Towards the optimization of IACTs as dark matter probes using DCNs

Advanced Workshop on Accelerating the Search for Dark Matter with Machine Learning

The Abdus Salam International Centre for Theoretical Physics

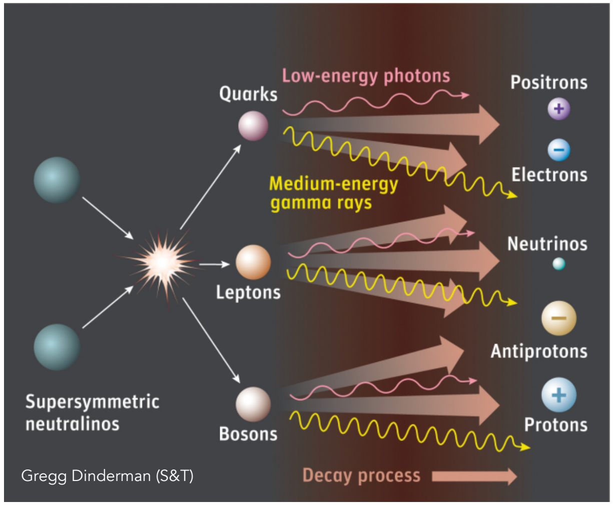
D. Nieto
on behalf of the Cherenkov Telescope Array Consortium

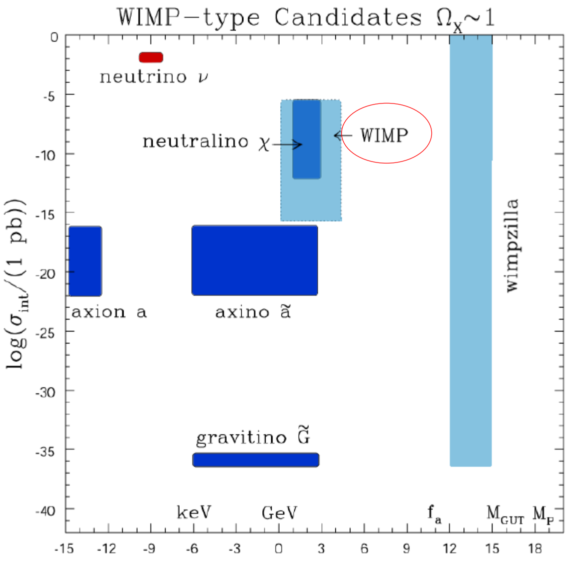
GOBIERNO DE ESPAÑA MINISTERIO DE CIENCIA, INNOVACIÓN Y UNIVERSIDADES
AGENCIA ESTATAL DE INVESTIGACIÓN
EUROPEAN UNION European Regional Development Fund
UNIVERSIDAD COMPLUTENSE MADRID
IPARCOS
cta cherenkov telescope array

Outline

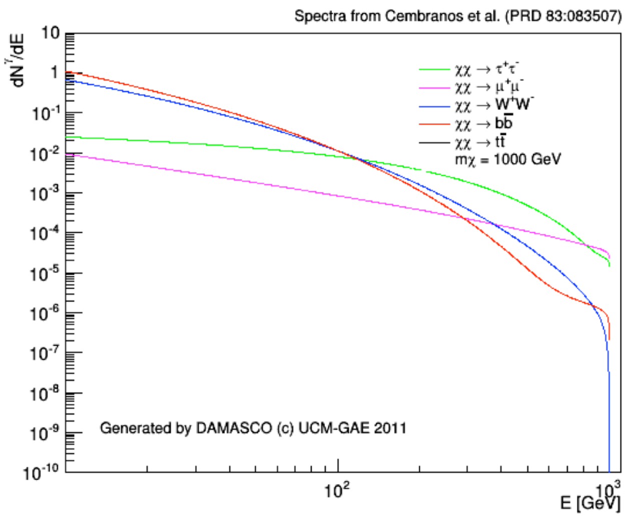
- Indirect dark matter searches in the γ-ray band
- Imaging atmospheric Cherenkov technique
- Machine learning & current-generation IACTs
- Prospects for dark matter searches with CTA
- Enhancing CTA's performance with deep learning

- Basis: Detection of DM annihilation or decay products (SM particles)
- In most cases, entangled with CR and subdominant
- WIMPs with masses > 100 GeV are good DM particle candidates
- Photons are privileged messengers
  - No deflection by B-fields, trace back to source
  - Observation of astrophysical targets
  - Characteristic spectral shape: identification





arXiv:0404052

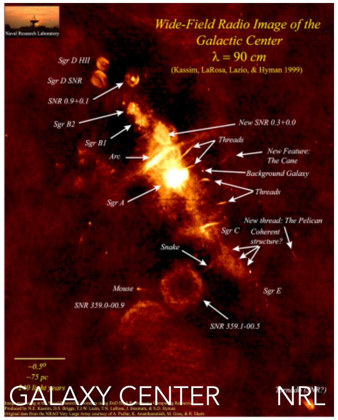


Expected spectrum from annihilating DM

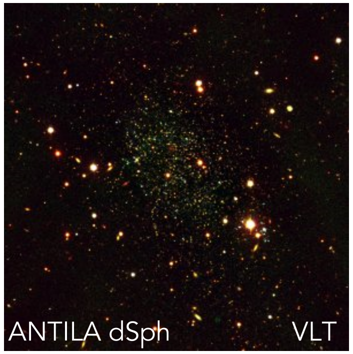
$$\frac{d\Phi}{dE} = \boxed{J(\Delta\Omega)} \times \boxed{\frac{d\Phi^{PP}}{dE}} = \boxed{\int_{l.o.s,V} \rho_{DM}^2(l)\, d\Omega\, dl} \times \boxed{\frac{1}{4\pi} \frac{\langle \sigma_{ann} v \rangle}{2 m_{DM}^2} \sum_i B_i \frac{dN_i^{\gamma}}{dE}}$$

Key concepts: ρ_{DM}, distance, background

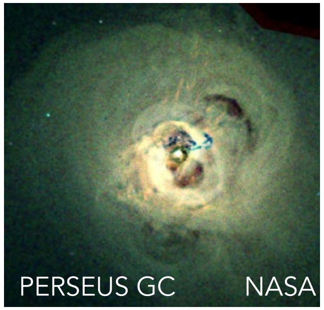
Galactic Center & Halo
- High flux
- Background Issues



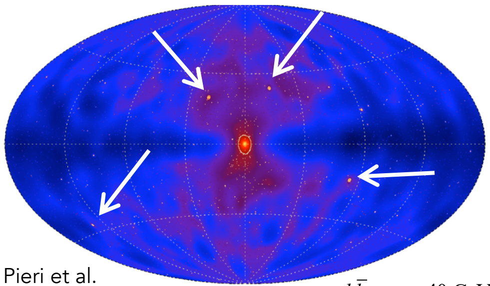
Dwarf Galaxies
- Large M/L
- No background
- Low flux



Galaxy Clusters
- Huge DM content
- Large distance
- High background



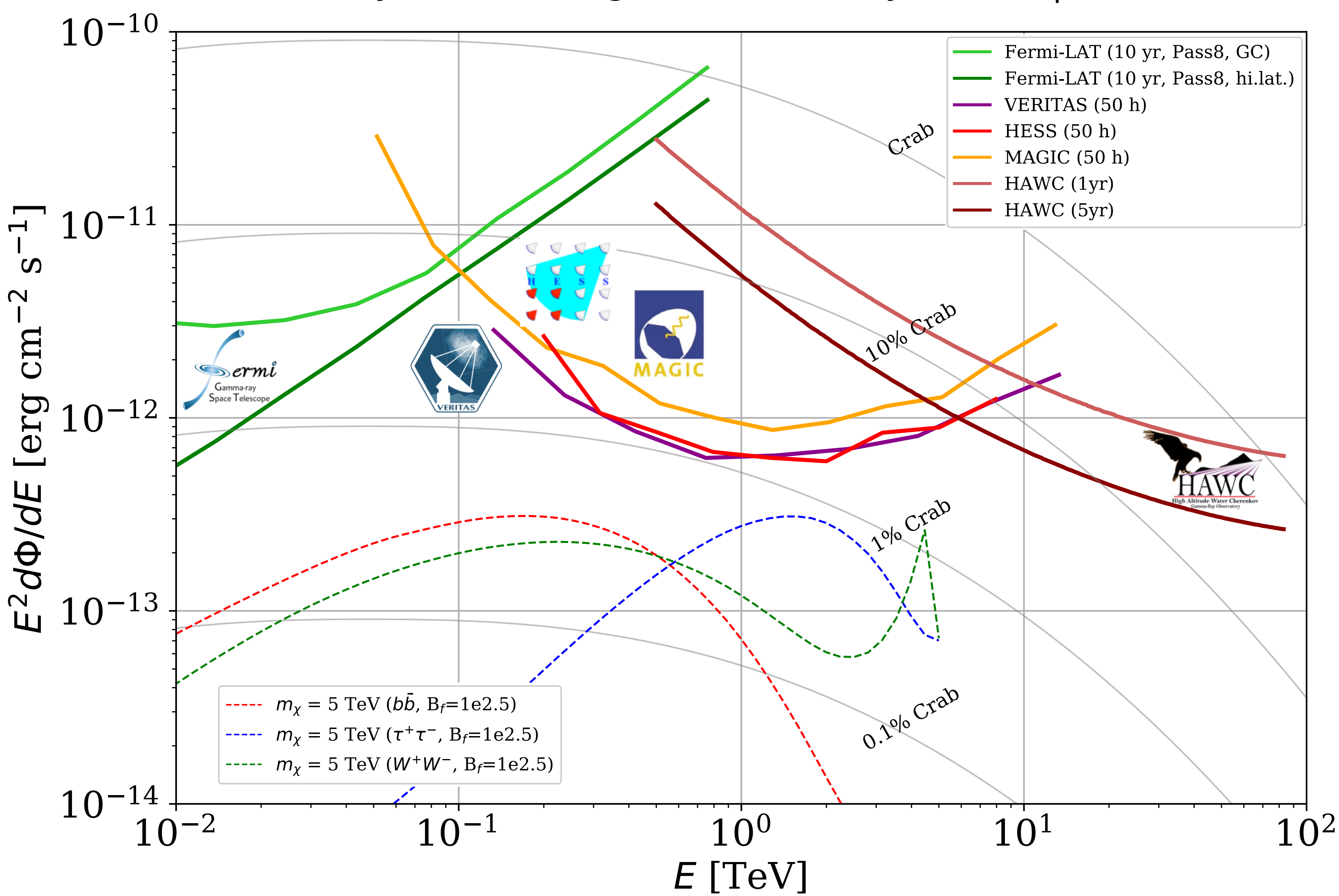
Unassociated HE Sources:
- DM Subhalos?



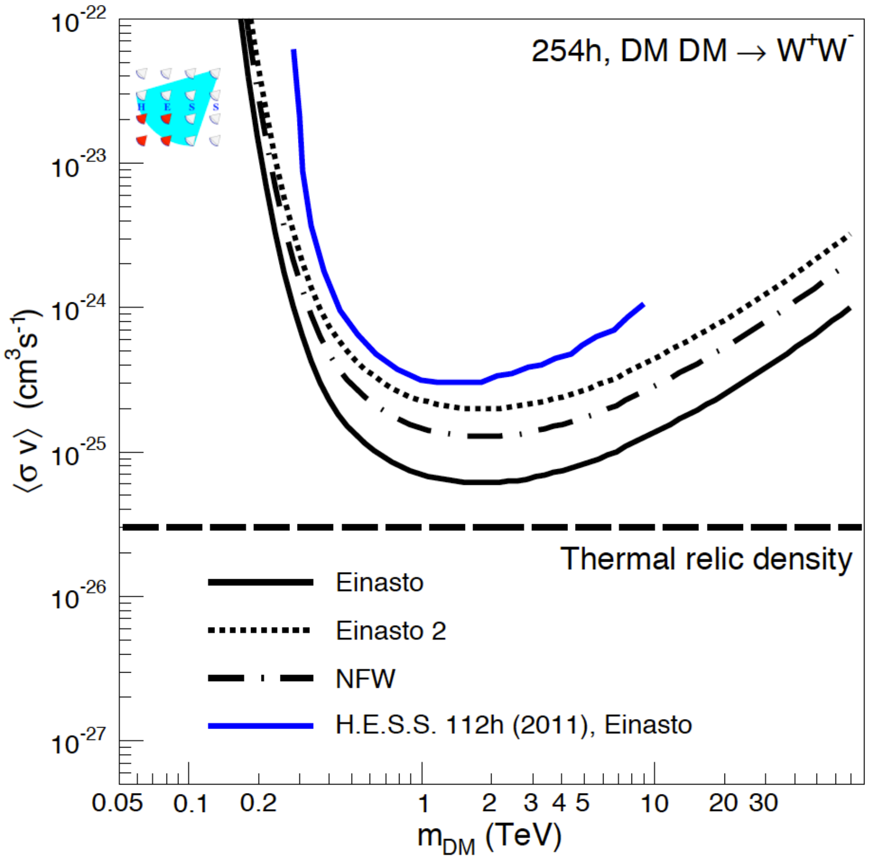
Pieri et al.
PRD 83:0235, 2008

$\chi\chi \rightarrow b\bar{b},\ m_\chi = 40$ GeV

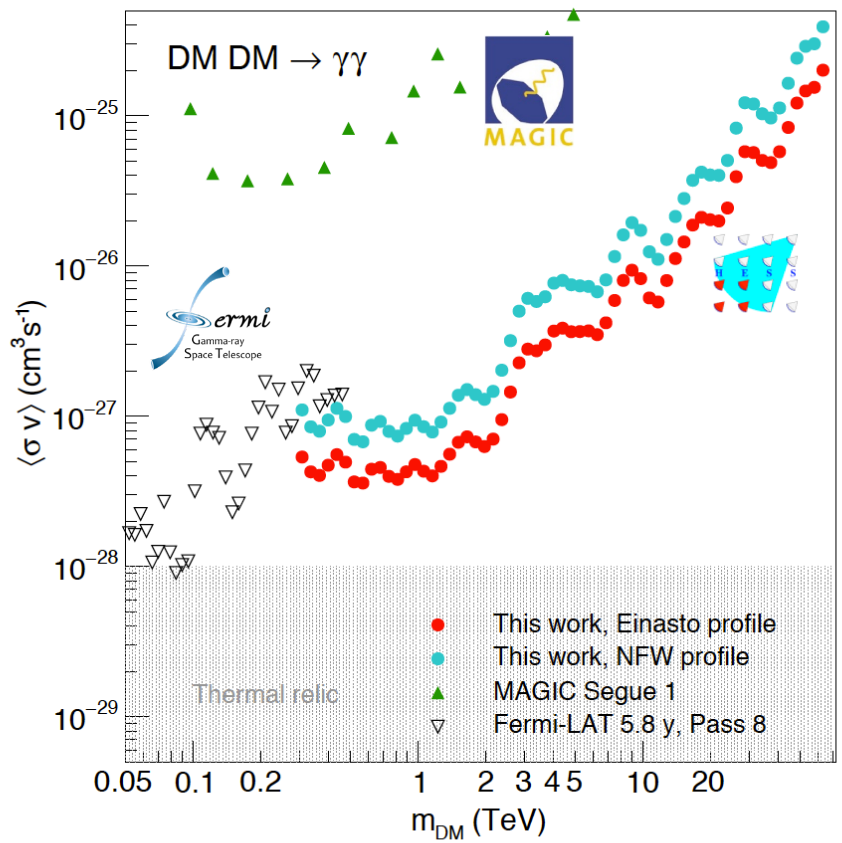
Sensitivity of current-generation γ-ray telescopes



