Event reconstruction at the LST1 telescope using image-based Deep Learning models

CTAO School 2025

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CTLearn Group

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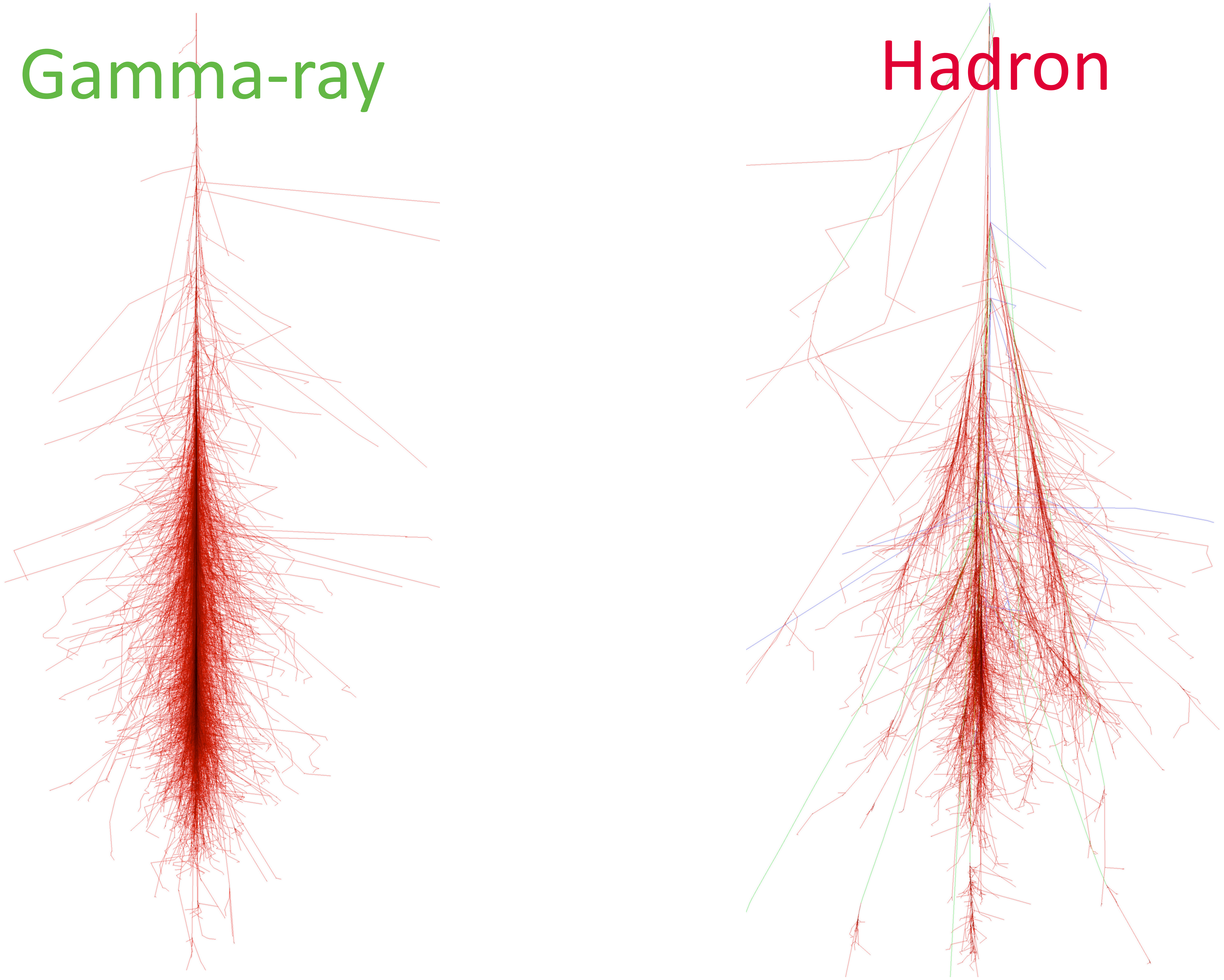
EXCELENCIA SEVERO OCHOA

