

CTA Large-Sized Telescope real data analysis using convolutional neural networks

Mathieu de Bony de Lavergne, for the CTA LST project

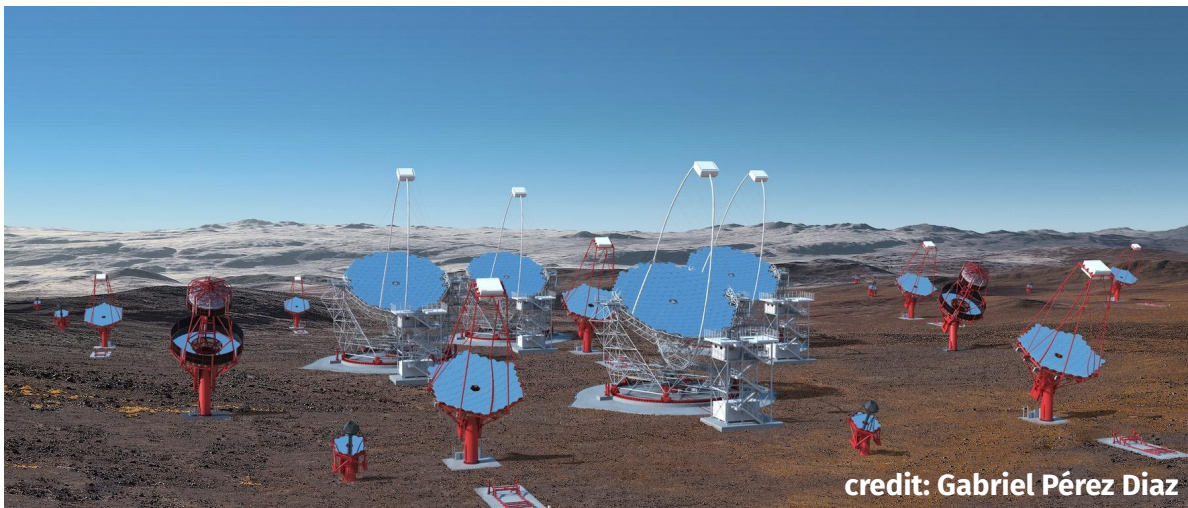
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CTA, the next generation of IACT



- 5 to 10 times better sensitivity than the current generation
- An energy range from 20 GeV up to 300 TeV
- Two sites, La Palma (Spain) and Paranal (Chile)
- Three different sizes of telescopes, specialized in energy range



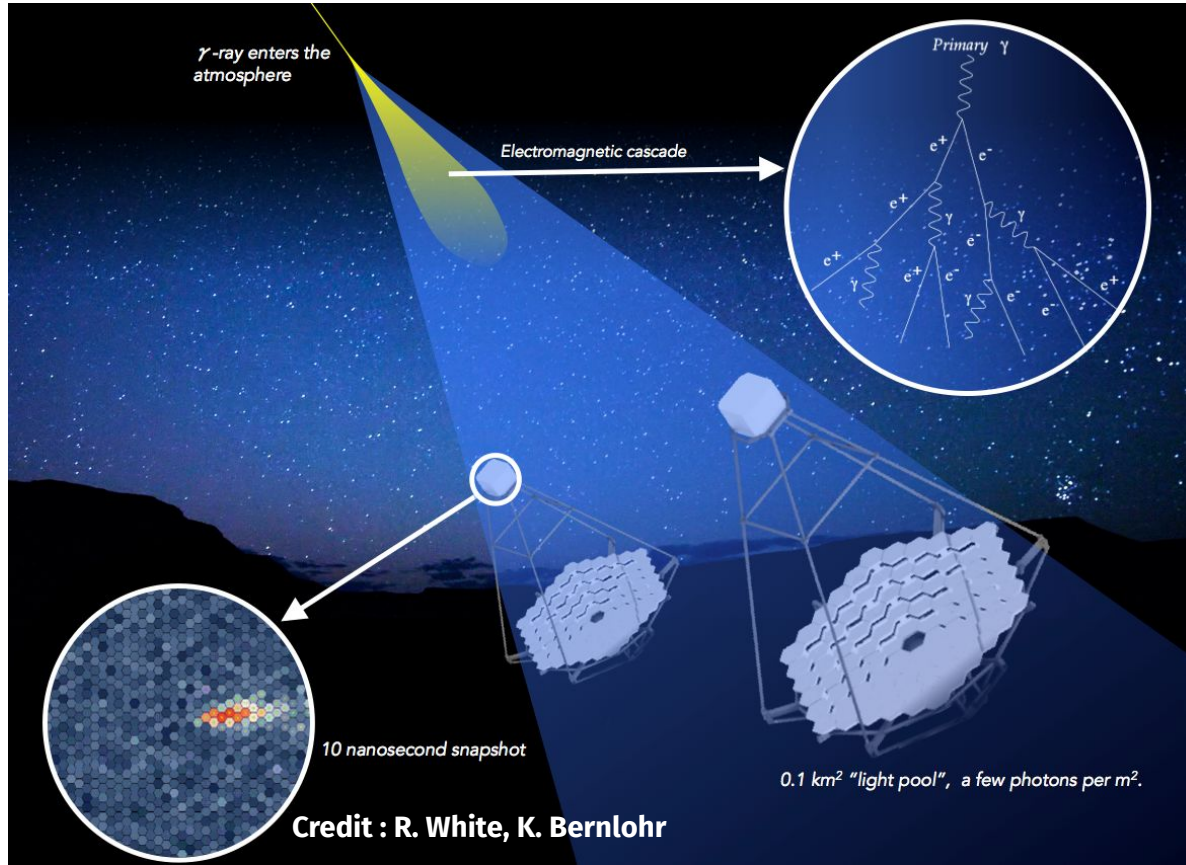
LST, a telescope focused on the low energies