Galactic Halo

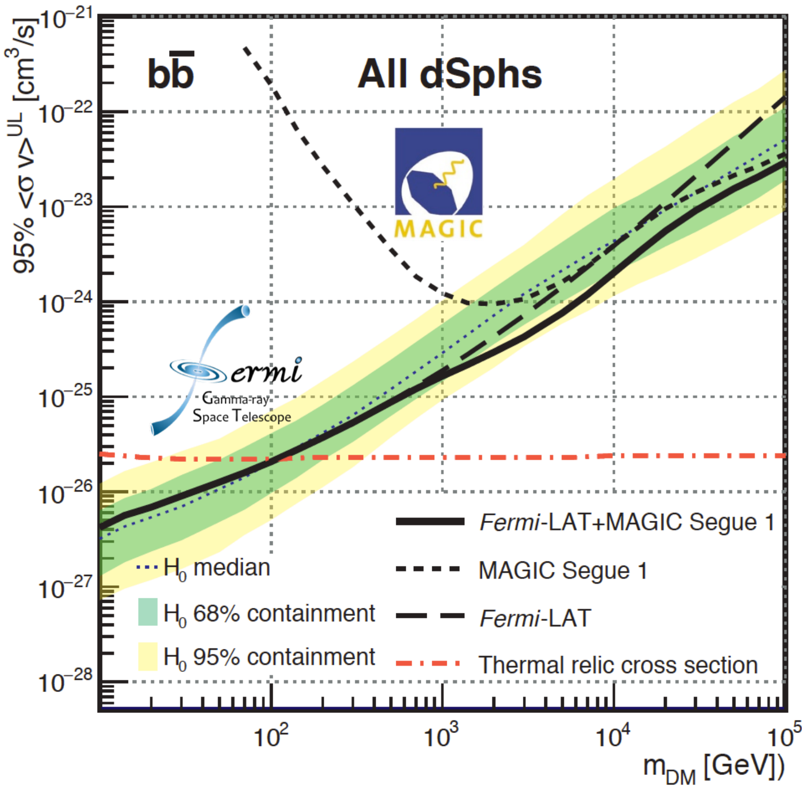


Abdallah et al., PRL 117, 111301 (2016)

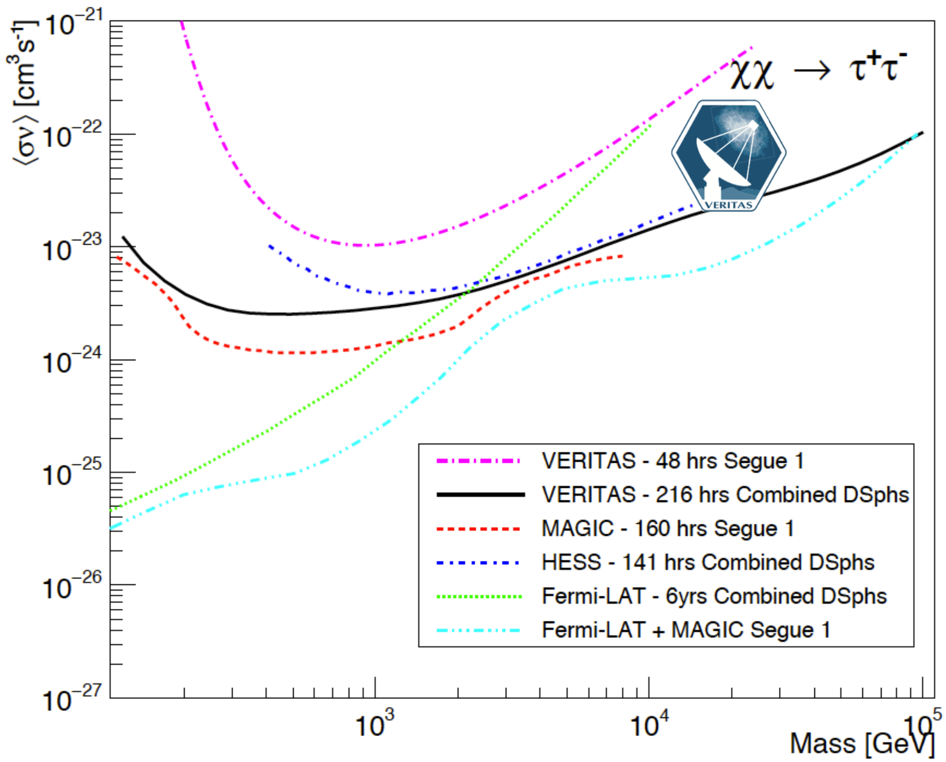


Abdallah et al., PRL 120, 201101 (2018)

Dwarf Spheroidal Galaxies

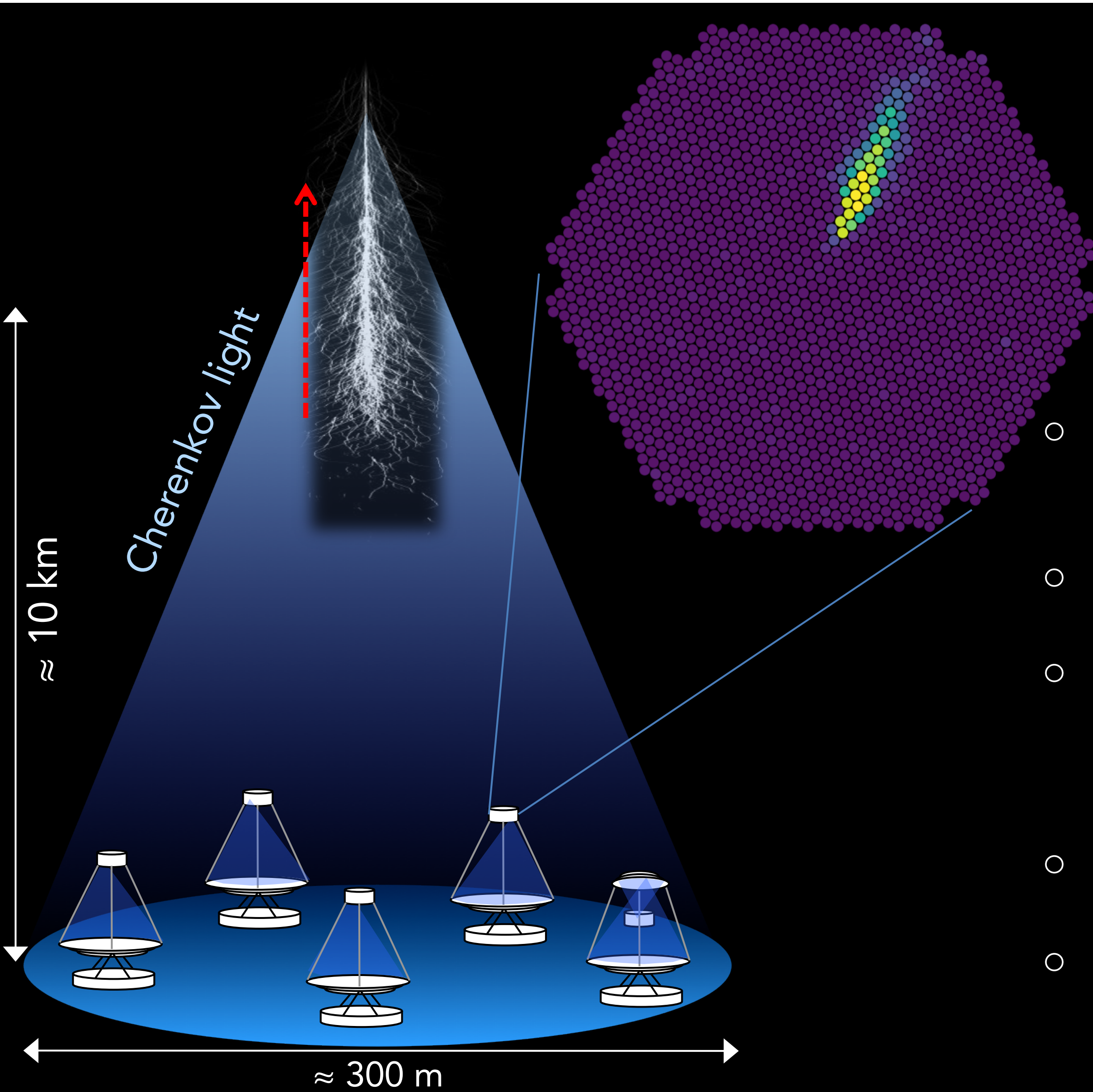


Ahnen et al., JCAP 02 (2016) 039

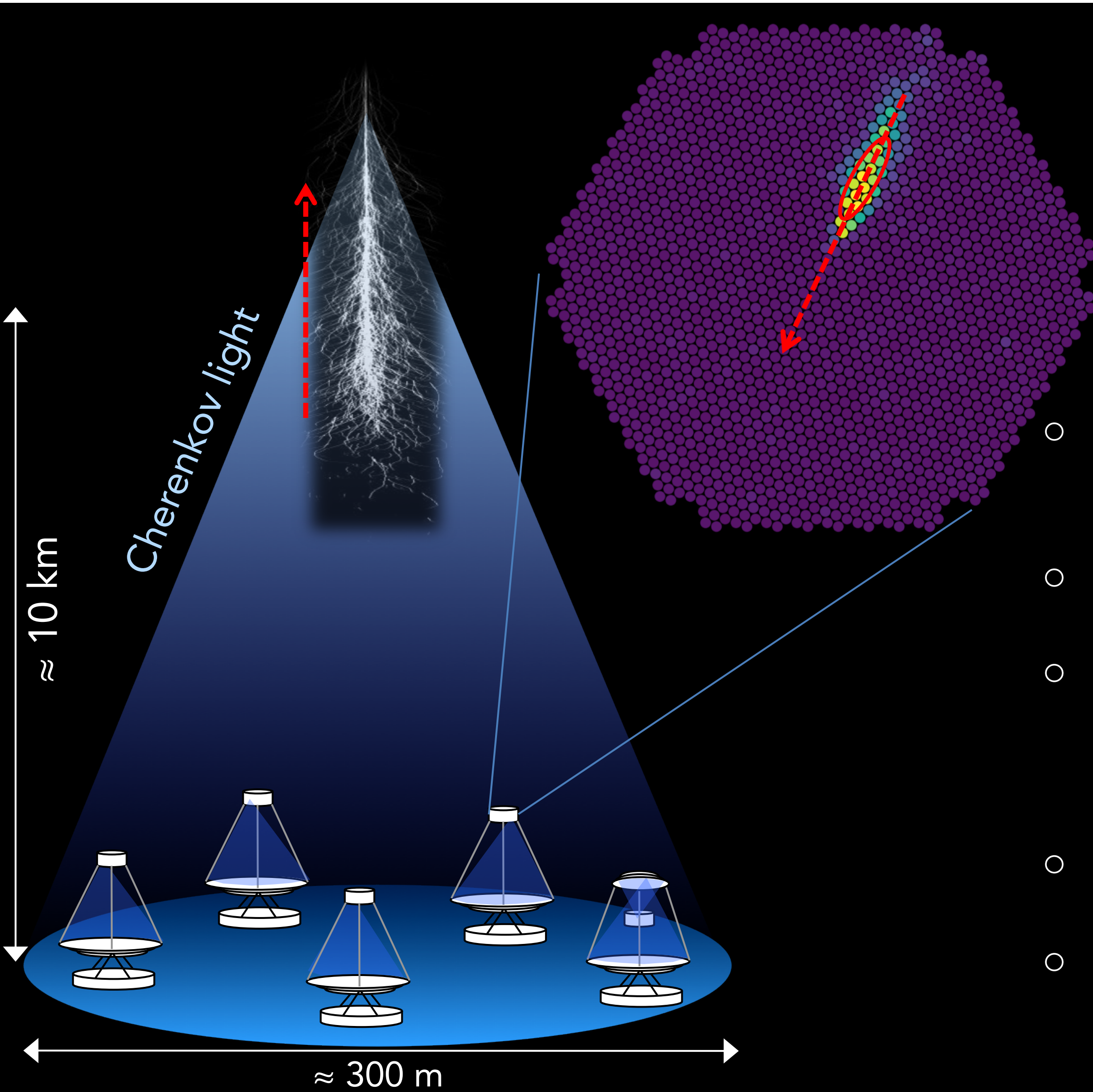


Archambault et al. PRD 95, 082001 (2017)

Imaging atmospheric Cherenkov technique

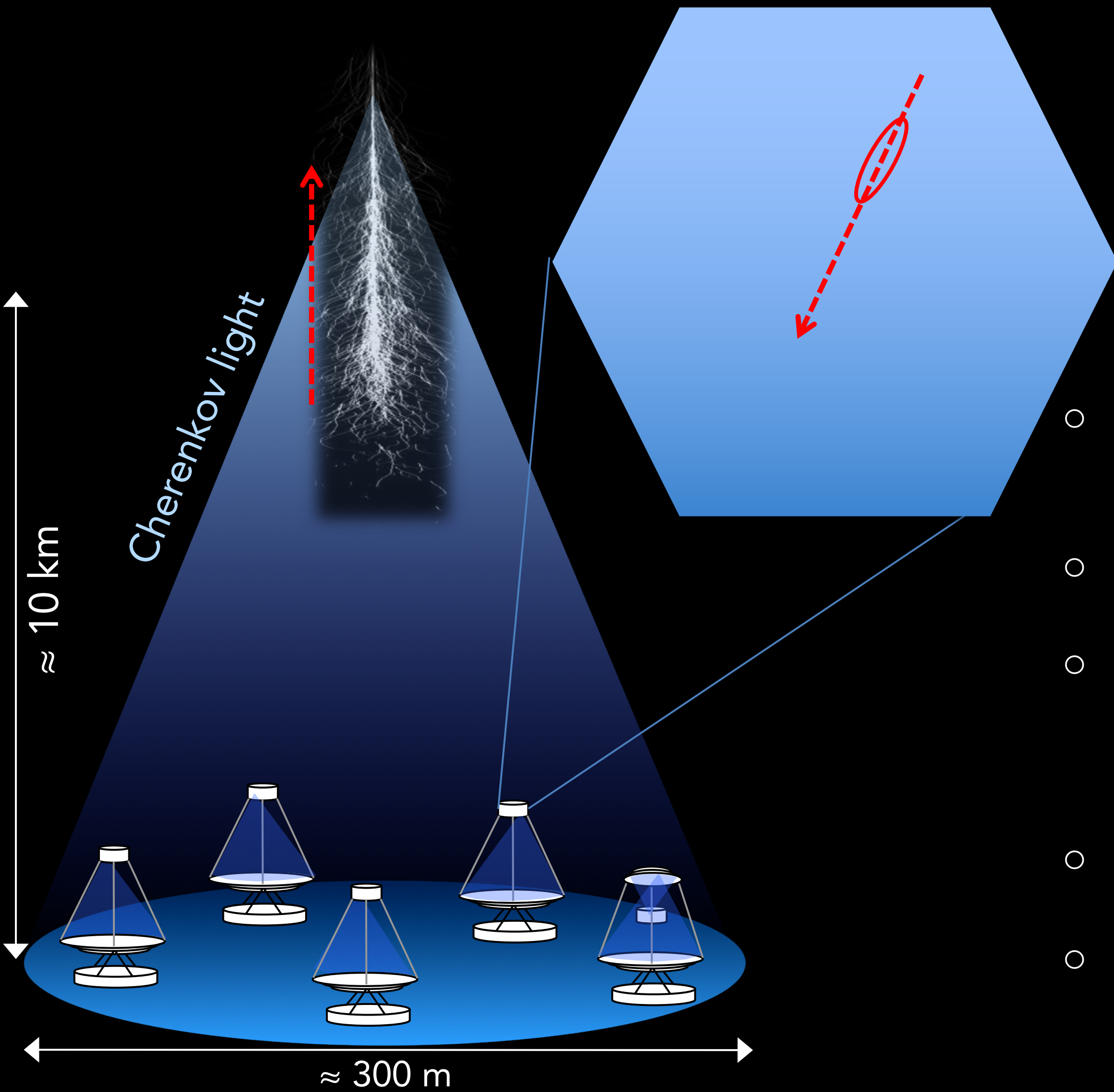


- Detection of extended air showers using the atmosphere as a calorimeter
- Huge γ–ray collection area (~10^5 m^2)
- Large background from charged CR
  - Partly irreducible (e^-/e^+, single-EM, with current methods)
- Energy window: tens GeV - tens TeV
- Event reconstruction from image:
  - Type of primary event
  - Primary energy estimation
  - Primary arrival direction