Cherenkov Imaging

Problem to solve

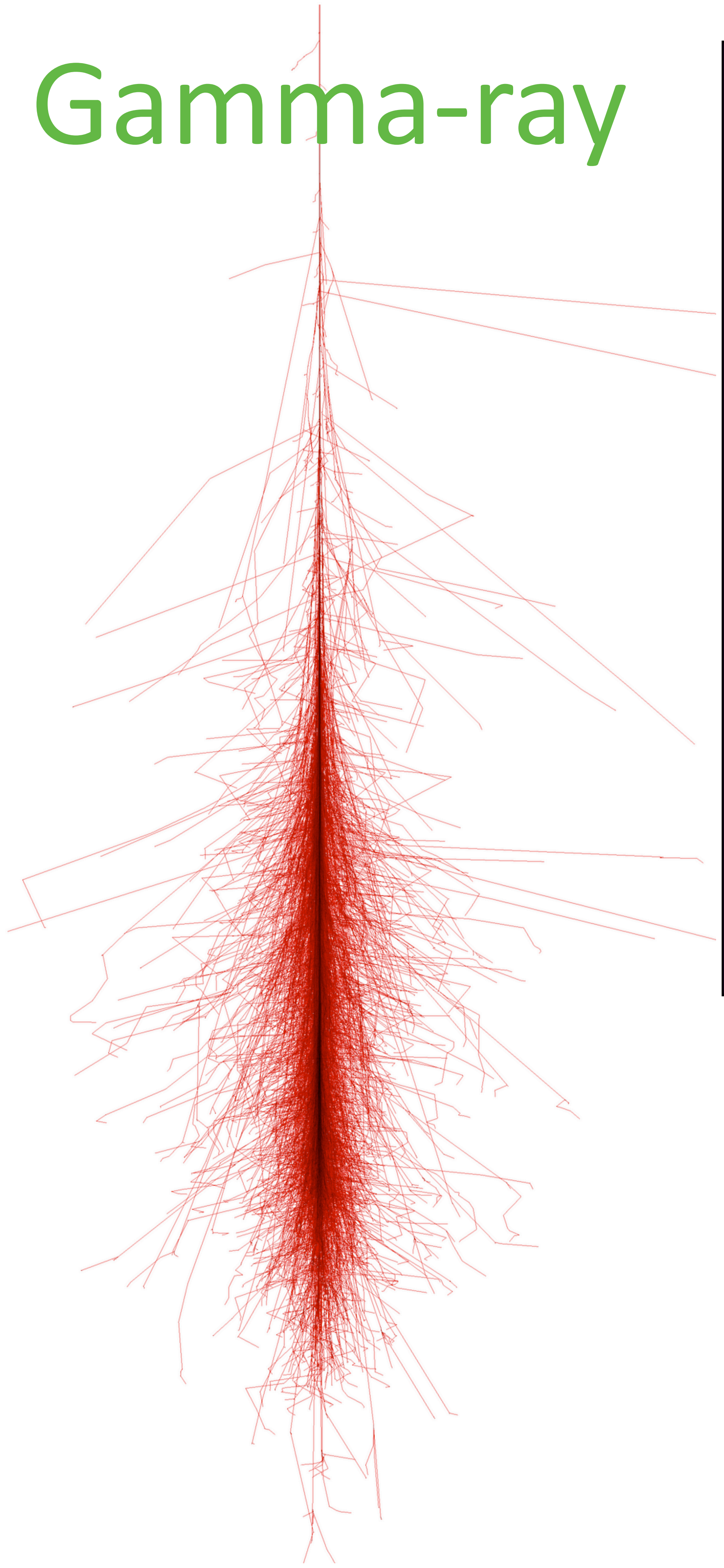


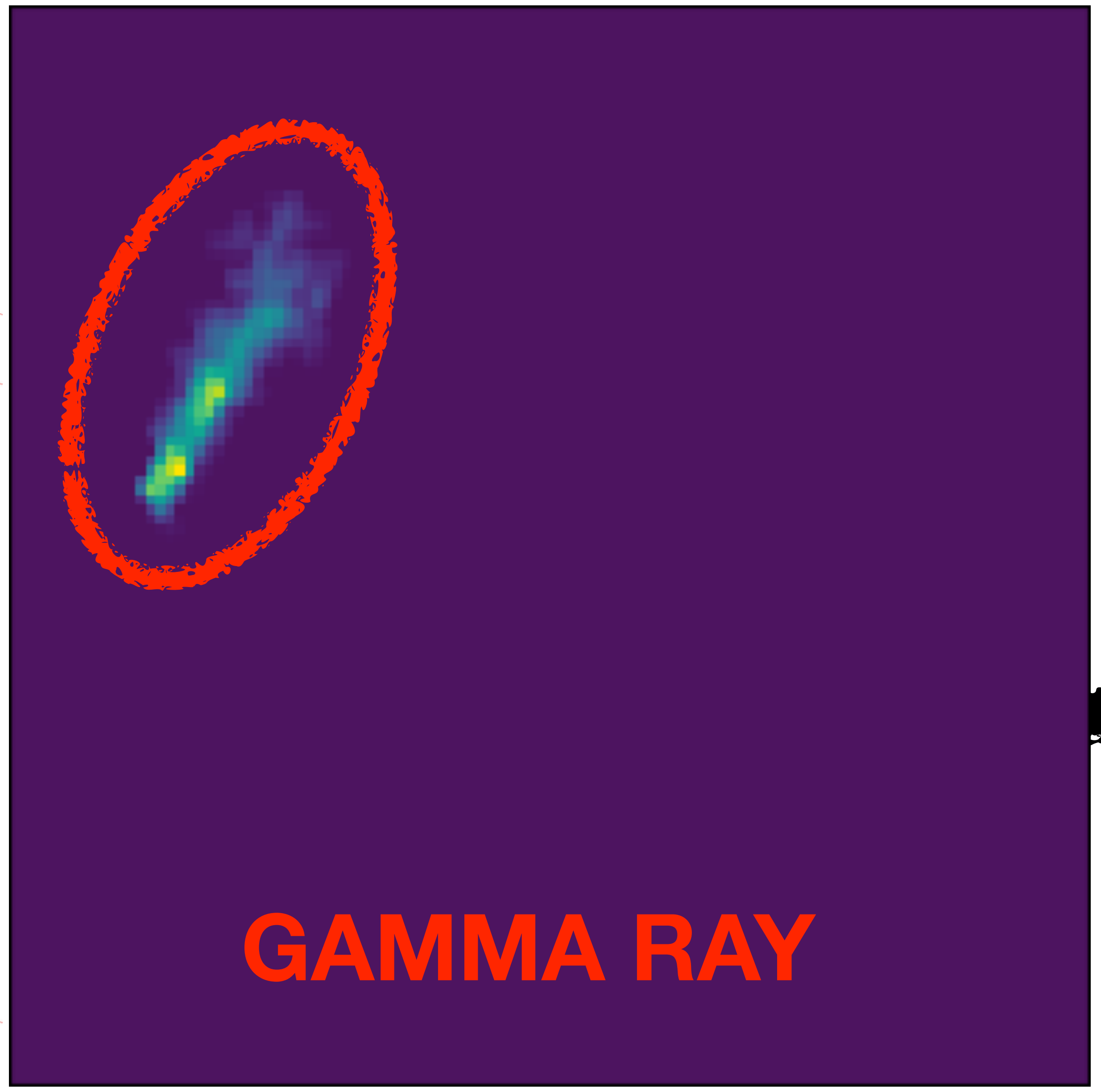
Cherenkov Imaging

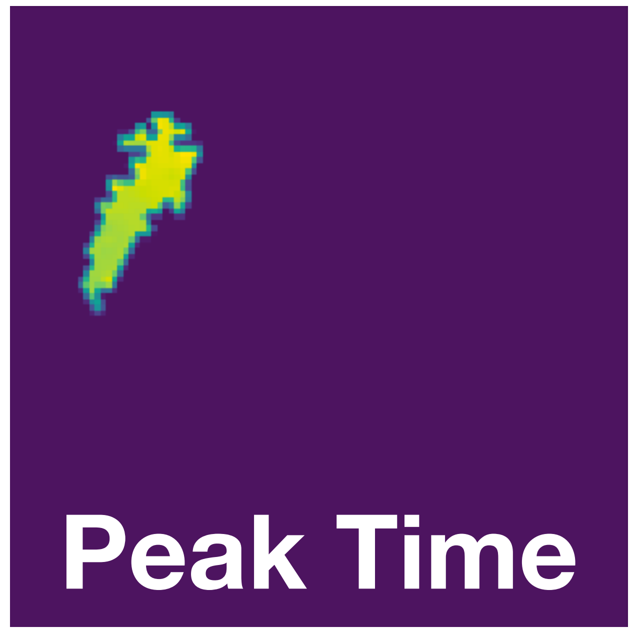
Problem to solve

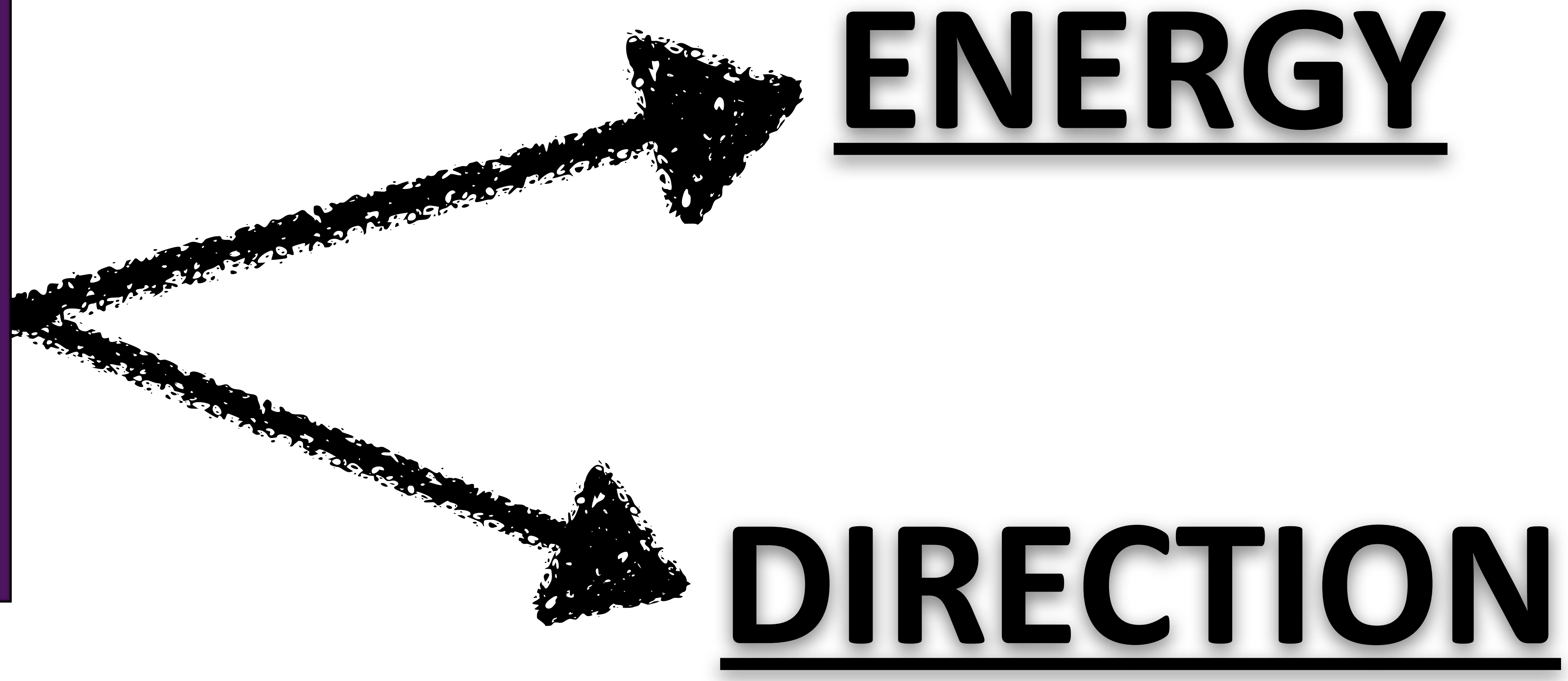
Cherenkov Imaging

Problem to solve





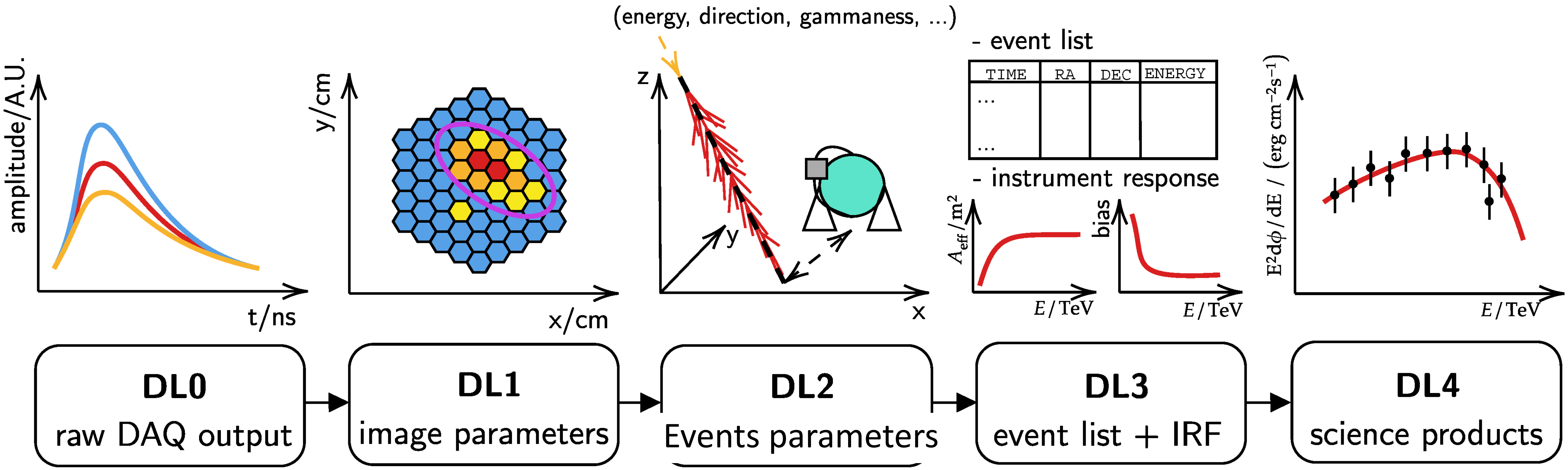




Cherenkov Imaging

DL -> Data Level

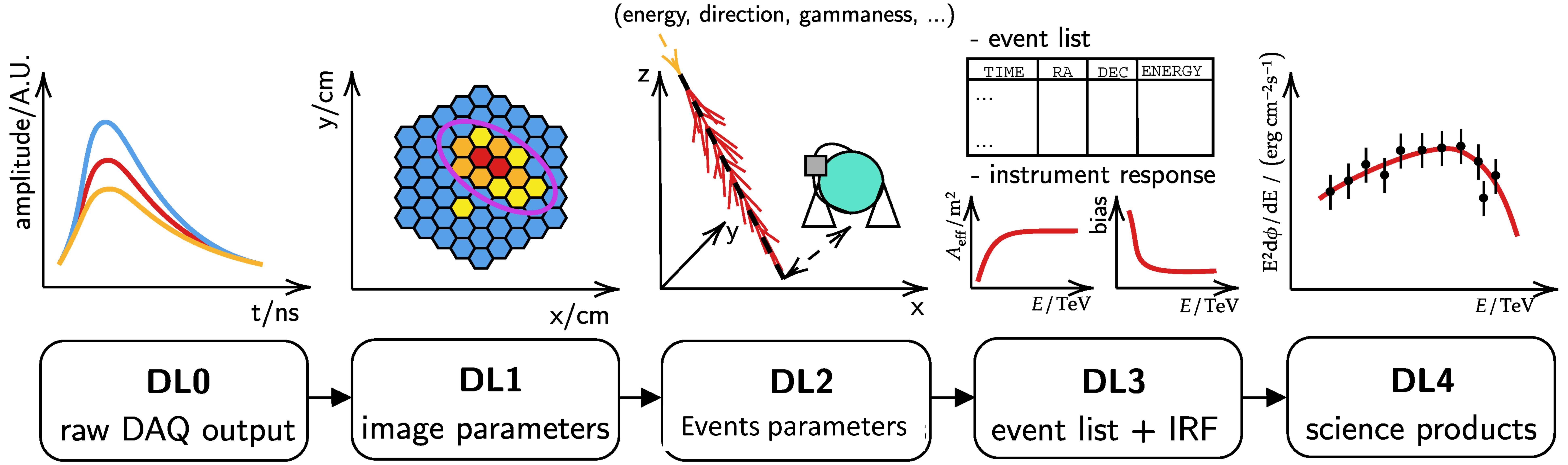
LST pipeline “lstchain”



Cherenkov Imaging

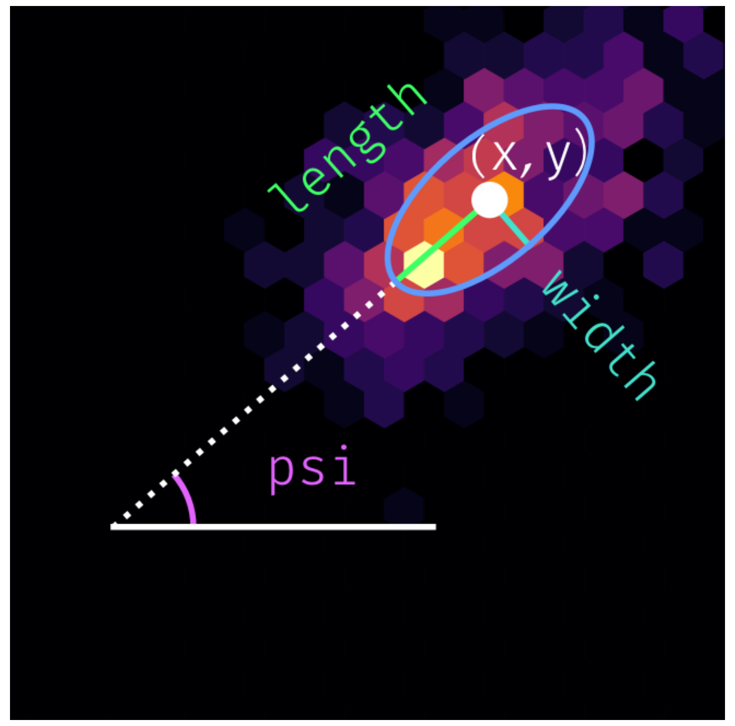
DL -> Data Level

LST pipeline “lstchain”