- A telescope of 23m diameter
- Low energy sensitivity for CTA (20-150 GeV)
- Fast repositioning (30s)



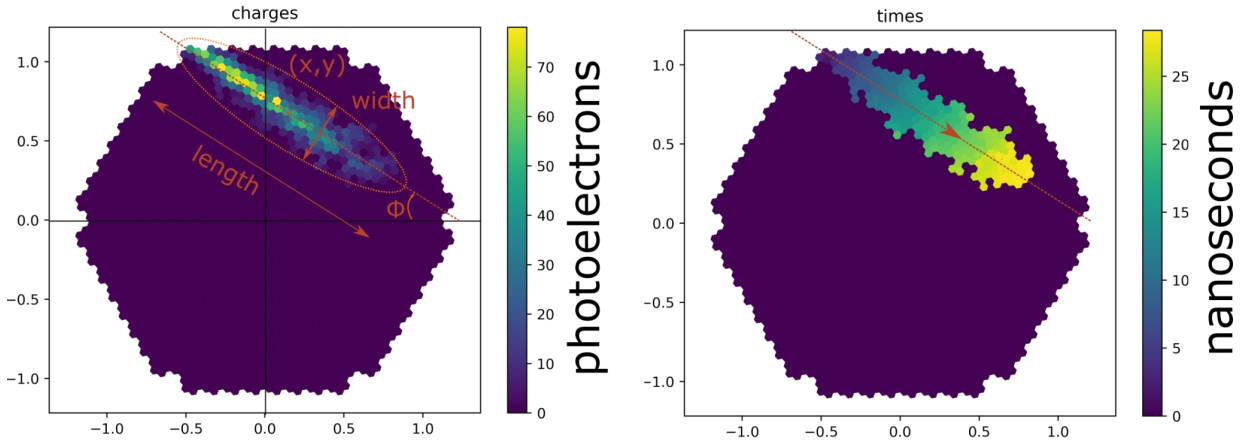
credit : Tomohiro Inada

Detection of gamma rays by IACT



Hillas + RF reconstruction

- Standard method (serves here as reference)
- Based on images parameters extraction



Images parameters
+
random forests
⇒

physical particle parameters
(type, energy, direction)

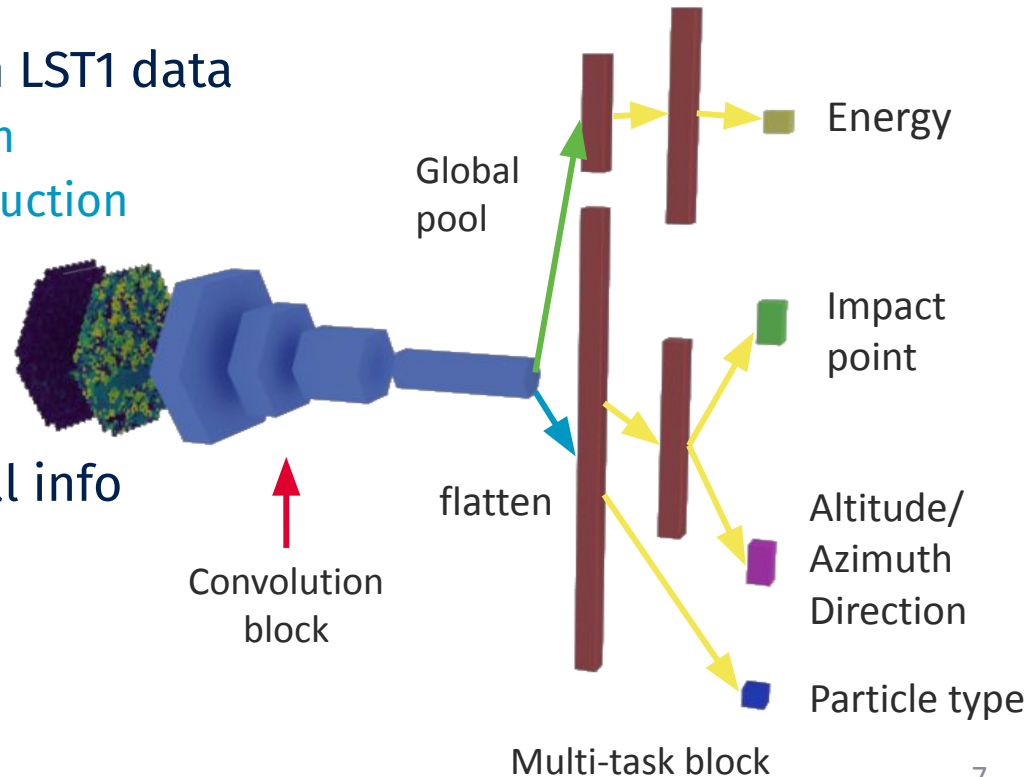
Why use deep-learning ?