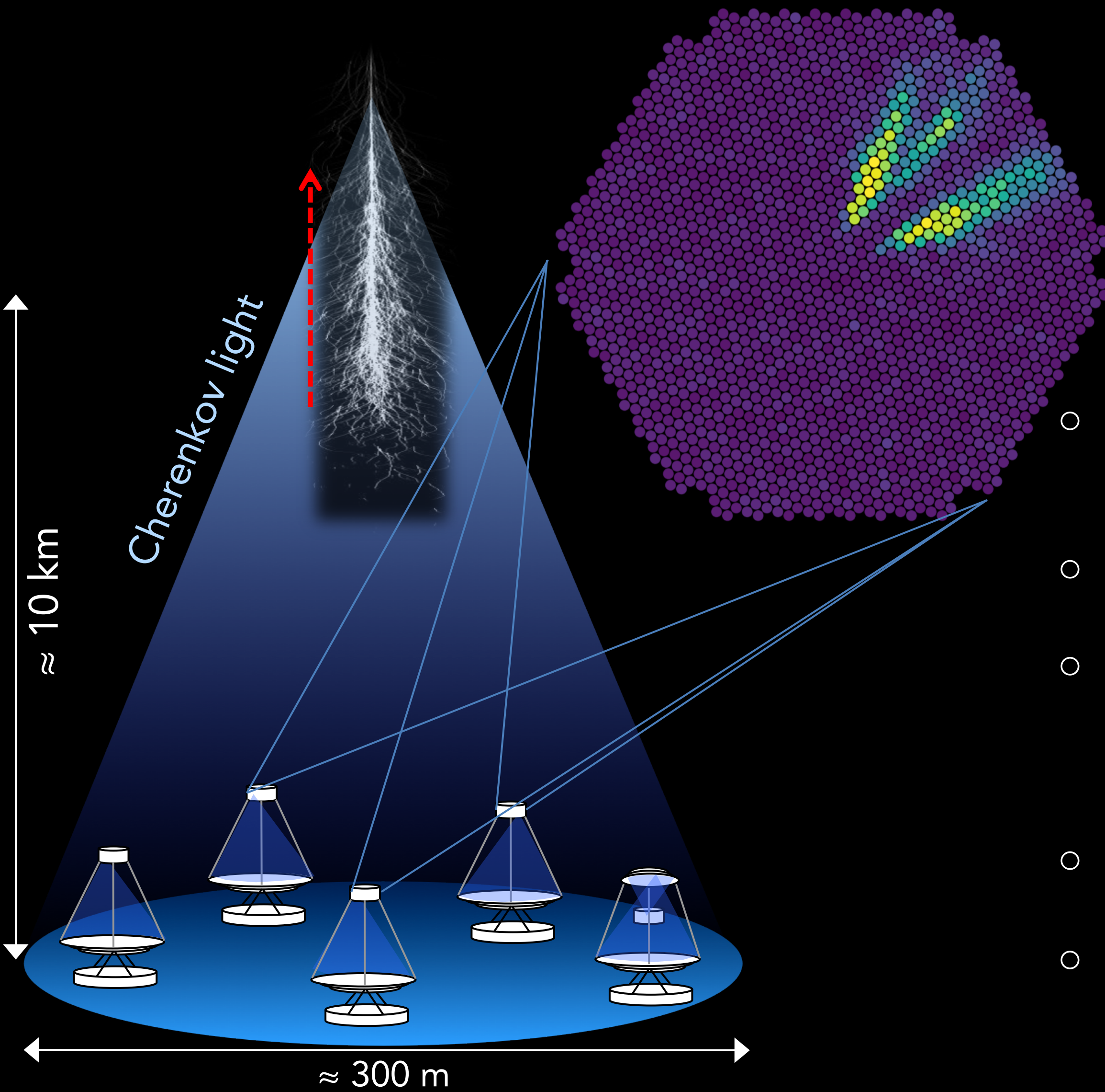


- Detection of extended air showers using the atmosphere as a calorimeter
- Huge γ–ray collection area ($\sim 10^5$ m^2)
- Large background from charged CR
  - Partly irreducible (e^-/e^+, single-EM, with current methods)
- Energy window: tens GeV - tens TeV
- Event reconstruction from image:
  - Type of primary event
  - Primary energy estimation
  - Primary arrival direction

Imaging atmospheric Cherenkov technique

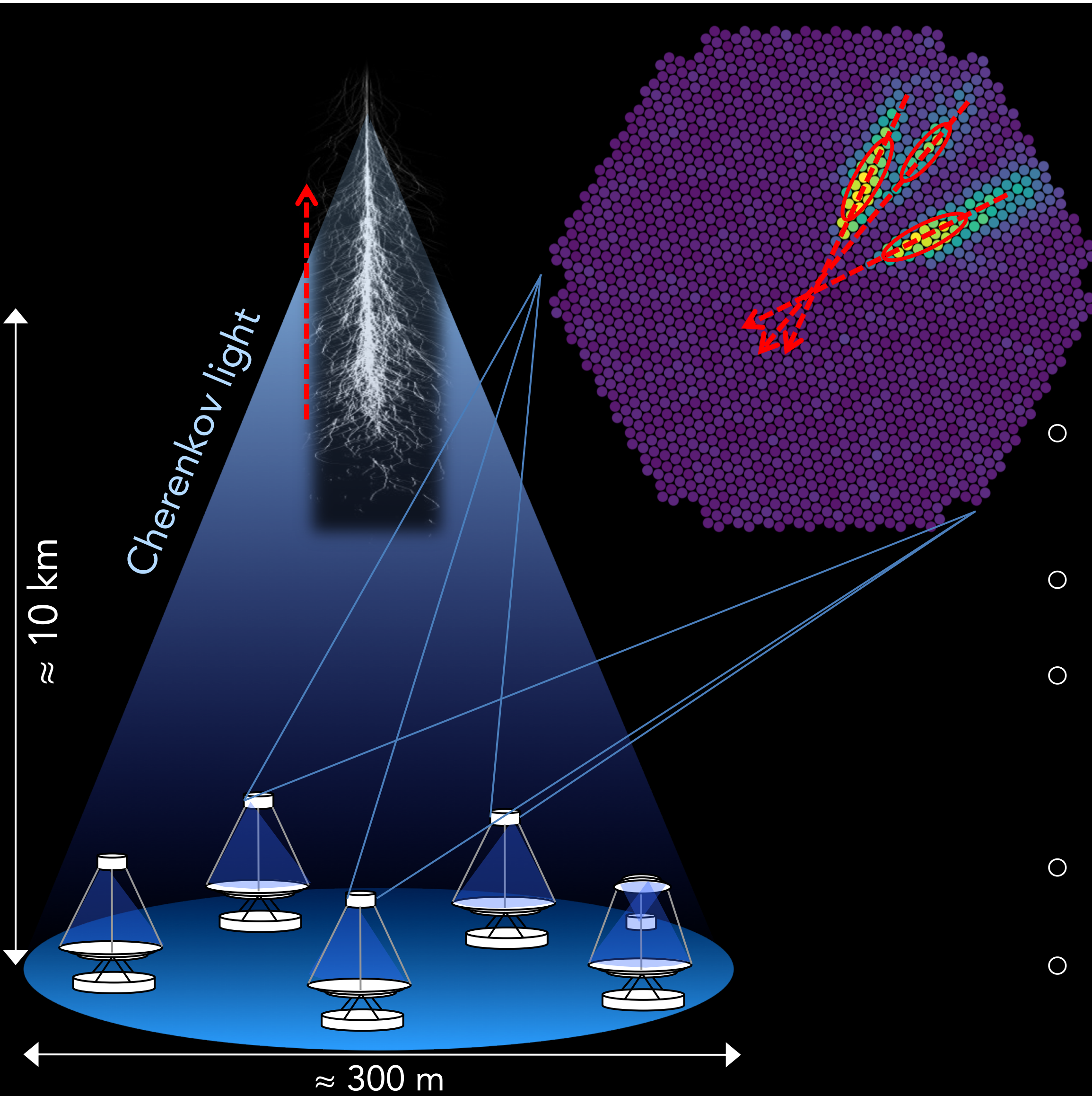


- Detection of extended air showers using the atmosphere as a calorimeter
- Huge γ–ray collection area (~10^5 m^2)
- Large background from charged CR
  - Partly irreducible (e^-/e^+, single-EM, with current methods)
- Energy window: tens GeV - tens TeV
- Event reconstruction from image:
  - Type of primary event
  - Primary energy estimation
  - Primary arrival direction



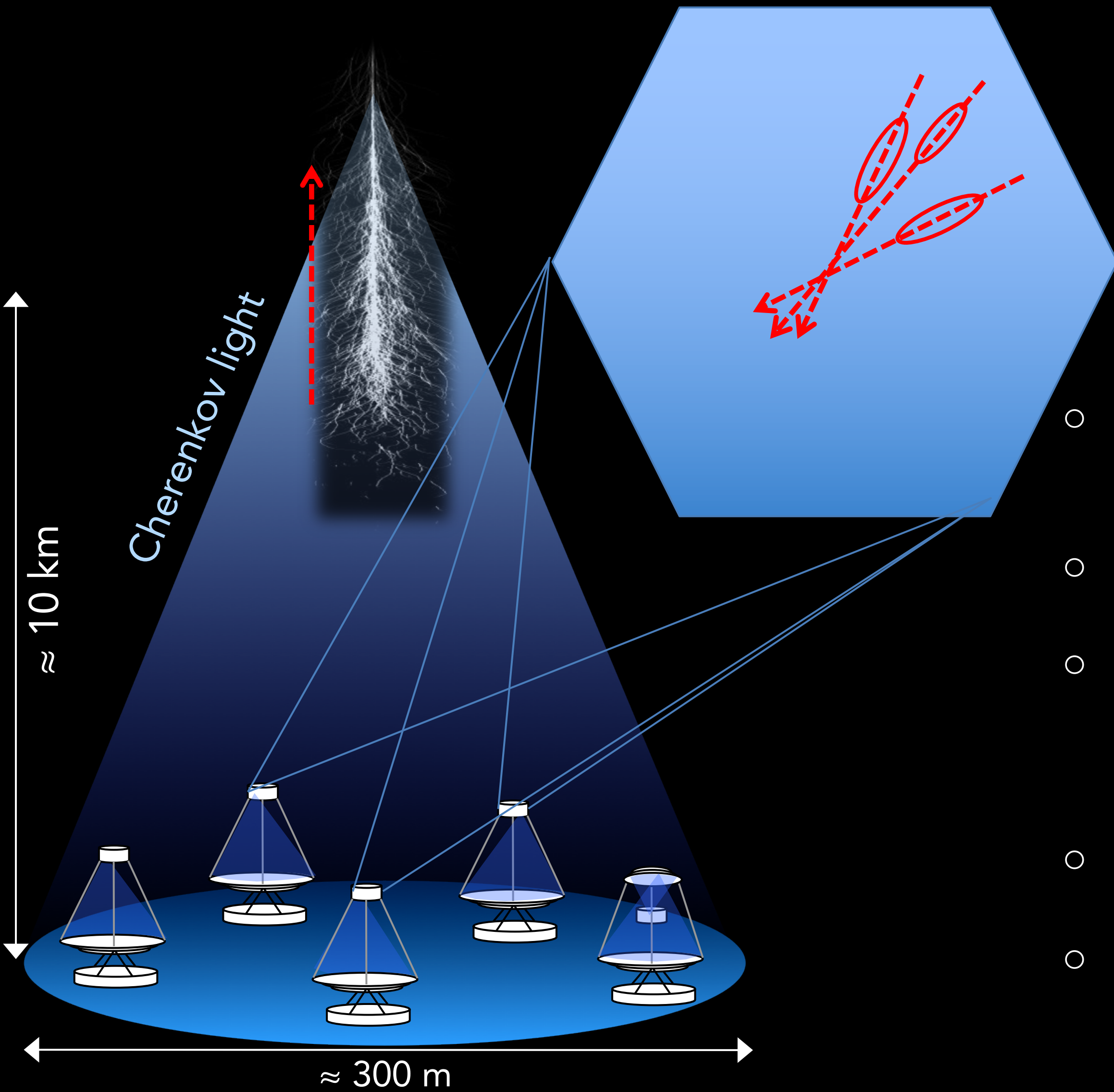
- Detection of extended air showers using the atmosphere as a calorimeter
- Huge γ–ray collection area (~10^5 m^2)
- Large background from charged CR
  - Partly irreducible (e^-/e^+ , single-EM, with current methods)
- Energy window: tens GeV - tens TeV
- Event reconstruction from image:
  - Type of primary event
  - Primary energy estimation
  - Primary arrival direction

Imaging atmospheric Cherenkov technique



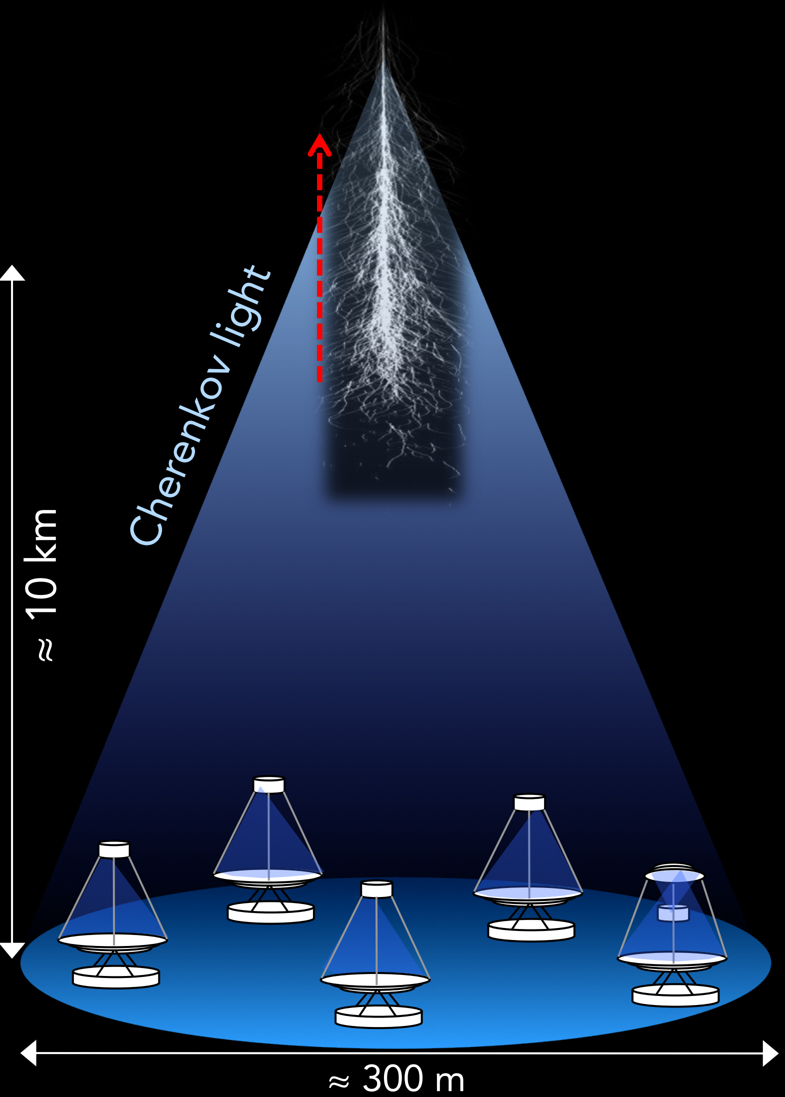
- Detection of extended air showers using the atmosphere as a calorimeter
- Huge γ–ray collection area (~10^5 m^2)
- Large background from charged CR
  - Partly irreducible (e^-/e^+ , single-EM, with current methods)
- Energy window: tens GeV - tens TeV
- Event reconstruction from image:
  - Type of primary event
  - Primary energy estimation
  - Primary arrival direction

