Constraining branon dark matter with MAGIC

from observations of the Segue 1 dwarf spheroidal galaxy

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Outline

Introduction

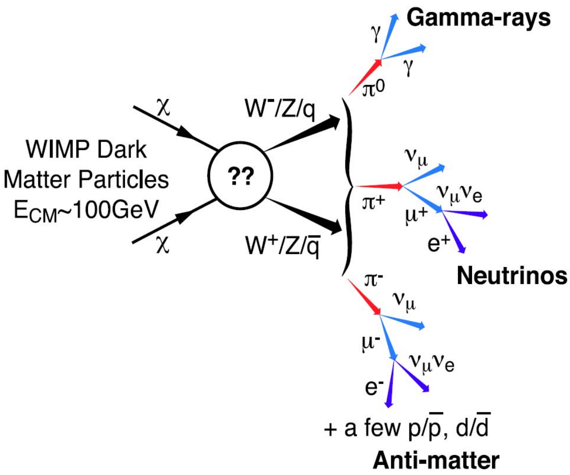


Figure : Dark matter (DM) self-annihilation. [Fermi-LAT]

Introduction

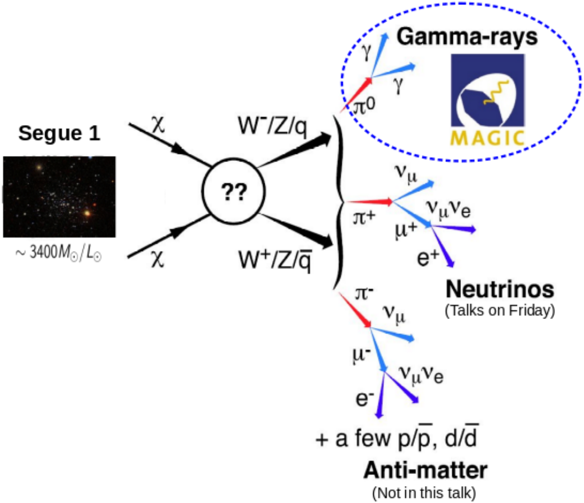


Figure : Dark matter (DM) self-annihilation. [Fermi-LAT]

MAGIC telescope & Segue 1 observations

- Current operating imaging atmospheric Cherenkov telescope
- Roque de los Muchachos Observatory on La Palma at about 2200m above sea level
- Two telescopes with 17m diameter reflecting surfaces placed at a distance of 85m
- Sensitive to VHE gamma-rays (between $\sim$ 50GeV and $\sim$ 50TeV)
- Segue 1 data set is almost 160 hours of good-quality data and was taking under four different experimental conditions

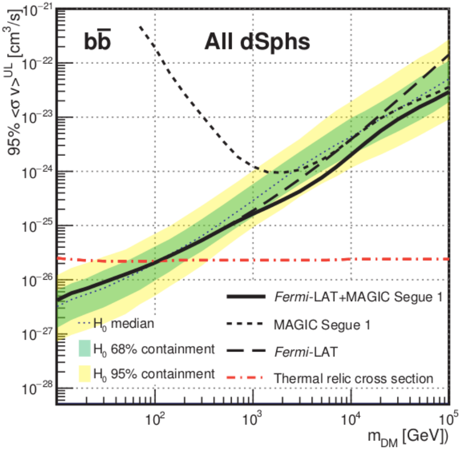
Profile likelihood

- The model describing our data depends on g and additional nuisance parameter $h = (h_1, \ldots, h_l)$.
- The full likelihood function is given by

$$\mathcal{L}(g; h|X) = \prod_{i=1}^{n} \mathrm{f}(X_i|g; h),$$

  where $X = (X_1, \ldots, X_n)$ are n independent observations and $\mathrm{f}(X|g; h)$ is the probability function (or density).
- We are interested in the parameter $g = (g_1, \ldots, g_k)$. (For DM searches g is $\langle \sigma v \rangle$)

Combined analysis of MAGIC and Fermi-LAT (2014) [Ahnen]