Amplitud vs Time per pixel

Hillas parameters

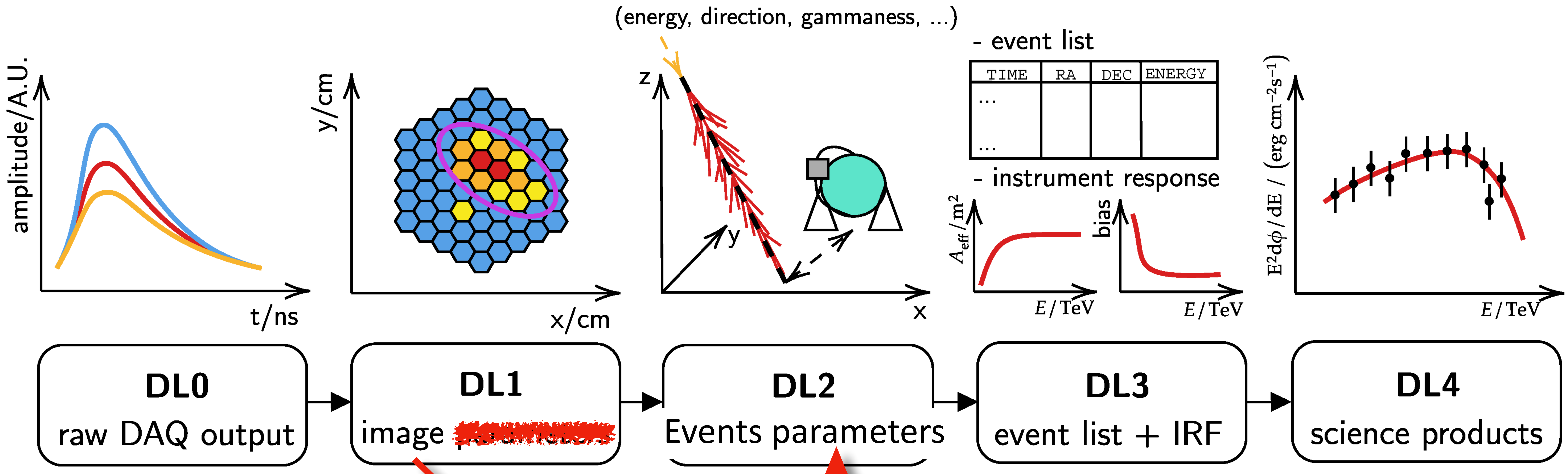


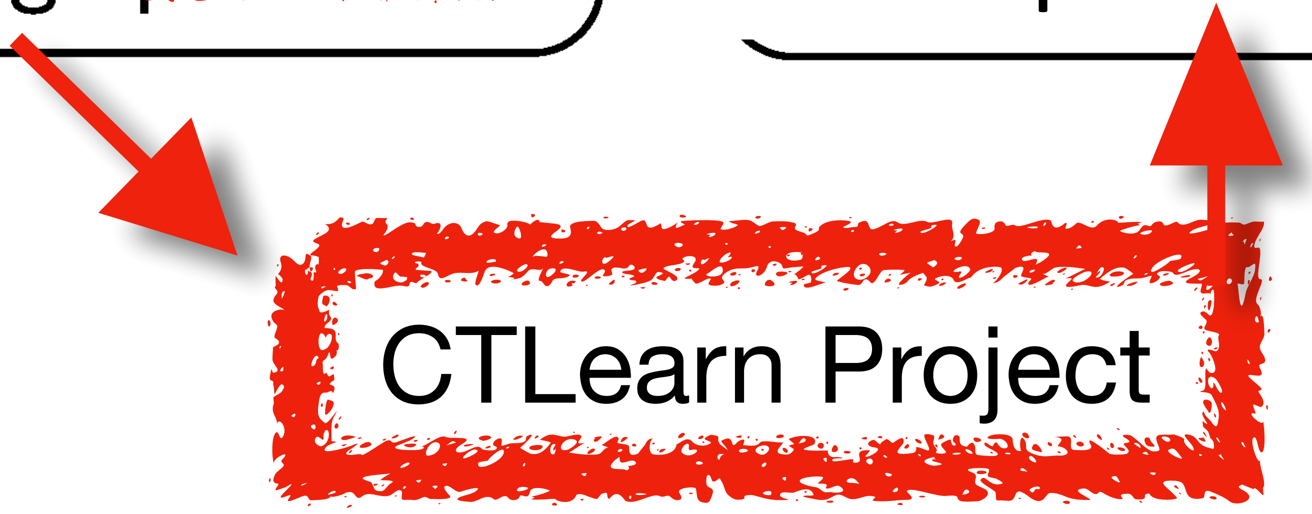
Product for Science

Cherenkov Imaging

DL -> Data Level

LST pipeline (CTLearn) <u>OUR WORK !!!</u>

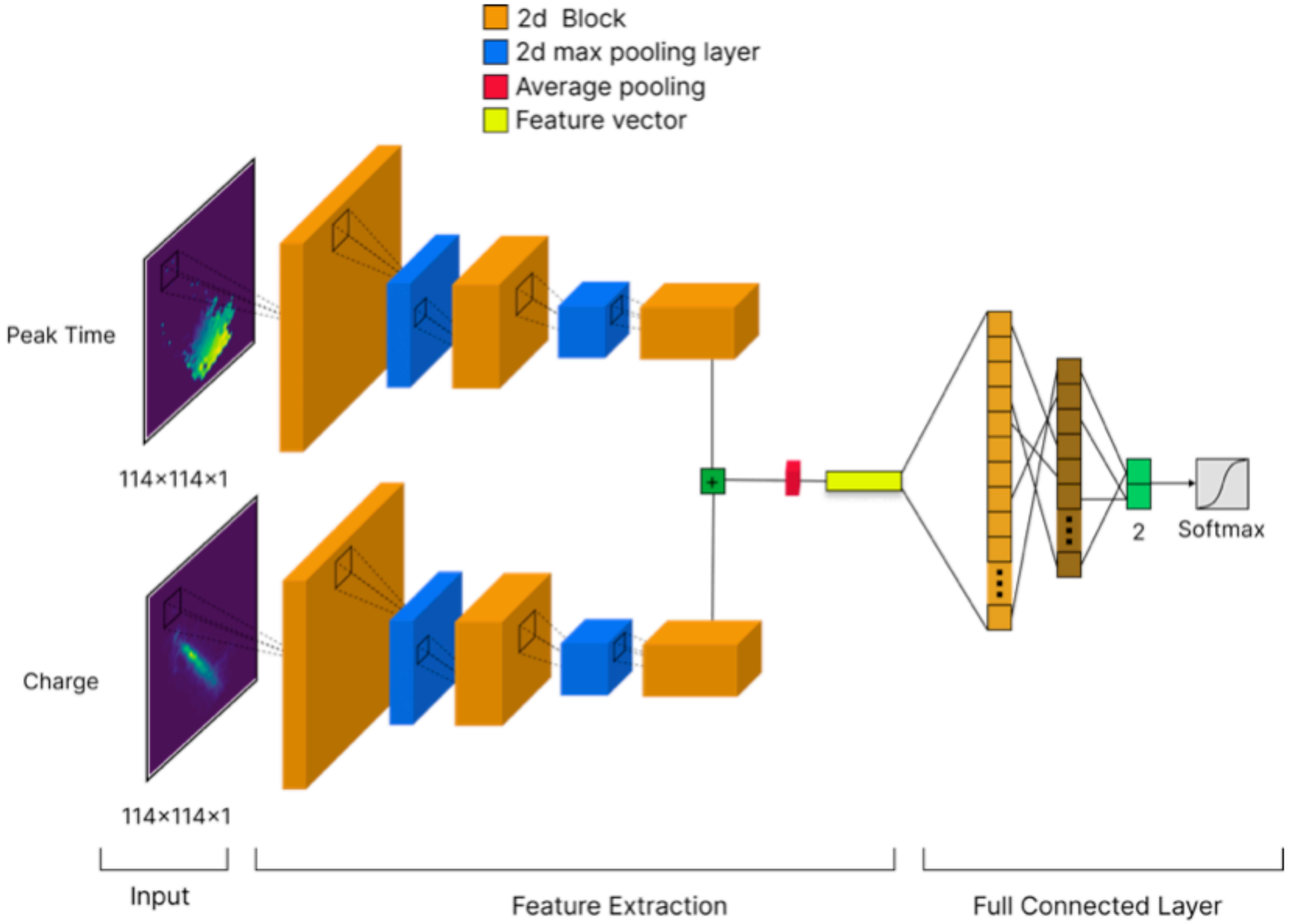




We use the images instead of the **<u>hillas parameter</u>**

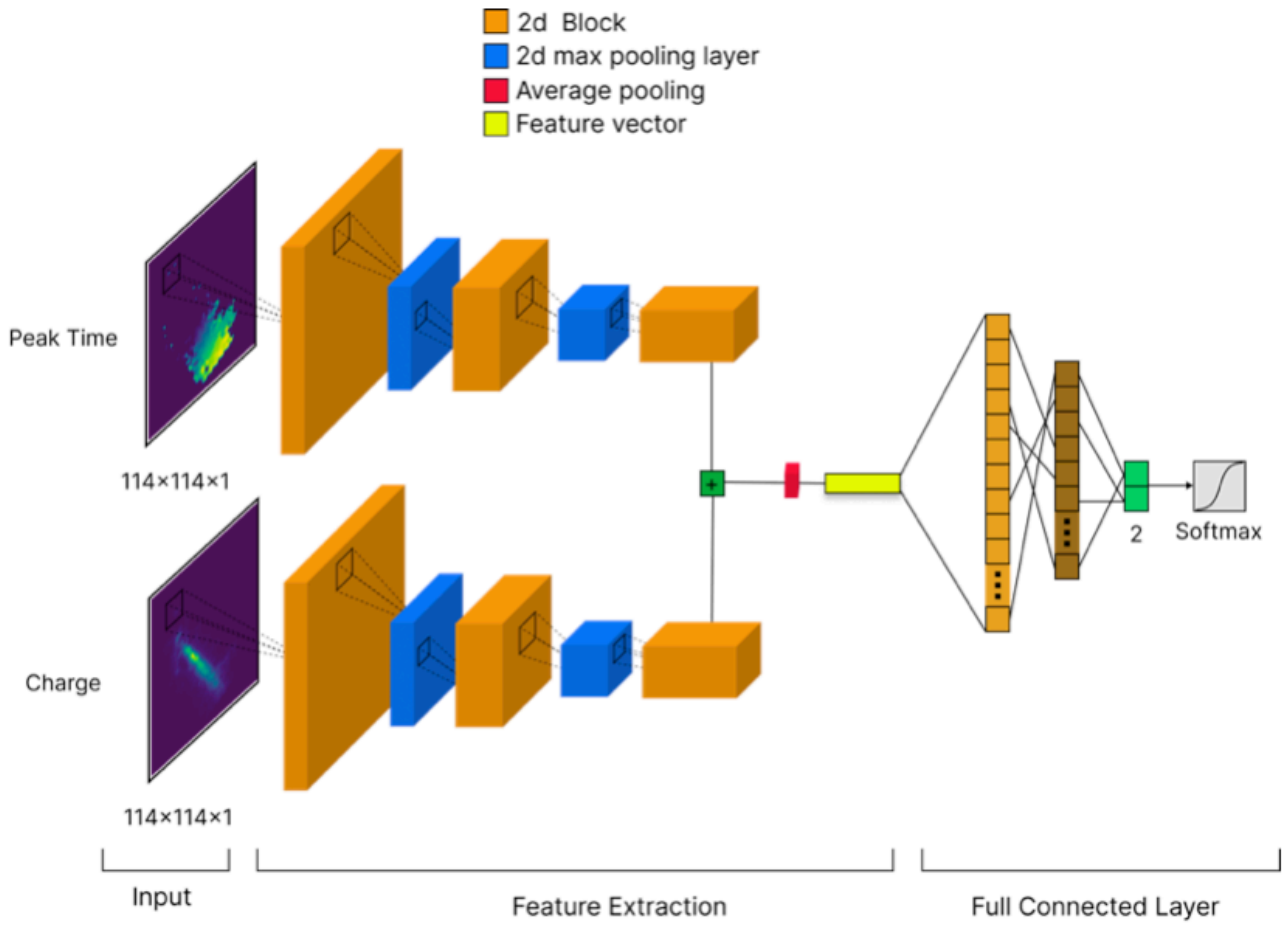
Cherenkov Imaging

Deep Learning Model



Cherenkov Imaging

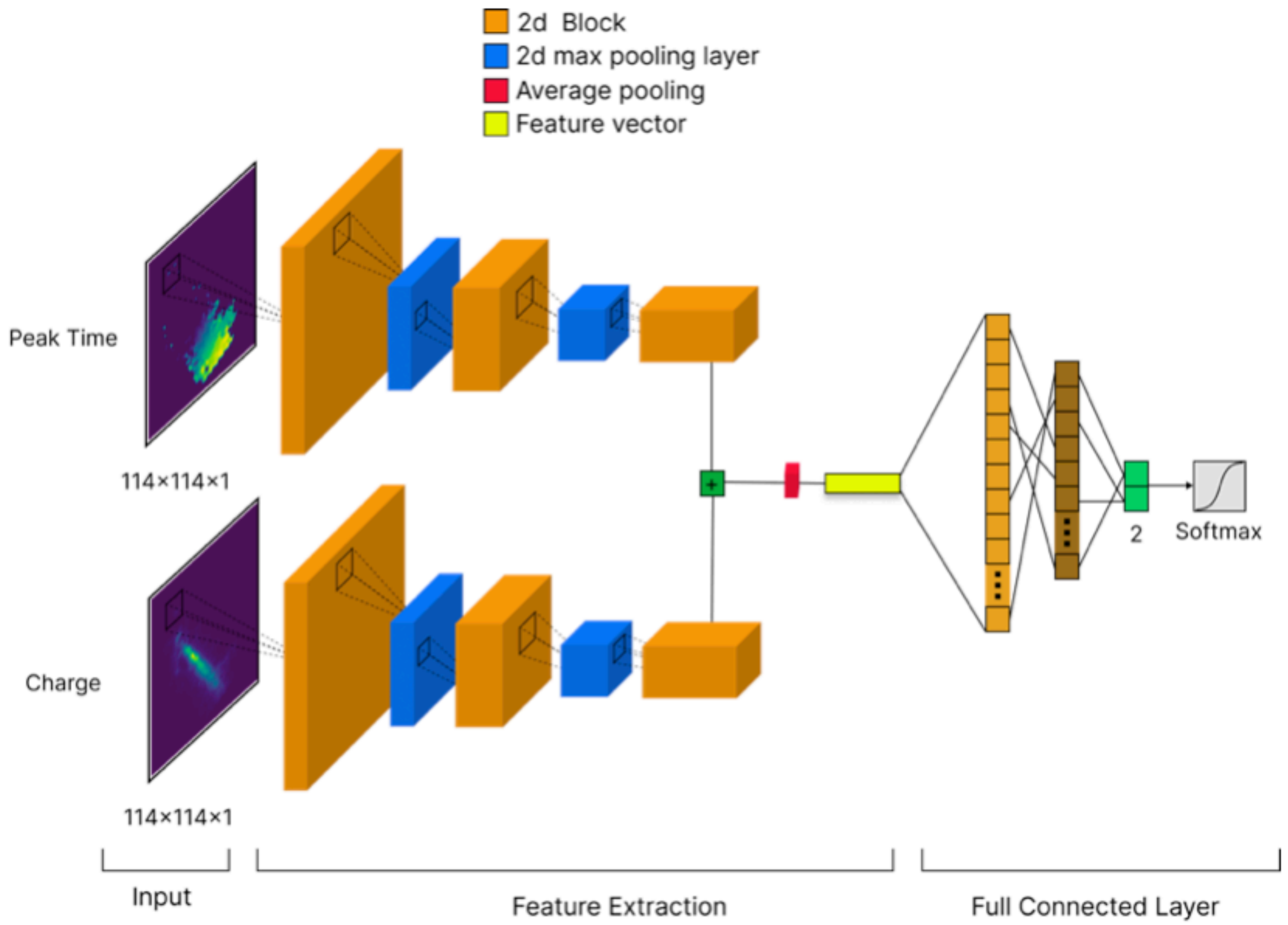
Deep Learning Model



How a deep learning model works?

Cherenkov Imaging

Deep Learning Model

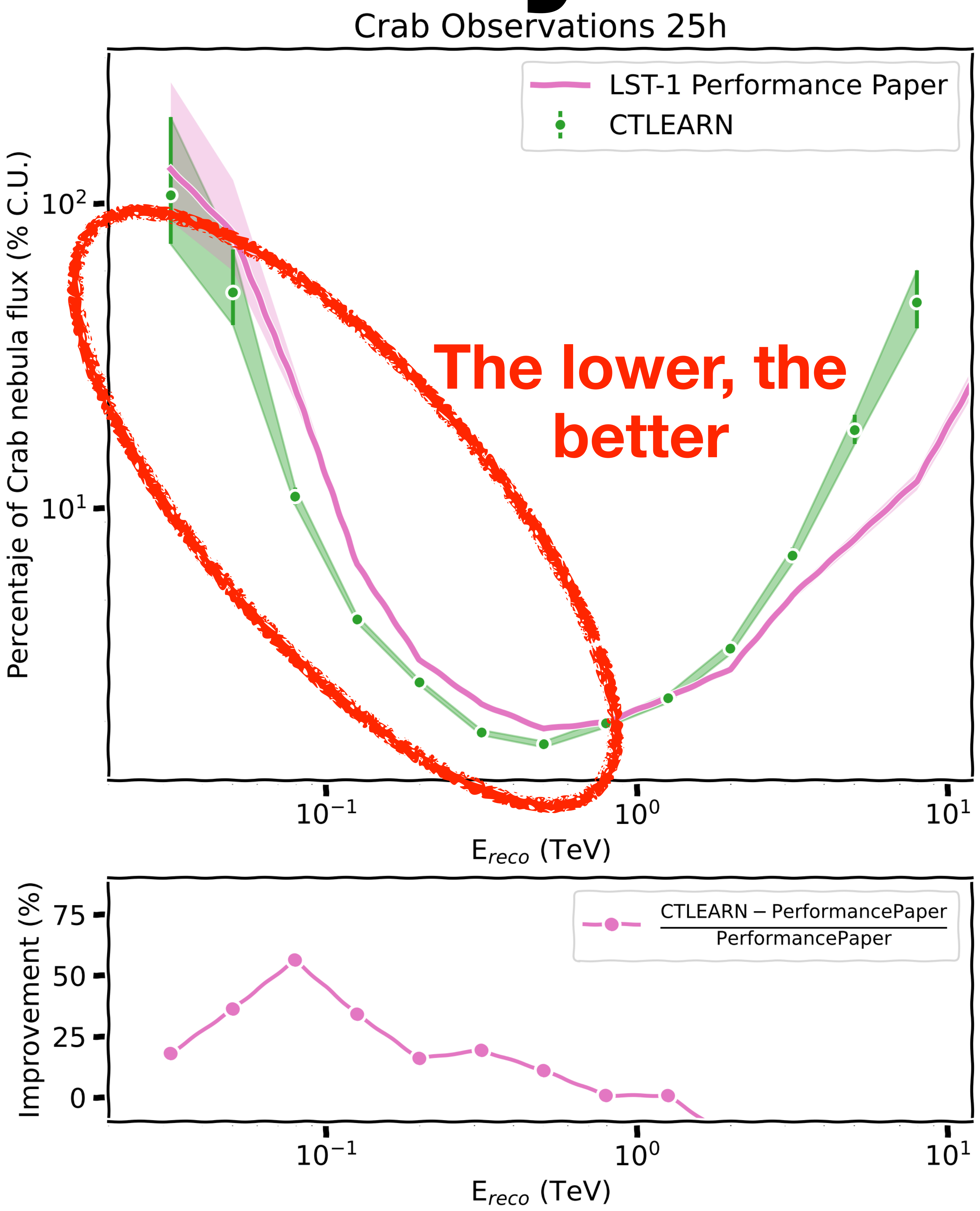