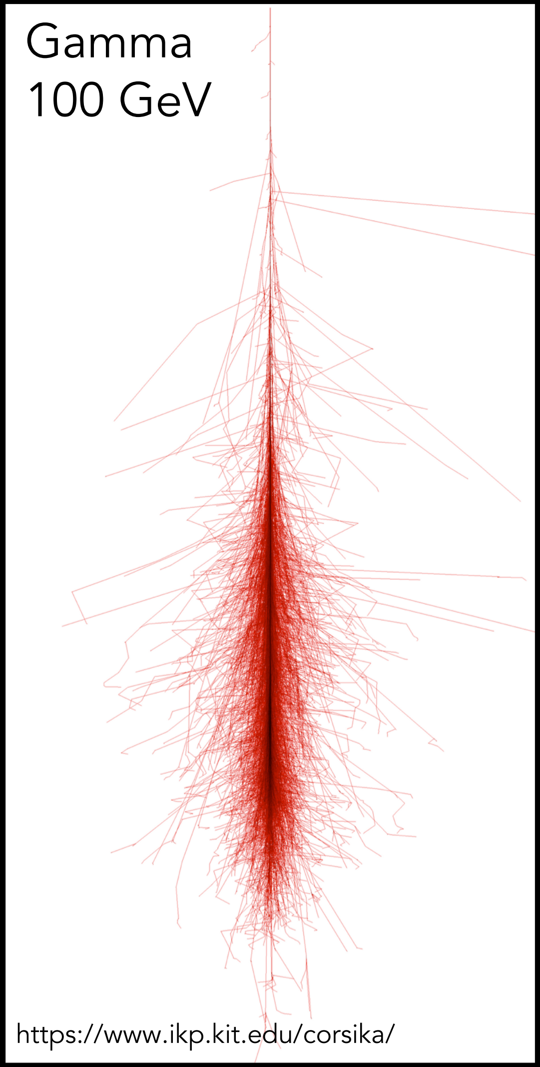
Imaging atmospheric Cherenkov technique

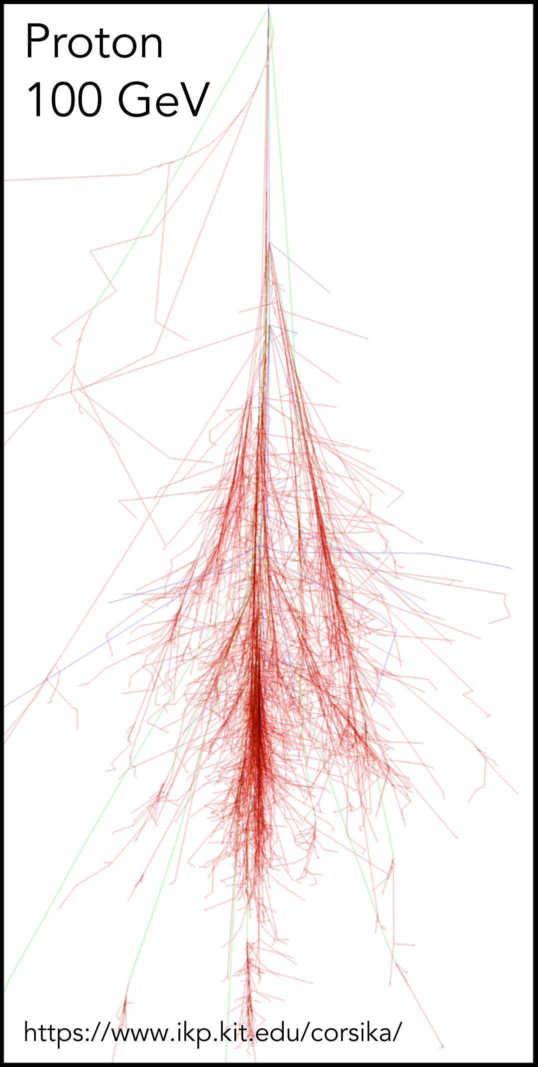


- Detection of extended air showers using the atmosphere as a calorimeter
- Huge γ–ray collection area (~10^5 m^2)
- Large background from charged CR
  - Partly irreducible (e^-/e^+, single-EM, with current methods)
- Energy window: tens GeV - tens TeV
- Event reconstruction from image:
  - Type of primary event
  - Primary energy estimation
  - Primary arrival direction

