Laboratoire d'Annecy de Physique des Particules

Étude de l'invariance de Lorentz par analyse combinée des rayons gamma de sources et d'observatoires inhomogènes pour la recherche de nouvelle physique

Comité de suivi de thèse – 1ère année – 22 septembre 2023

Cyann Plard – Supervisée par Sami Caroff et David Sanchez

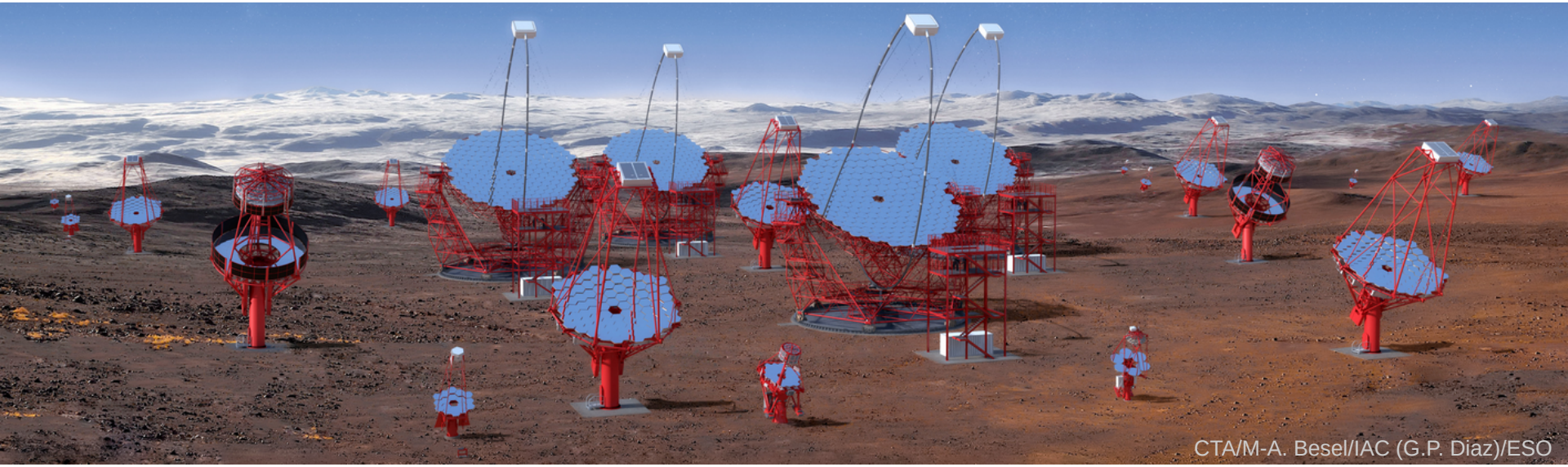
Enigmass

cnrs

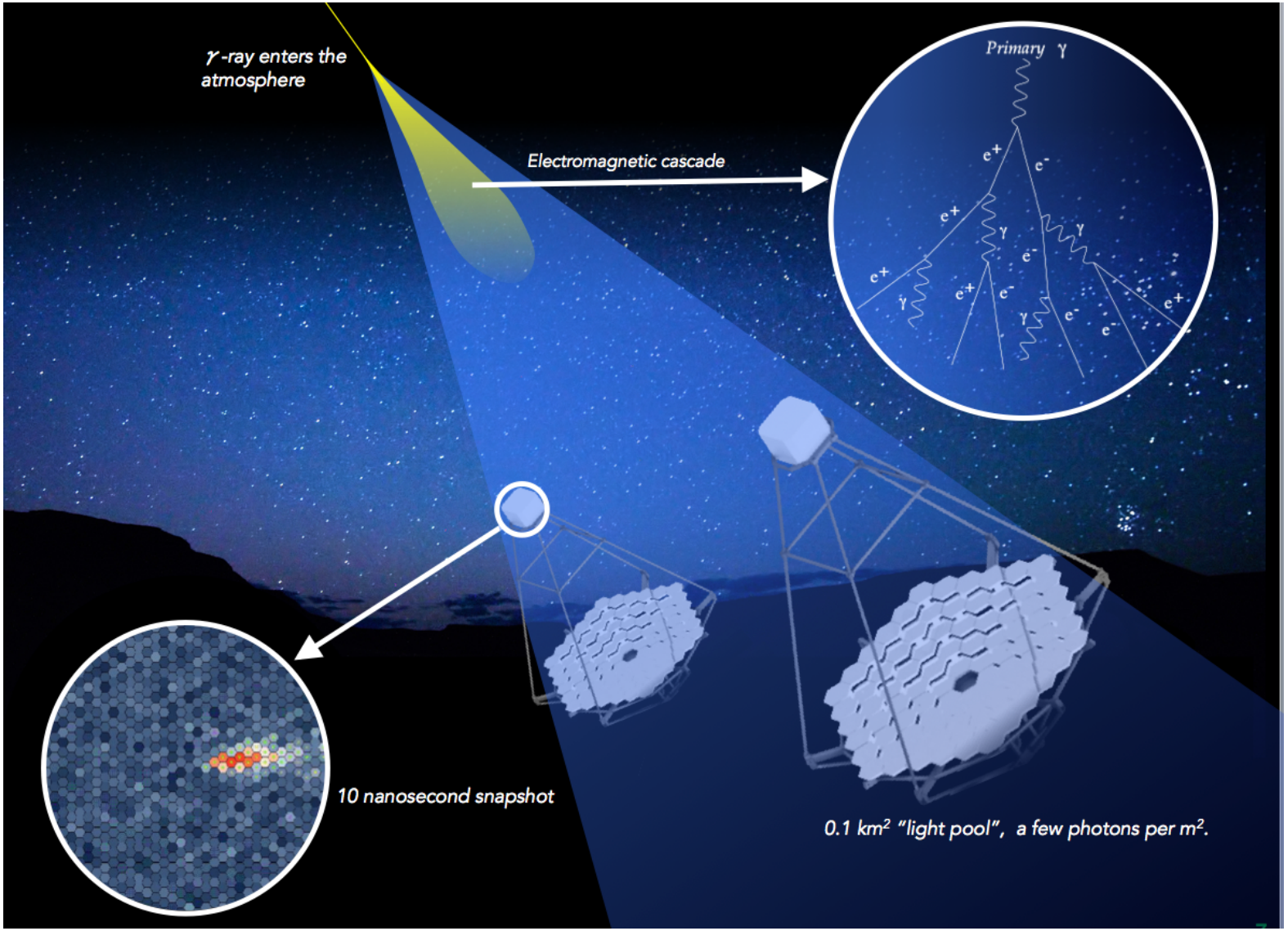
UNIVERSITÉ SAVOIE MONT BLANC

Cherenkov telescope array observatory

- Next generation of Cherenkov telescopes
- Tens of telescopes split into 2 geographic sites : North (La Palma, Spain) and South (Chile)
- 3 types of telescopes
- One telescope constructed so far : the Large-Sized Telescope-1 (LST-1)



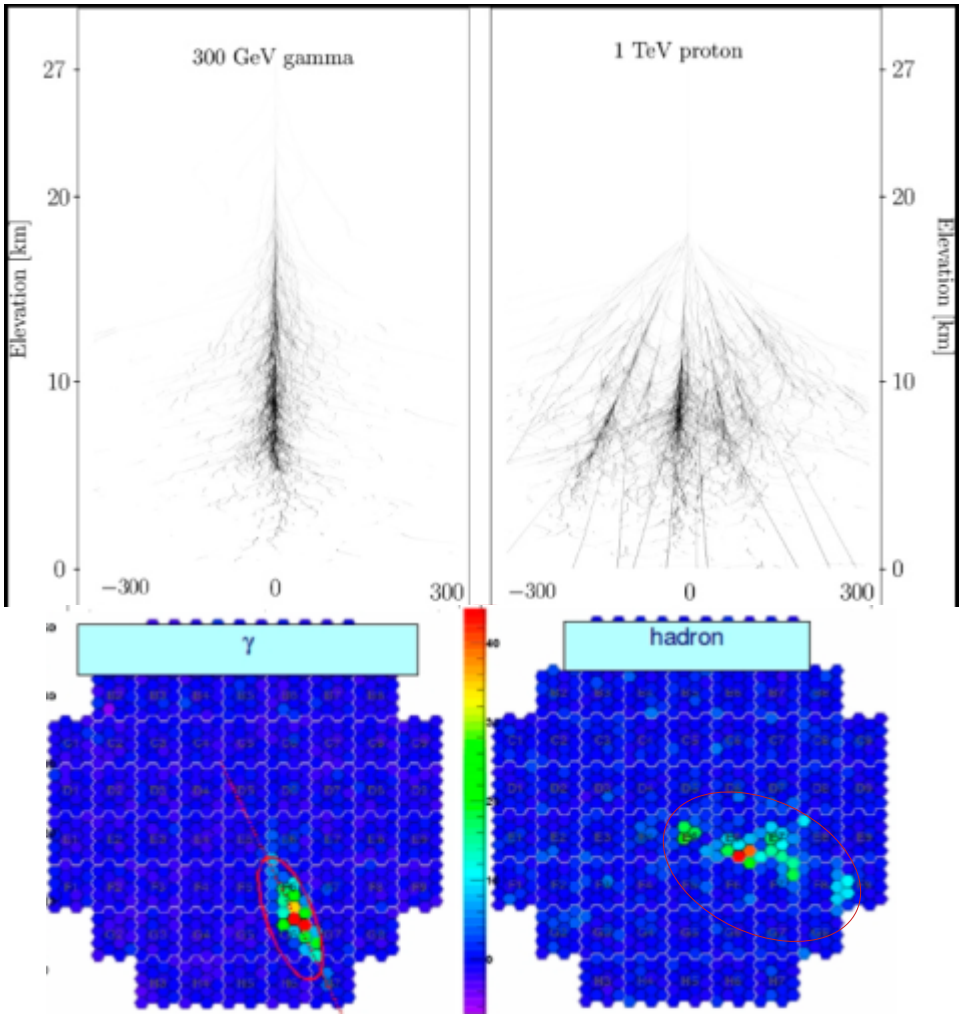
Indirect detection : Cherenkov astronomy



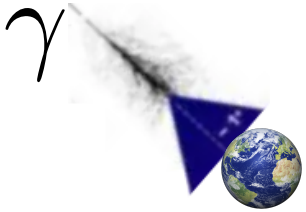
Cherenkov astronomy : hadronic background

Gamma-ray

Hadron (proton)



The data production chain



Cherenkov light

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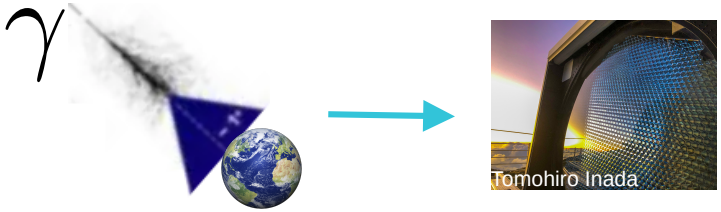
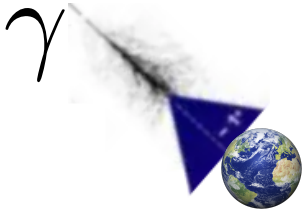


Cherenkov light

Raw data
(DL0)

The data production chain



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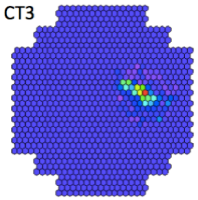

Calibration
(DL1)

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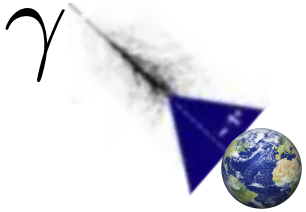

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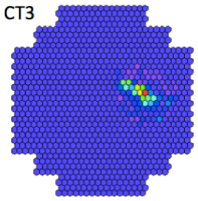

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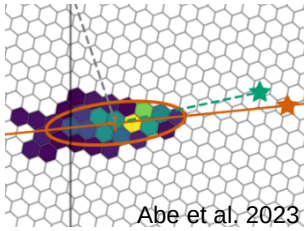
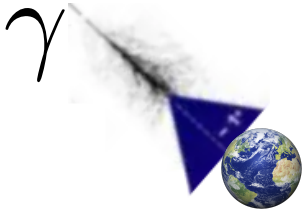


Reconstruction
(DL2)

The data production chain



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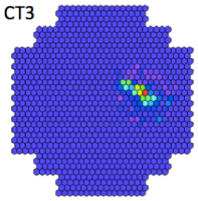

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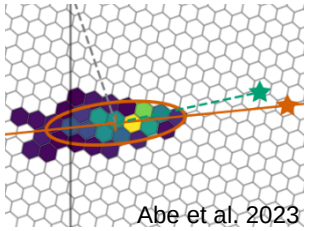

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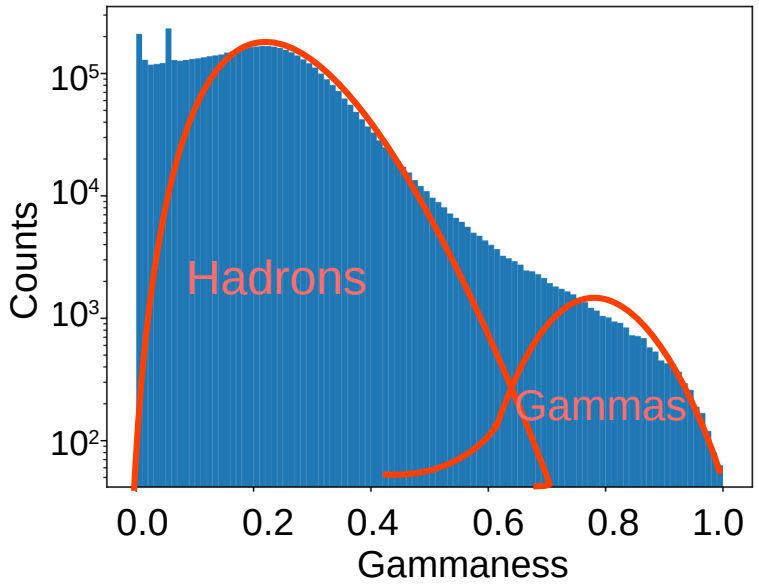
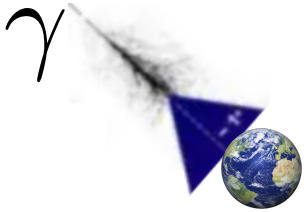


Gammaness
score indicating how likely the primary event is a gamma ray

The data production chain



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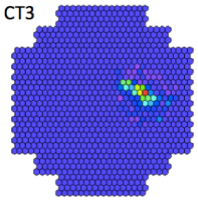

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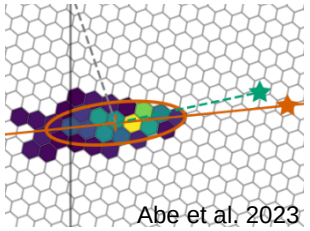

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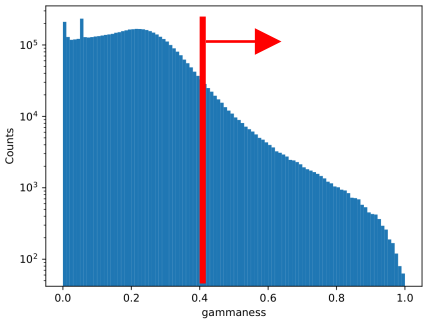
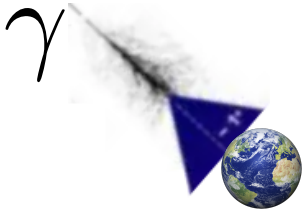


Selection (cuts) +
Instrumental response functions
(DL3)

The data production chain



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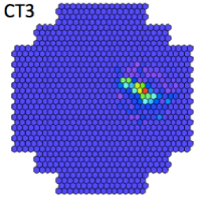