- Better gamma/hadron separation
- Better angular and energy reconstruction

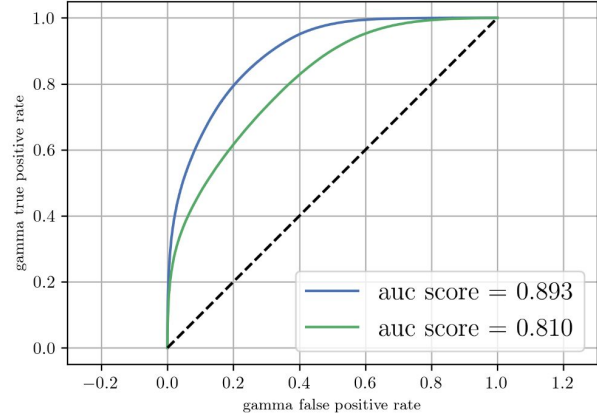
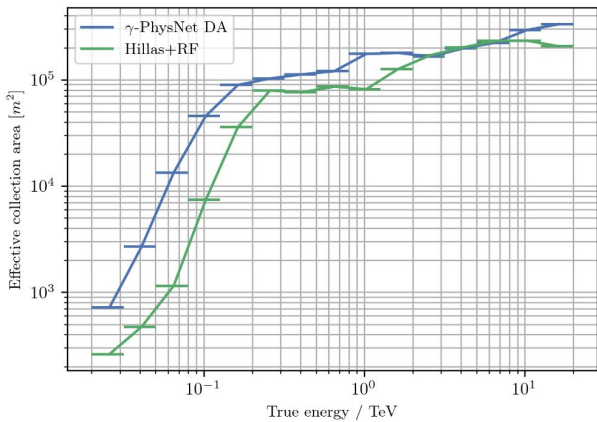
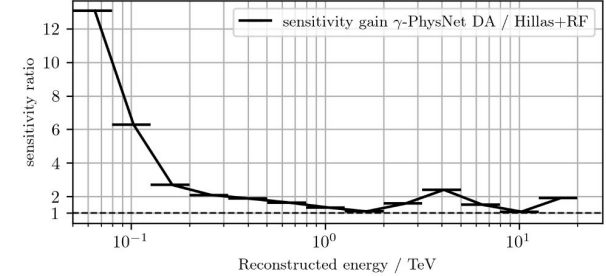
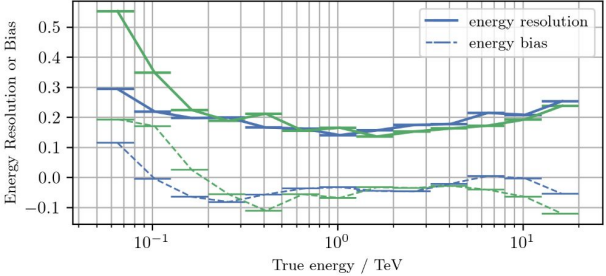
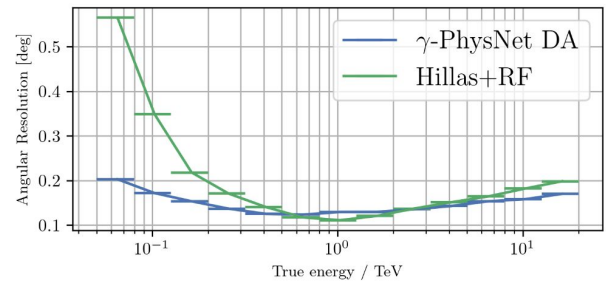
⇒ overall better sensitivity

- Fast application to data (compatible with real-time requirements)

- A single network
- Full-event reconstruction from LST1 data
 - Gamma/proton discrimination
 - Direction and energy reconstruction
- Hard parameter sharing
- Input: Image charge + temporal info
- Convolution block:
 - ResNet-56 backbone
 - Full pre-activation
 - Indexed Convolutions



Analysis of simulated data



Gains in :

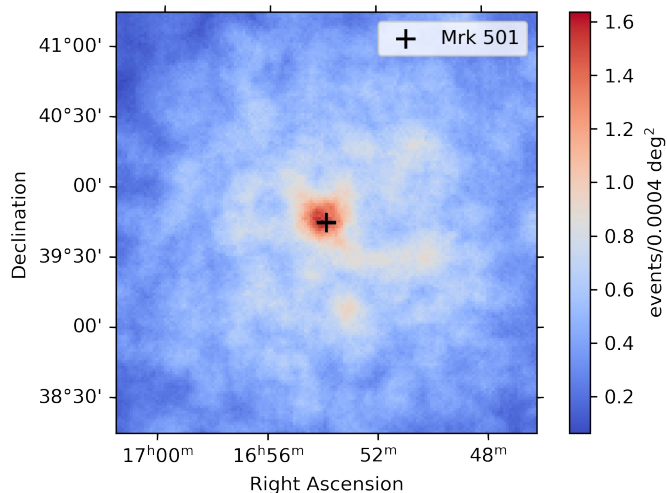
- Angular resolution
- Energy resolution
- Effective collection area
- Background rejection
- Sensitivity