Name	l [deg]	b [deg]	D [kpc]	r_s/D [deg]	$\log_{10}(J_{\rm obs})$ [$\log_{10}(\rm GeV^2cm^{-5})$]
Bootes I	358.08	69.62	66	0.23	18.8 ± 0.22
Canes Venatici II	113.58	82.70	160	0.071	17.9 ± 0.25
Carina	260.11	-22.22	105	0.093	18.1 ± 0.23
Coma Berenices	241.89	83.61	44	0.23	19.0 ± 0.25
Draco	86.37	34.72	76	0.26	18.8 ± 0.16
Fornax	237.10	-65.65	147	0.17	18.2 ± 0.21
Hercules	28.73	36.87	132	0.081	18.1 ± 0.25
Leo II	220.17	67.23	233	0.071	17.6 ± 0.18
Leo IV	265.44	56.51	154	0.072	17.9 ± 0.28
Sculptor	287.53	-83.16	86	0.25	18.6 ± 0.18
Segue 1	220.48	50.43	23	0.36	19.5 ± 0.29
Sextans	243.50	42.27	86	0.13	18.4 ± 0.27
Ursa Major II	152.46	37.44	32	0.32	19.3 ± 0.28
Ursa Minor	104.97	44.80	76	0.35	18.8 ± 0.19
Willman 1	158.58	56.78	38	0.25	19.1 ± 0.31

gLike - code framework for the numerical maximization of joint likelihood functions

List of examples where gLike is useful:

- Estimating the number of signal events (with uncertainties) in a dataset whose background content is in turn estimated from an independent measurement in a signal-free control-region. (Li & Ma)
- Same as before, but considering in addition a systematic uncertainty in the estimation of the background. (Rolke)
- Estimating the dark matter annihilation cross-section combining observations of dwarf spheroidal galaxies by different ground-based gamma-ray telescopes, satellite gamma-ray detectors, neutrino telescopes, ...
- ...

https://github.com/javierrico/gLike

gLike output

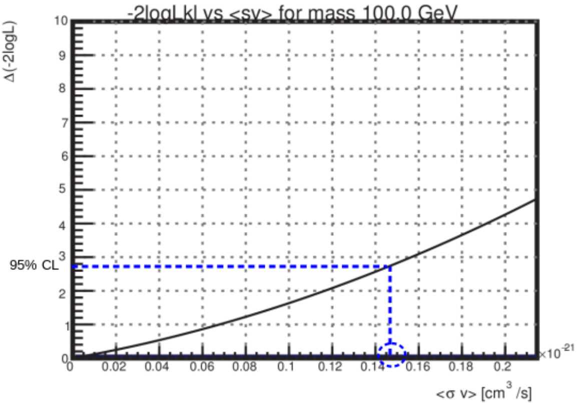


Figure : The sensitivity (for a given confidence level, CL) is the average limit (with that CL) we would obtain on the free parameter, under the null hypothesis. [Rico]

Branon dark matter

$$\frac{\mathrm{d}\Phi\left(\Delta\Omega, E_\gamma\right)}{\mathrm{d}E_\gamma} = \underbrace{\mathcal{J}\left(\Delta\Omega\right)}_{\text{Astrophysics}} \cdot \frac{1}{4\pi} \underbrace{\frac{\langle\sigma_{ann} v\rangle}{2m_\chi^2} \sum_i \mathrm{BR}_i \frac{\mathrm{d}N_\gamma^i}{\mathrm{d}E_\gamma}}_{\text{Particle physics}}$$

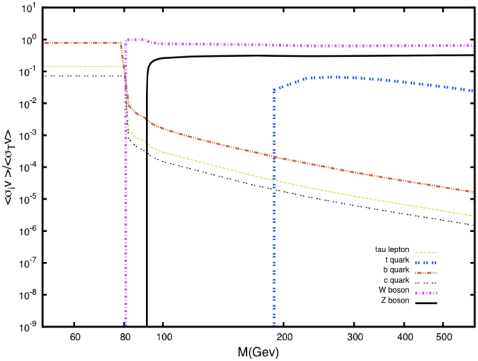


Figure : Branon annihilation branching ratios into SM particles. [Cembranos]

Summary & Outlook

- We are analyzing the MAGIC Segue 1 high-level data set, which is deepest observational campaign on any dwarf galaxy
- We have to perform a full joint likelihood analysis due to four different instrument conditions
- The previous presented tool 'gLike' will be used to numerical maximize the full joint likelihood functions
- We will modify gLike to include the branon dark model in our full likelihood analysis.