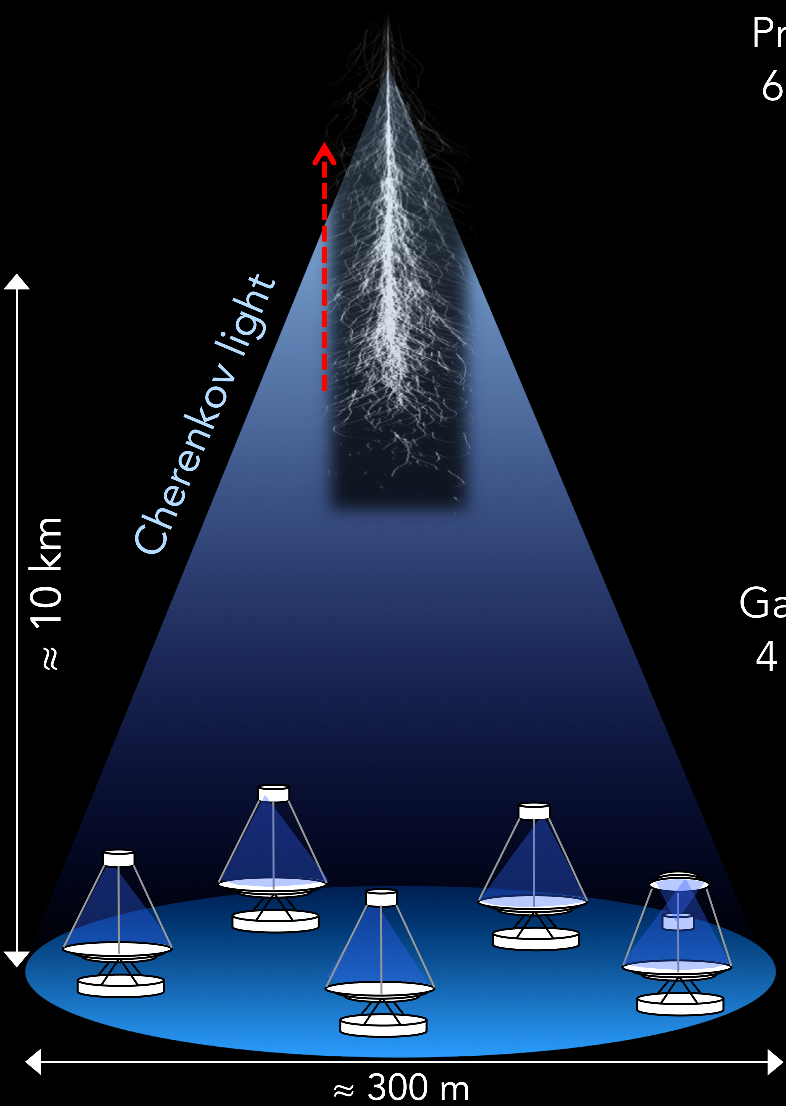
Imaging atmospheric Cherenkov technique

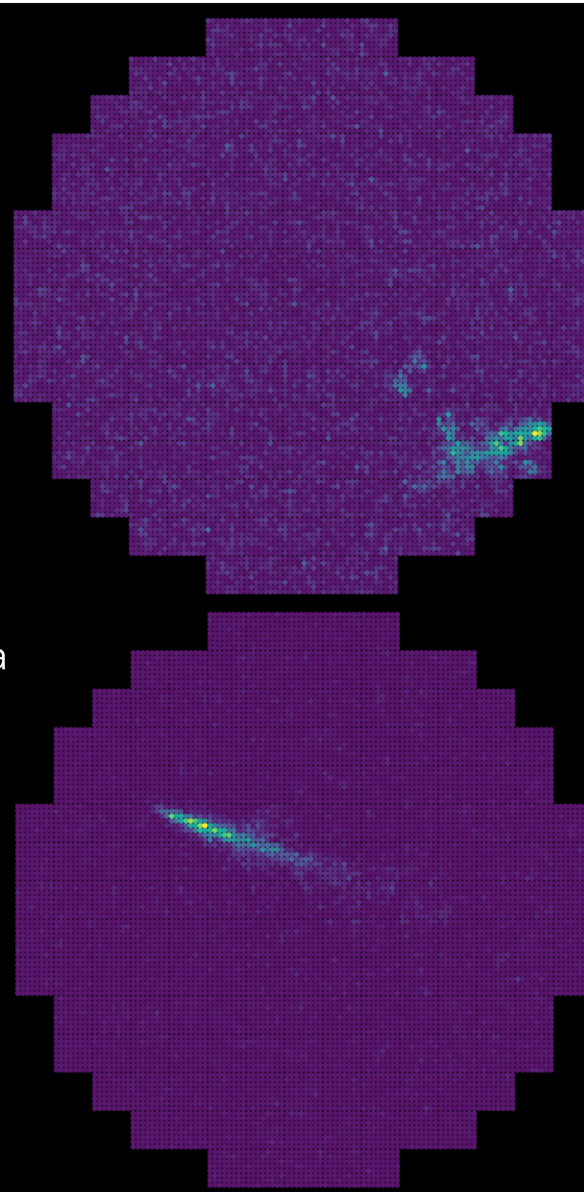




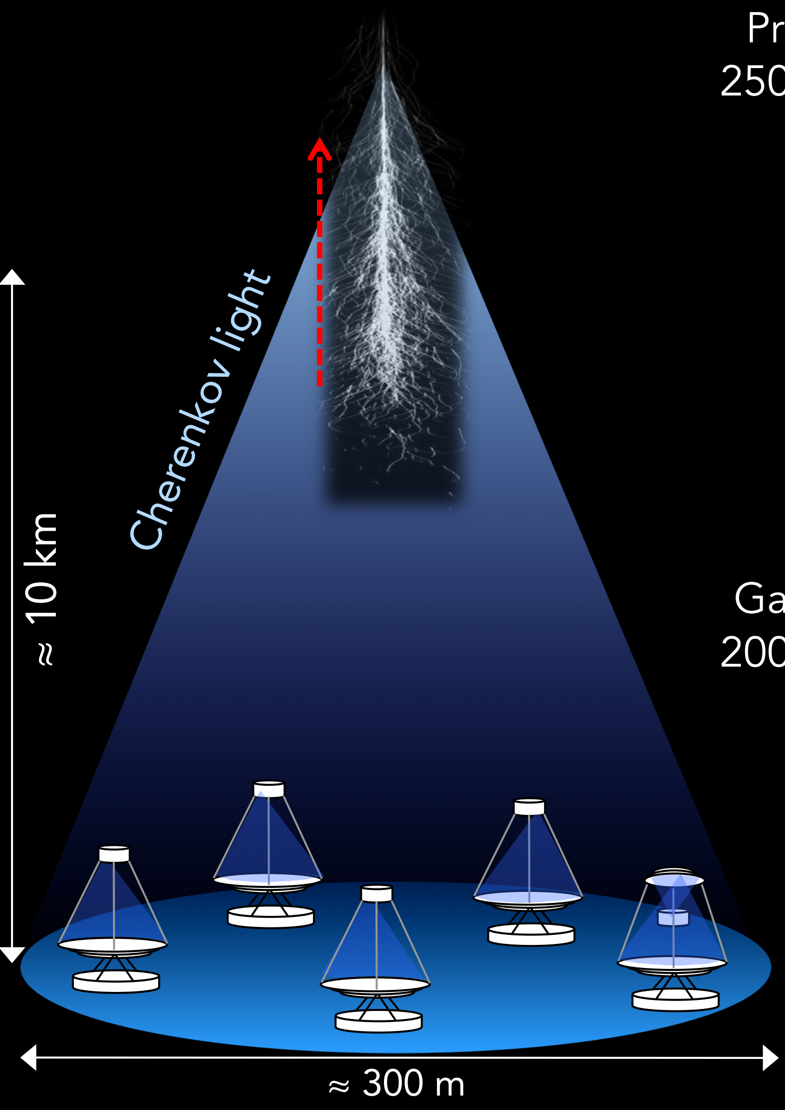


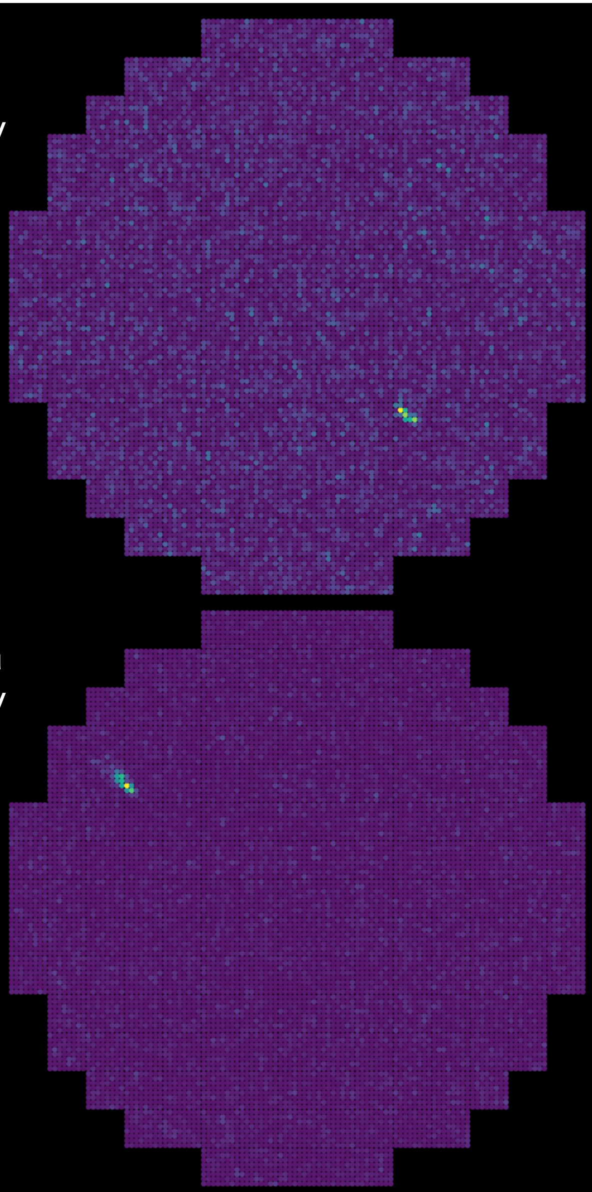
Imaging atmospheric Cherenkov technique

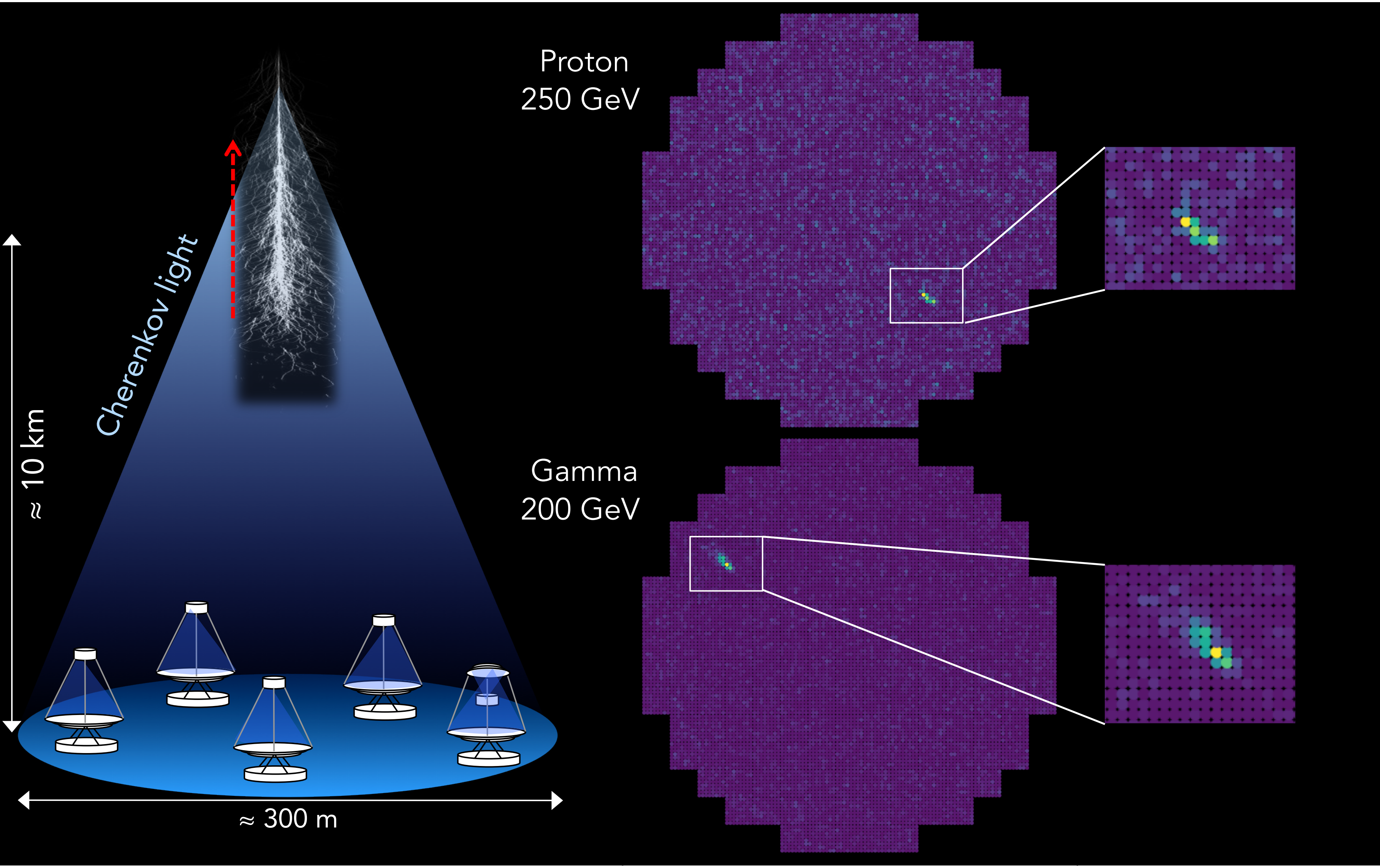




Imaging atmospheric Cherenkov technique

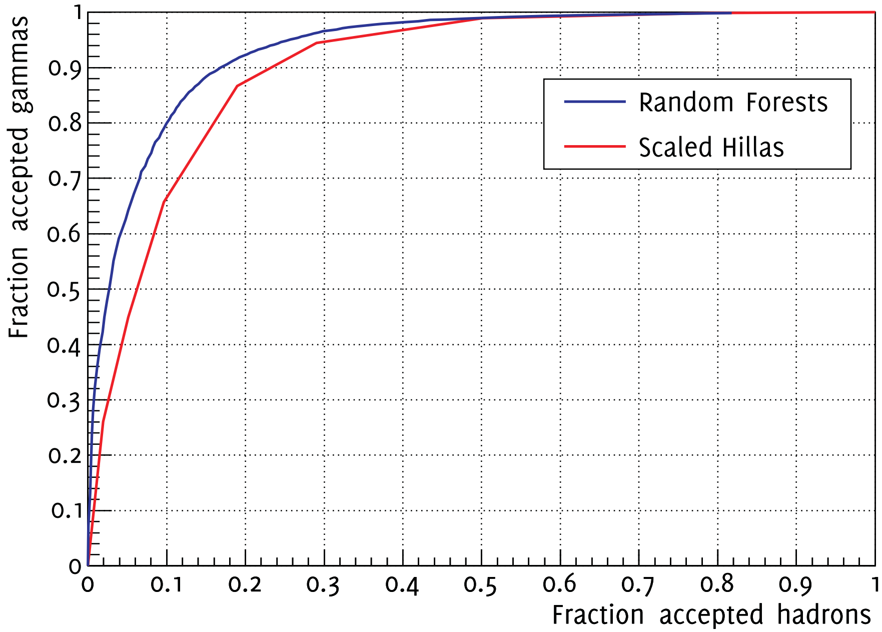




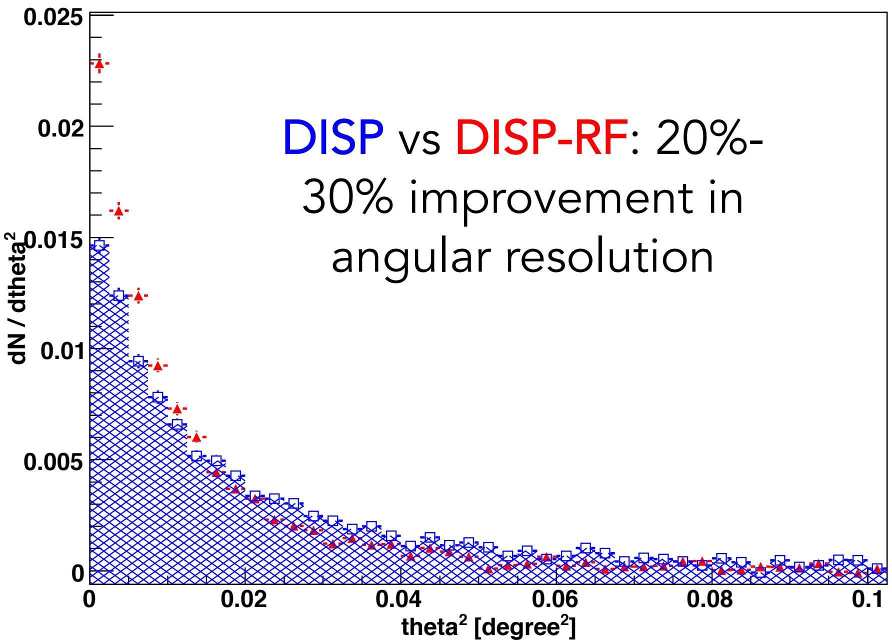

Cherenkov light
≈ 10 km
≈ 300 m
Proton
250 GeV
Gamma
200 GeV

MAGIC

- ML method: Random Forest (RF)
- Applied to: background rejection, arrival direction

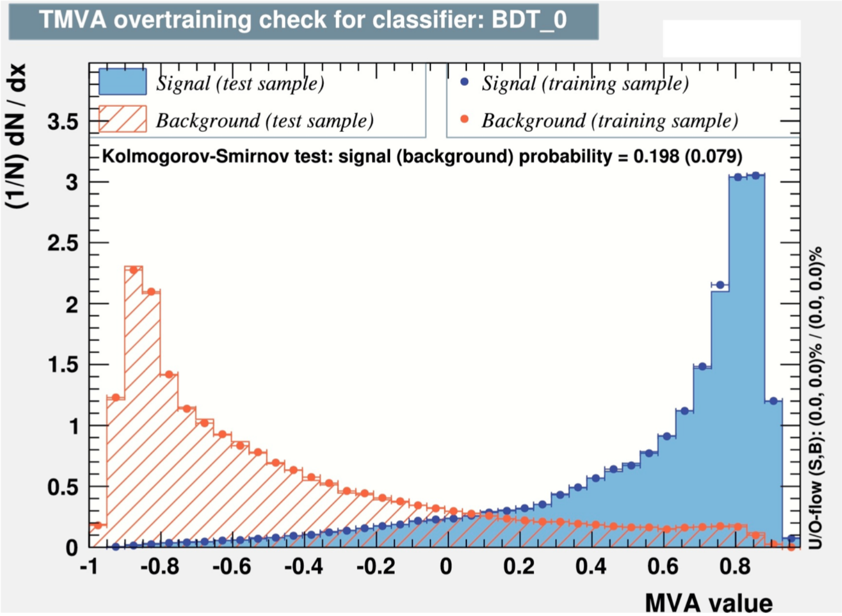


Albert et al., NIM-A 588:424-432 (2008)

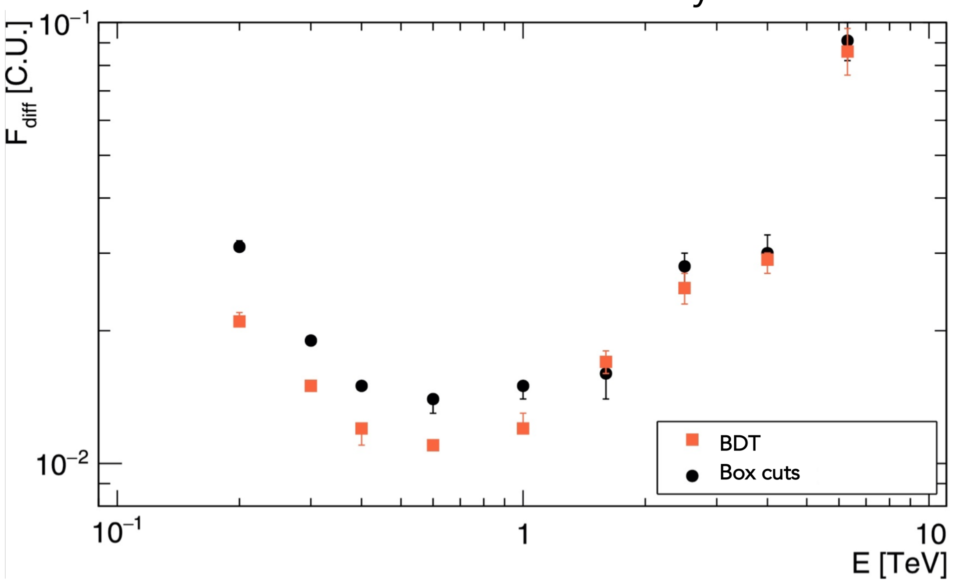


Aleksic et al., A&A 524 A77 (2010)

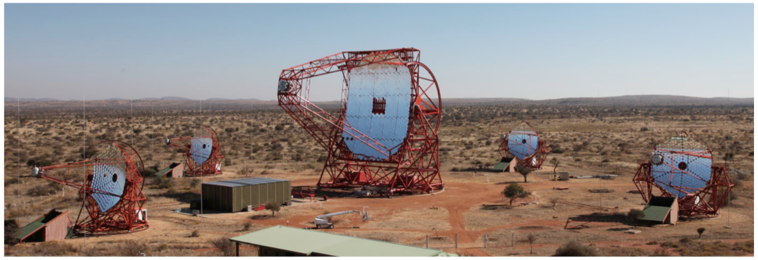
- ML method: Boosted Decision Trees (BDT)
- Applied to: background rejection



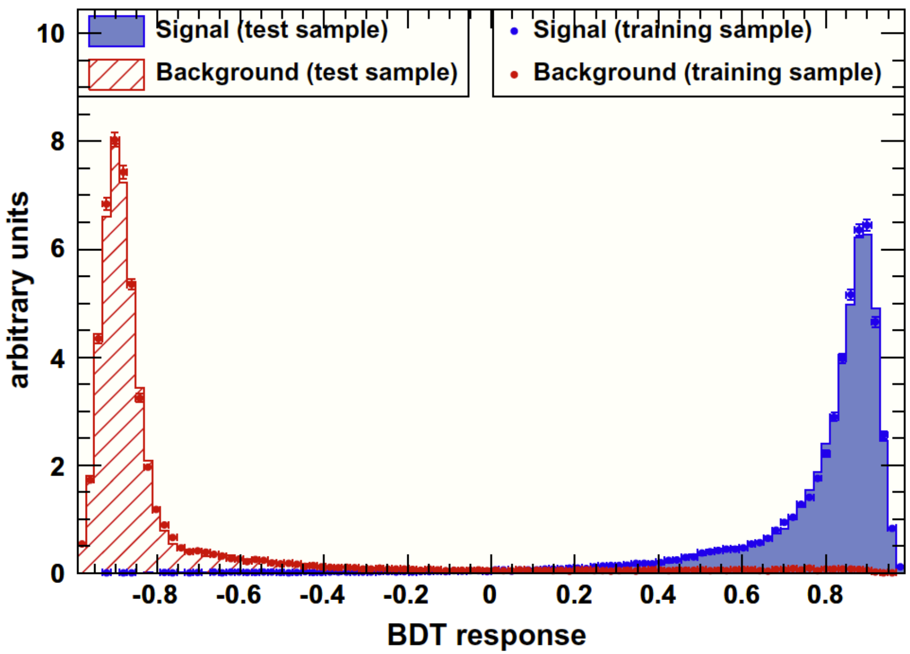
VERITAS diff. sensitivity



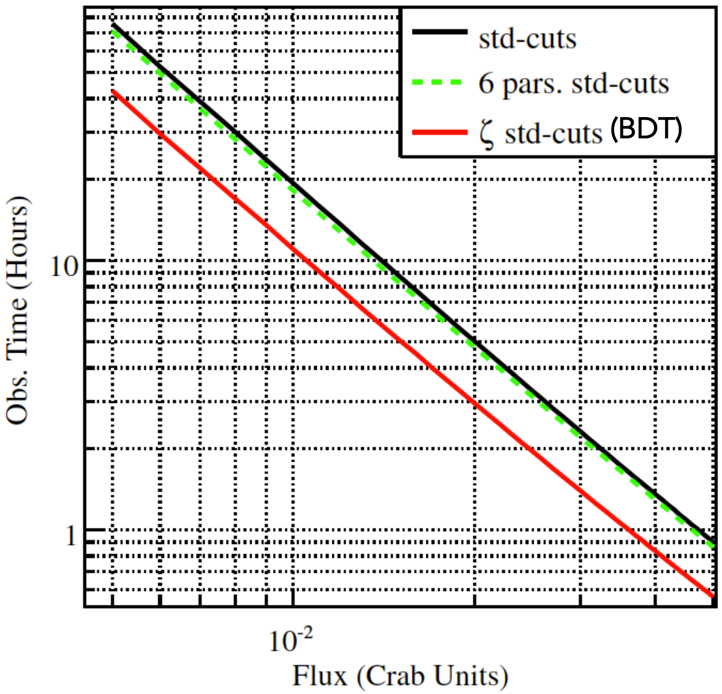
Krause et al., APP V89 P1-9 (2017)



- ML method: Boosted Decision Trees (BDT)
- Applied to: background rejection



Becherini et al., APP V34-12 P858-870 (2011)



Ohm et al., APP V31-5 P383-391 (2009)

(Results for H.E.S.S. I only)

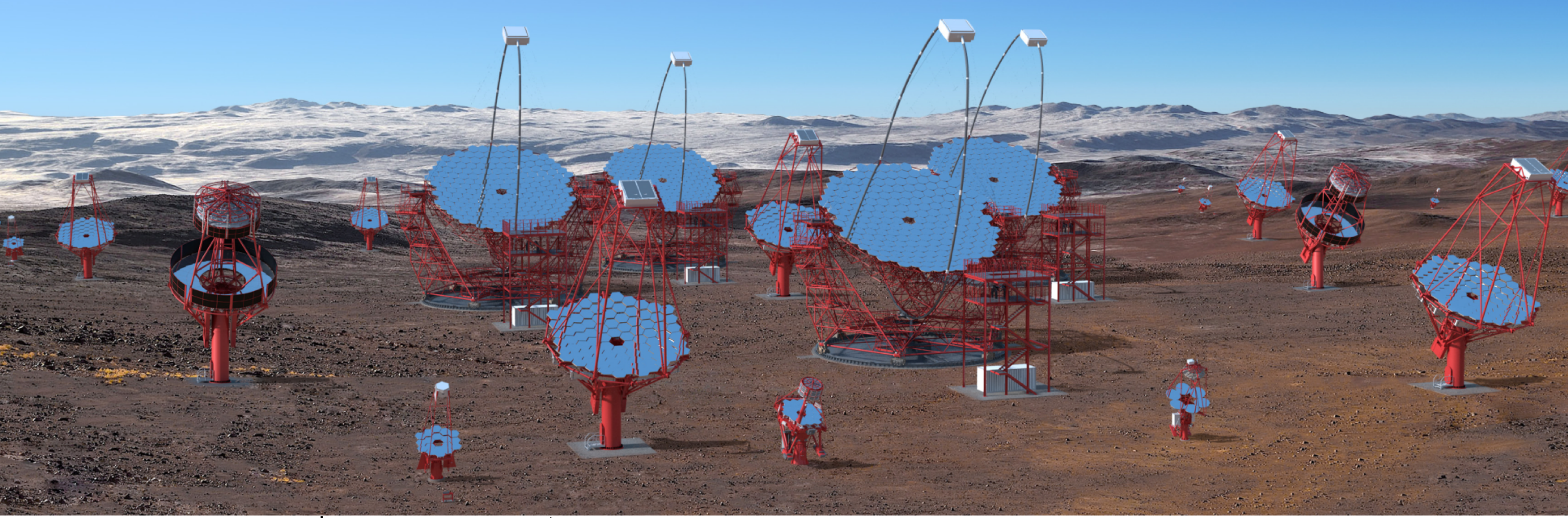
The Cherenkov Telescope Array

- 5-20 fold better sensitivity w.r.t. current IACTs
- 4 decades of energy coverage: 20 GeV to 300 TeV
- Improved angular and energy resolution
- Two arrays (North/South)

Low-energy range:
23 m ø
Parabolic reflector
4° - 5° FoV
Energy threshold 20 GeV

Mid energy-range:
12 m ø modified Davies-Cotton reflector
9.7 m ø Schwarzschild-Couder reflector
7° - 8° FoV
Best sensitivity in the 100 GeV – 10 TeV range