Detection of Markarian 501

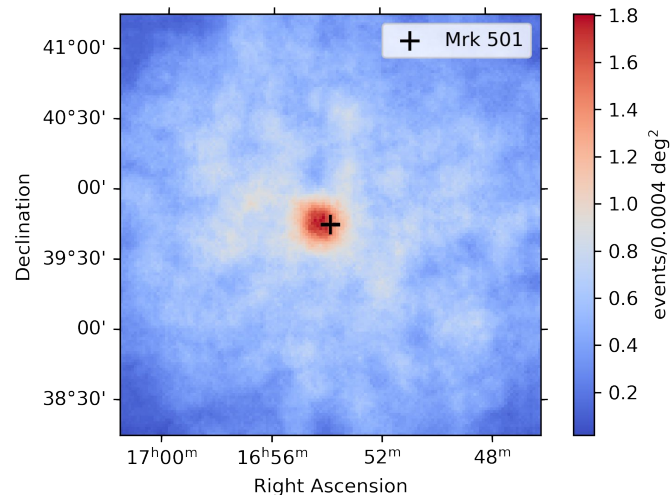


- 4 runs taken on Markarian 501 in wobble with a 0.4° offset

Smoothed Count Maps around Mrk 501



Hillas+RF

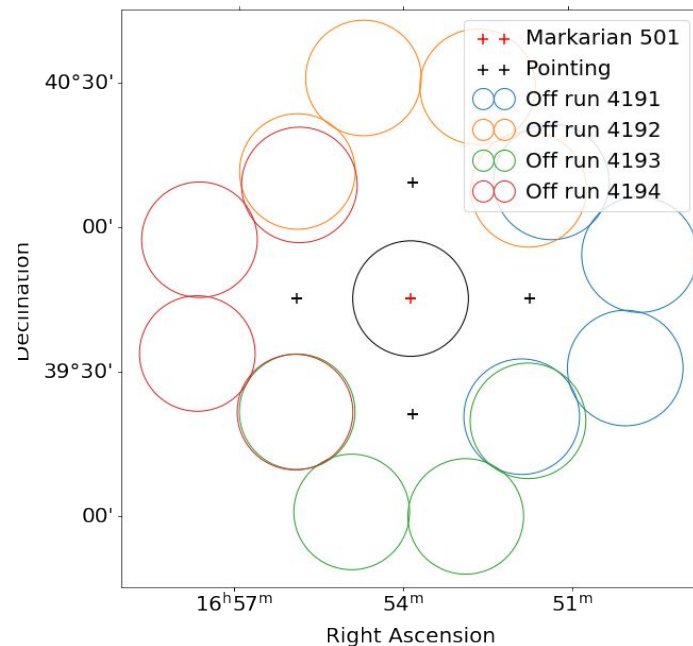


γ -PhysNet DA

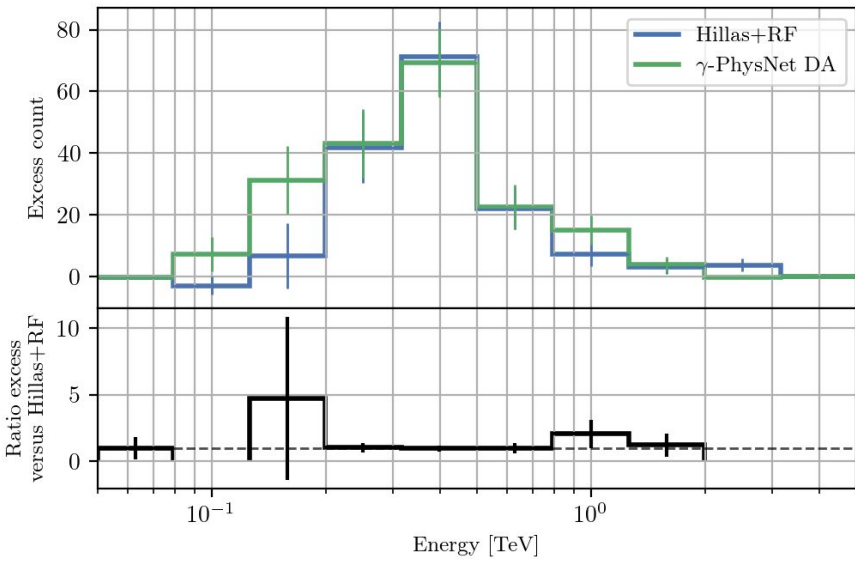
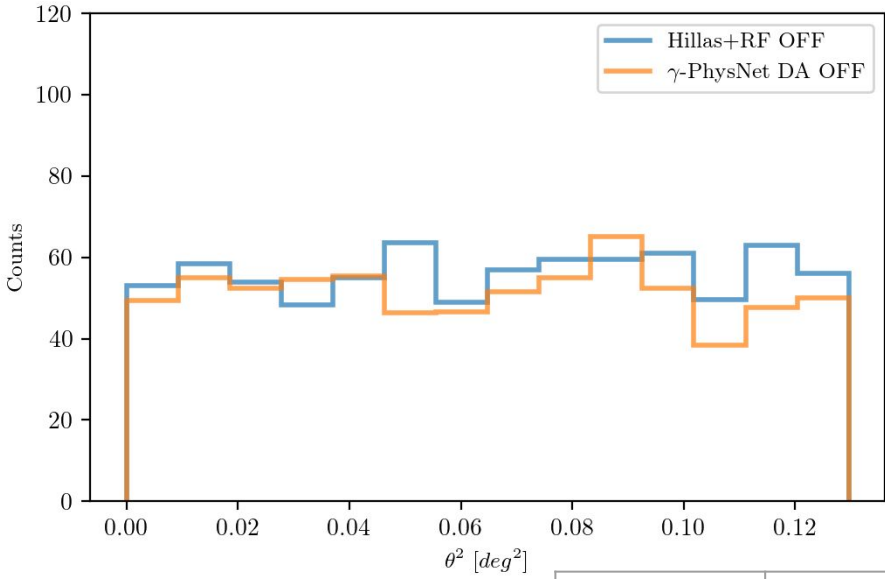
Mrk 501 - High level analysis