Deep learning for imaging atmospheric Cherenkov telescopes

CTLearn

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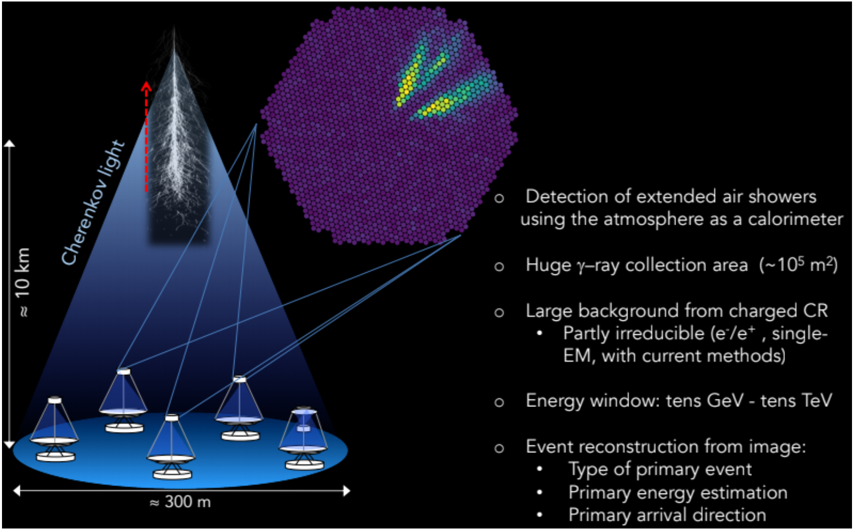
IACT technique [Nieto]



Deep neural networks

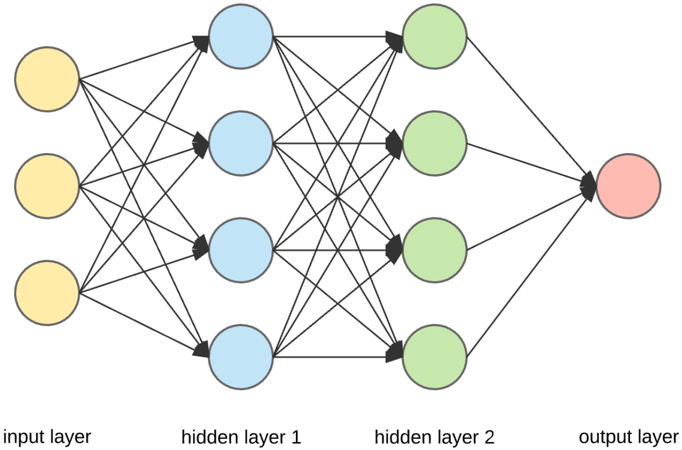


Figure : Basic concept of a deep neural network. [Dertat]

Deep convolutional neural networks (DCNs)

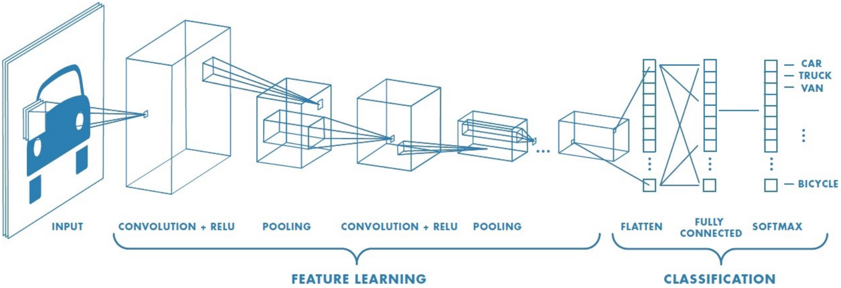


Figure : Basic concept of deep convolutional neural networks. [Prabhu]

Convolutional layer

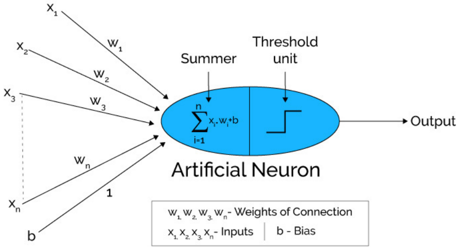


Figure : Working flow of an artificial neuron. [Gill]

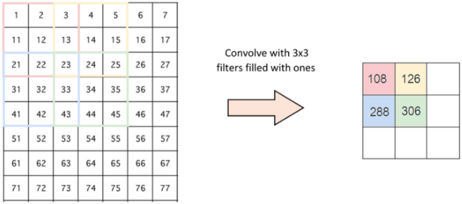


Figure : Example of a convolutional layer. [Prabhu]