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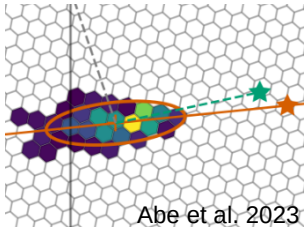
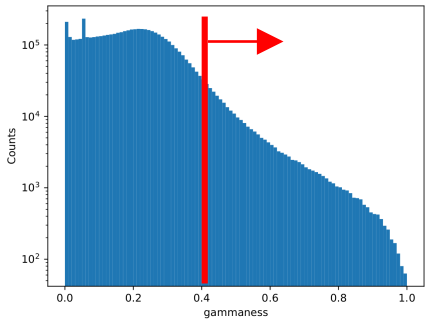


Reconstruction
(DL2)



Gammaness cut +
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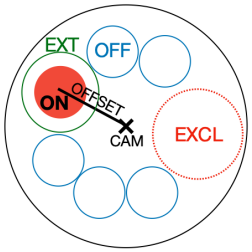
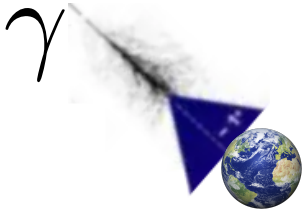


Background substraction

The data production chain



Cherenkov light

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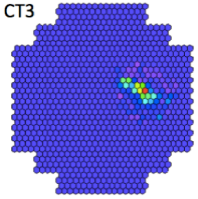

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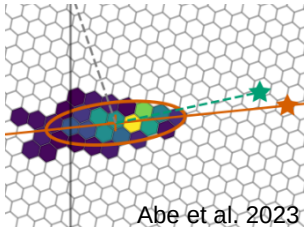

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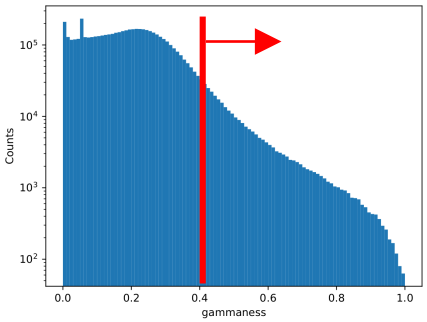

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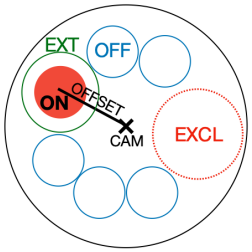

Background
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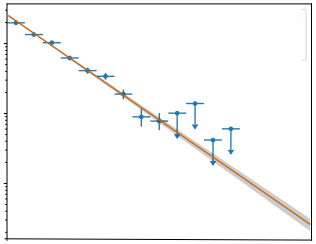
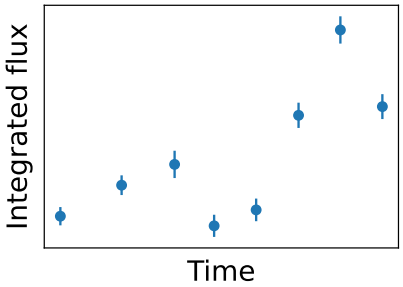
Spectra



Lightcurve



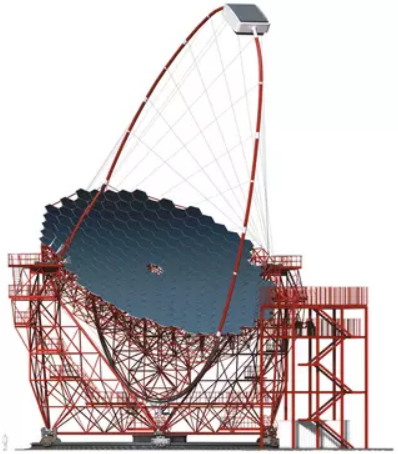
High level products

- **Main project :**

  Lorentz invariance violation study with the first data of the LST-1

- **Second project :**

  Gammalearn : deep learning applied on CTA with Michaël Dell'Aiera and Thomas Vuillaume



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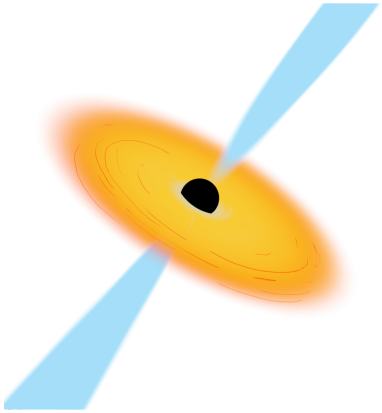

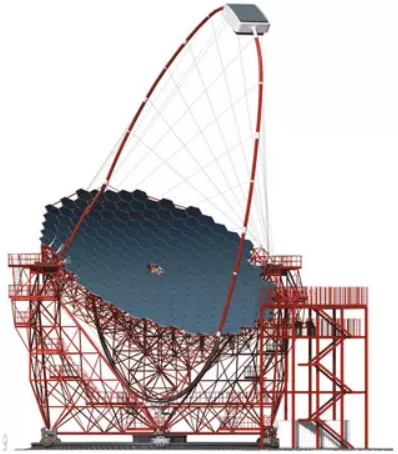

- Unification of general relativity and quantum field theory

  Difficulties at Planck scale $E_P \sim 10^{19}\mathrm{GeV}$

  → quantization of space-time

- Some quantum gravity theories allow a violation of Lorentz invariance

  → may be observable

Lorentz invariance violation (LIV)

Lorentz invariance : speed of light c in vacuum is a constant

- Quantization of space-time

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- Modification of the dispersion relation : $$E^2 = p^2c^2 \times \left[1 \pm \sum_{n=1}^{\infty} \alpha_n \left(\frac{E}{E_{QG}}\right)^n\right]$$

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↓

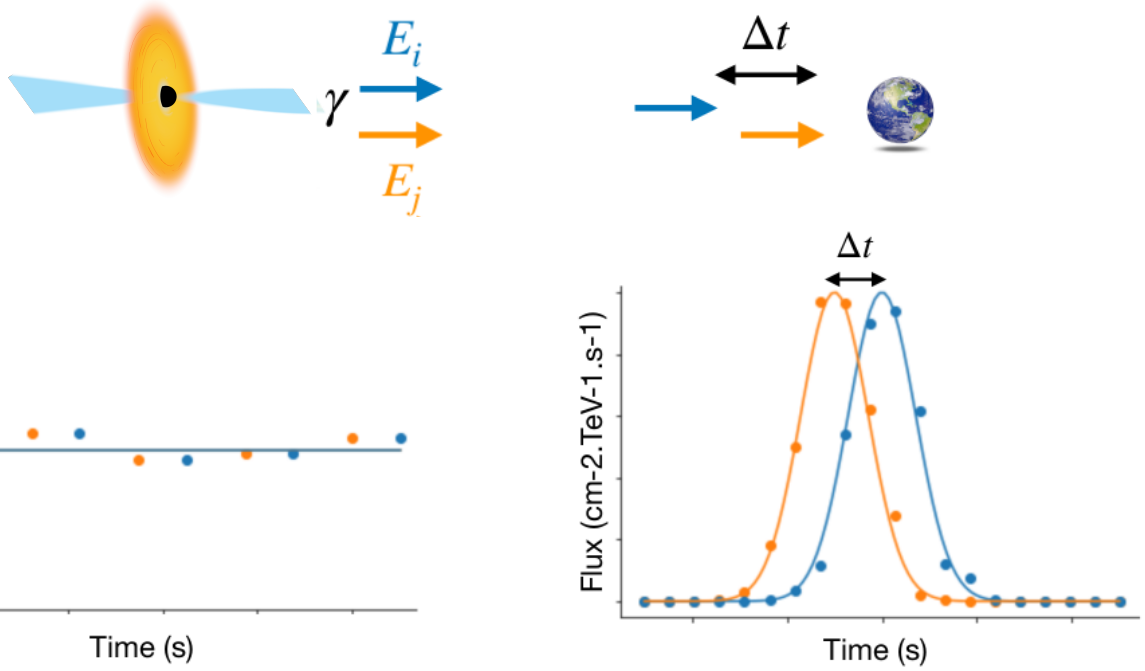
- Measurement of $\lambda_n = \frac{\Delta t_n}{\Delta E_n \kappa_n(z)} = \pm \frac{n+1}{2H_0 E_{QG}^n}$

Search for $E_{QG,lim}^n$ for $n = 1$

- Large range of energy
- Cosmological distance
- Highly variable and active source

$$\Delta t = \pm \frac{n+1}{2} \frac{\Delta E^n}{E^n_{QG}} \times \kappa_n(z)$$

→ Blazars, gamma-ray bursts, pulsars



Intrinsic source delay

- No guarantee that photons are emitted at the same time

  → Intrinsic source delay :

$$\Delta t = \Delta t_{LIV} + \Delta t_{source}$$

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  - Intrinsic source delay : redshift-independent, source and flare-dependent (stochastic)
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→ Combination of different flares and different sources

Consortium between different experiments : H.E.S.S., MAGIC, VERITAS, LST-1

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→ None of these delays have been observed at TeV scale

Analysis : step 1

All blazar data of LST-1 until June 2023

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All blazar data of LST-1 until June 2023

↓

Variability test on each significant observation night

Constant fit :
pvalue < 5σ ?

Analysis : step 2

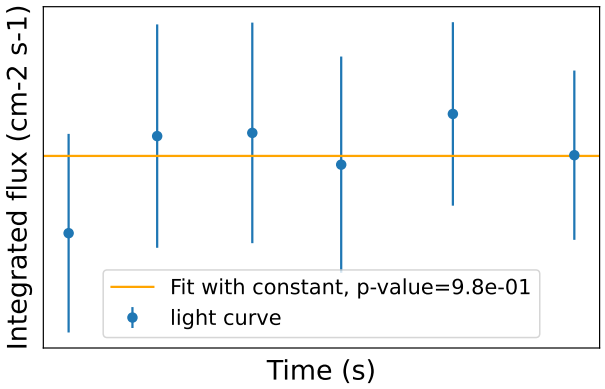
All blazar data of LST-1 until June 2023

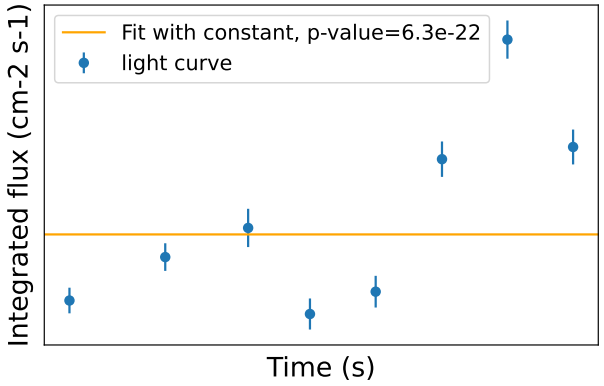
Variability test on each significant observation night

Non-variable sample

Constant fit : pvalue < 5σ ?

Variable sample

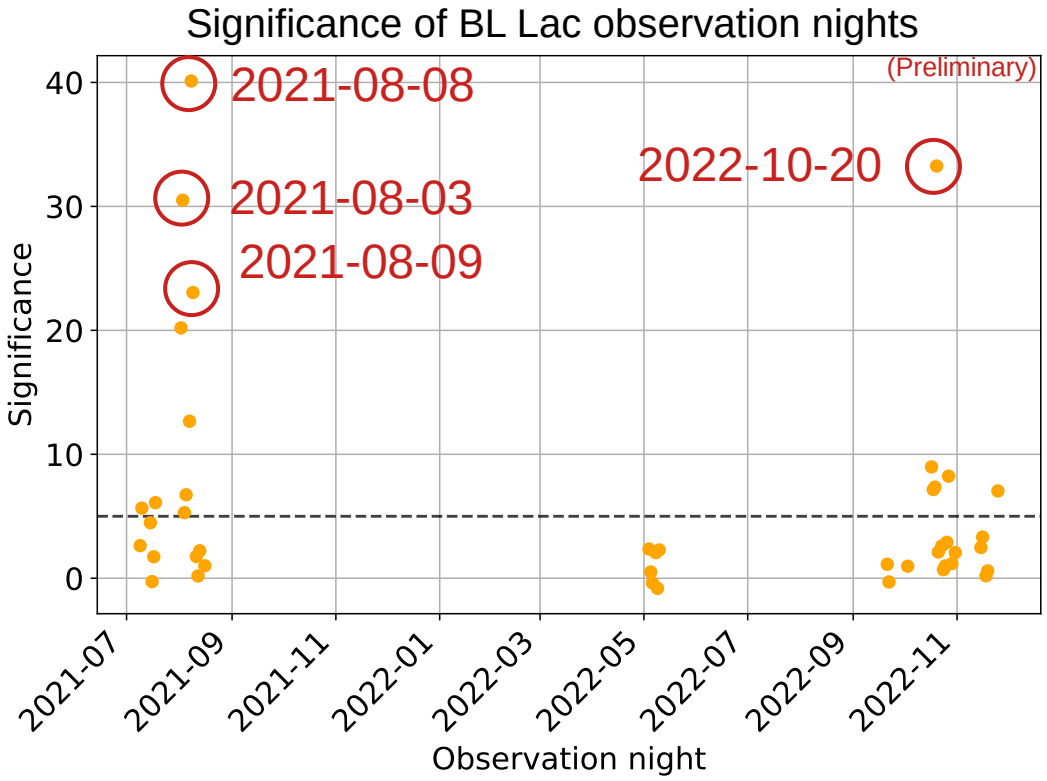




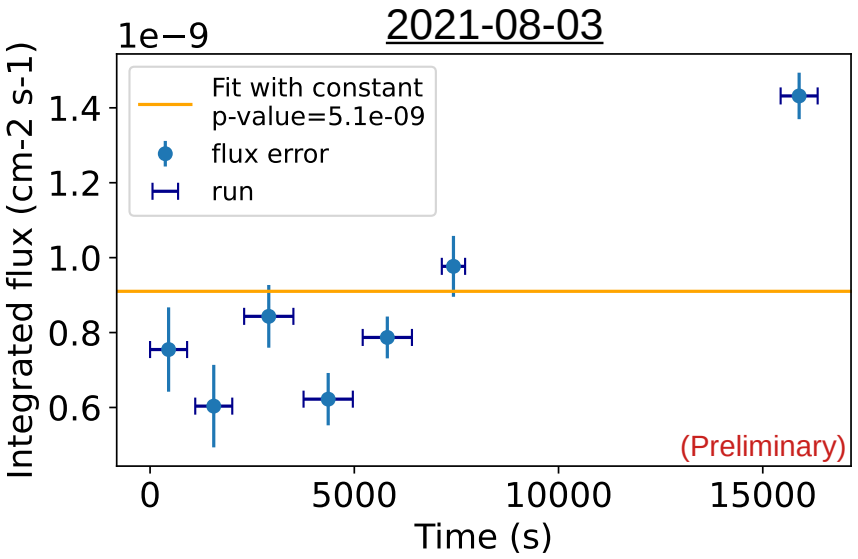
Step 1 : variable nights

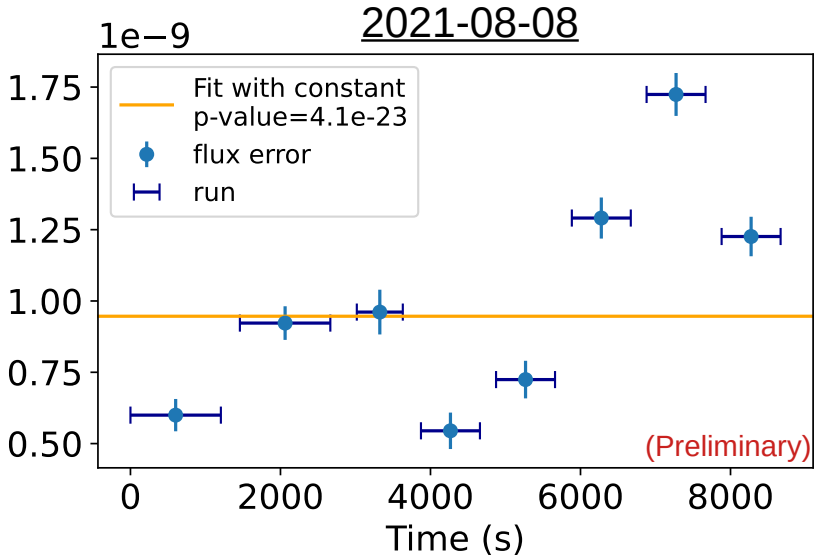
All blazar data of LST-1 until June 2023