- Analysis performed with gammapy 0.18.2
- Multiple OFF background estimation

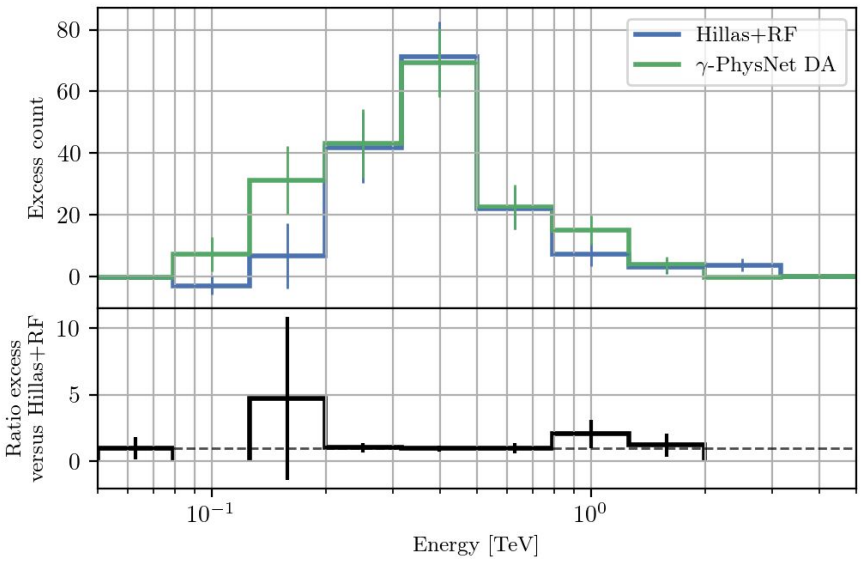
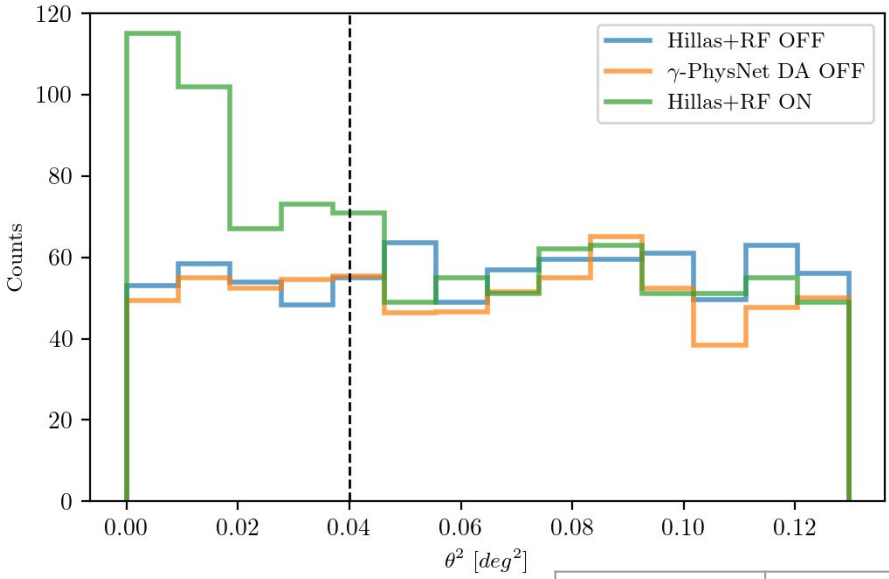


Mrk 501 - Significance



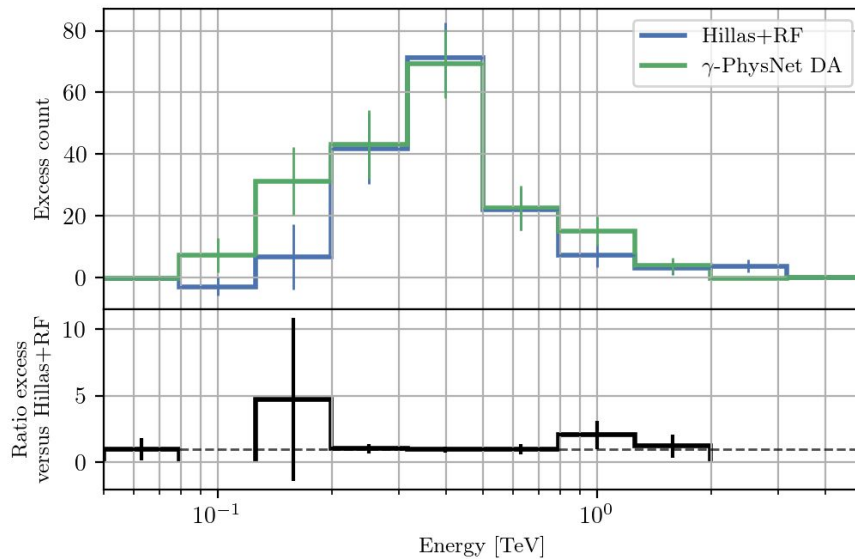
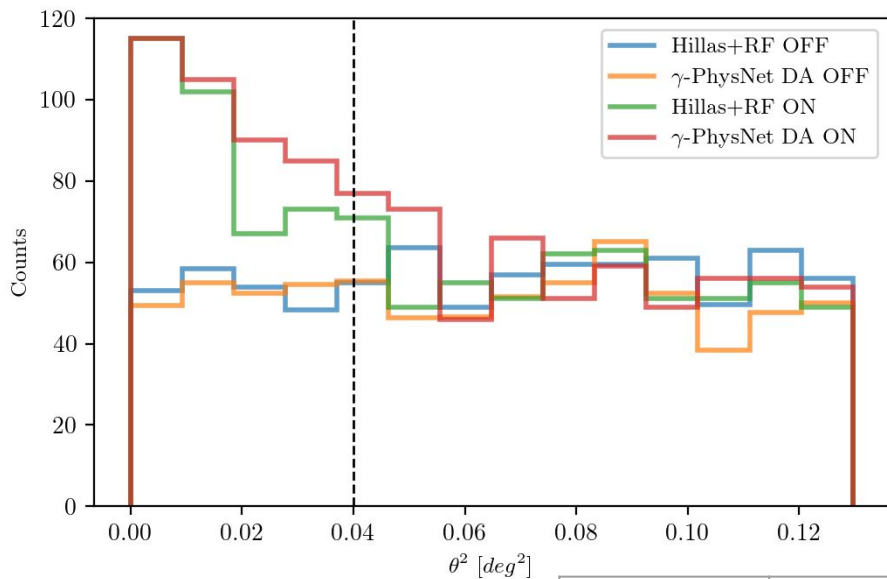
	Bkg	Excess	Significance
Hillas+RF	238.3	148.7	7.6 σ
γ -PhysNet DA	226.3	192.75	9.8 σ