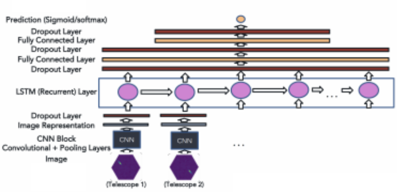
CTLearn

- High-level Python package for using deep learning for IACT event reconstruction
- Configuration-file-based workflow and installation with conda drive reproducible training and prediction
- Supports any TensorFlow model that obeys a generic signature
- Open source on GitHub: https://github.com/ctlearn-project/ctlearn

CTLearn

Primary developers
Ari Brill, Qi Feng (Columbia)
Bryan Kim (UCLA)
Daniel Nieto, Tjark Miener, Jaime Sevilla (UCM)

CTLearn results (Version 2.0)



Telescope Type	Total Events	Validation Accuracy	Validation AUC
LST	85401	73.43%	0.8285
MSTF	249813	80.23%	0.8961
MSTN	269362	83.10%	0.9169
MSTS	223051	81.18%	0.9048
SST1	197878	81.47%	0.8997
SSTA	183669	75.27%	0.8556
SSTC	190638	80.64%	0.9072

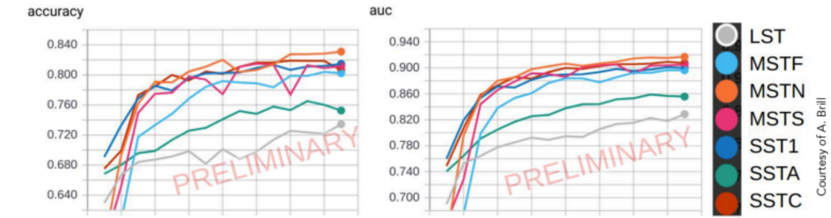
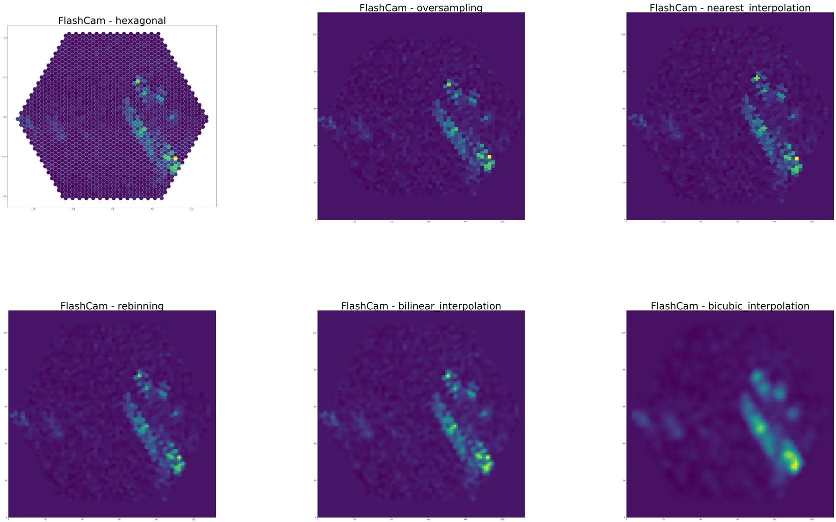


Figure : CNN-RNN validation results for oversampling. [CTLearn]

ImageMapper: DL1 data → 2D image



ImageMapper: DL1 data → 2D image

Camera	Oversamp.	Nearest	Rebin.	Bilinear	Bicubic	Shifting	Axial ad.
LSTCam	✓✓	✓✓	✓✓	✓✓	✓✓	✓	✓
FlashCam	✓✓	✓✓	✓✓	✓✓	✓✓	✓	✓
NectarCam	✓✓	✓✓	✓✓	✓✓	✓✓	✓	✓
DigiCam	✓✓	✓✓	✓✓	✓✓	✓✓	✓	✓
SCTCam	✓✓	✓✓	✓✓	✓✓	✓✓	NA	NA
ASTRICam	✓✓	✓✓	✓✓	✓✓	✓✓	NA	NA
CHEC	✓✓	✓✓	✓✓	✓✓	✓✓	NA	NA
MAGICCam	✓	✓	✓	✓	✓	✓	✓
VERITAS	✓	✓	✓	✓	✓	✓	✓
HESS-I	✓	✓	✓	✓	✓	✓	✓
HESS-II	✓	✓	✓	✓	✓	✓	✓
FACT	✓	✓	✓	✓	✓	✓	✓