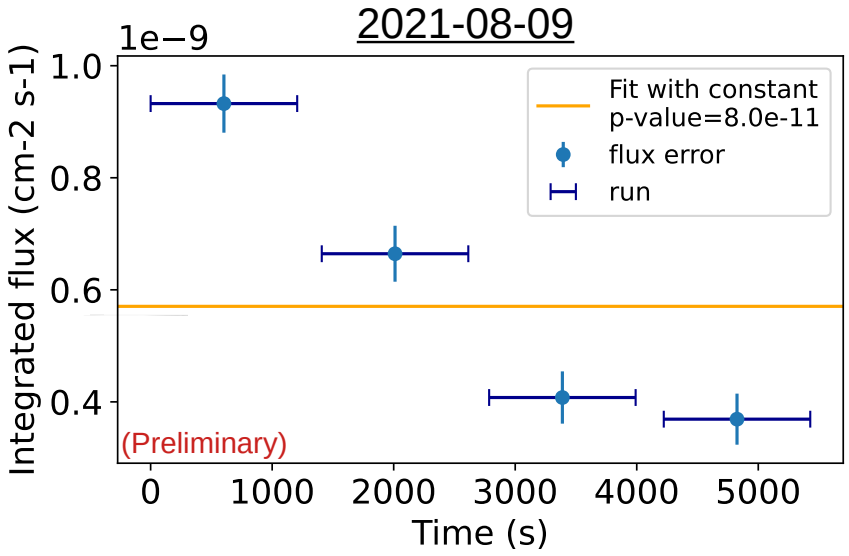
Found 1 variable source : BL Lacertae, redshift 0.069 with 4 variable nights

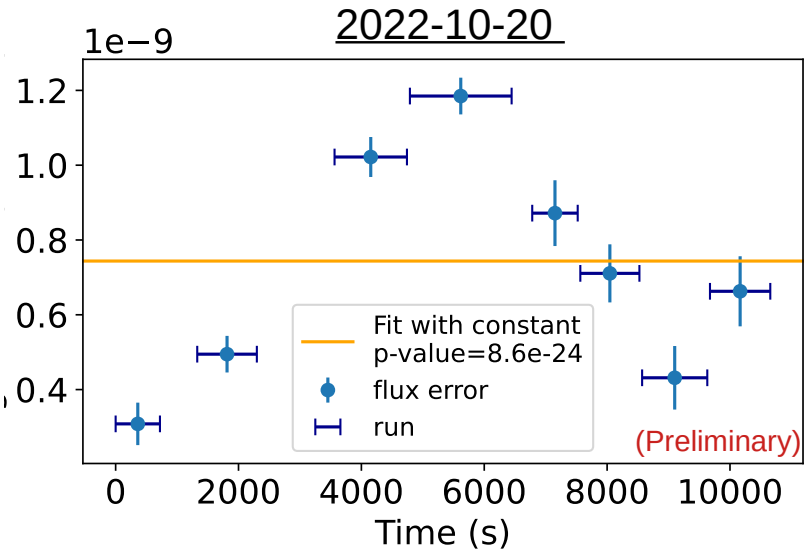


Lightcurves of BL Lac variable nights









Analysis : step 2

All blazar data of LST-1 until June 2023

Variability test on each significant observation night

Non-variable sample

Constant fit
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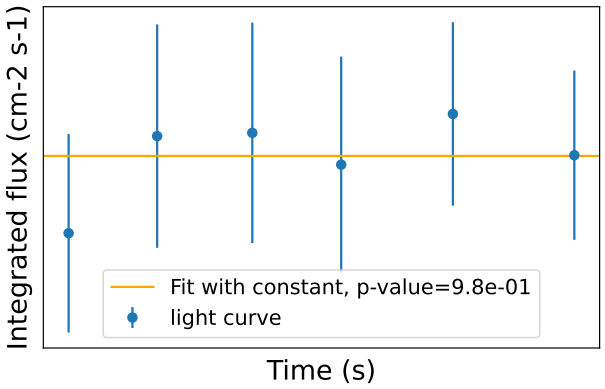
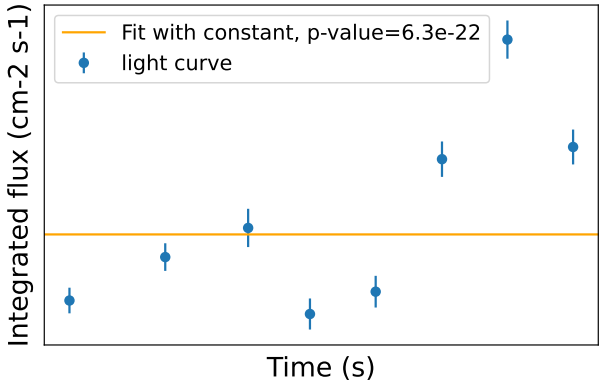
Variable sample





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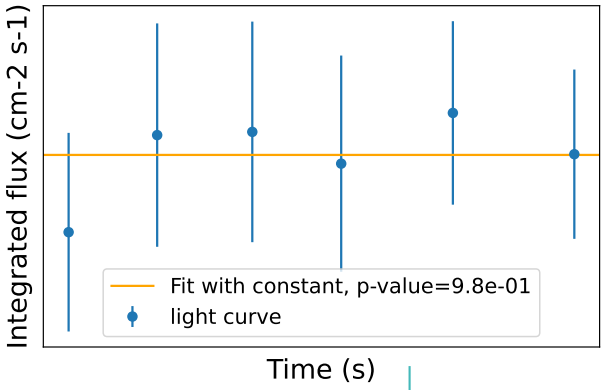
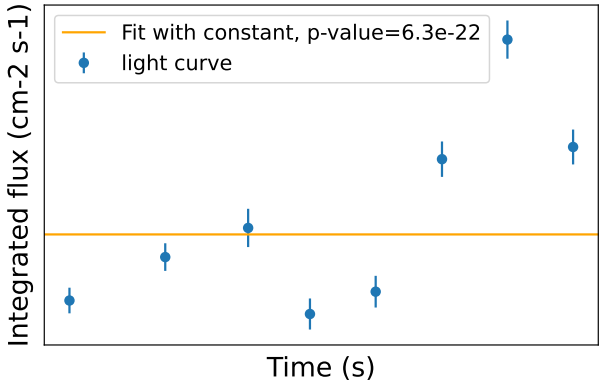
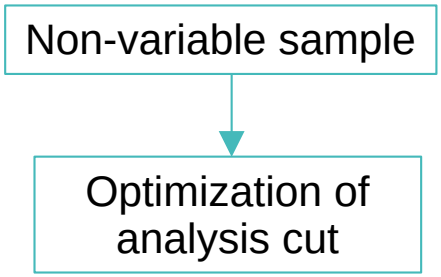




Optimization of analysis cut

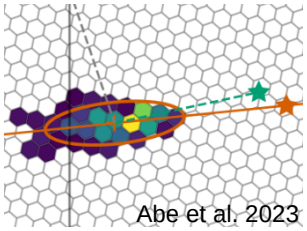
Step 2 : cut optimization



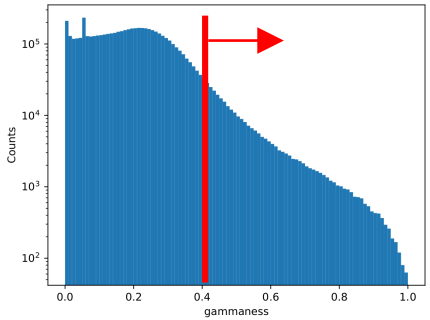
Step 2 : cut optimization

Non-variable sample

Optimization of analysis cut



Reconstruction (DL2)



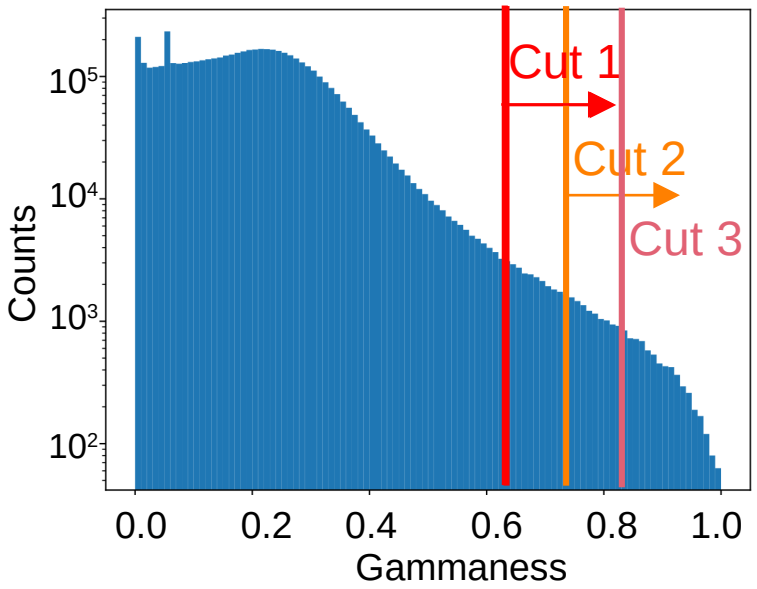
Gammaness cut (DL3)

Step 2 : cut optimization

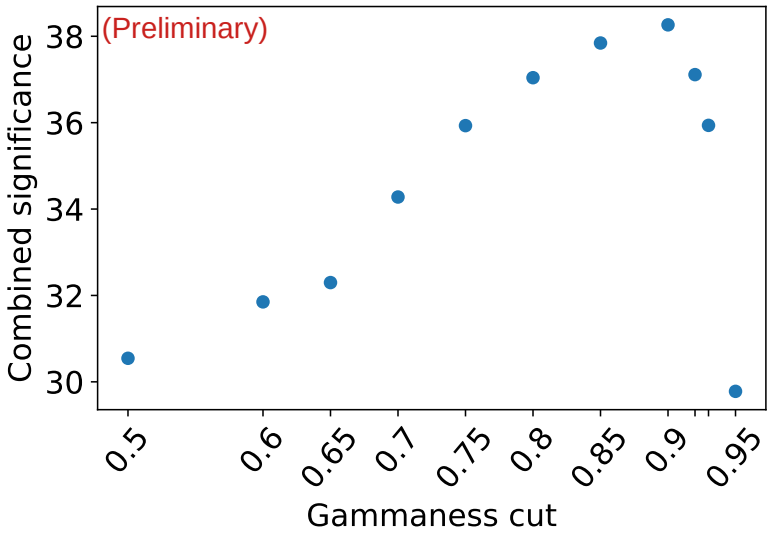
Non-variable sample

↓

Select different gammaness cuts and search for the significance



BL Lac



$$S_{cut} = \sqrt{\sum_{non-var\ night} S_n^2}$$

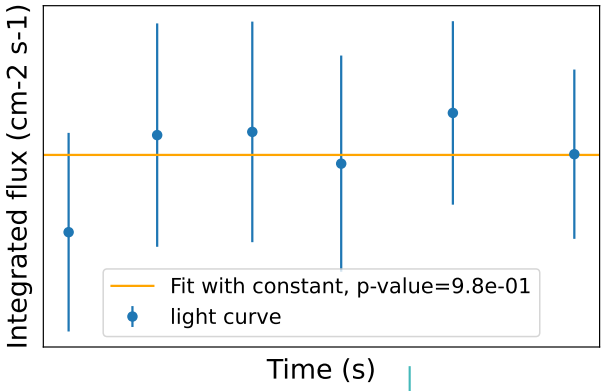
Analysis : step 3

All blazar data of LST-1 until June 2023

Variability test on each significant observation night

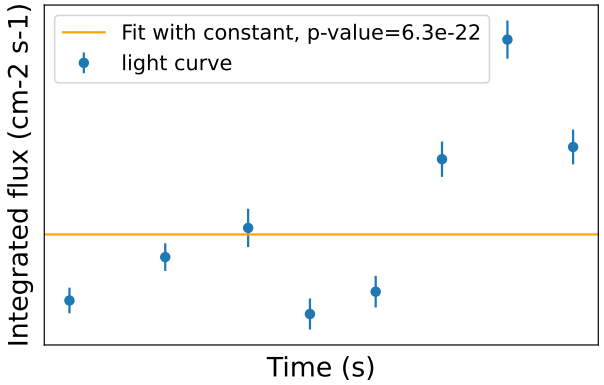
Constant fit pvalue < 5σ ?

Non variable sample



Optimization of analysis cut : 0.9

Variable sample



Analysis : step 3

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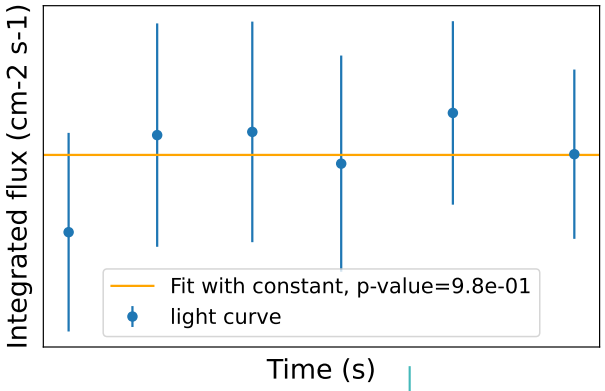

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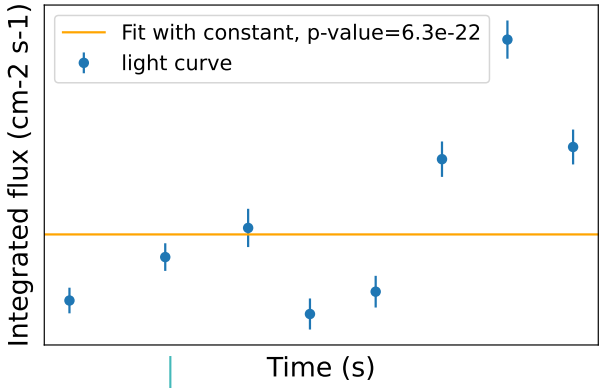
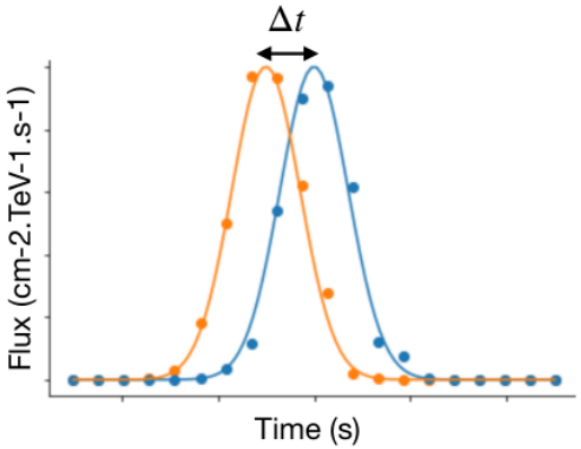


Search for a variability template and extract sample properties (energetic and temporal distributions)

Step 3 : variability pattern

Search for a variability template and extract sample properties (energetic and temporal distributions)