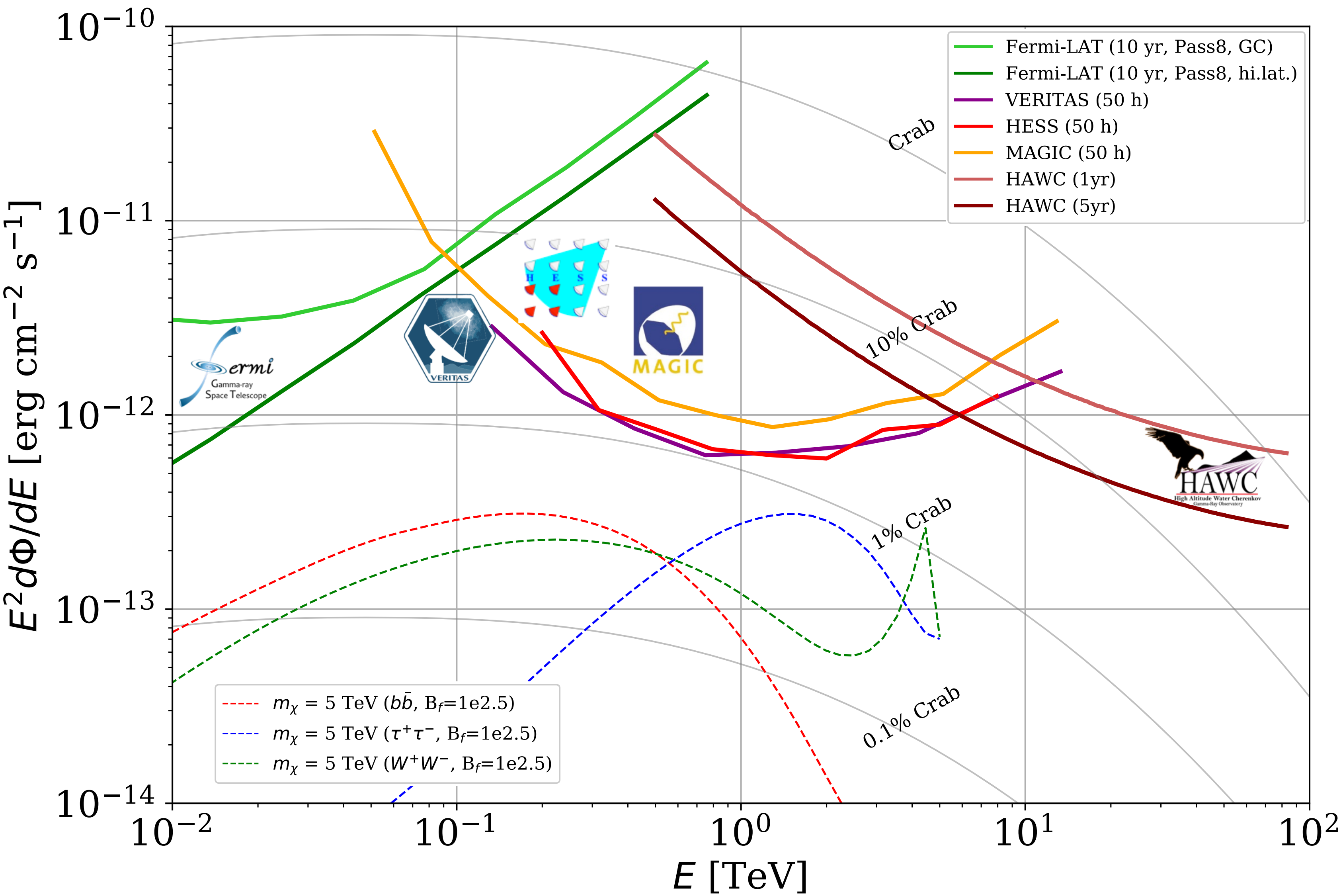
High-energy range:
4 m ø Davies-Cotton reflector
4 m ø Schwarzschild-Couder reflector
9 - 10° FoV
Several km^2 area at multi-TeV energies



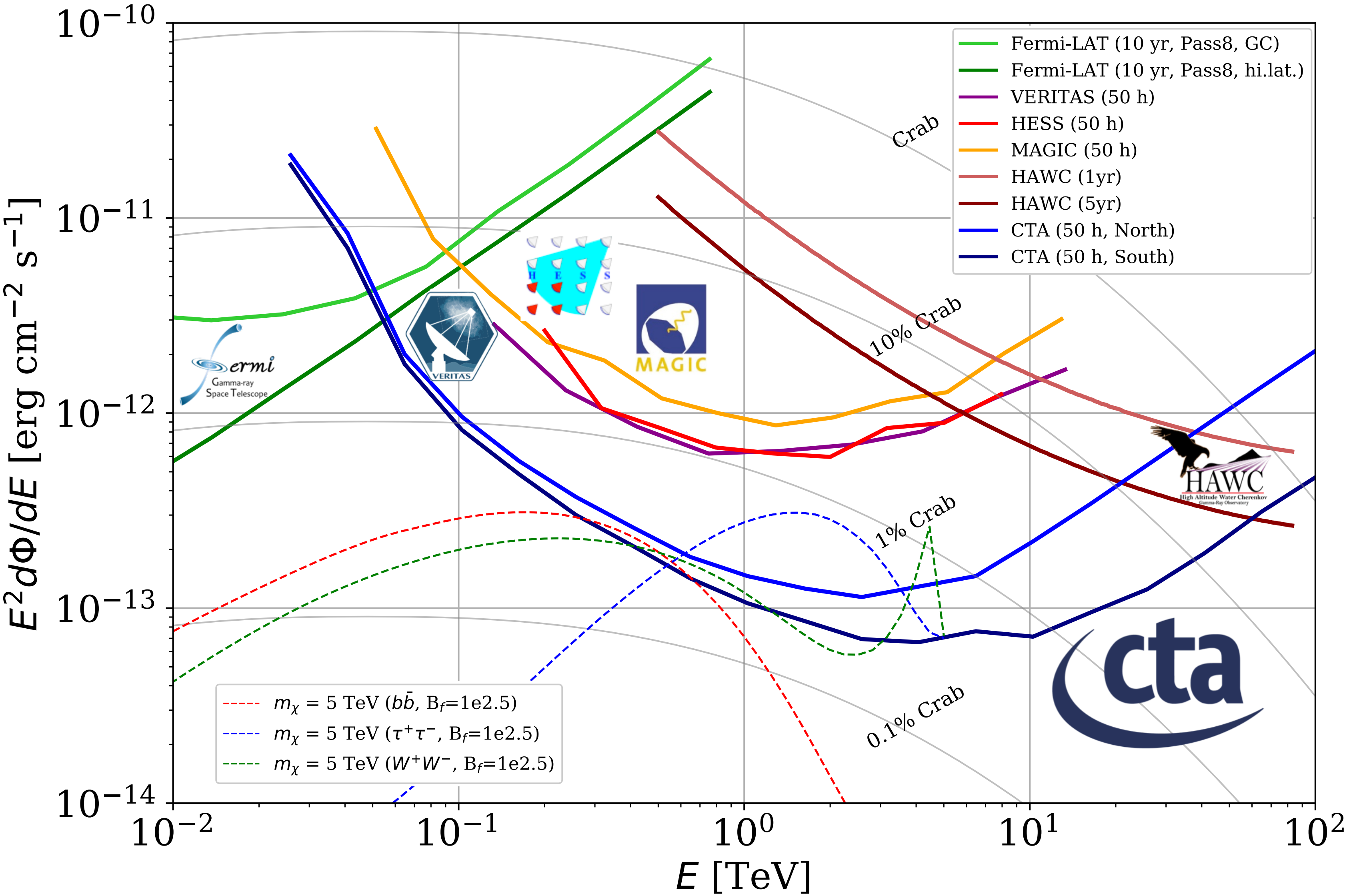
www.cta-observatory.org/

Science with CTA, arXiv:1709.07997

Sensitivity of current-generation γ-ray telescopes

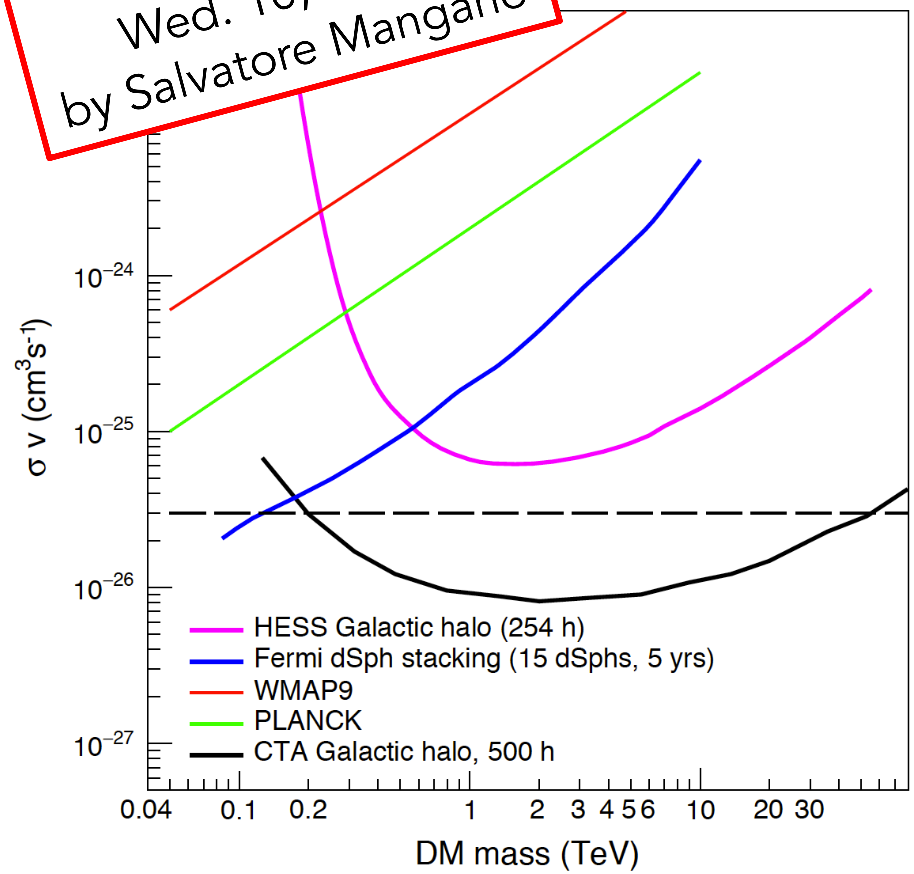


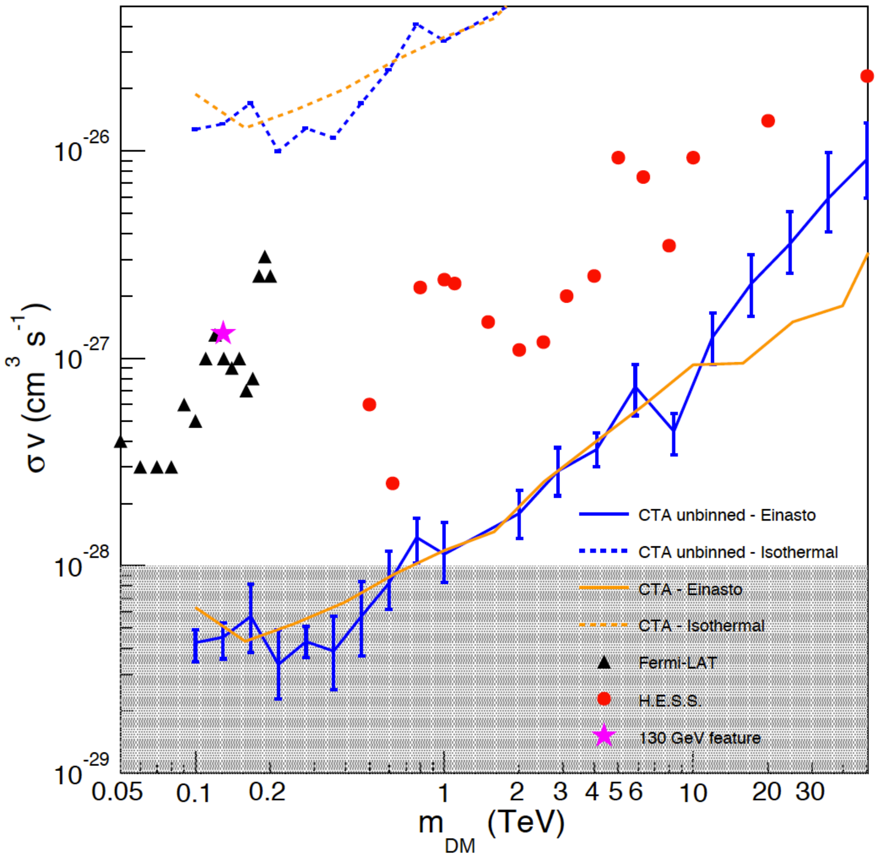
Sensitivity of CTA: the next-generation γ-ray observatory



Galactic Halo

More details on
Wed. 10, 15:30
by Salvatore Mangano

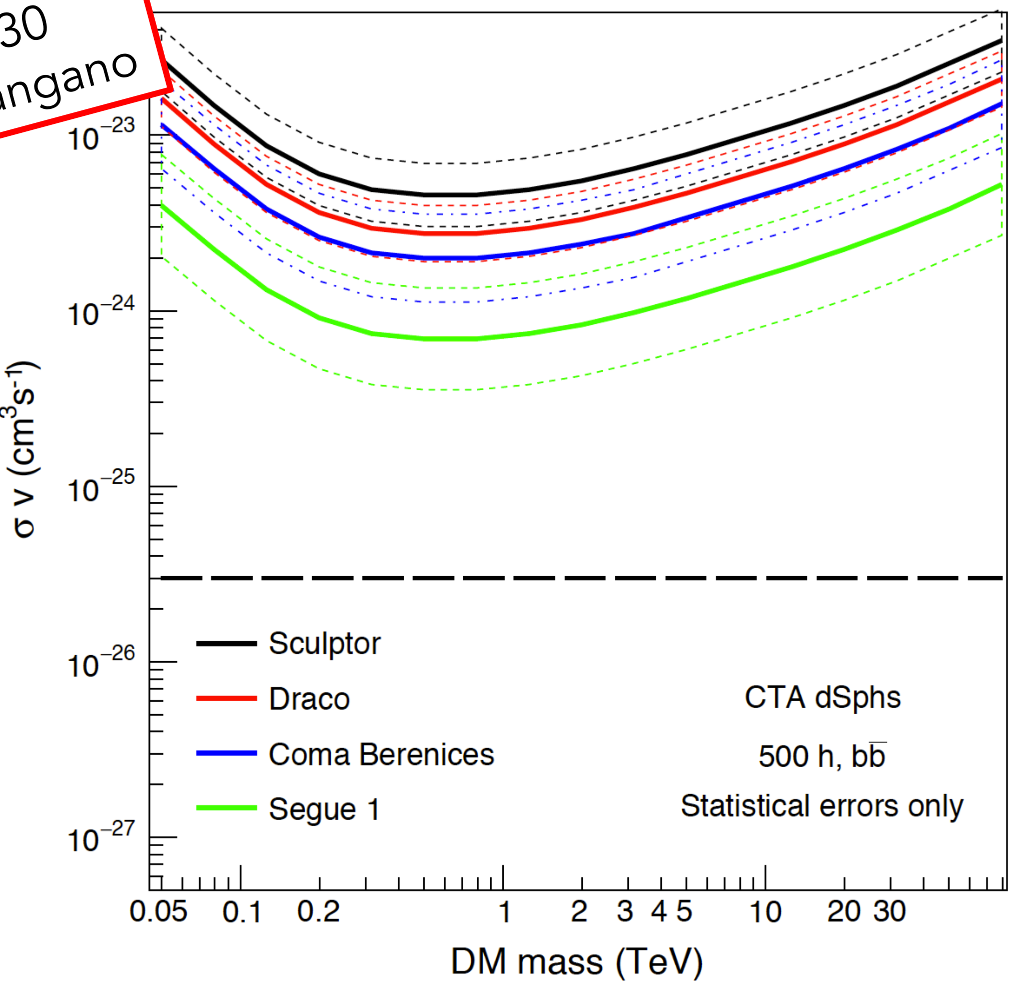




Science with CTA, arXiv:1709.07997

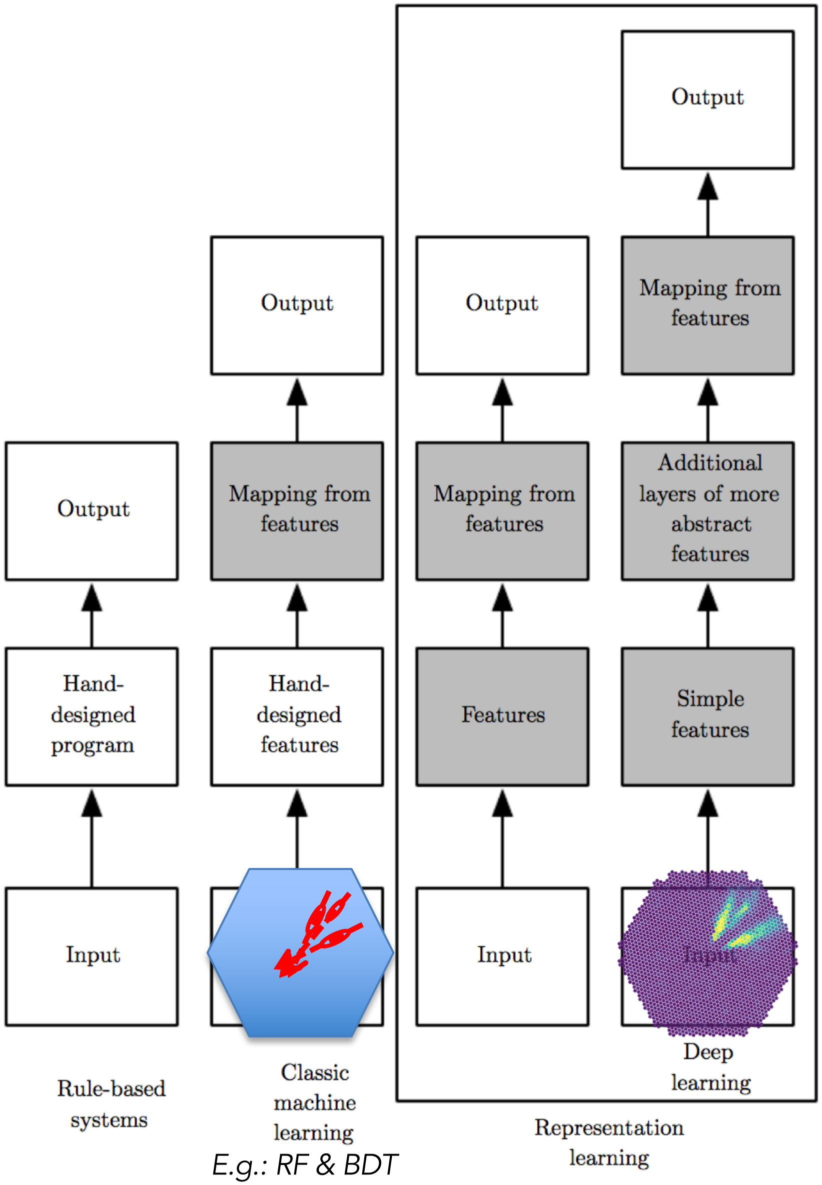
More details on Wed. 10, 15:30 by Salvatore Mangano