How a deep learning model works?

Do you remember the Alex talk?

Go to **slide 6**

Sensitivity of the Telescope



The improvement in the lower energies in more than **40%**

GREEEN: CTLEARN (Our Work)

PINK: LST CURRENT SENSITIVITY[1]

[1]Observations of the Crab Nebula and Pulsar with the Large-sized Telescope Prototype of the Cherenkov Telescope Array. (2023). APJ, *956*(2), 80. doi:10.3847/1538-4357/ace89d

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Questions?

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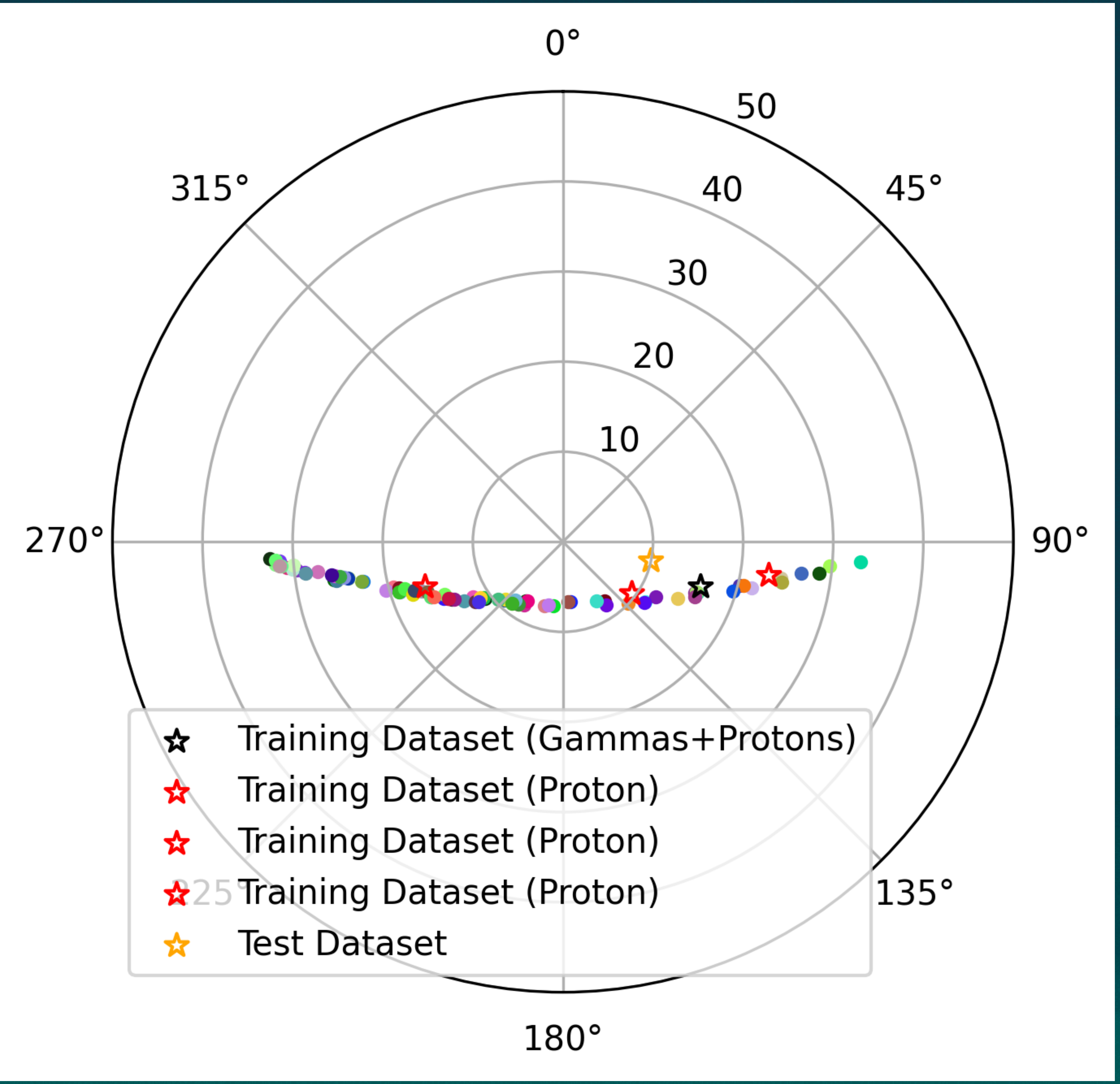
BACKUP