✓✓: method benchmarked ✓: tested with data ✓: tested with dummy data

Summary & Outlook

- We learned the basics of deep learning and deep convolutional neural networks (DCNs)
- We saw that it's possible to classify gamma and proton events using the CTLearn framework
- Recent work on the transformation of camera pixels to a 2D image has been shown
- Next steps would be to implement regression for energy and arrival direction reconstruction and hexagonal convolutions

CTLearn

Back up

Joint likelihood

- Combining likelihood functions for different targets:

$$\mathcal{L}\left(\langle \sigma v \rangle; \nu | X\right) = \prod_{i=1}^{N_{target}} \mathcal{L}_i\left(\langle \sigma v \rangle; J_i, \mu_i | X_i\right) \cdot \mathcal{J}\left(J_i | J_{obs,i}, \sigma_i\right)$$

- Combining likelihood functions (of a particular target) for different experiments:

$$\mathcal{L}_i\left(\langle \sigma v \rangle; J_i, \mu_i | X_i\right) = \prod_{j=1}^{N_{instrument}} \mathcal{L}_{ij}\left(\langle \sigma v \rangle; J_i, \mu_{ij} | X_{ij}\right)$$

Deep learning

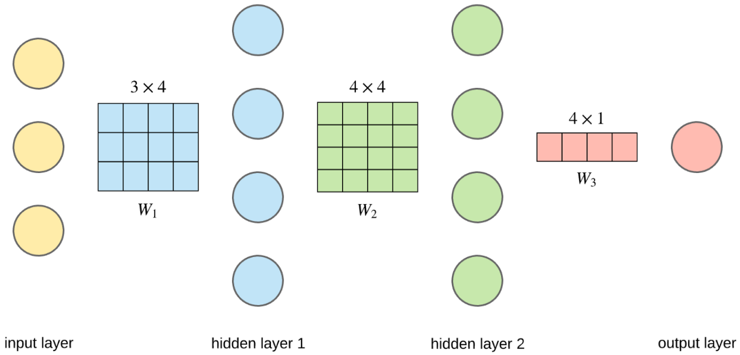


Figure : Weight matrices of a neural network. [Dertat]

Rectified Linear Unit (ReLU)

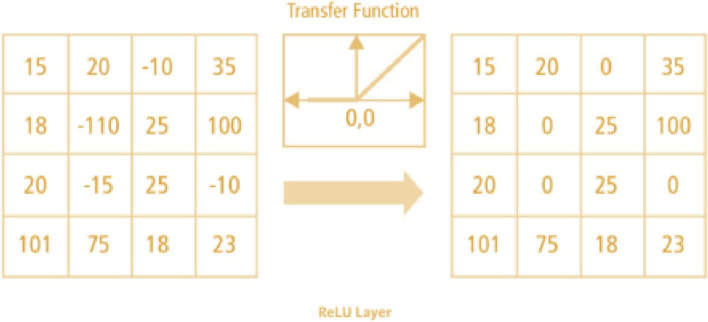


Figure : Example of the ReLU function $f(x) = \max(0, x)$. [Prabhu]