Mrk 501 - Significance



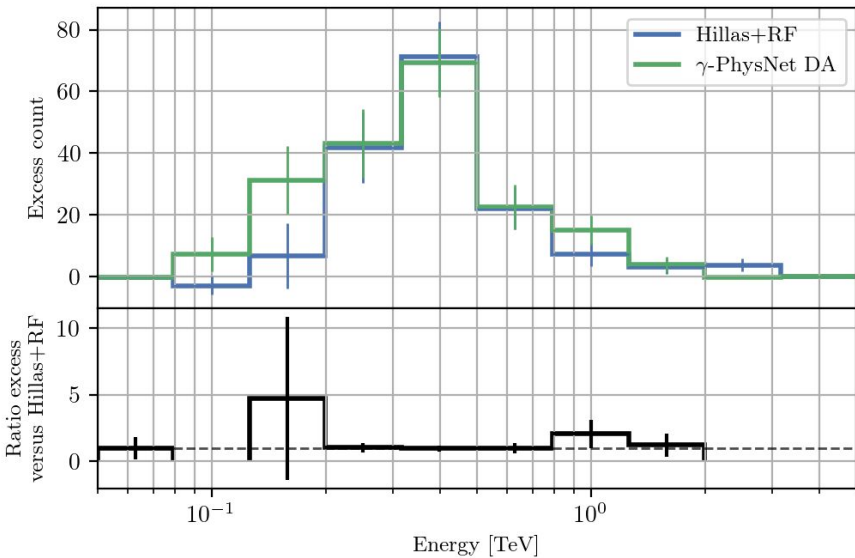
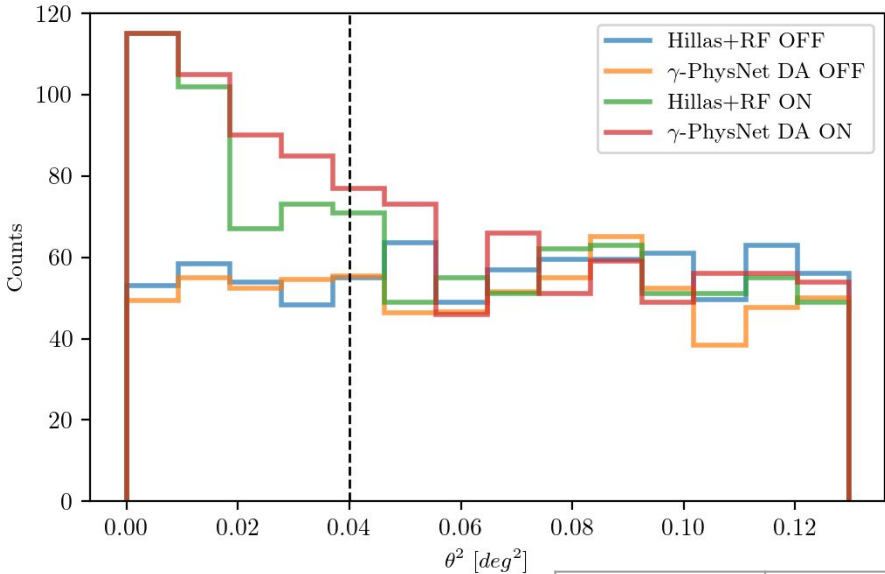
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Mrk 501 - Significance