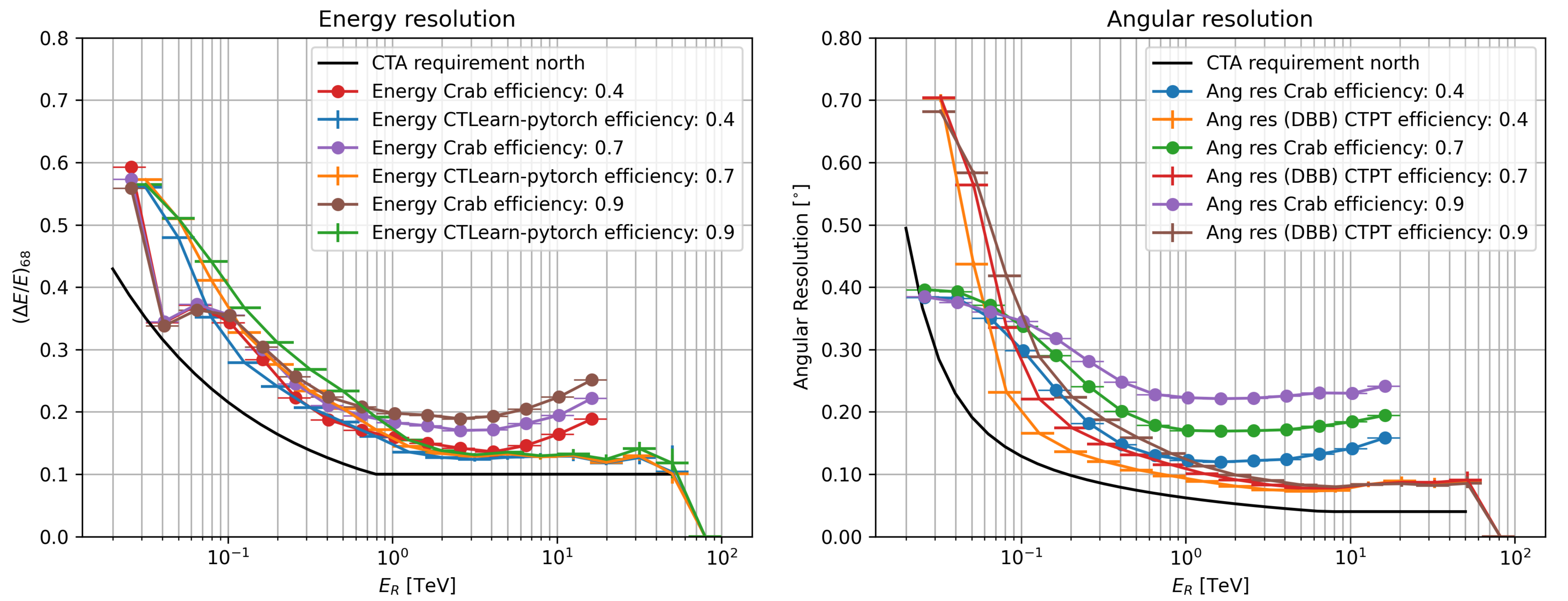
Crab Nebula Dataset

- 87 Crab Runs
- Obs time ~ 25 h
- Training Nodes: zd=[10,20]



MC performance

Energy & Angular Resolution



Pablo Guzman Work !!

Sensitivity using Crab Nebula real data

Two different ways to calculate

With the same Background of RF

1. **Divide both datasets in half.**

2. Compute the cuts in gammaness and theta² on the first half of the RF dataset.

3. Repeat the same process for the second half of the RF dataset and determine which set of cuts gives the best sensitivity.

4. Apply the same procedure to the Ctlearn-PyTorch dataset, but adjust the gammaness cut to achieve the same background level per solid angle.

With different Background levels

1. **Divide both datasets in half.**.

2. Compute the sensitivity for both datasets separately.

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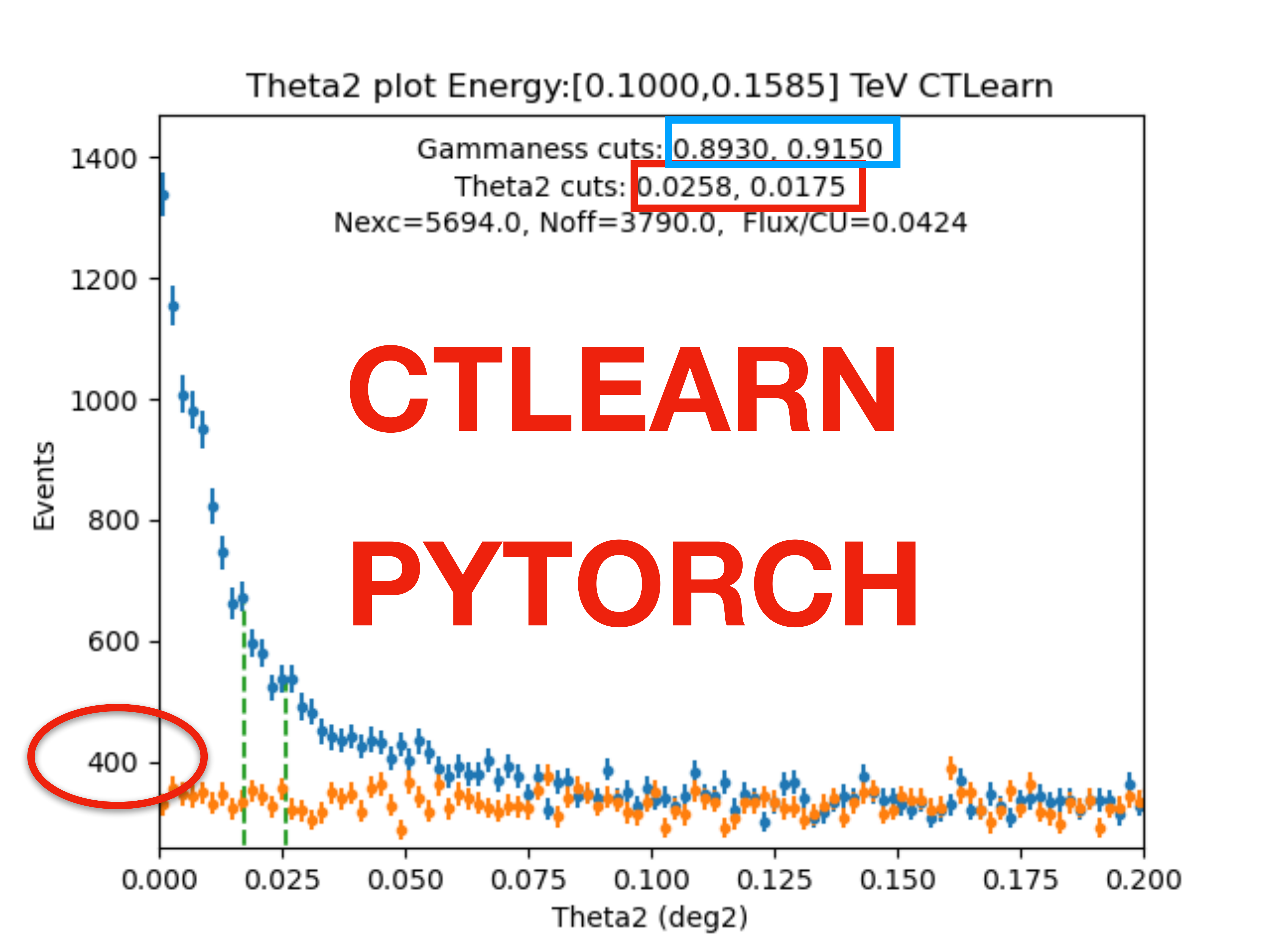
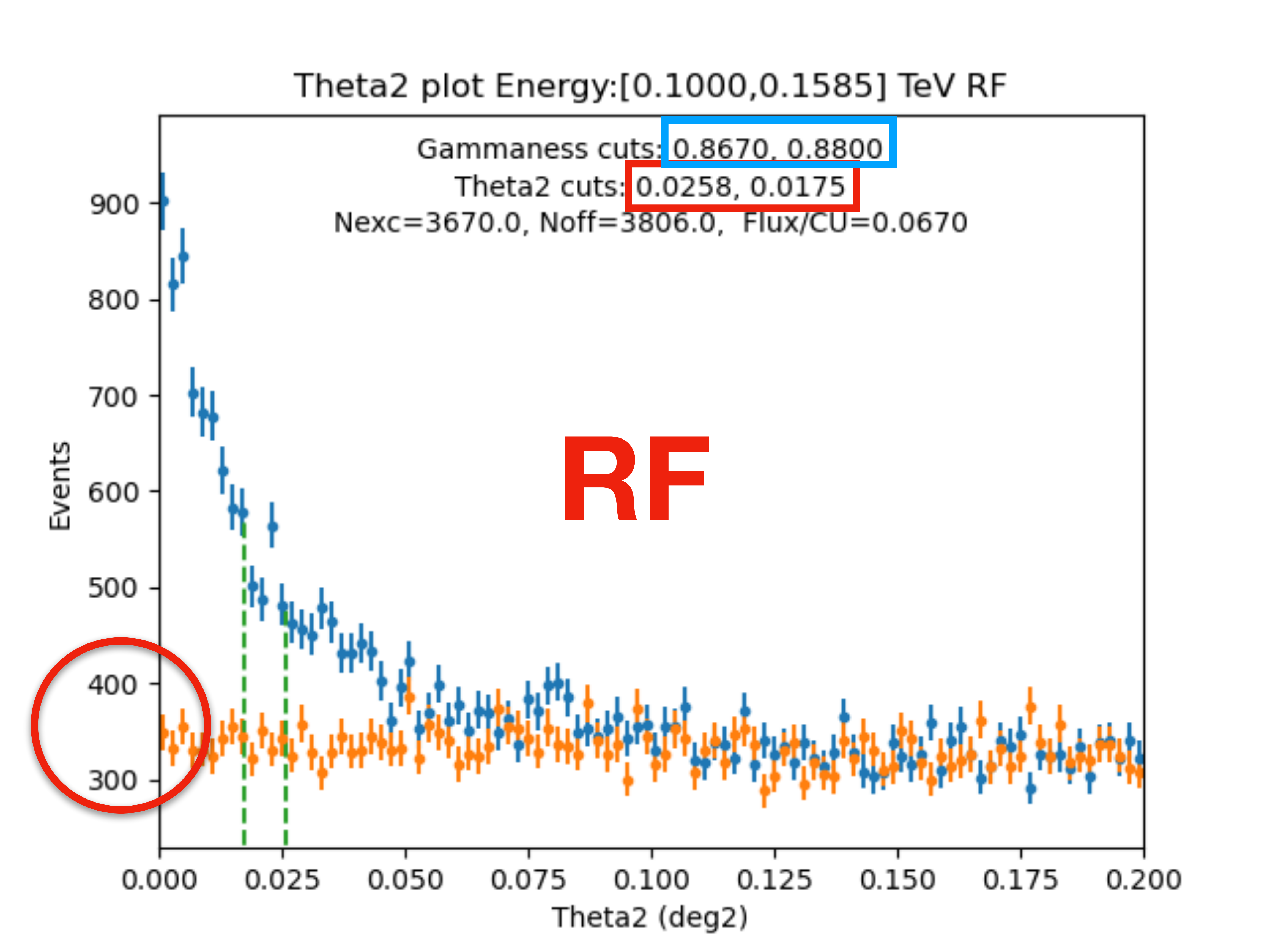
Sensitivity using Crab Nebula real data

Theta2 - Background level optimized using RF dataset.