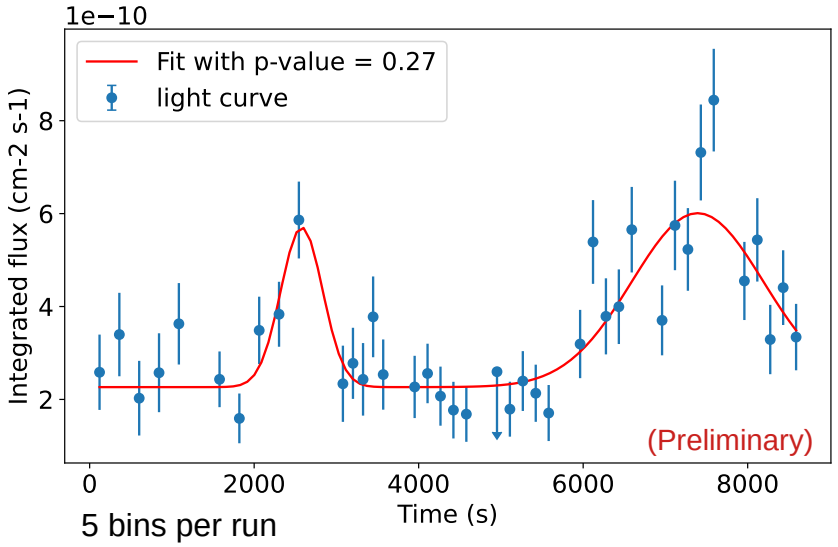
- Define two energy bins : **lower** and **higher** than median of counts
- Find a parametric model for the lightcurve of the low energies sample : selected if p-value > 0.05 (2σ)
- No significant disagreement between low and high energies
- No significant time-variation of spectra (flux vs energy) parameters



Step 3 : variability pattern

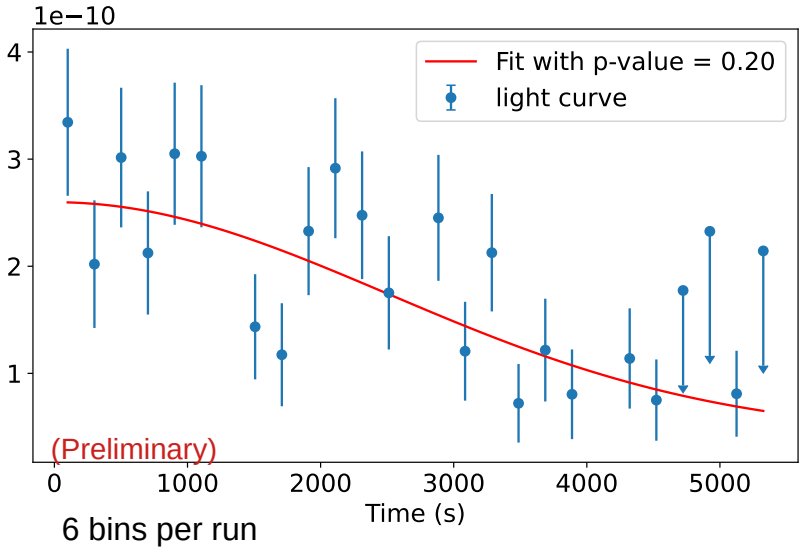
Parametric models of the low energies variability

BL Lac 2021-08-08



5 bins per run

BL Lac 2021-08-09



6 bins per run

$$f(t) = A_1 e^{-\frac{(t-\mu_1)^2}{2\sigma_1^2}} + A_2 e^{-\frac{(t-\mu_2)^2}{2\sigma_1^2}} + C_0$$

$$g(t) = A e^{-\frac{(t-\mu)^2}{2\sigma^2}} + C$$

p-value > 0.05 (2σ)

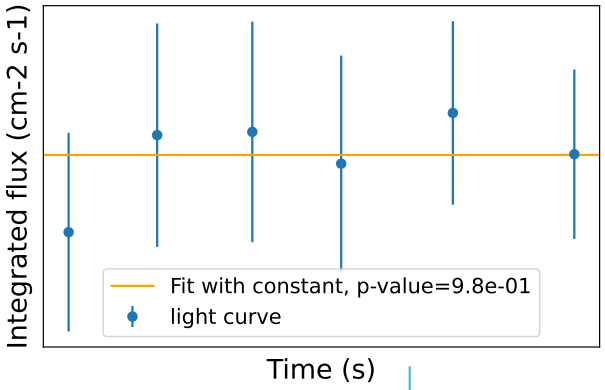
Analysis : step 4

All blazar data of LST-1 until June 2023

Variability test on each significant observation night

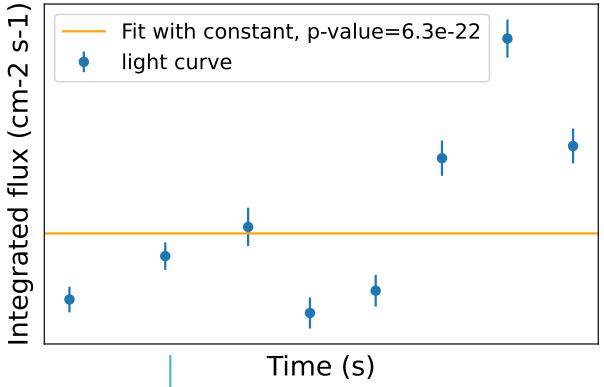
Constant fit pvalue < 5σ ?

Non-variable sample



Optimization of analysis cut : 0.9

Variable sample



Search for a variability template and extract sample properties (energetic and temporal distributions)

Analysis : step 4

All blazar data of LST-1 until June 2023

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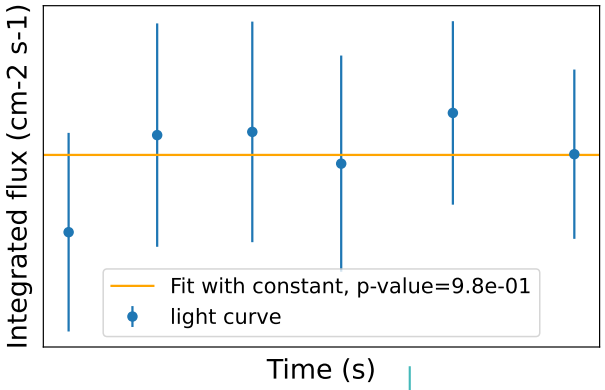

Optimization of analysis cut : 0.9

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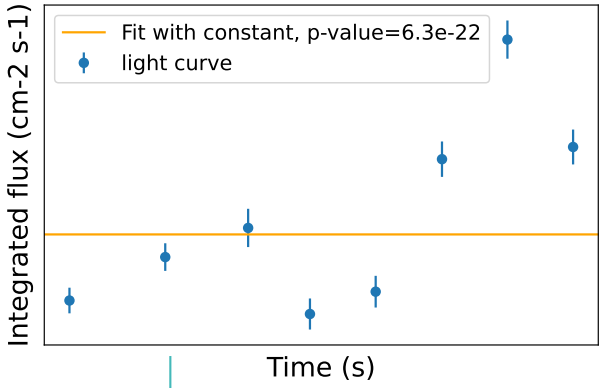


Search for a variability template and extract sample properties (energetic and temporal distributions)

Sample simulations to validate LIV analysis

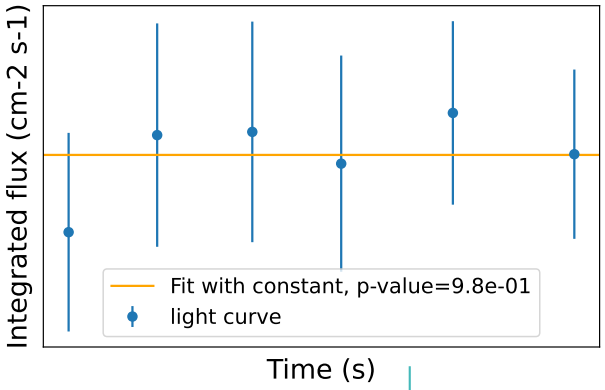
Analysis : step 4

All blazar data of LST-1 until June 2023

Variability test on each significant observation night

Constant fit pvalue < 5σ ?

Non-variable sample



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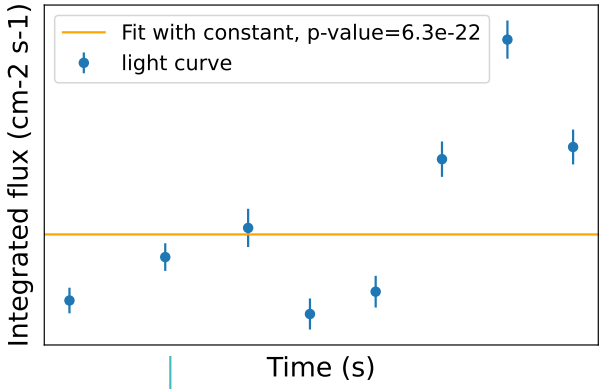
Variable sample



Search for a variability template and extract sample properties (energetic and temporal distributions)

Sample simulations to validate LIV analysis

LIV analysis on real data with the variability template

Sample simulations to validate LIV analysis

LIV analysis on real data with the variability template

LIVelihood

- Code developped for time lag study and combination of different experiments data
- Uses the likelihood method :
  the time lag is a free parameter that can be shared between sources with different redshift and that minimizes the likelihood function :

$$\mathcal{L}(\lambda_n) = -\sum_{\text{event}\ \mathbf{i}} \log\left(\frac{dP(E_{R,\mathbf{i}}, t_{\mathbf{i}}; \lambda_n)}{dE_R dt}\right)$$

Step 4 : Likelihood method

Lag λ_n : free parameter, can be shared between sources with different redshifts

For one night : $$\mathcal{L}(\lambda_n) = -\sum_{\text{event i}} \log\left(\frac{dP(E_{R,\mathbf{i}}, t_{\mathbf{i}}; \lambda_n)}{dE_R dt}\right)$$

with $$\frac{dP}{dE_R dt} = W_s \frac{\int \mathrm{E_{ff}A}(E_T, \vec{\epsilon})\mathrm{MM}(E_T, E_R) \times \mathrm{F}_s(E_T, t; \lambda_n) dE_T}{N'_s}$$

$$+ \sum_k W_{b,k} \frac{\int \mathrm{E_{ff}A}(E_T, \vec{\epsilon})\mathrm{MM}(E_T, E_R) \times \mathrm{F}_{b,k}(E_T) dE_T}{N'_{b,k}}$$

Step 4 : Likelihood method

Lag λ_n : free parameter, can be shared between sources with different redshifts

For one night : $$\mathcal{L}(\lambda_n) = -\sum_i \log\left(\frac{dP(E_{R,i}, t_i; \lambda_n)}{dE_R dt}\right)$$

with $$\frac{dP}{dE_R dt} = W_{\mathbf{s}} \frac{\int \mathrm{E_{ff}A}(E_T, \vec{\epsilon})\mathrm{MM}(E_T, E_R) \times \mathrm{F_{\mathbf{s}}}(E_T, t; \lambda_n) dE_T}{N'_{\mathbf{s}}}$$

Signal

$$+ \sum_{\mathbf{k}} W_{\mathbf{b,k}} \frac{\int \mathrm{E_{ff}A}(E_T, \vec{\epsilon})\mathrm{MM}(E_T, E_R) \times \mathrm{F_{\mathbf{b,k}}}(E_T) dE_T}{N'_{\mathbf{b,k}}}$$

Backgrounds k : hadrons and baseline

Step 4 : Likelihood method

Lag λ_n : free parameter, can be shared between sources with different redshifts

For one night : $$\mathcal{L}(\lambda_n) = -\sum_i \log\left(\frac{dP(E_{R,i}, t_i; \lambda_n)}{dE_R dt}\right)$$

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Instrumental response functions

$$+\sum_k W_{b,k} \frac{\int \mathrm{E_{ff}A}(E_T, \vec{\epsilon})\mathrm{MM}(E_T, E_R) \times \mathrm{F}_{b,k}(E_T) dE_T}{N'_{b,k}}$$

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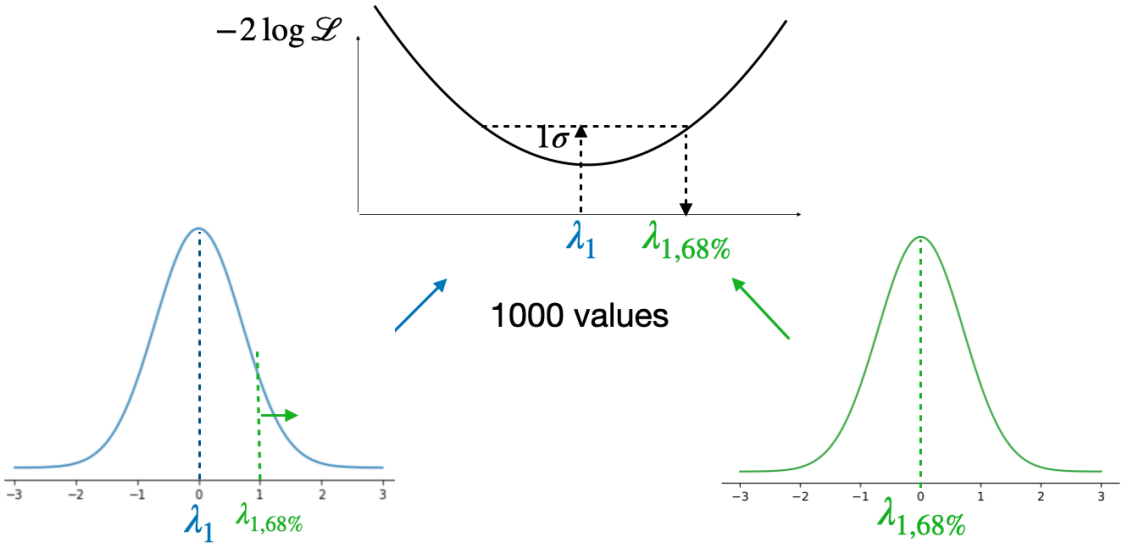
Lightcurve x spectra

$$+ \sum_k W_{b,k} \frac{\int \mathrm{E_{ff}A}(E_T, \vec{\epsilon})\mathrm{MM}(E_T, E_R) \times \mathrm{F}_{b,k}(E_T) dE_T}{N'_{b,k}}$$

Step 4 : simulations for calibration

Sample simulations to validate LIV analysis

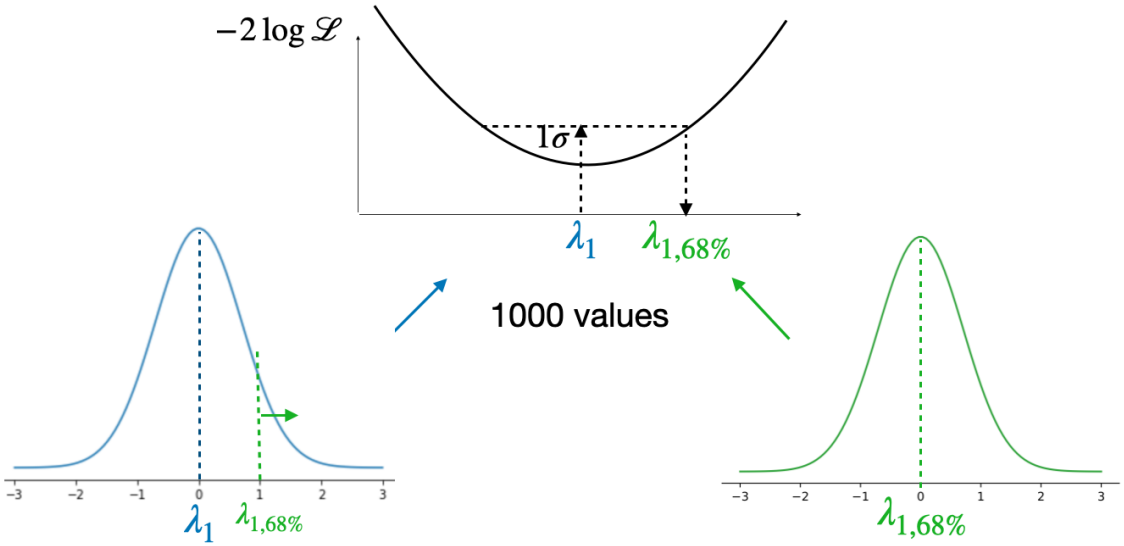
- Perform 1000 dataset simulations



Step 4 : simulations for calibration

Sample simulations to validate LIV analysis

- Perform 1000 dataset simulations
- Calibration : inject lag to verify that LIVelihood reconstruct it well