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Mrk 501 - Significance

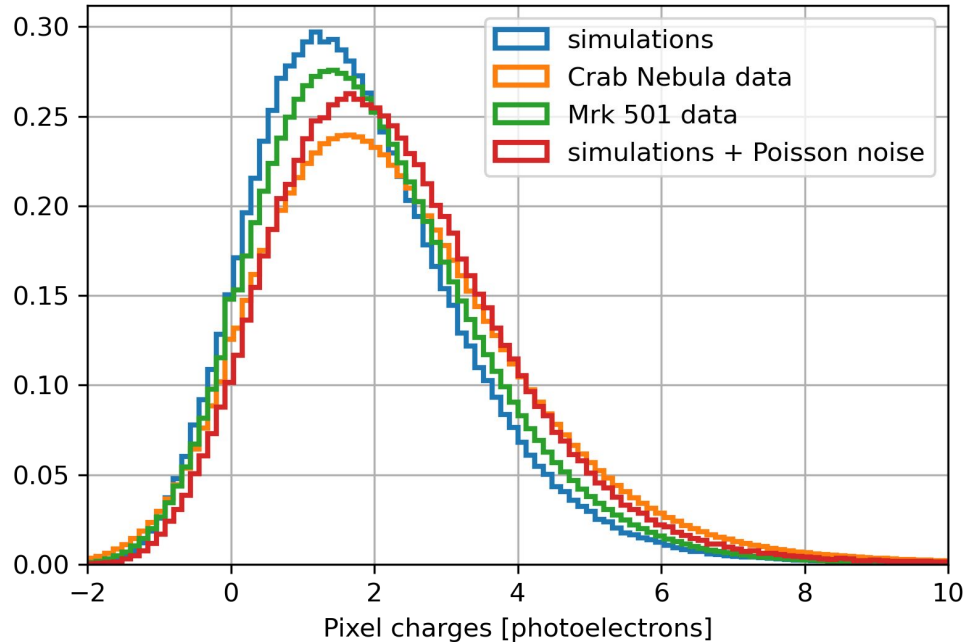


	Bkg	Excess	Significance
Hillas+RF		148.7	7.6 σ
γ -PhysNet DA	+30%	192.75	9.8 σ

Detection of the Crab Nebula

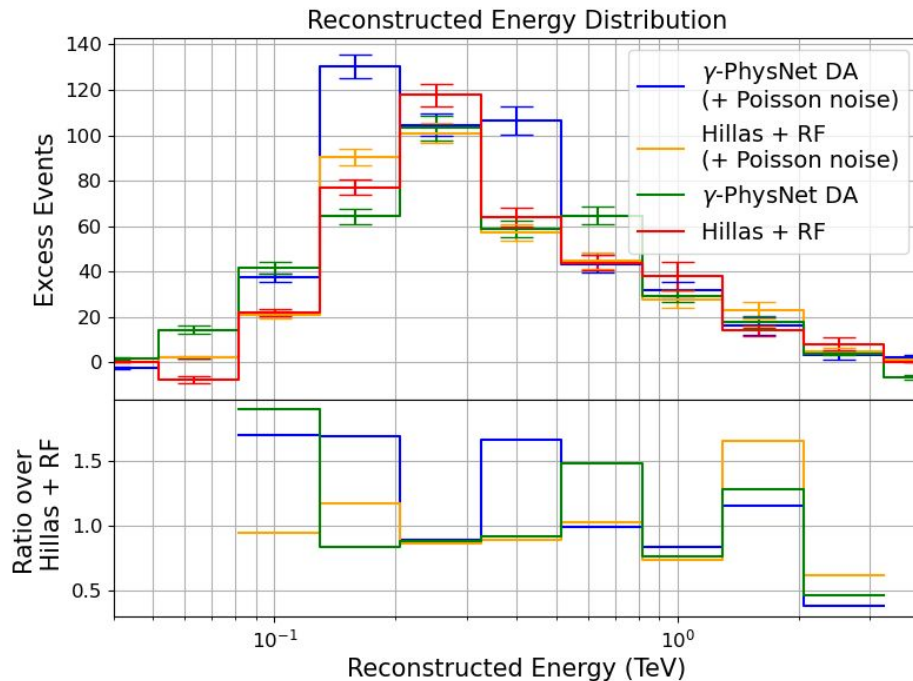
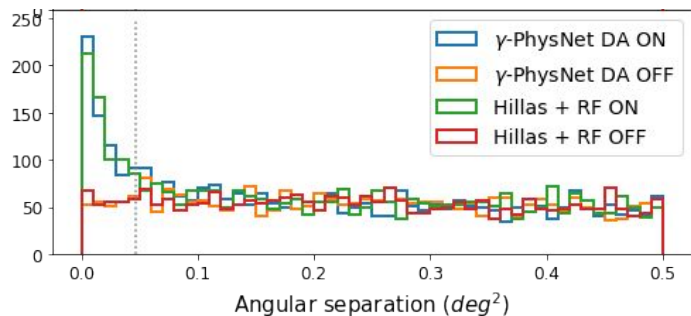


- 2 runs taken in ON/OFF mode on the Crab Nebula

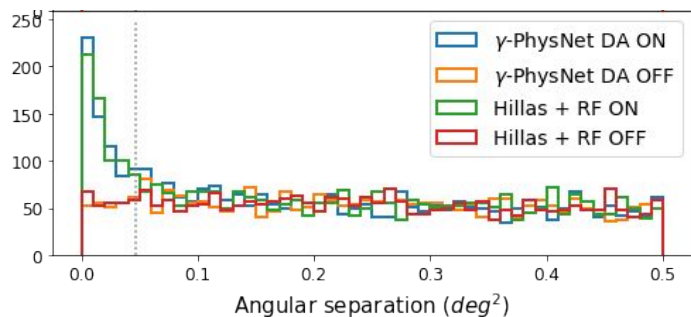


Matching Night Sky Background (noise) distributions between simulations and observations by adding poissonian noise to simulated data