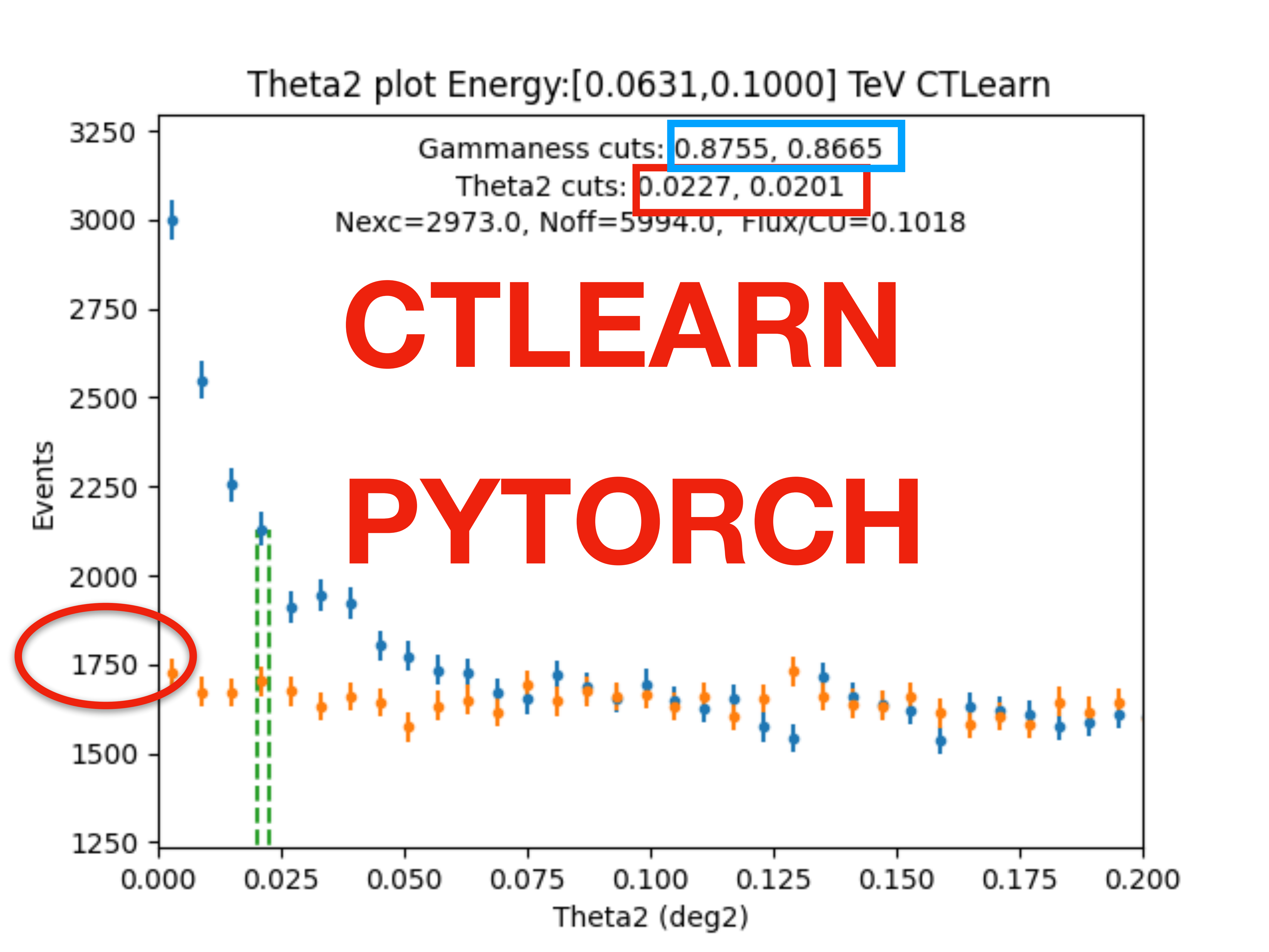


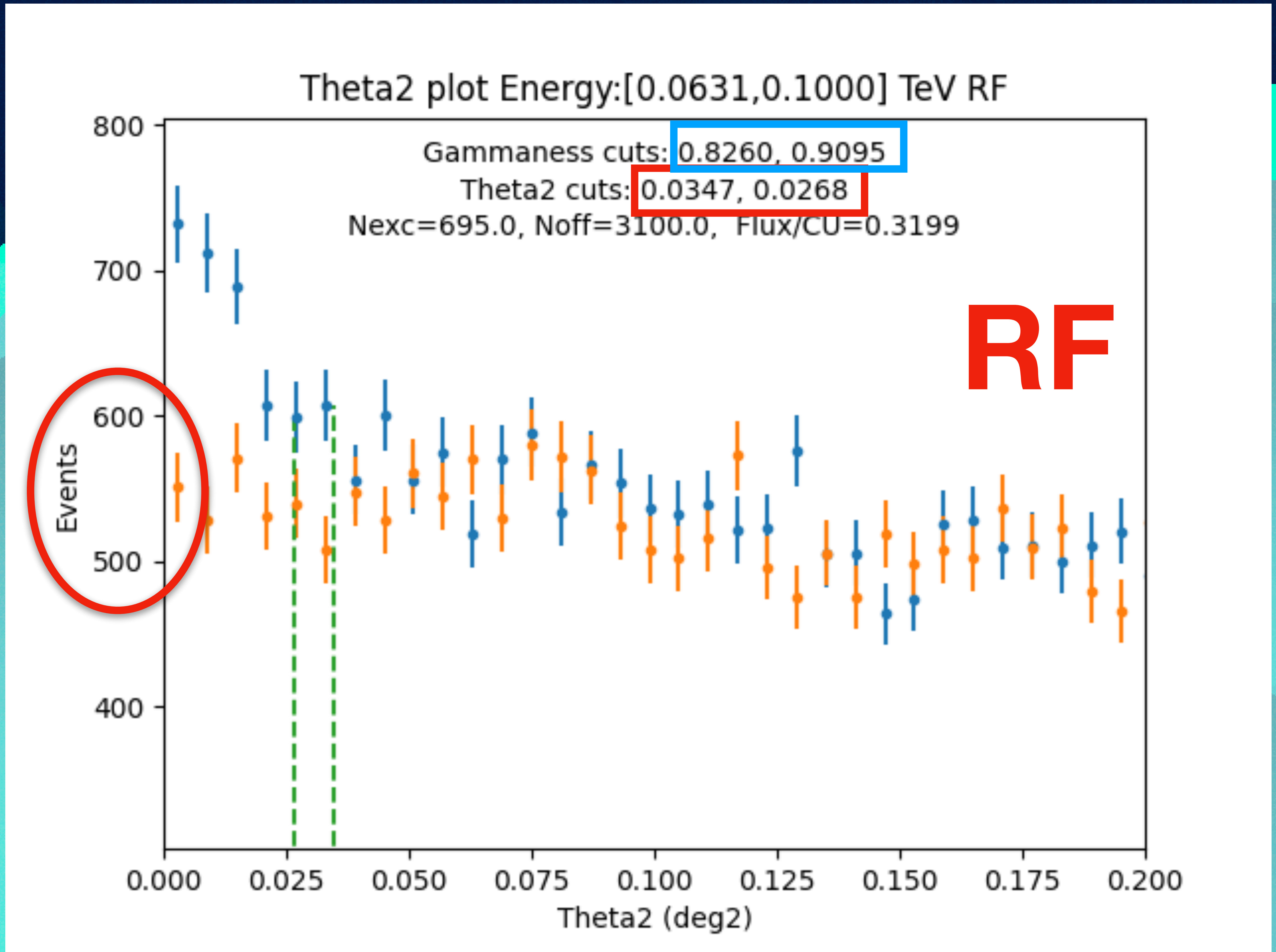


Cut applied to the CTlearn-Pytorch dataset give the same background level per solid angle.

Sensitivity using Crab Nebula real data

Theta2 - Different Background level.





Sensitivity using Crab Nebula real data

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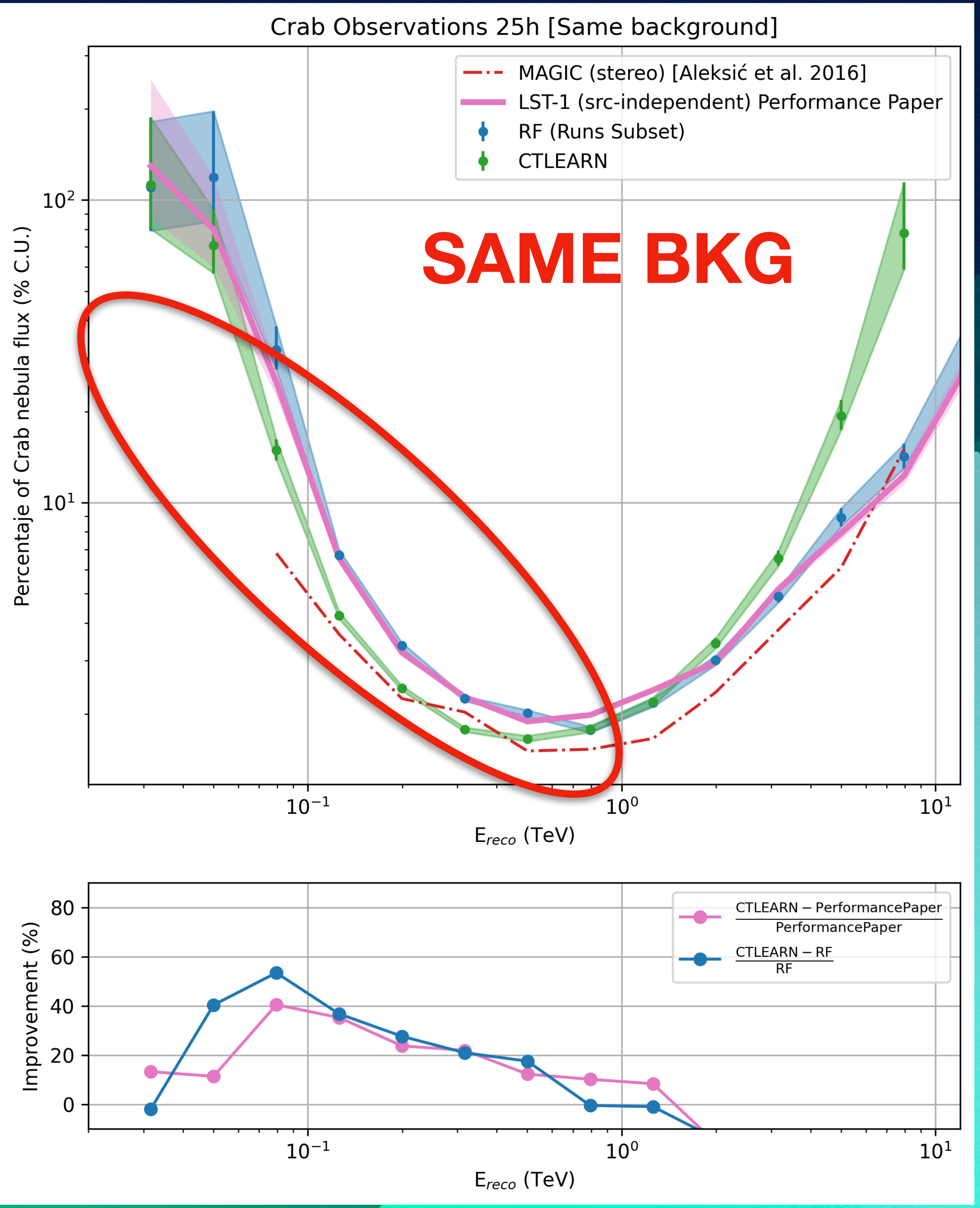


The model shows **improved performance** at low energies **< 500 GeV.**

The improvement in the lower energies is more than **20%**

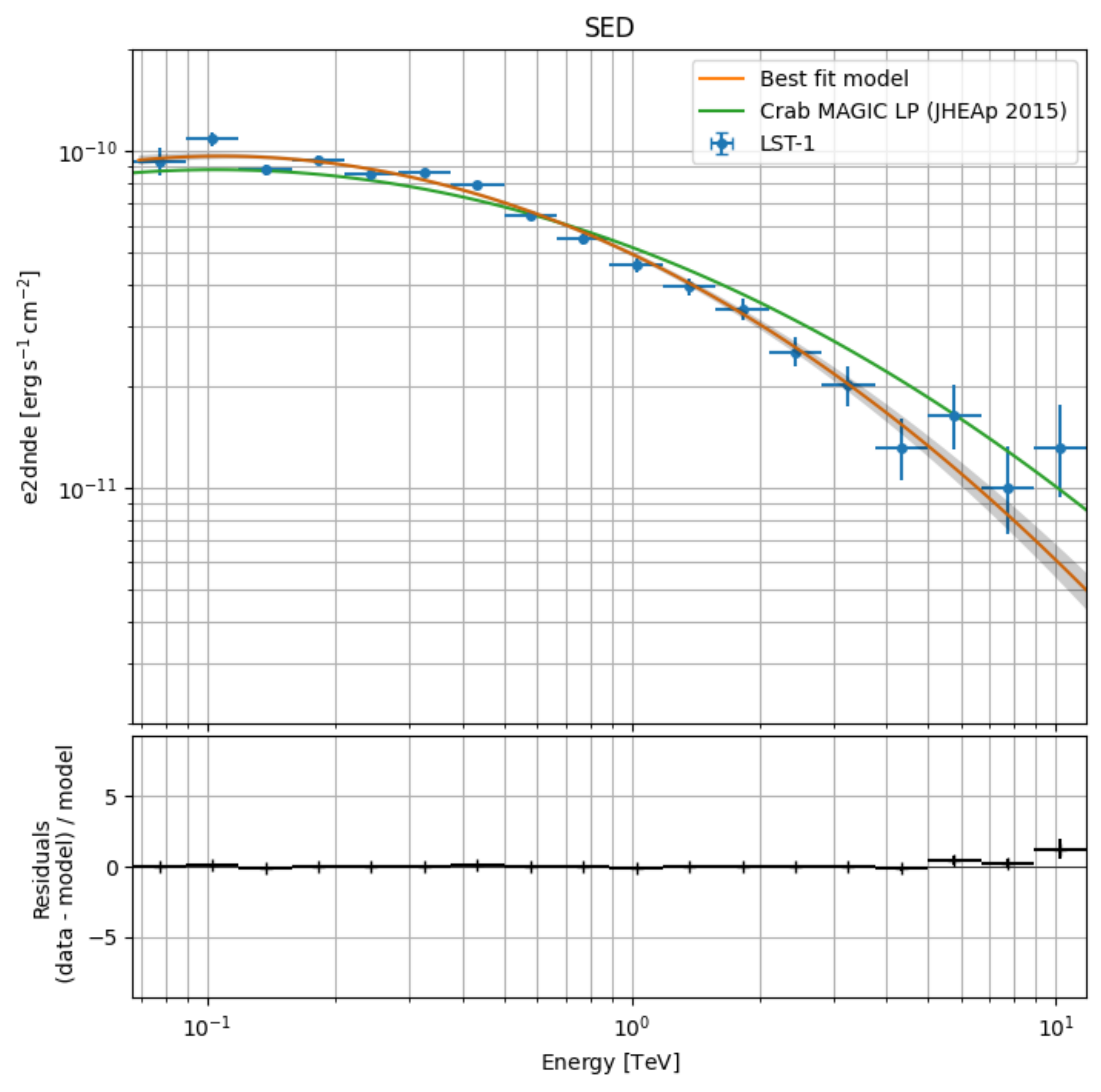
The difference between the performance paper and the RF curves is because we only analyze **25 h.**