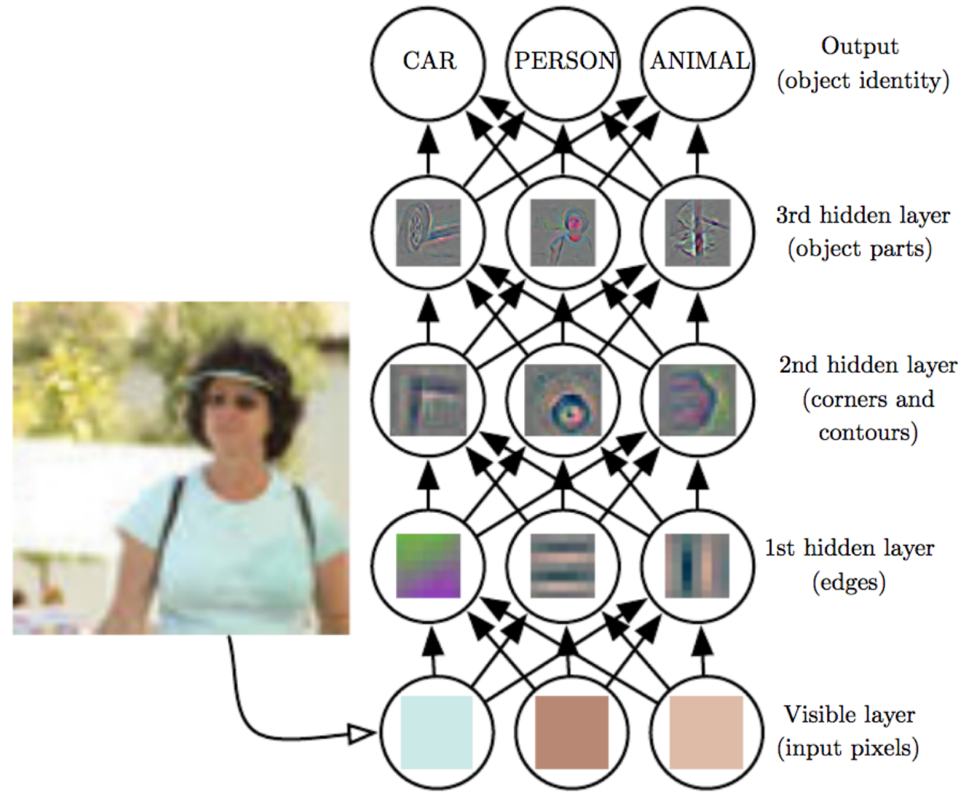
Dwarf Spheroidal Galaxies



Science with CTA, arXiv:1709.07997

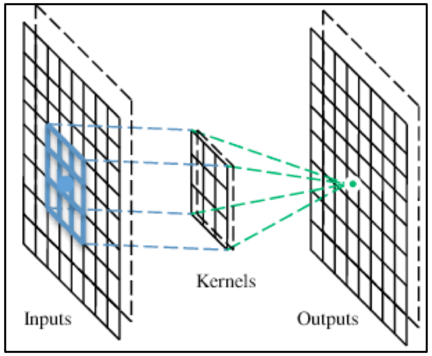
Enhancing CTA's performance with deep learning





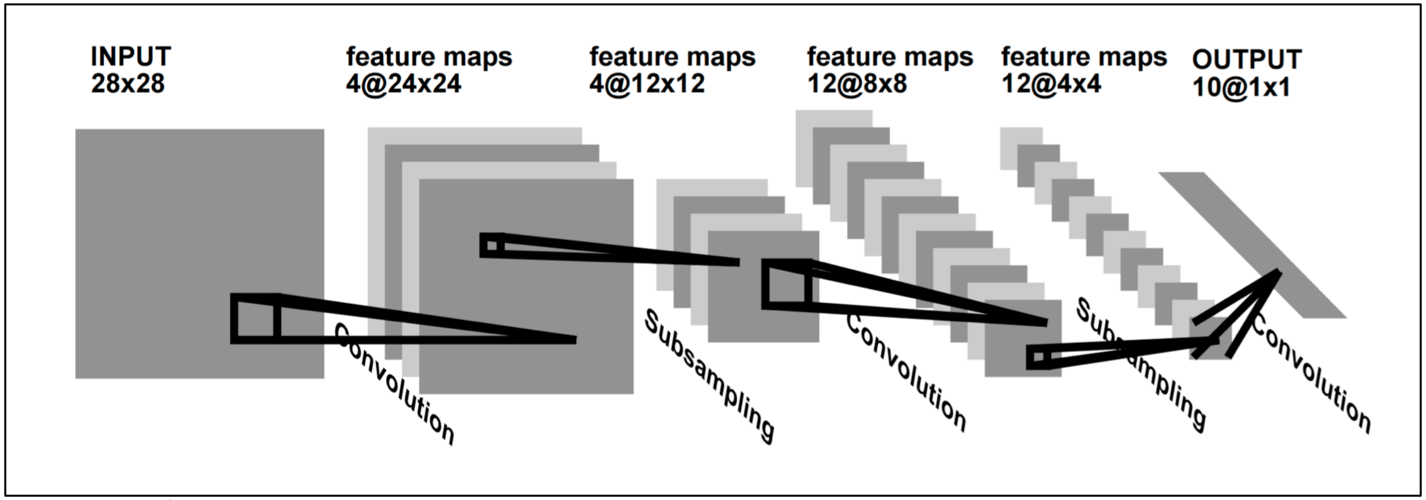
Deep Learning, Goodfellow et al.

Convolution



Guo et al.

Convolutional Neural Network (CNN)



LeCunn et al.

- DL capable of ***extracting*** and mapping image features automatically with unprecedented classification accuracy. Hyper-active CS research field constantly improving
- Many HEP/Astro experiments already exploring/utilizing the technique (LIGO, LHC, MicroBooNe, NOVa, etc…)

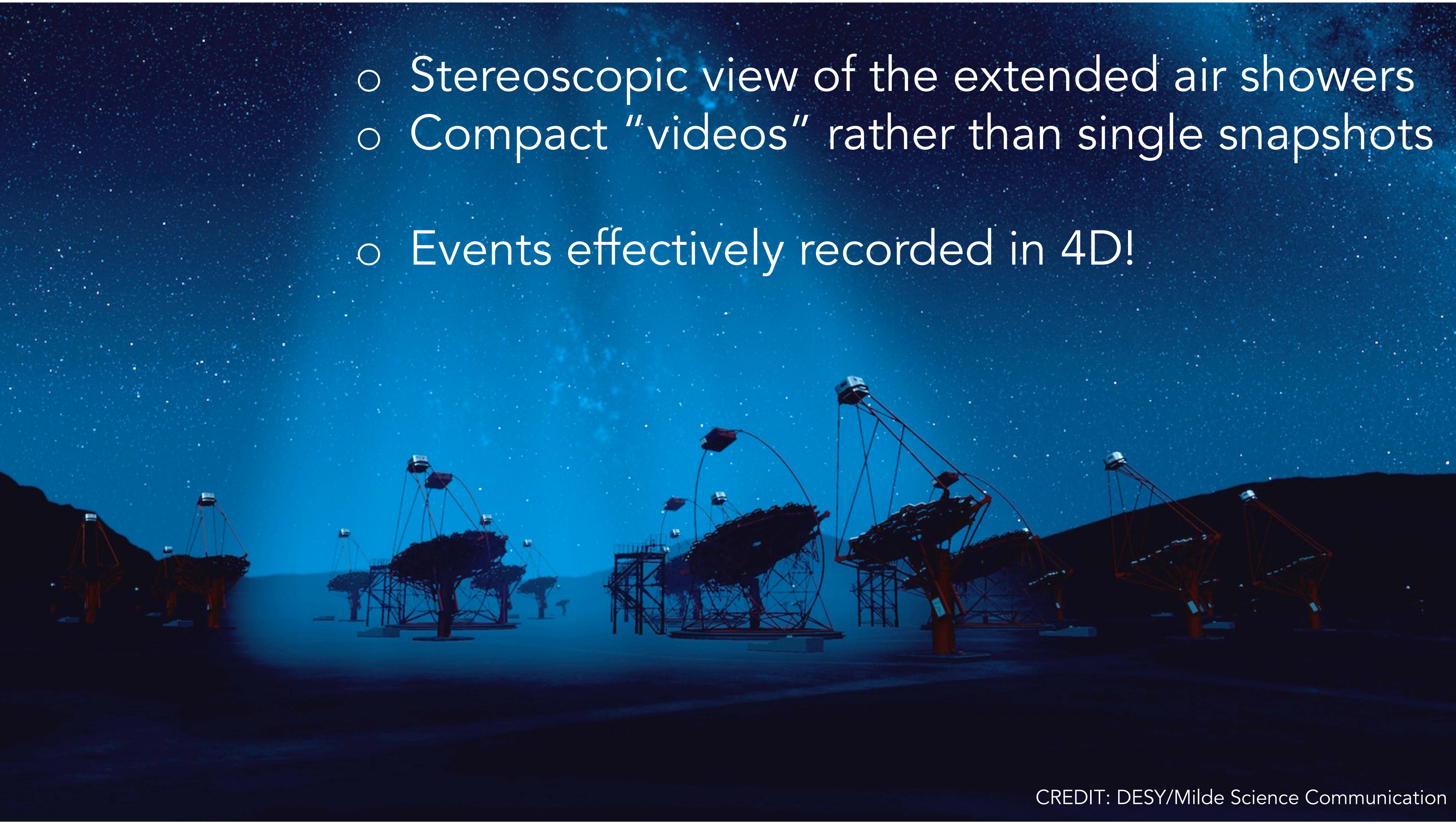
Method:

- Use deep learning to reconstruct CTA events from non-parameterized images
  - Performance enhancement -> better sensitivity to DM

But there are risk…

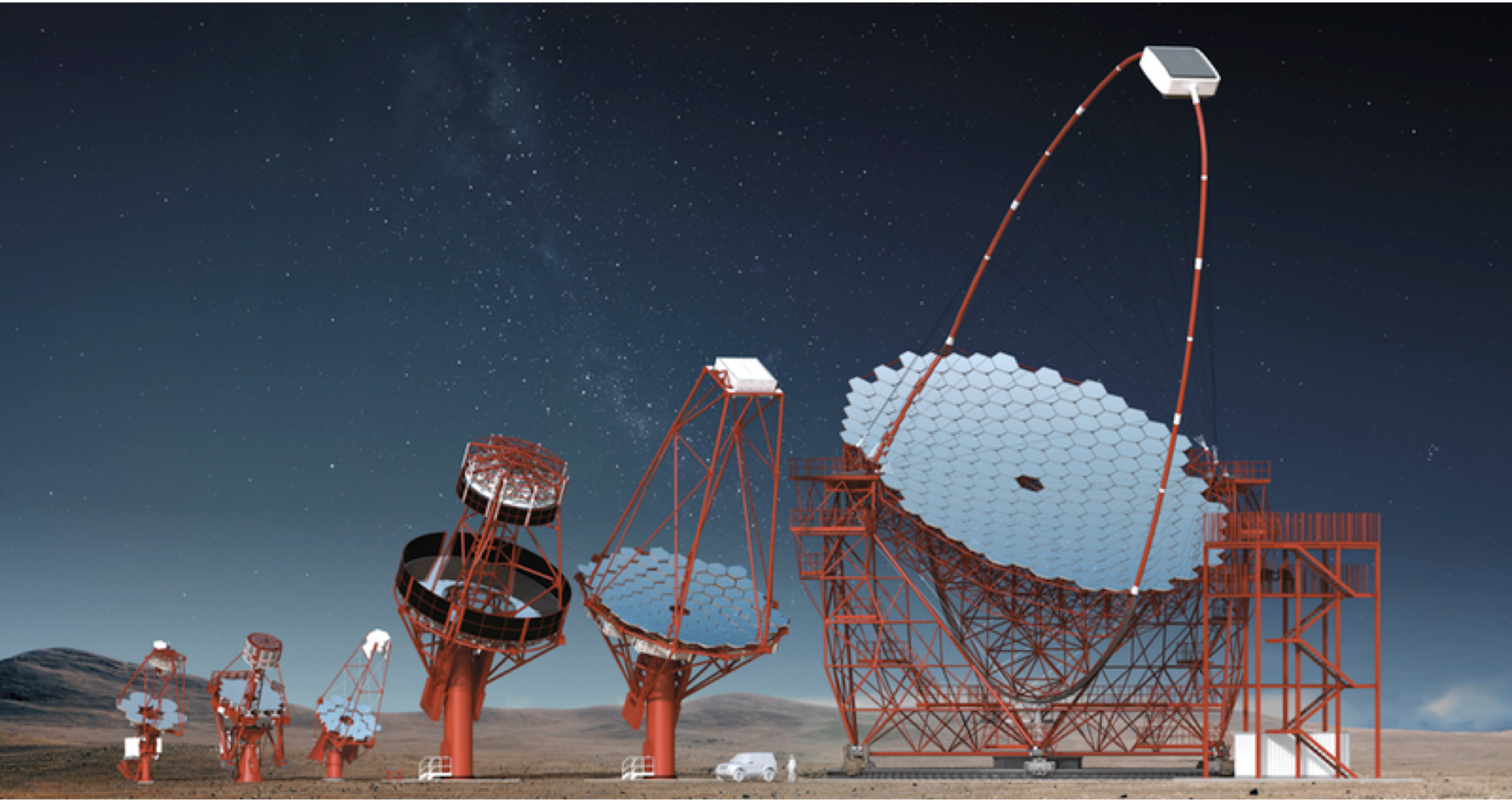
- MC reliability (e.g. network selecting some features from your MC not present in real data)

- Stereoscopy:
  - Stereoscopic view of the extended air showers
  - Compact "videos" rather than single snapshots
  - Events effectively recorded in 4D!