Step 4 : simulations for calibration

Sample simulations to validate LIV analysis

- Perform 1000 dataset simulations
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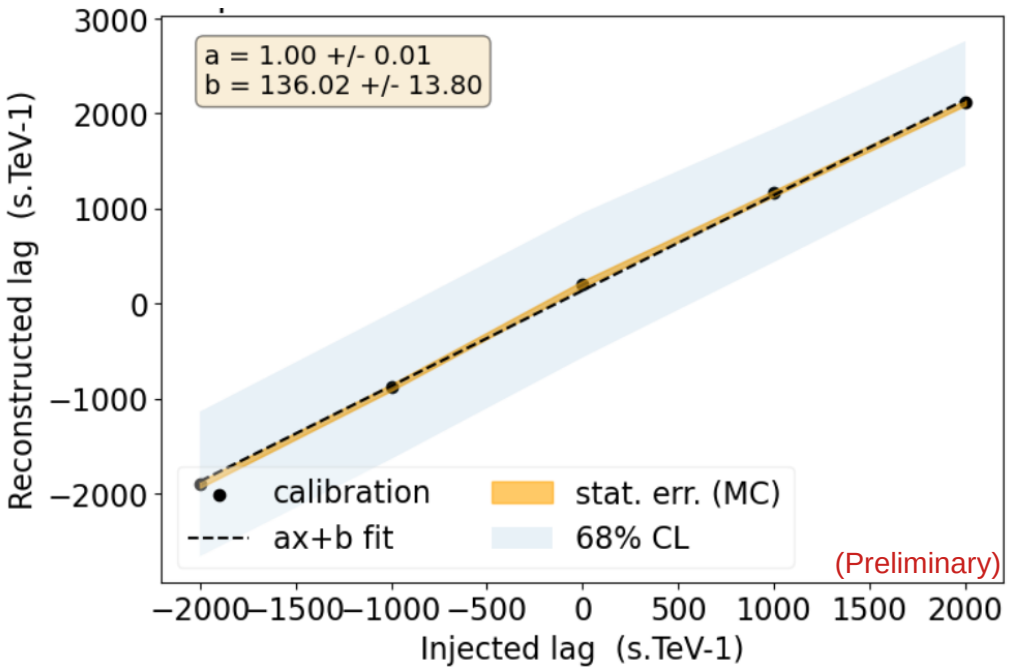
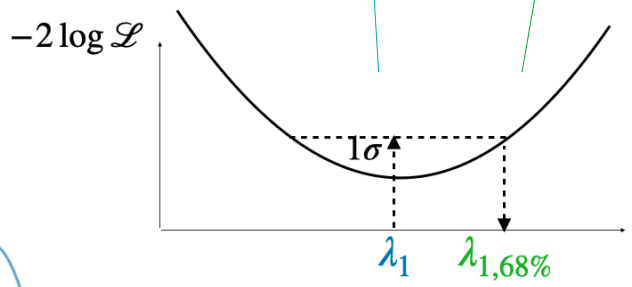
BL Lac 2021-08-08 and 08-09 combined



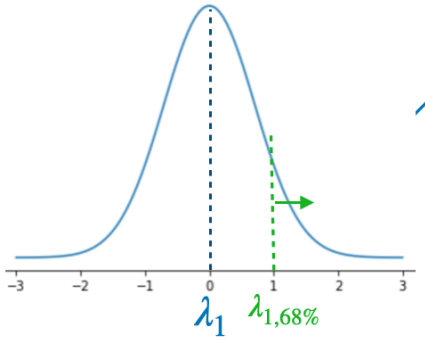
Step 4 : Extraction of E_{QG} limit

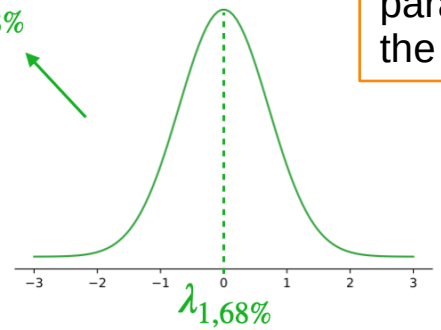
LIV analysis on real data

Time delay : $\lambda_1 = (2060 \; ^{+2811}_{-2899} \; ^{+2479}_{-2143})$ s.TeV^{-1}



1000 values



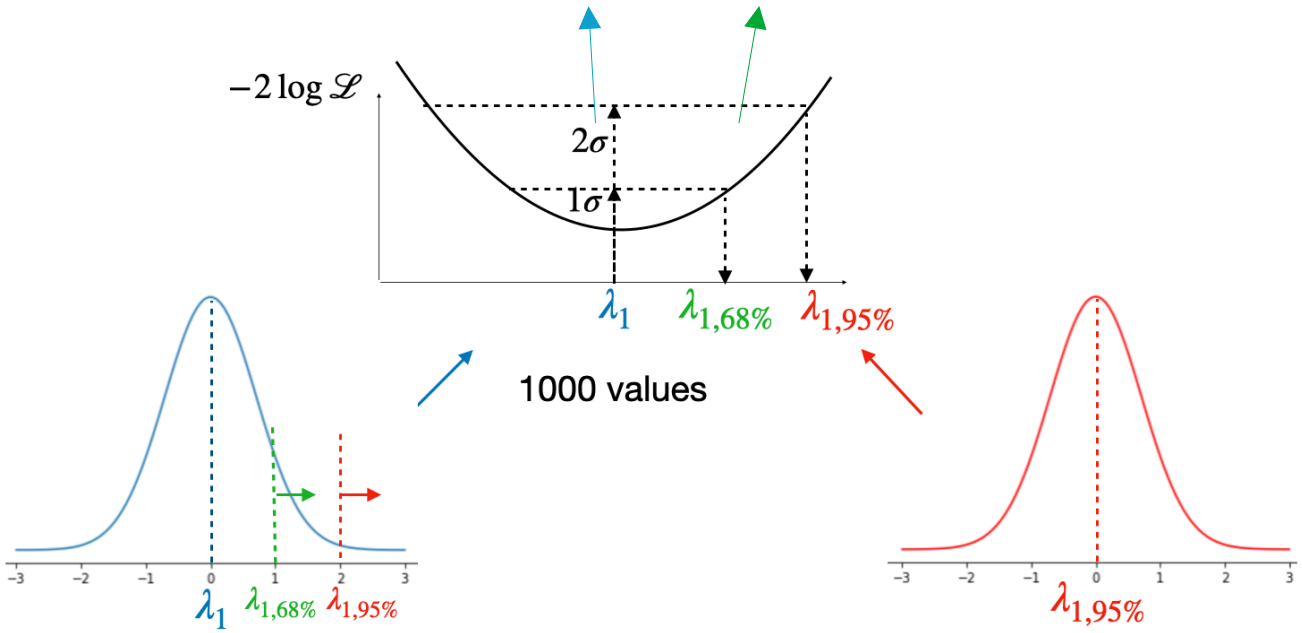


Systematics :
Statistical uncertainty of the light curve template : obtained by letting all parameters free in each of the 1000 simulations

Step 4 : Extraction of E_{QG} limit

LIV analysis on real data

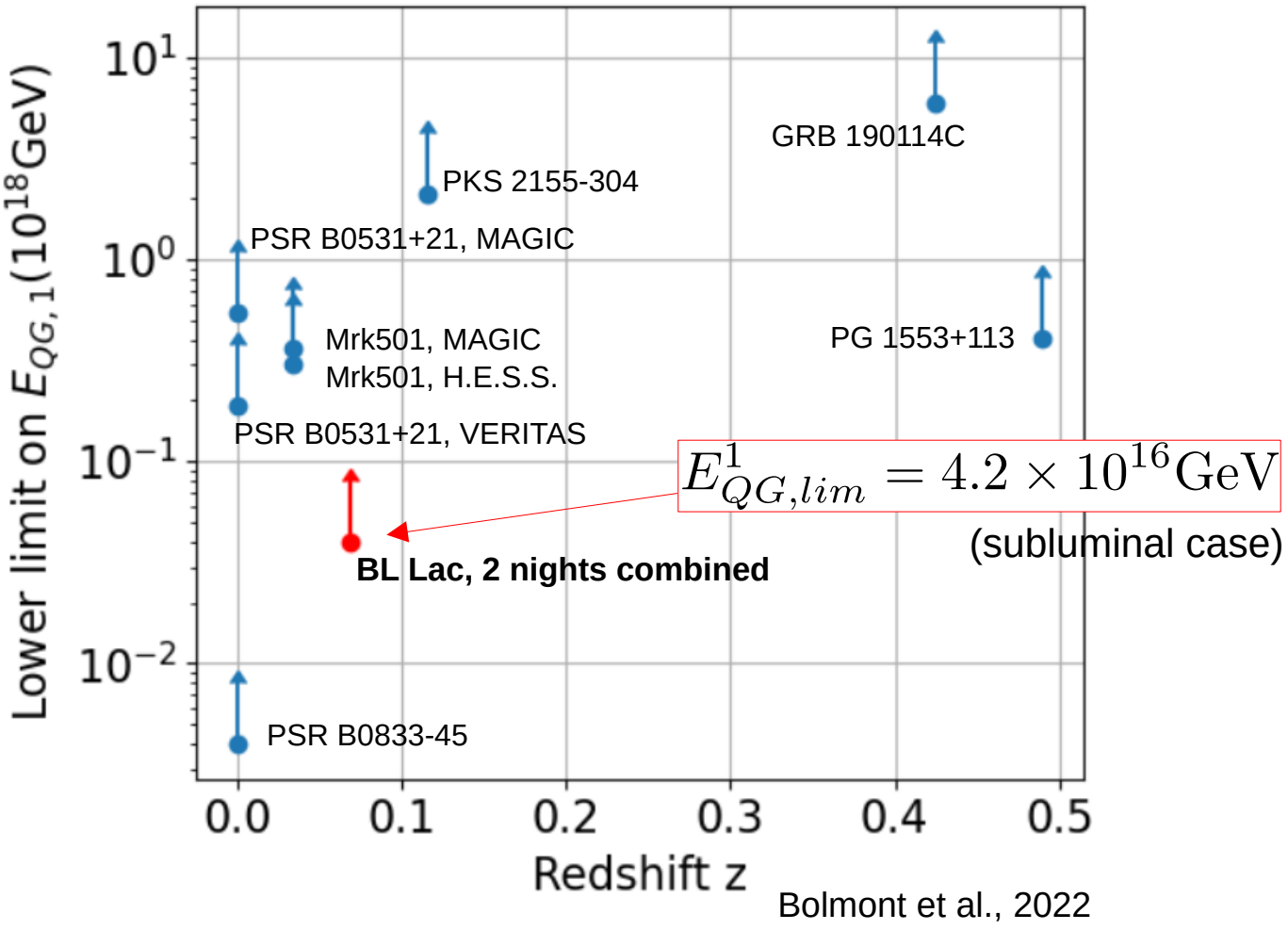
Time delay : λ_1 = (2060 $^{+2811}_{-2899}$ $^{+2479}_{-2143}$)s.TeV^{-1}



Use $\lambda_{1,95\%} = \pm\dfrac{n+1}{2H_0 E^1_{QG,lim}}$ to extract : $\boxed{E^1_{QG,lim} = 4.2 \times 10^{16}\mathrm{GeV}}$

(subluminal case)

Comparison with other limits



Bolmont et al., 2022

Main project conclusion

- Analysed all LST database searching for variability
- Combined 2 variable nights of BL Lac to extract a limit on E_{QG} at the order n=1 on real data

Ongoing work :

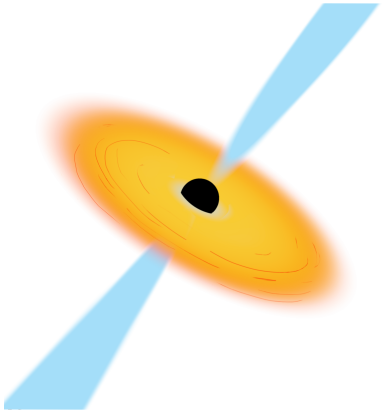
- Combine with the BL Lac 2022-10-20 night
- Combination of LST data with the consortium data

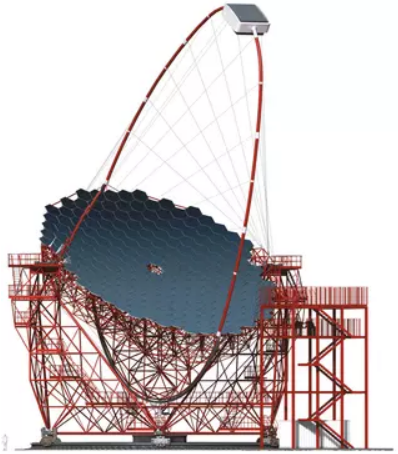
- **Main project :**

  Lorentz invariance violation study with the first data of the LST-1

- **Second project :**

  Gammalearn : deep learning applied on CTA with Michaël Dell'Aiera and Thomas Vuillaume





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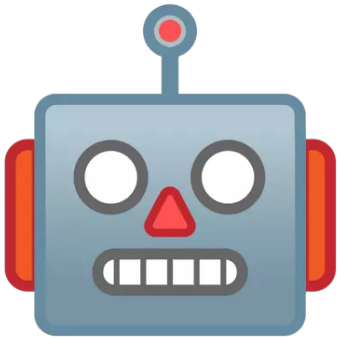
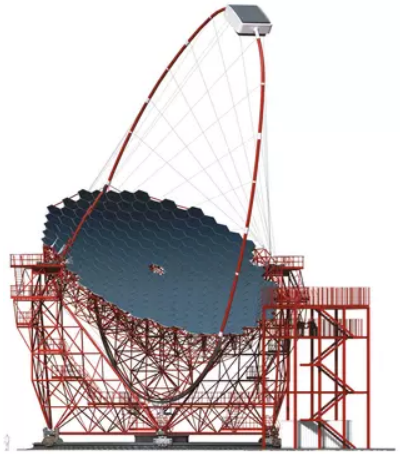
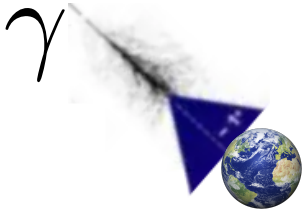




The gammalearn project

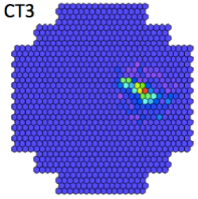
- Goal : propose new methods for CTA data production with deep learning
- Our role : explore the application on real data
- Practically : production and analysis of Crab Nebula data under different conditions

Context : the data production chain

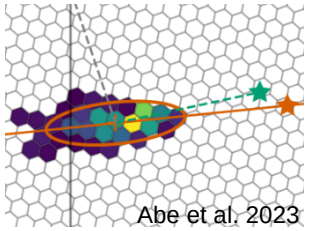


Cherenkov light

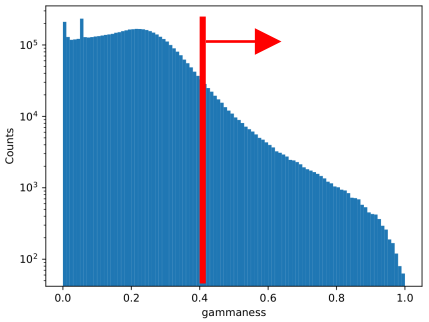
Raw data
(DL0)



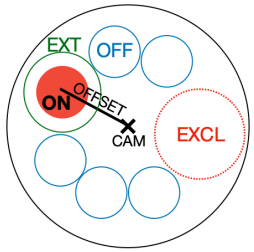
Calibration
(DL1)



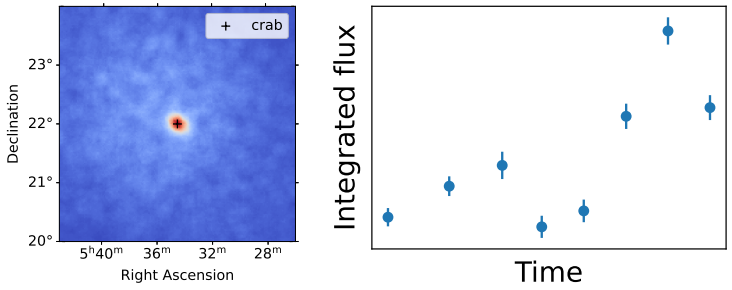
Reconstruction
(DL2)



