
[5] https://arxiv.org/abs/1801.07829

Acknowledgments

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GammaLearn: : https://purl.org/gammalearn/acknowledgements

Thank you !

γlearn CTAO Cherenkov Telescope Array Observatory anr LISTIC LAPP cnrs

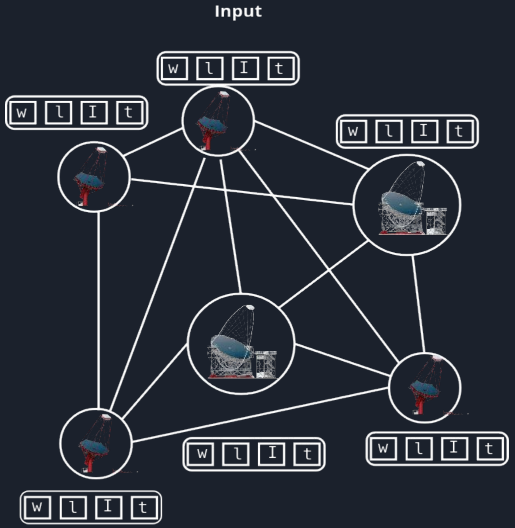
OSCARS Open Science Clusters' Action for Research & Society

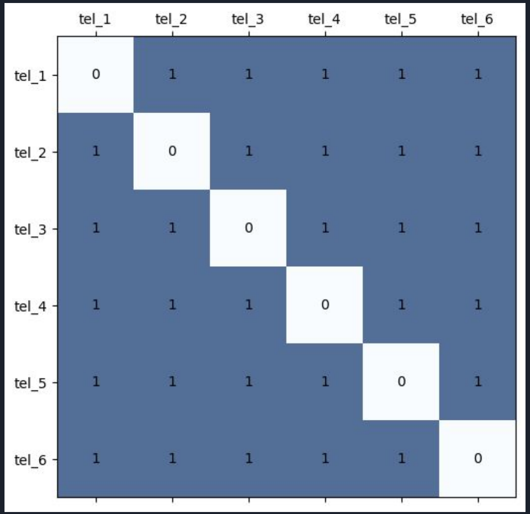
Funded by the European Union

BACKUP

Graph representation

- The characteristics of the nodes are stored in a matrix.
- The edge weights are stored, depending on the case, either in the adjacency matrix or in an independent vector.





Boolean matrix describing the edges of the graph

Node	Adjacent Vertices
1	[2, 3, 4, 5, 6]
2	[1, 3, 4, 5, 6]
3	[1, 2, 4, 5, 6]
4	[1, 2, 3, 5, 6]
5	[1, 2, 3, 4, 6]
6	[1, 2, 3, 4, 5]

A list containing the list of adjacent vertices.

Learning on graphs

1. **Message passing:** Each node in the graph collects the embeddings of its neighbors (messages).
   Message passing function: Affine, or a neural network (MLP).
2. **Aggregation:** using an aggregation function (sum, max, average).
3. **Update of embeddings**