GREEEN: CTLEARN - PYTORCH

BLUE: RF

PINK: P. PAPER

Spectral Analysis

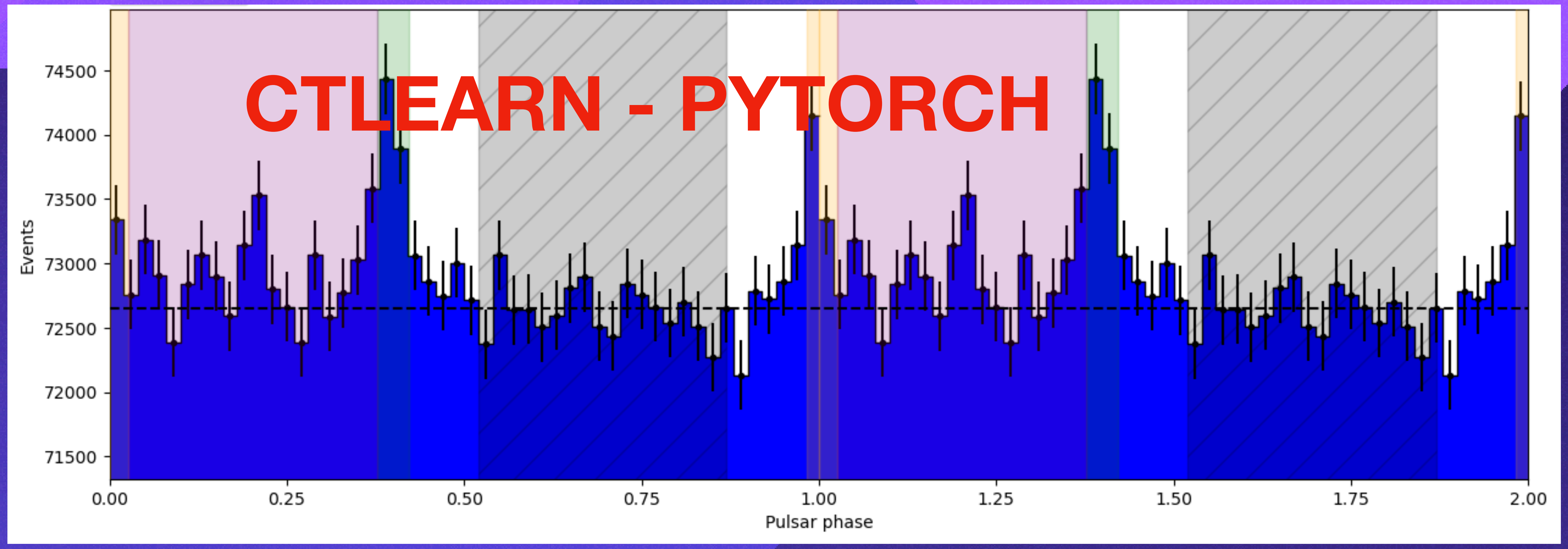


The CTLEARN-Pytorch **reproduce** the Crab Nebula spectrum

This is a good **cross check of our model**

Pulsar Analysis

Phaseogram E < 1 TeV

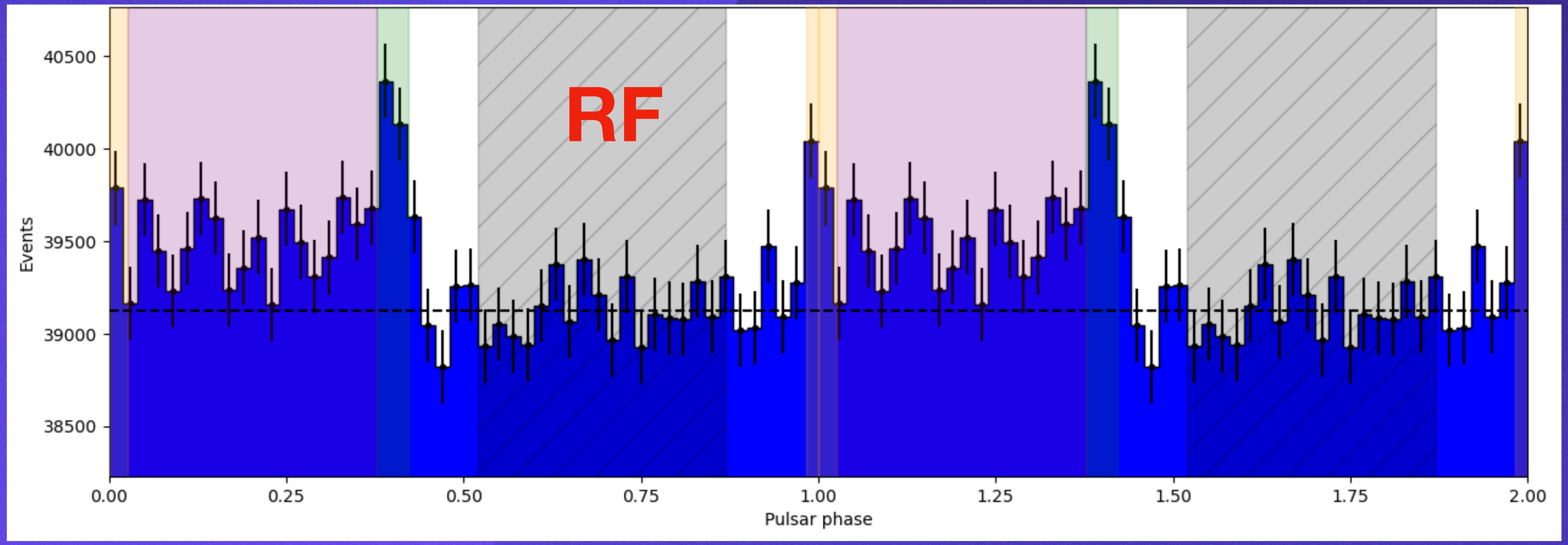


P1 Sig(Li&Ma): 5.21

P2 Sig(Li&Ma): 7.63

Bridge Sig(Li&Ma): 5.29

P1 + P2 Sig(Li&Ma): 8.63



P1 Sig(Li&Ma): 5.7

P2 Sig(Li&Ma): 7.1

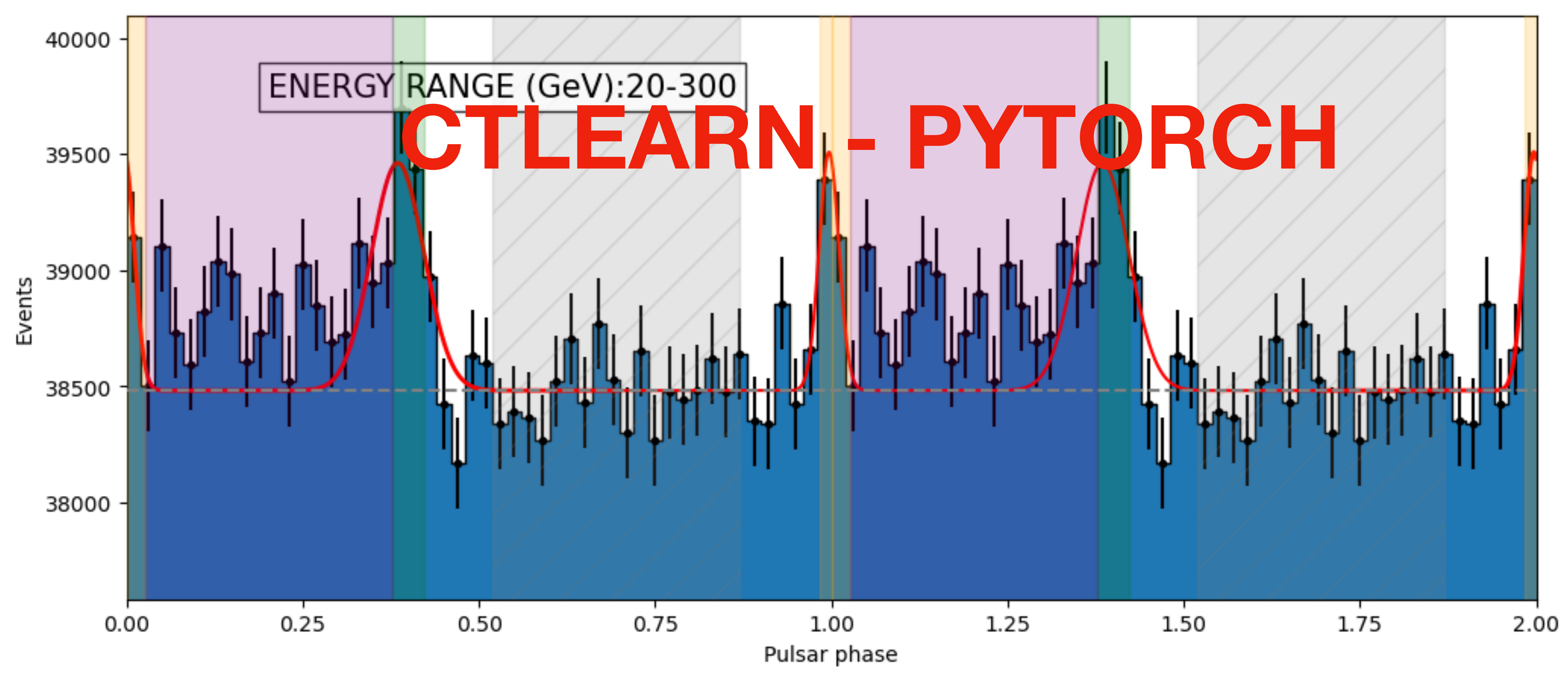
Bridge Sig(Li&Ma): 2.79

P1 + P2 Sig(Li&Ma): 8.6

This method improve the significance in **P2 and in the Bridge**

Pulsar Analysis

Phaseogram E < 0.3 TeV

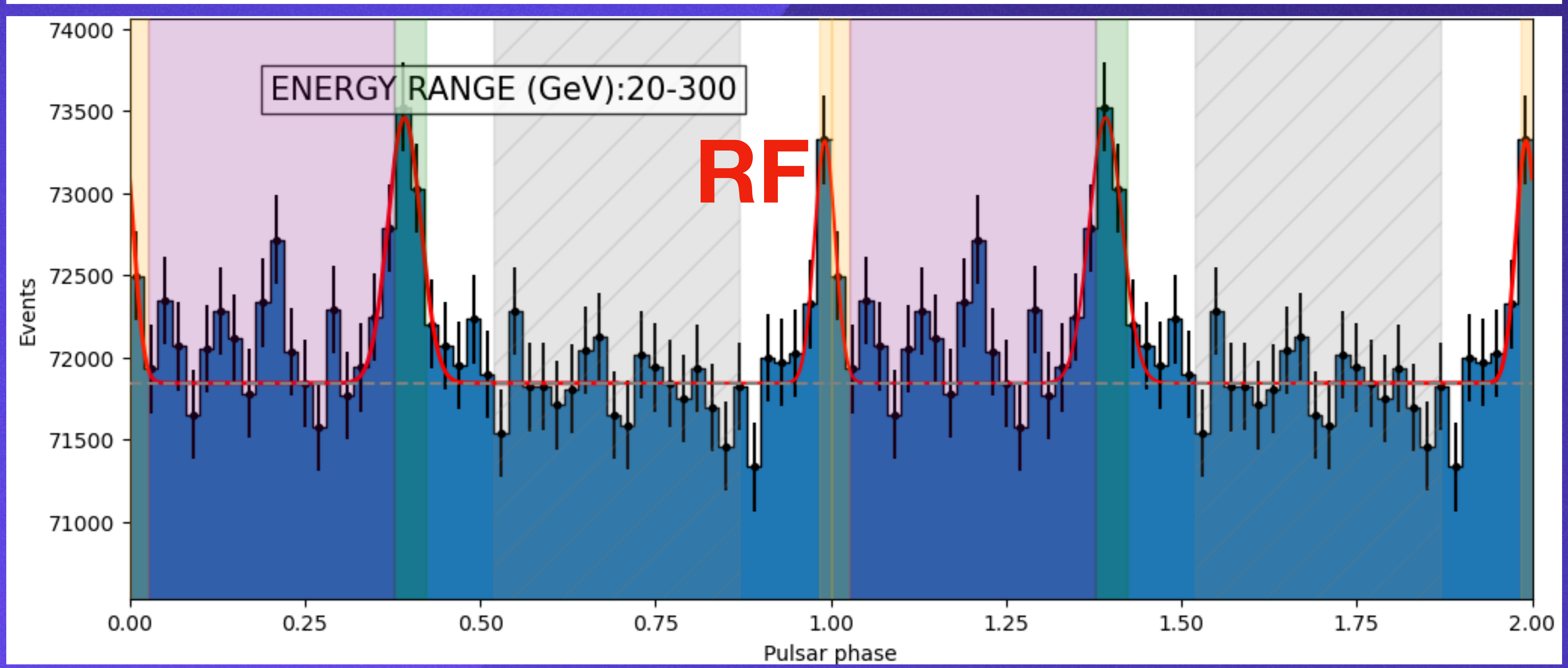


P1 Sig(Li&Ma): 5.21

P2 Sig(Li&Ma): 7.42

Bridge Sig(Li&Ma): 5.29

P1 + P2 Sig(Li&Ma): 8.49



P1 Sig(Li&Ma): 5.56

P2 Sig(Li&Ma): 6.73

Bridge Sig(Li&Ma): 2.9

P1 + P2 Sig(Li&Ma): 8.25

This method improve the significance in **<u>P2 and in the Bridge</u>**

Pulsar Analysis

RED: CTLEARN

GREEEN: RF

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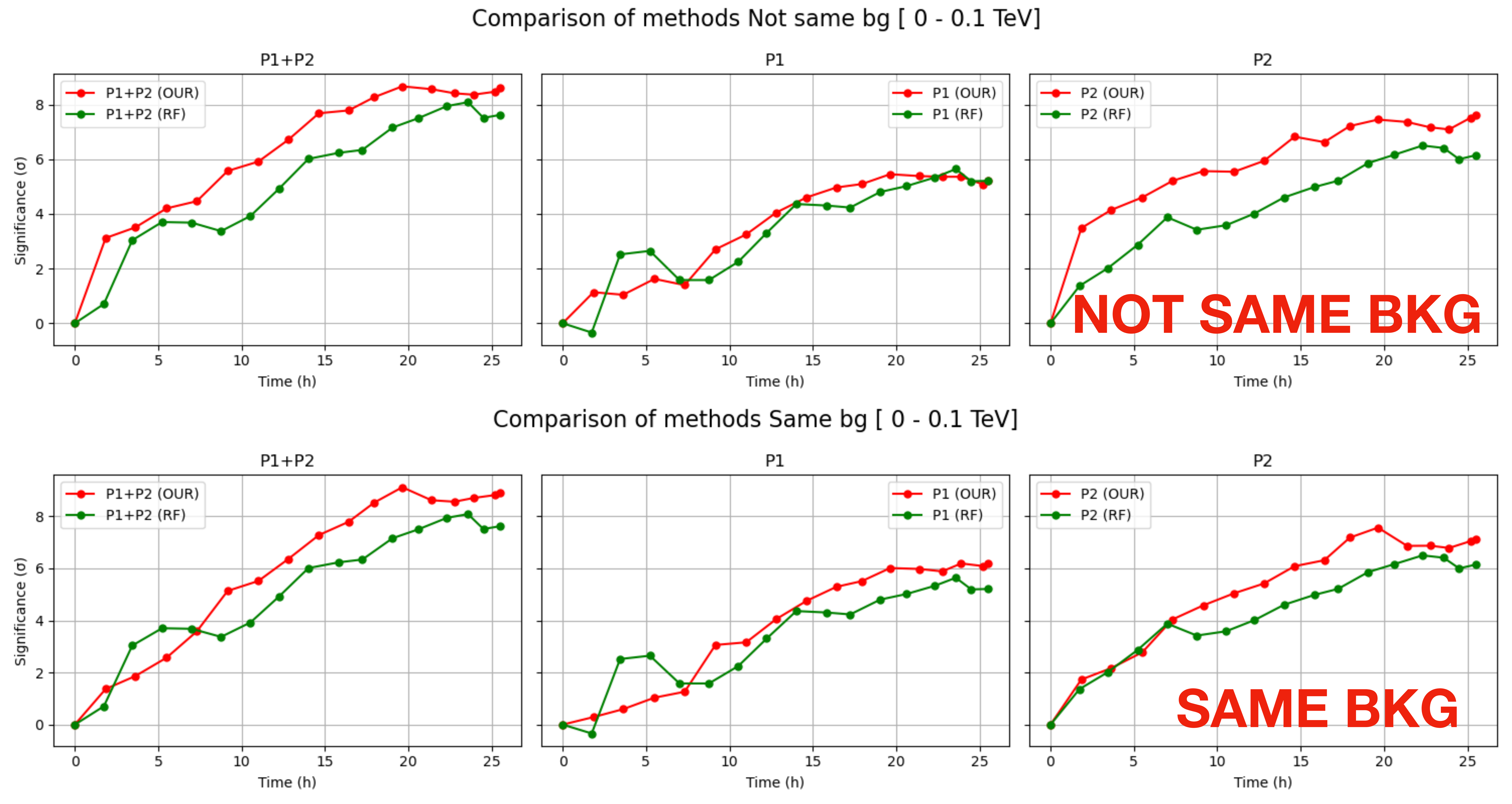
Significance Evolution vs Time E < 0.1 TeV



Future Work

Models and Versions

The results shown in this presentation were obtained with **V3 of our model**, we have already foreseen evolutions and improvements in the future