Gammaness cut +
Instrumental response functions
(DL3)

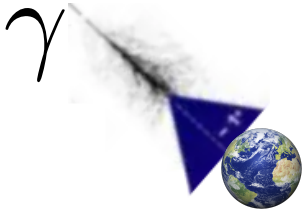


Background
substraction



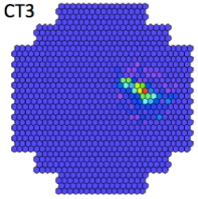
High level products

Context : the data production chain

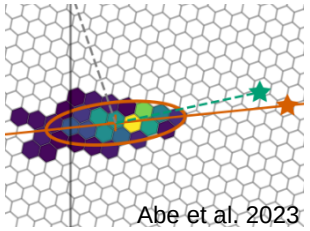


Cherenkov light

Raw data
(DL0)

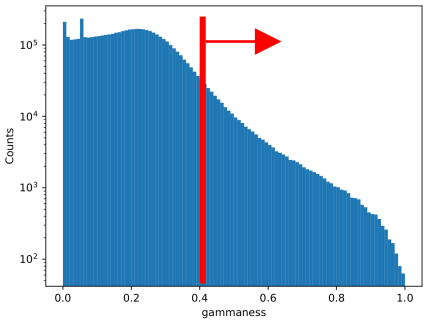


Calibration
(DL1)

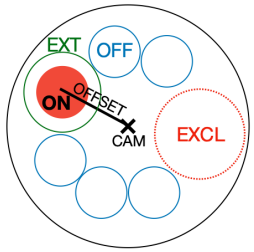


Reconstruction
(DL2)

Lstchain



Gammaness cut +
Instrumental response functions
(DL3)



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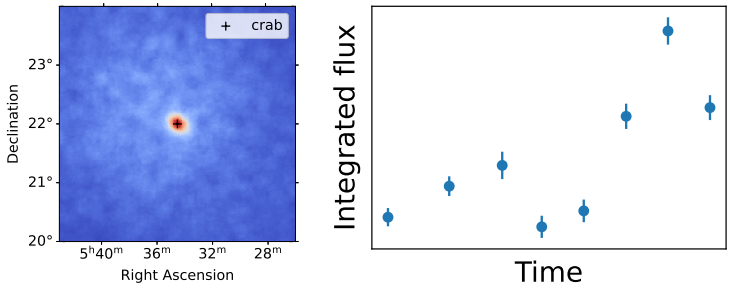
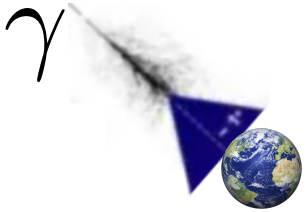


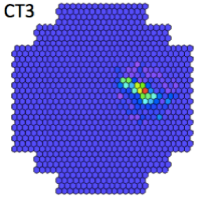
High level products

Context : the data production chain

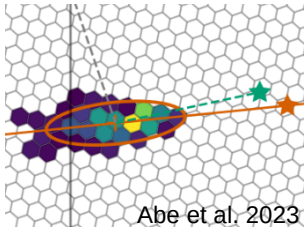


Cherenkov light

Raw data
(DL0)

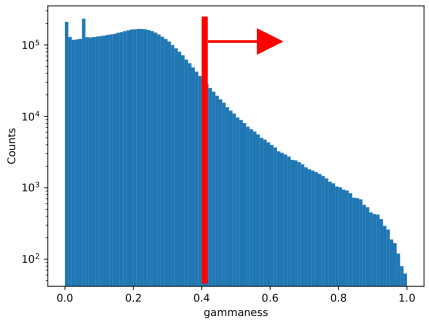


Calibration
(DL1)

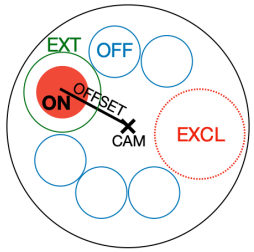


Reconstruction
(DL2)

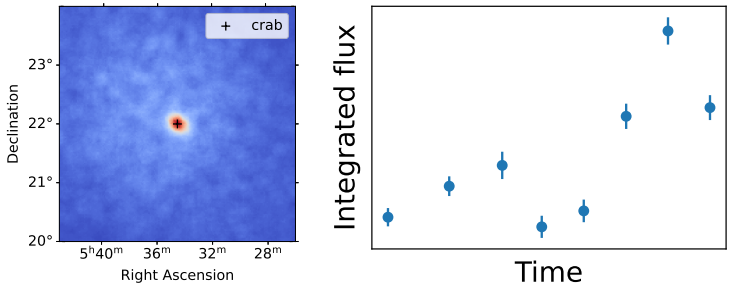
Lstchain : random forest



Gammaness cut +
Instrumental response functions
(DL3)

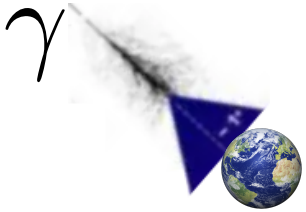


Background substraction



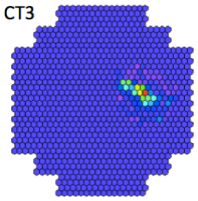
High level products

Context : the data production chain

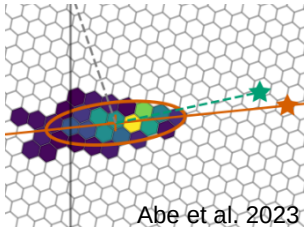


Cherenkov light

Raw data
(DL0)

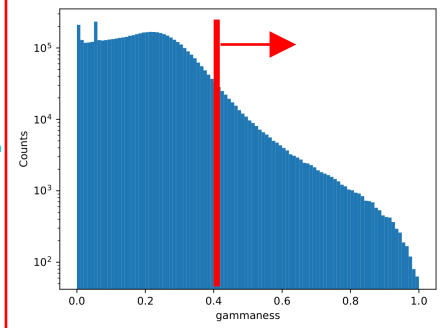


Calibration
(DL1)

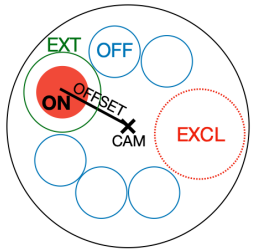


Reconstruction
(DL2)

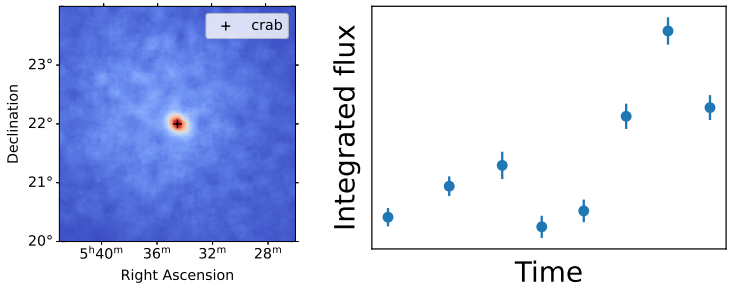
Gammalearn : γ-PhysNet



Gammaness cut +
Instrumental response functions
(DL3)

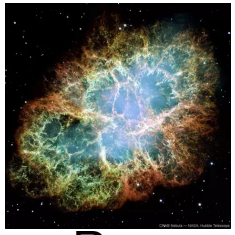


Background substraction



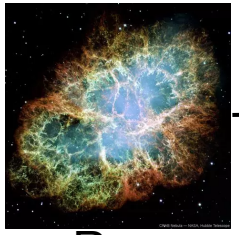
High level products

Step 1 : Crab nebulae data



Runs
6894, 6895

Step 2 : production with the 2 methods



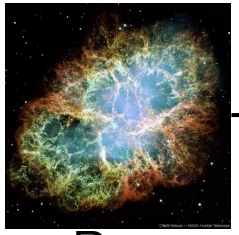
Runs
6894, 6895

γ-PhysNet

Lstchain

DL2 — DL3

Step 3 : gammaness cut optimization



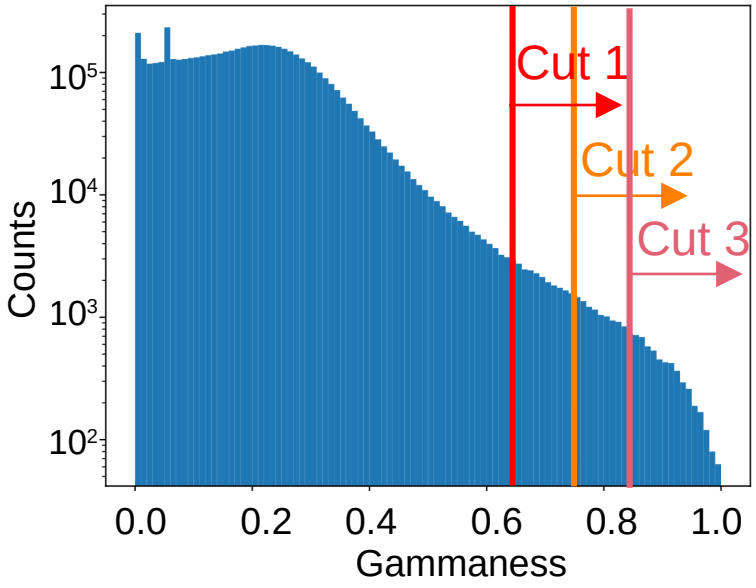
Runs
6894, 6895

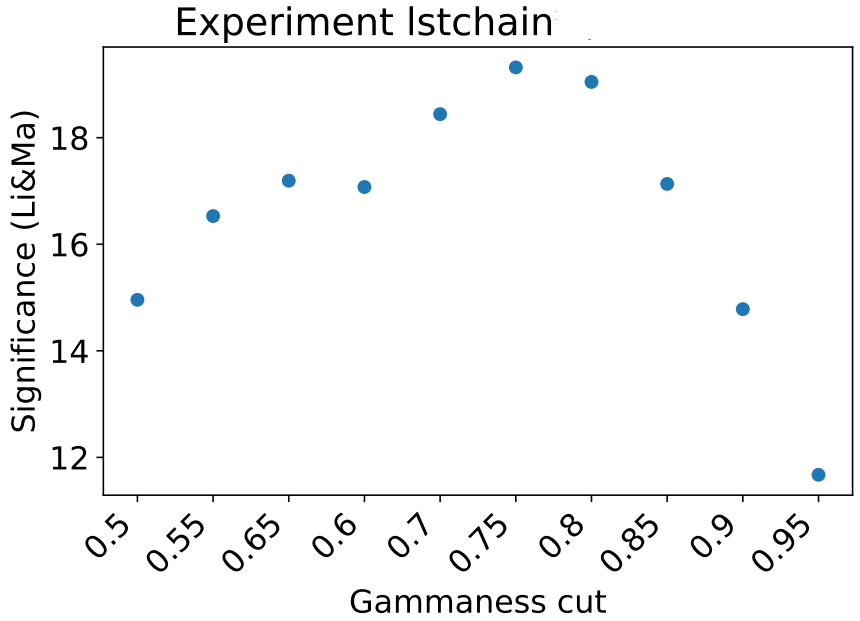
γ-PhysNet

Lstchain

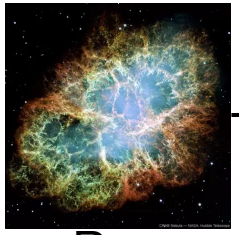
DL2 — DL3 — Gammaness cut optimization on run 6894

Select different gammaness cuts and search for the significance





Step 4 : comparison of the 2 methods



Runs
6894, 6895

γ-PhysNet

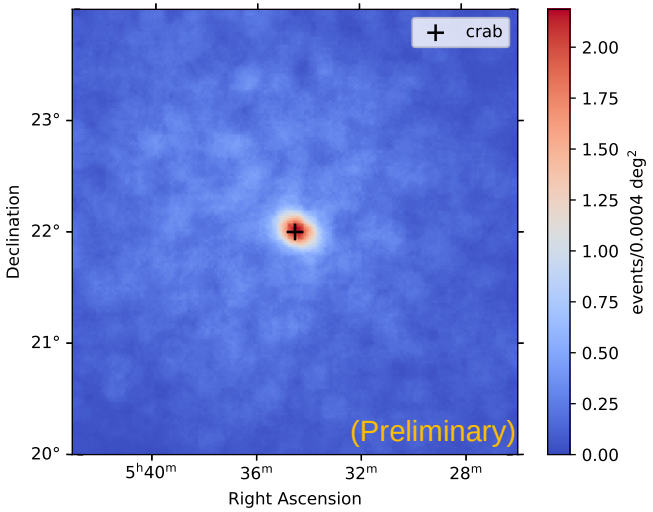
Lstchain

DL2 — DL3 — Gammaness cut optimization on run 6894 — Analysis on run 6895

Comparison of the two methods

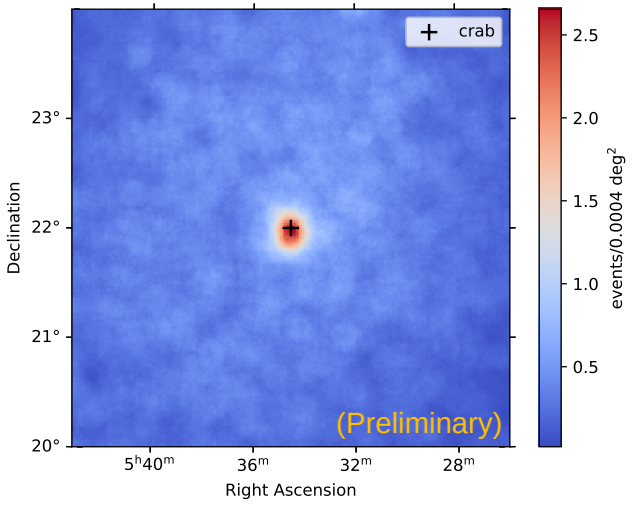
Lstchain

Significance : 20.3σ



γ-PhysNet

Significance : 22.4σ



Second project conclusion

- Comparison between gammalearn (γ-PhysNet) methods and classic one (Lstchain)
- Gammalearn shows promising results

Ongoing work :

- Use different observations conditions (moonlight)
- Apply on different sources, especially weaker

Second project conclusion

- Comparison between gammalearn (γ-PhysNet) methods and classic one (Lstchain)
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Ongoing work :

- Use different observations conditions (moonlight)
- Apply on different sources, especially weaker

And… maybe use gammalearn data for a LIV analysis ??