Pooling layer

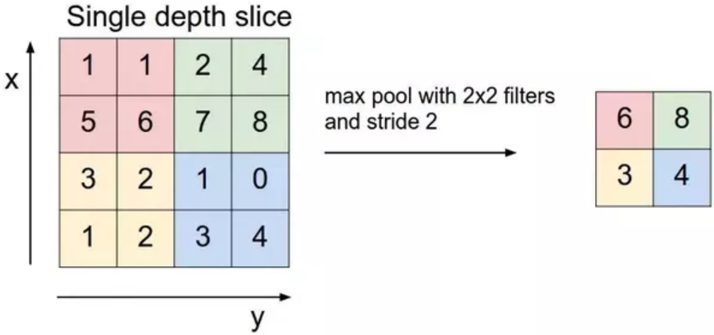
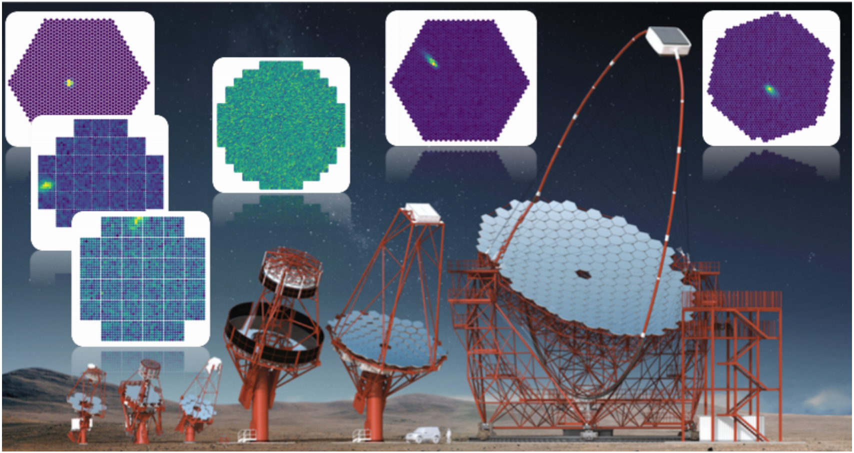


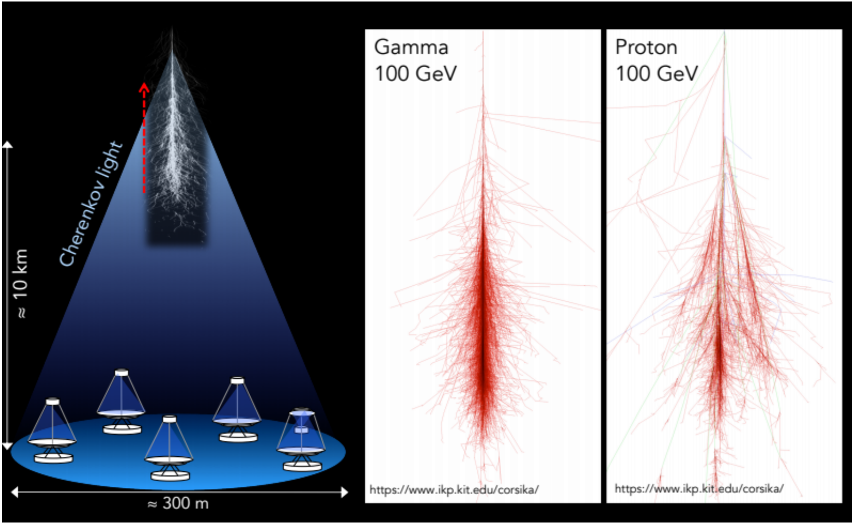
Figure : Example of a max pooling layer. [Prabhu]

CTA array [Nieto]

Camera images courtesy of T. Vuillaume



Gamma or proton? [Nieto]



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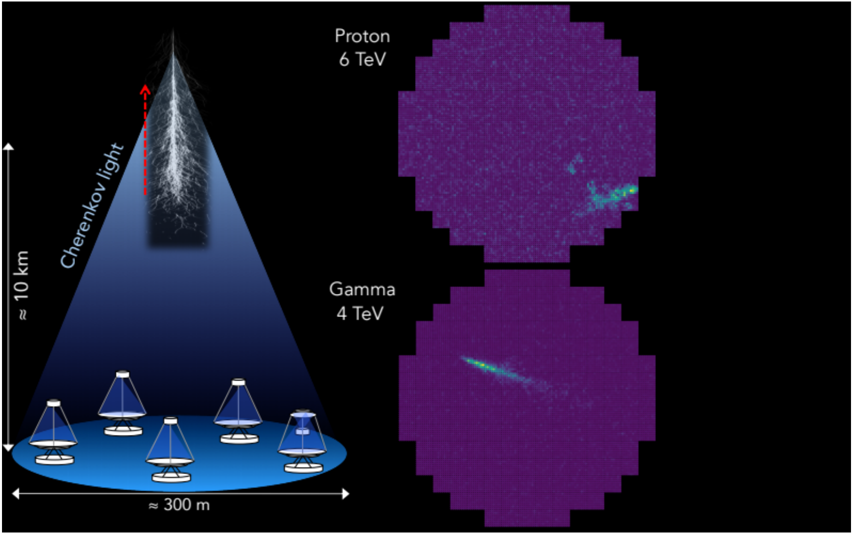

Gamma or proton? [Nieto]