STEP	V4	V5	V6
Model	Same	Same	New model in Dev
Training	Already Trained	Training in Process	Not Started
Data Reduction	Reduction in Process	TBD	TBD

V3 -> Was trained with a MC simulated at a reduced set of locations in the sky.

V4 -> Will be trained with an all-sky MC simulation of the Crab Nebula

V5 -> Training with **REAL DATA**.

V6 -> Improve the arquitecture.

Conclusions

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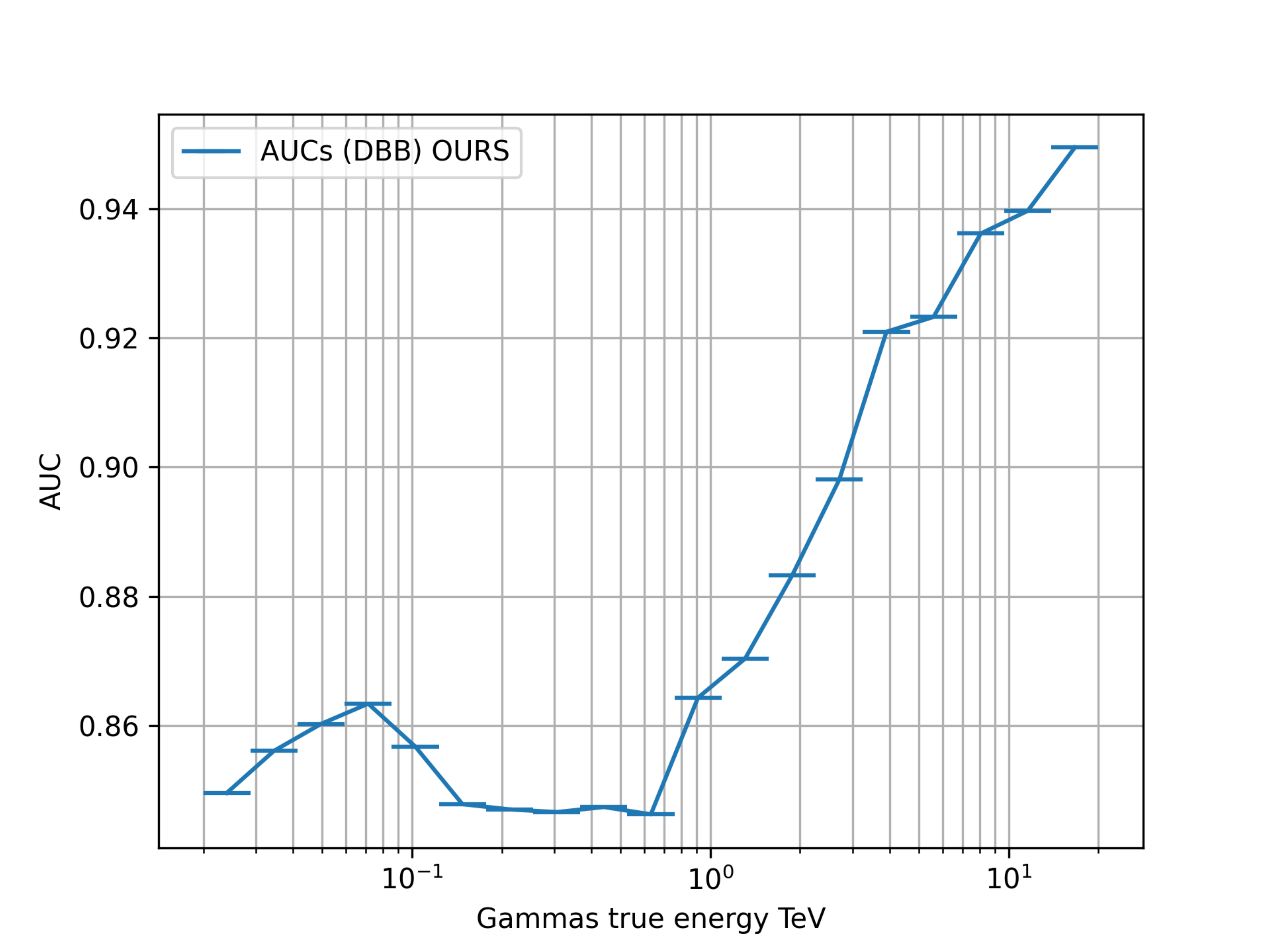
- The model shows improved performance at low energies.
- It is promising, is giving good results even when trained on a single node.
- Further comparison is needed with multi-node training setups (V4, which is on the way).

Future Work

- Optimize and normalize the training dataset (V4, which is on the way).
- Optimize the network architecture.

MC performance

Classification



Project

CTLEARN-Pytorch

We use the CTLEARN pipeline, but we implement all the models using PyTorch.

We use a **Double Backbone** model.

One network per task — three tasks, three networks.

- Two EfficientNet-based models for regression: Energy and Direction.
- ThinResNet architecture used for the classification task.

Training augmentations: flipping, rotation, DVR mask … etc