LIV project

- Presented results at the CTA France meeting, LST general meeting and the COST action QGMM conference in Rijeka
- Paper draft planned for January 2024

Gammalearn project

- Presented results at the LST general meeting with Michaël
- Co-author of a poster presented at the ADASS conference (November) by Michaël

Collaboration involvement

Shift at the LST-1 (La Palma) in November

Total : 135h

Disciplinaire : 40h

- Winter school of theoretical physics : Quantum gravity & phenomenology (COST action QGMM)

Transversales : 55h

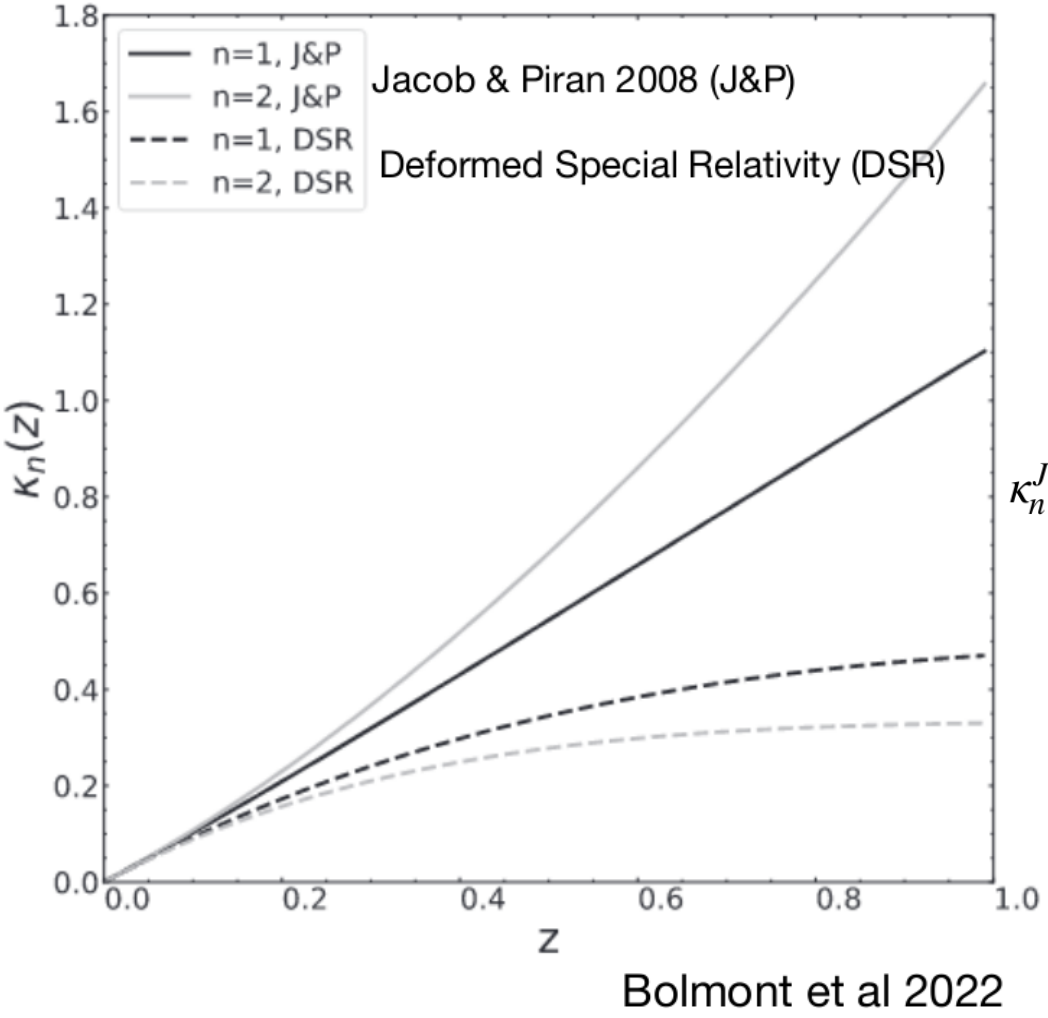
- Journée de rentrée
- MOOC éthique de la recherche
- Encadrer efficacement des TD
- Initiation à l'écrit journalistique scientifique
- Animation à l'évènement "Les tribulations savantes"

Professionnelles : 40h

- Vacation pour l'USMB : 41h de TP
- Mission de médiation scientifique
- Travailler son identité professionnelle et son réseau
- Insertion professionnelle après le doctorat


Thank you !

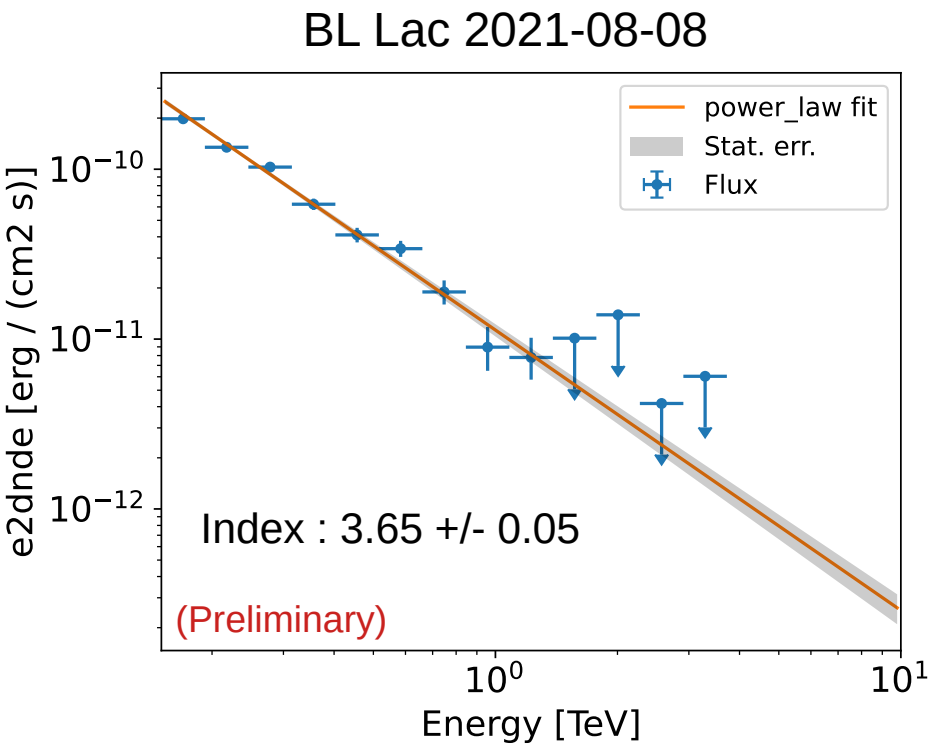
Redshift correction

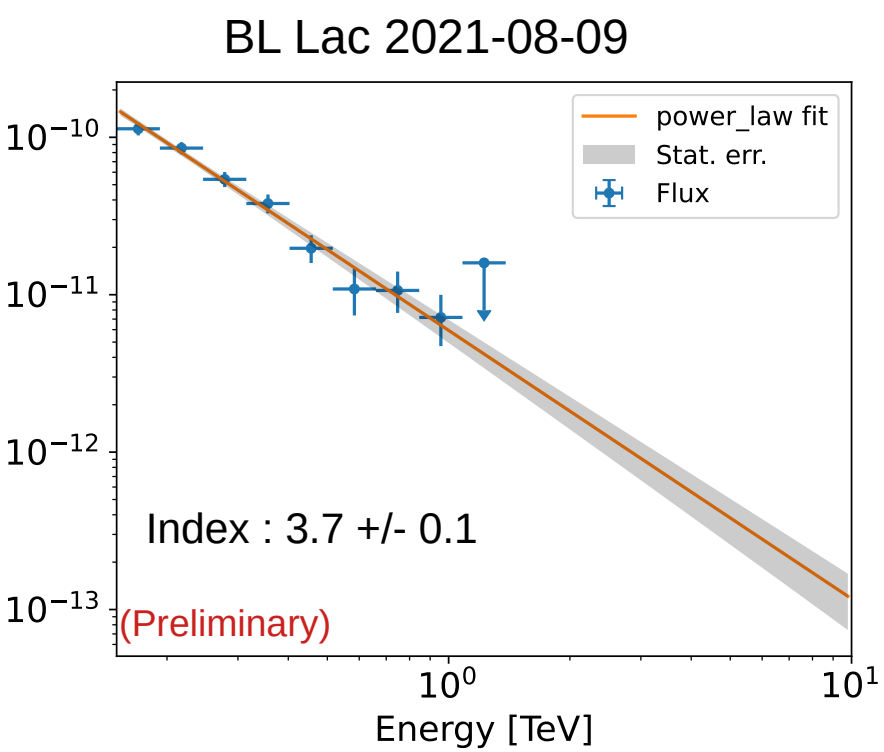


Bolmont et al 2022

$$\kappa_n^{J\&P}(z) = \frac{1}{z_0}\int_0^z \frac{(1+z')^n}{\sqrt{\Omega_m(1+z')^3+\Omega_\Lambda}}dz'$$

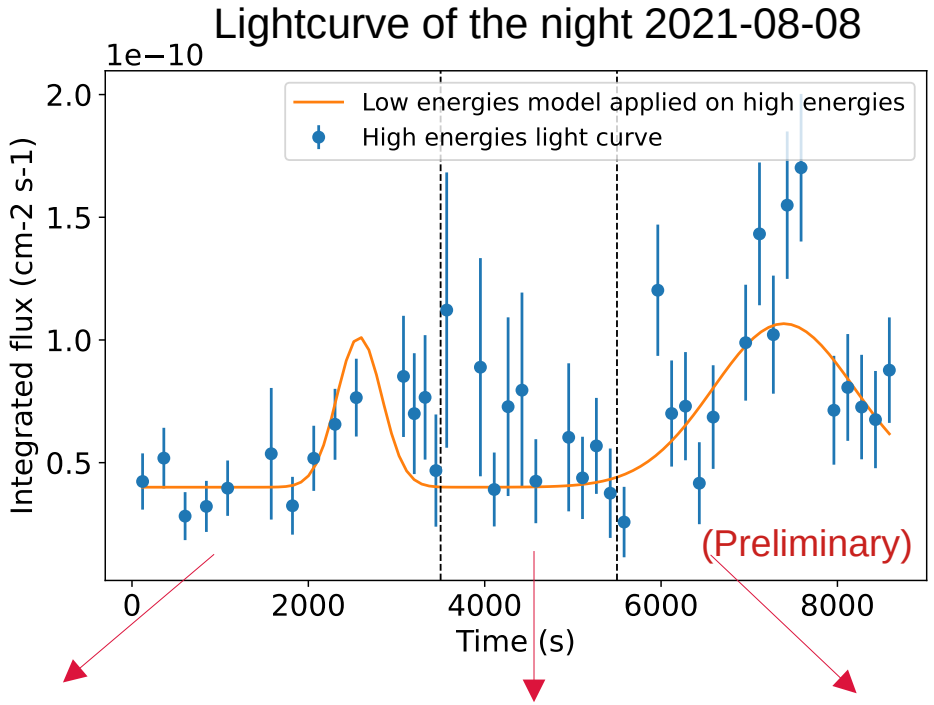
Spectra

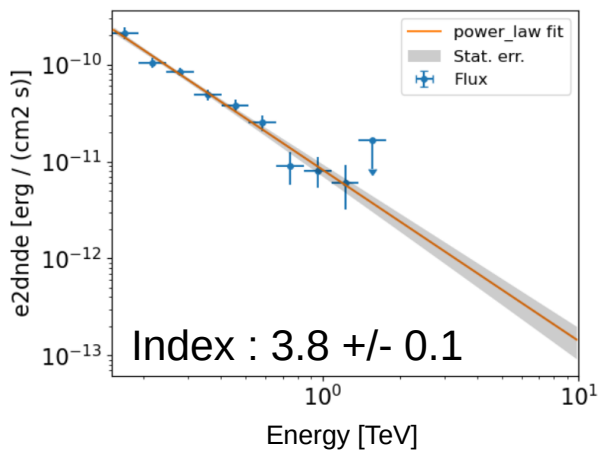


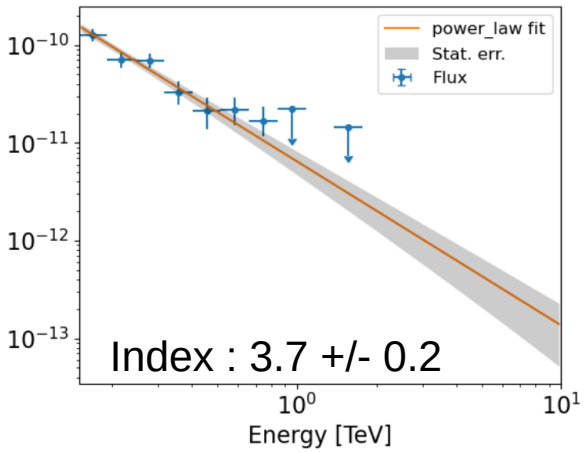


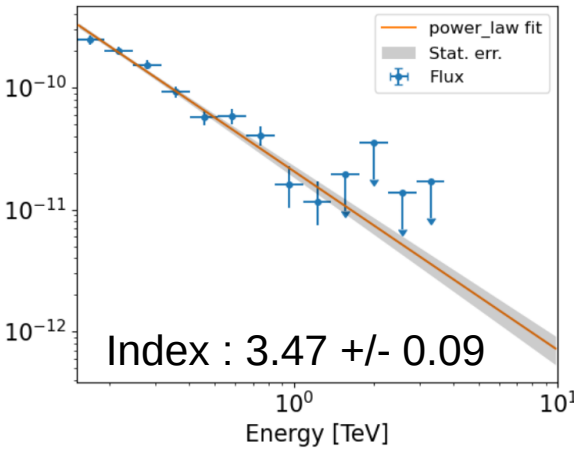
10 bins per decade, ON radius = 0.2°, energy reco : [150GeV , 10TeV]

Time-independency of the energetic distribution



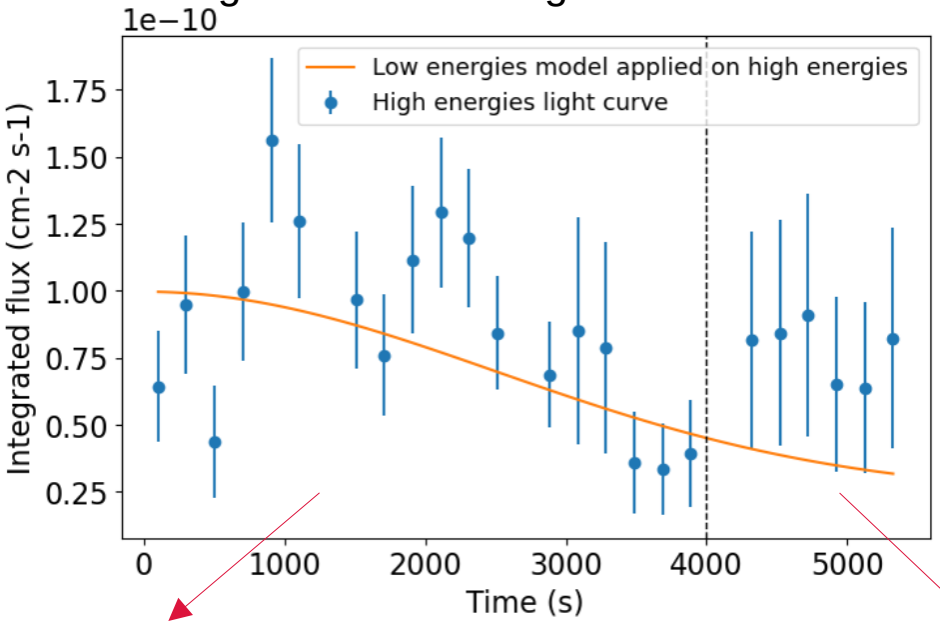


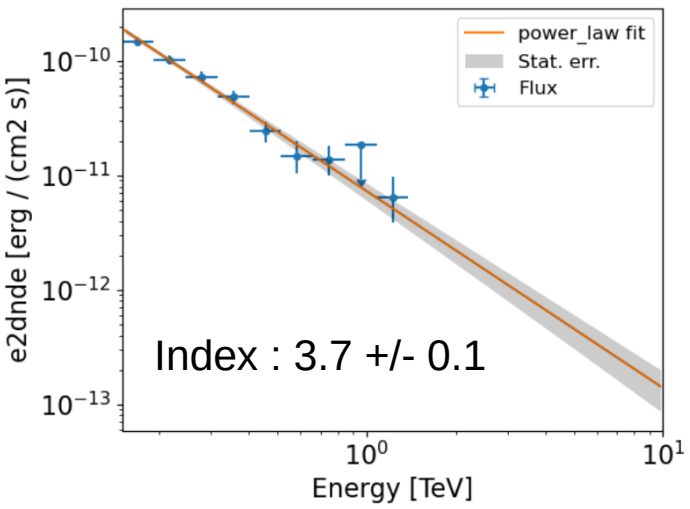


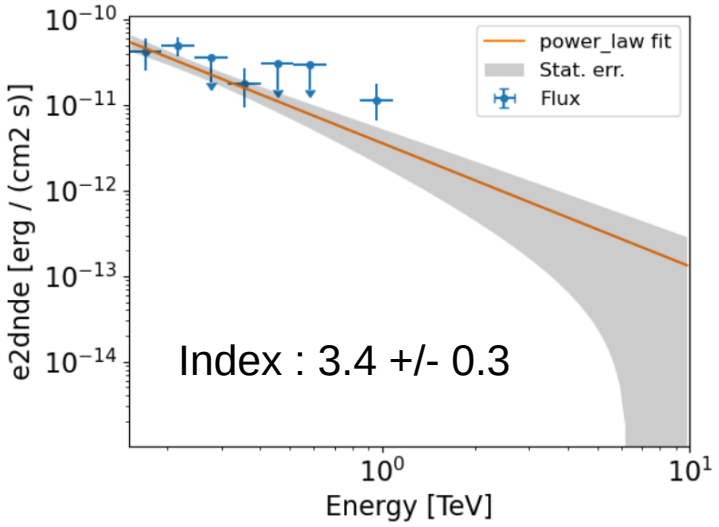


Time-independency of the energetic distribution

Lightcurve of the night 2021-08-09







Likelihood for simulations

Lag λ_n : free parameter, can be shared between sources with different redshifts

For one night : $$\mathcal{L}(\lambda_n) = -\sum_{\text{event } \mathbf{i}} \log\left(\frac{dP(E_{R,\mathbf{i}}, t_{\mathbf{i}}, \lambda_n)}{dE_R dt}\right)$$

with $$\frac{dP}{dE_R dt} = W_{\mathbf{s}} \frac{\int \mathrm{E_{ff}A}(E_T, \vec{\epsilon})\mathrm{MM}(E_T, E_R) \times \mathrm{F_{\mathbf{s}}}(E_T, t; \lambda_n) dE_T}{N'_{\mathbf{s}}}$$