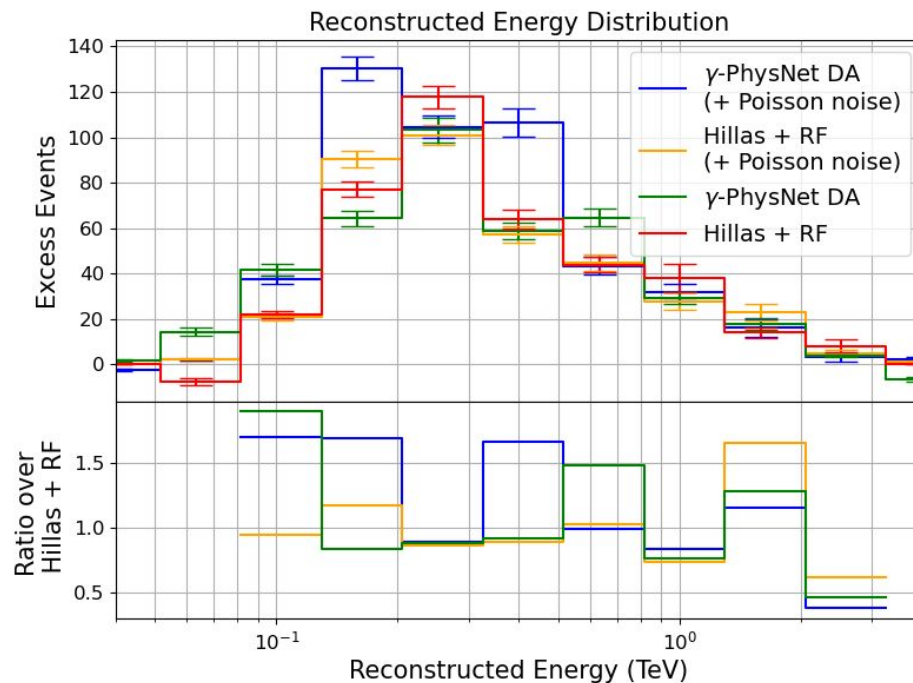
Detection of the Crab Nebula



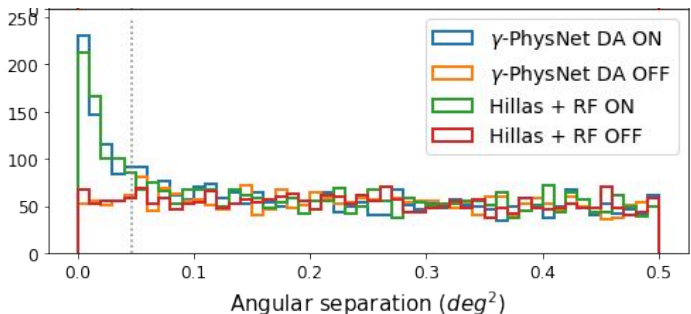
Detection of the Crab Nebula



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Hillas+RF	308	379	12.0 σ
Hillas + RF + noise	305	376	11.9 σ
γ -PhysNet DA	302	395	12.5 σ
γ -PhysNet DA + noise	317	476	14.3 σ

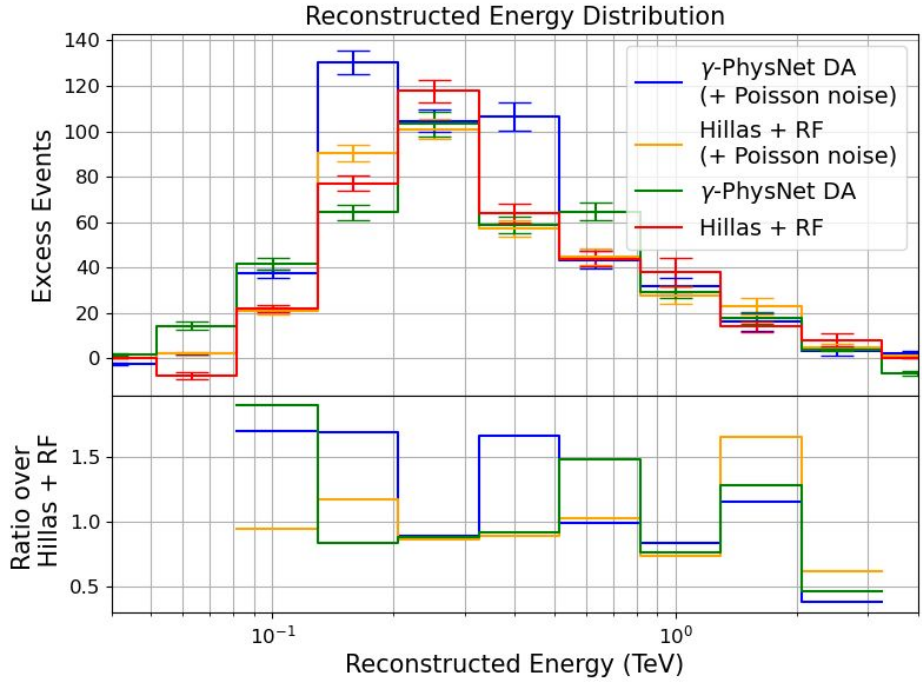


Detection of the Crab Nebula



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Hillas + RF + noise		376	11.9σ
γ -PhysNet DA	302	395	12.5σ
γ -PhysNet DA + noise	317	476	14.3σ

+26%



Results:

- Detection of two sources using convolutional neural networks on LST-1 data
- Higher sensitivity on simulated data confirmed on observed data
- Importance of close matching between simulations and observations

Future work:

- Spectral analysis
- Improve the robustness to simulations/observations differences