IRFs

Signal

Lightcurve x spectra

$$+ \sum_{\mathbf{k}} W_{\mathbf{b,k}} \frac{\int \mathrm{E_{ff}A}(E_T, \vec{\epsilon})\mathrm{MM}(E_T, E_R) \times \mathrm{F_{b,k}}(E_T) dE_T}{N'_{\mathbf{b,k}}}$$

Backgrounds k : hadrons and baseline

$$\mathcal{L}(\lambda_n) = -\sum_i \log\left(\frac{dP(E_{R,i}, t_i, \lambda_n)}{dE_R dt}\right)$$

$$\frac{dP}{dE_R dt} = W_s \frac{\int \mathrm{E_{ff}A}(E_T, \vec{\epsilon})\mathrm{MM}(E_T, E_R) \times \mathrm{F}_S(E_T, t; \lambda_n) dE_T}{N'_s}$$

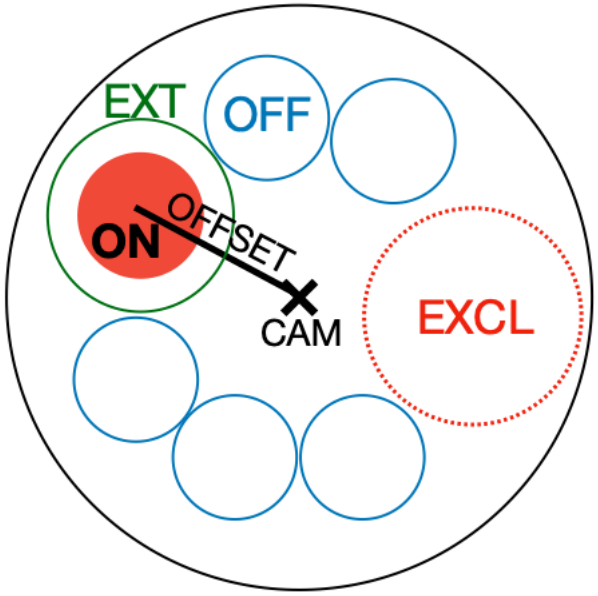
$$+W_b \frac{\int \mathrm{E_{ff}A}(E_T, \vec{\epsilon})\mathrm{MM}(E_T, E_R) \times \mathrm{F}_b(E_T) dE_T}{N'_b}$$

$$+W_h \frac{dN_{off}}{dE_R} \times \frac{1}{T} \times \frac{1}{N'_h}$$

Reflected region background method

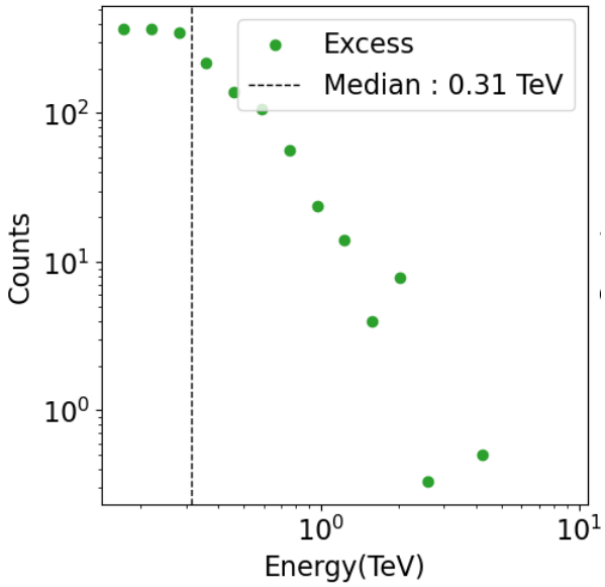
Hypothesis : background is purely radial in the field-of-view.

- X CAM : camera pointing direction
- OFFSET : regions dispersion radius
- ON : source (gammas) + background
- EXT : exclusion of potential remaining source events
- EXCL : exclusion of a potential other source
- OFF : background

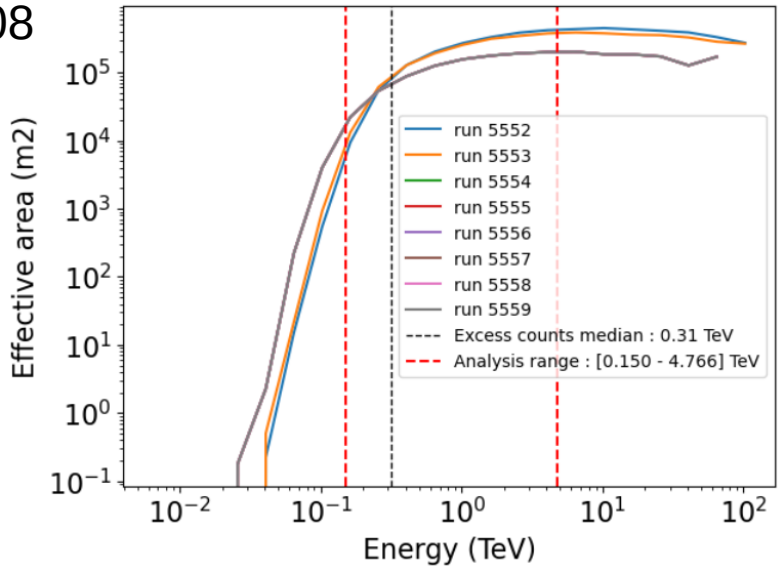


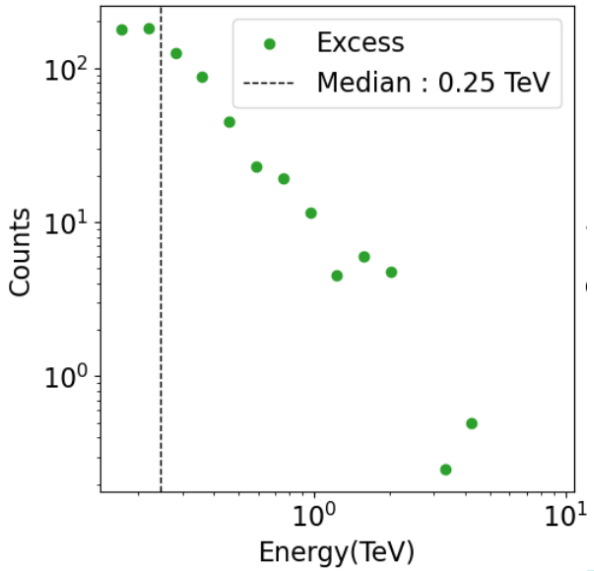
$$N_\gamma = N_{excess} = N_{on} - \frac{1}{n}\sum_n N_{n,off}$$

Median of counts

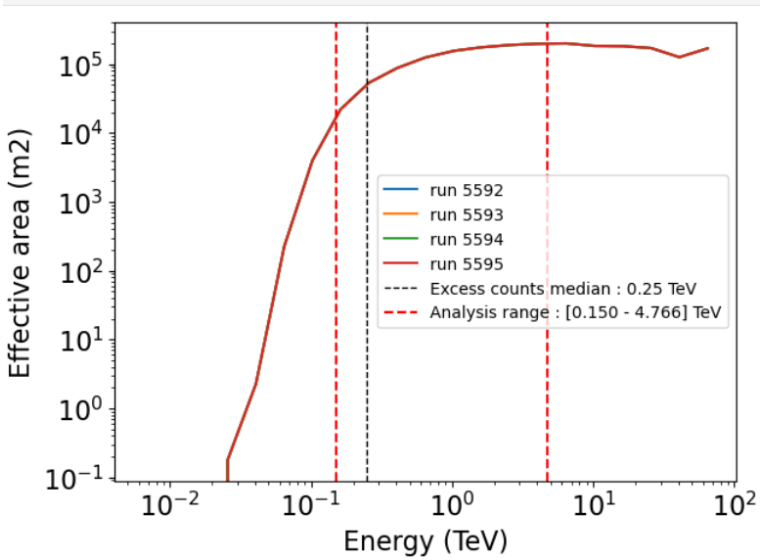


2021-08-08



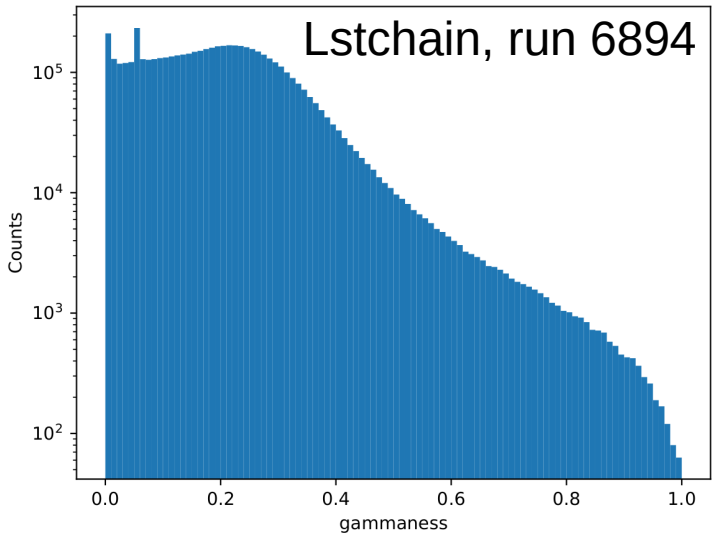


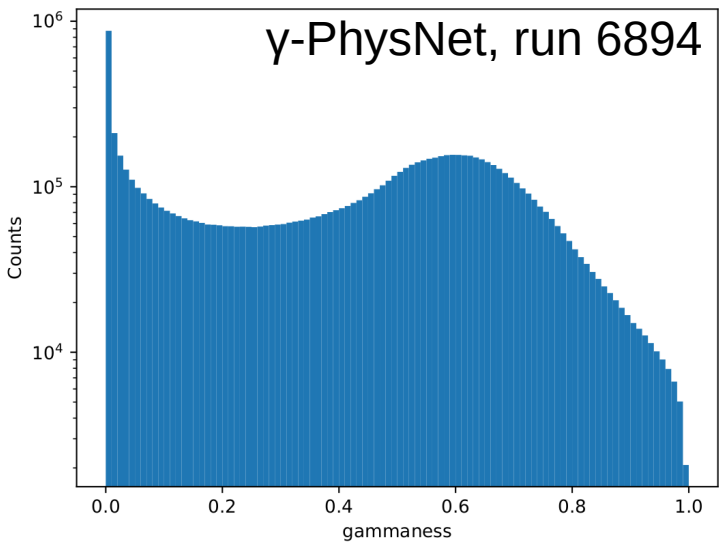
2021-08-09

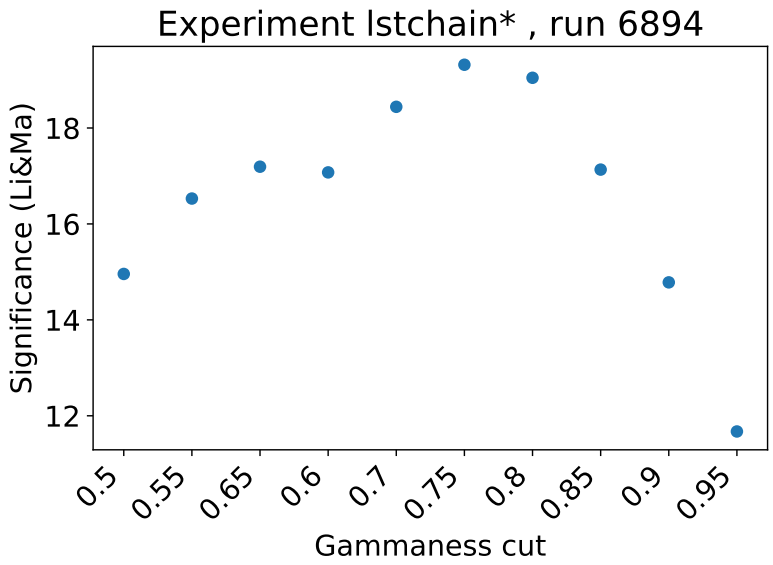


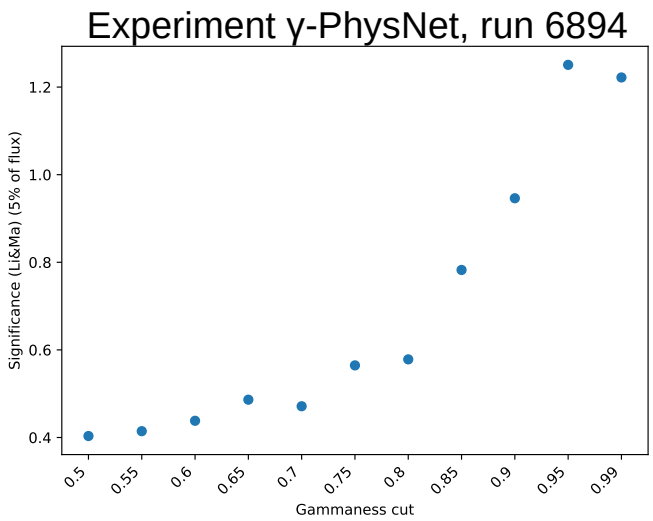
Gammalearn

Cut optimizations

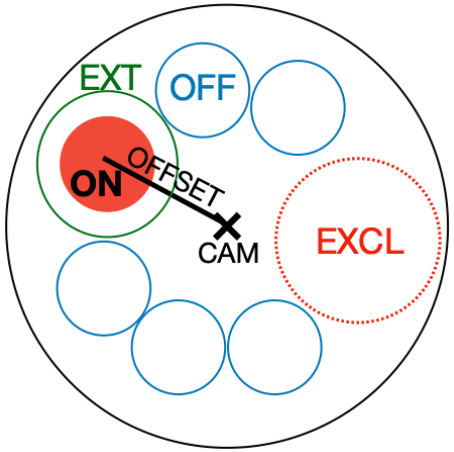


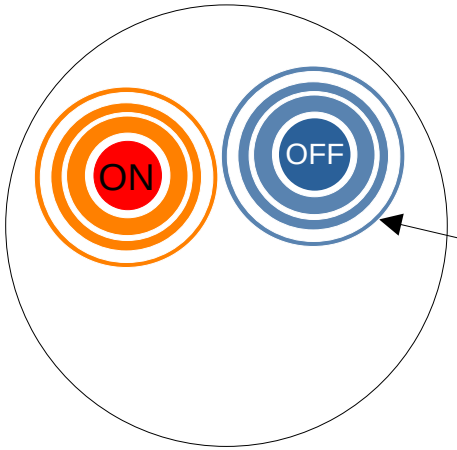






Other results from analysis





θ : angle between source and integrated events

θ^2