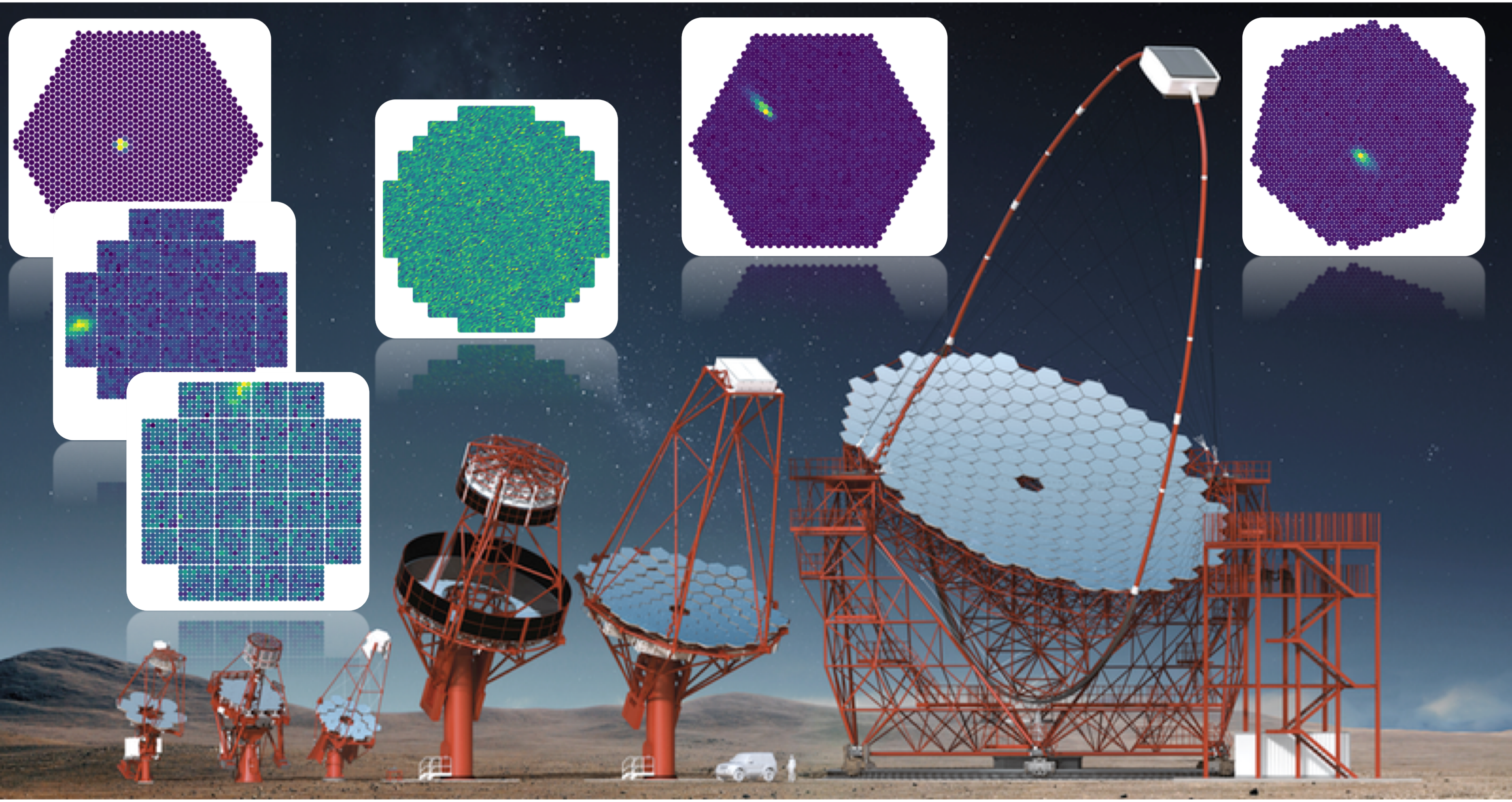
CREDIT: DESY/Milde Science Communication

- Heterogeneity of instruments:



- Heterogeneity of instruments:

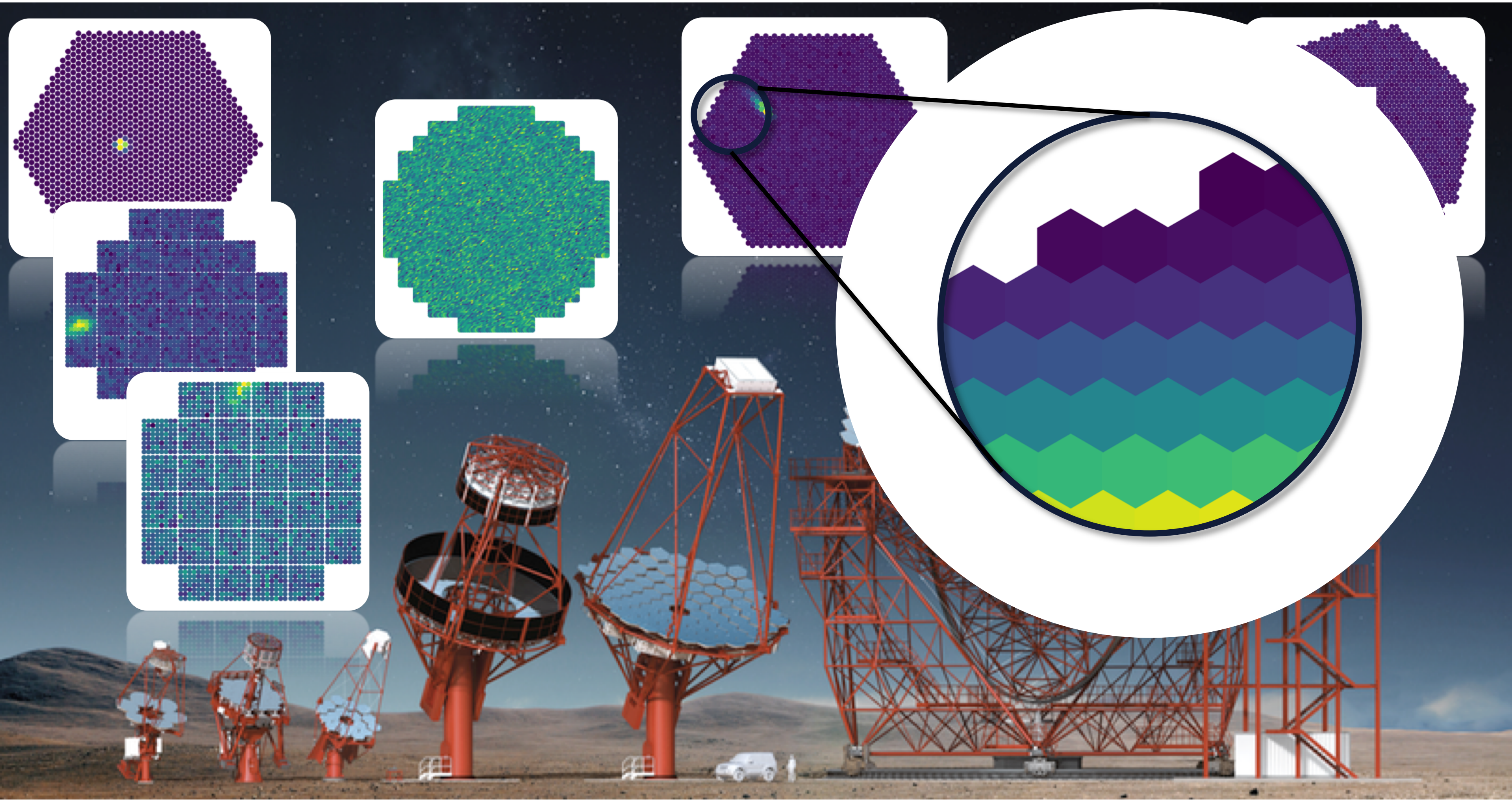
Camera images courtesy of T. Vuillaume



- Heterogeneity of instruments:

Hexagonal pixels

Camera images courtesy of T. Vuillaume



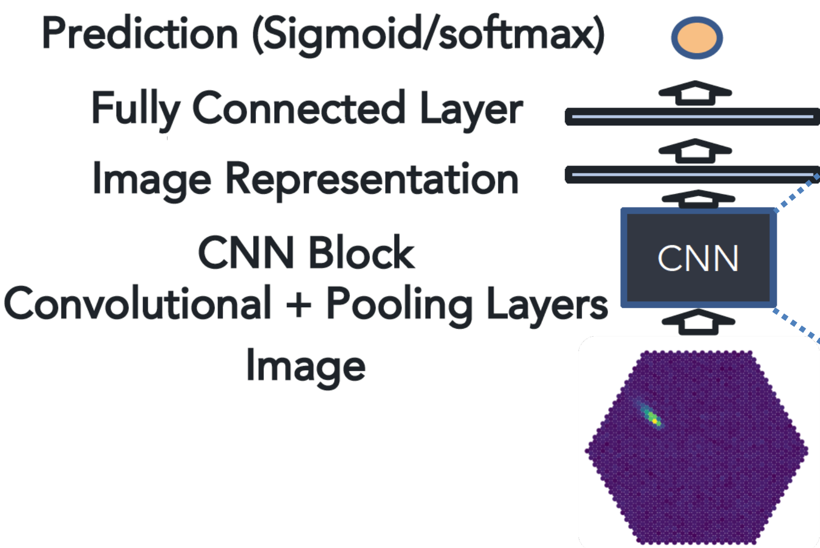
A. Brill, B. Kim, Q. Feng,
D. Nieto, T. Miener,
et al.

CTLearn

https://github.com/ctlearn-project/

- DL can actually classify CTA events!

CTLearn: *single telescope* model



3x3x128 CONV → 2x2 stride 2 MAX_POOL

↑

3x3x64 CONV → 2x2 stride 2 MAX_POOL

↑

3x3x32 CONV → 2x2 stride 2 MAX_POOL

↑

48x48x1 INPUT

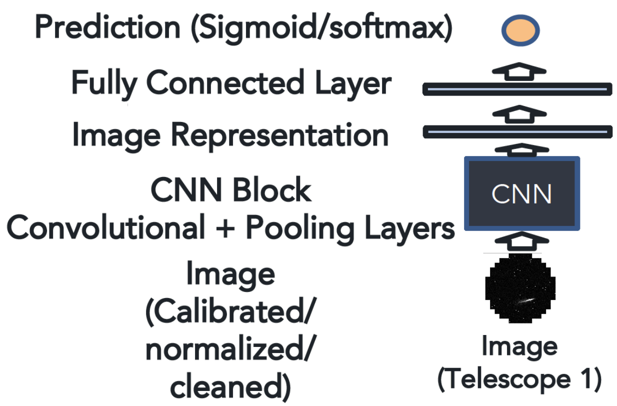
Courtesy of A. Brill

- DL can actually classify CTA events!

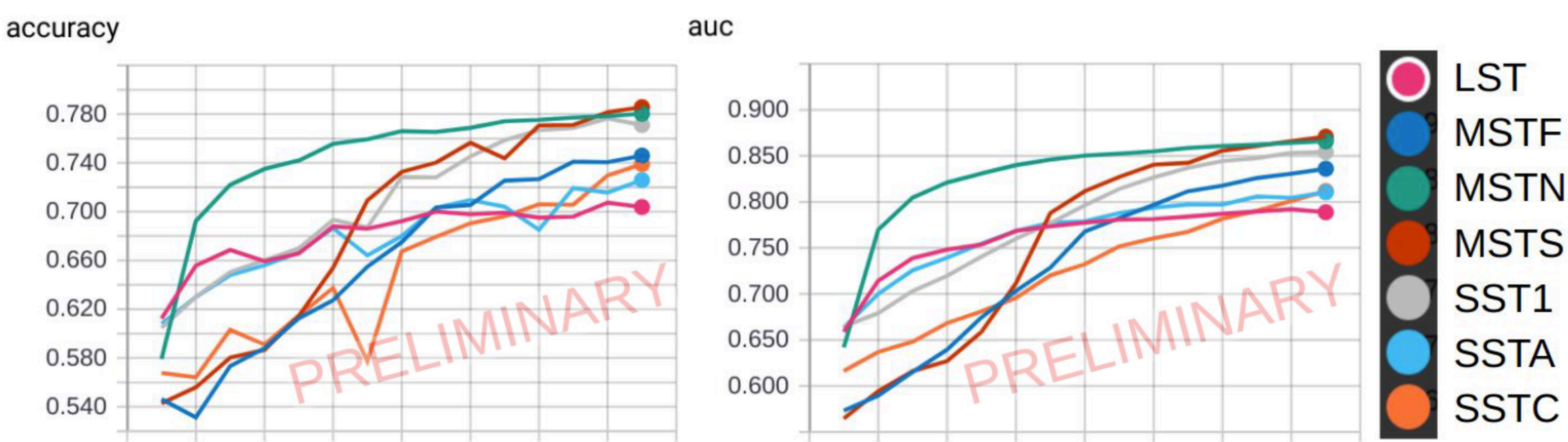
CTLearn: *single telescope* model

A. Brill, B. Kim, Q. Feng, D. Nieto, T. Miener, et al.

https://github.com/ctlearn-project/



Telescope Type	Gamma Images	Proton Images	Validation Accuracy	Validation AUC
LST	89165	90426	70.38%	0.7887
MSTF	360787	379533	74.60%	0.8360
MSTN	414502	443704	78.04%	0.8659
MSTS	307498	294714	78.57%	0.8709
SST1	213795	207996	77.11%	0.8542
SSTA	221810	228042	72.59%	0.8105
SSTC	217940	218312	73.90%	0.8118



Courtesy of A. Brill

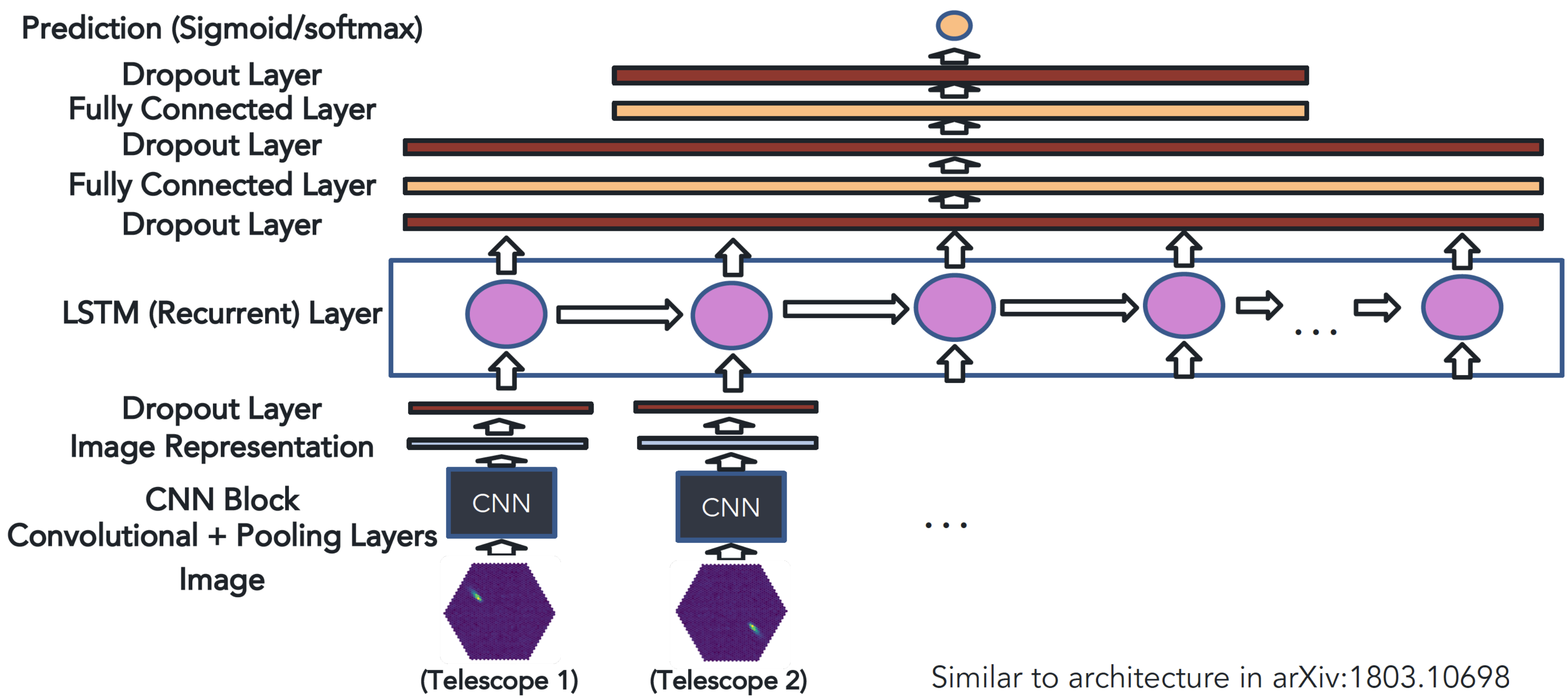
- Tackling the stereo challenge:

  CTLearn: *CNN-RNN* model

A. Brill, B. Kim, Q. Feng, D. Nieto, T. Miener, et al.

CTLearn

https://github.com/ctlearn-project/



Similar to architecture in arXiv:1803.10698

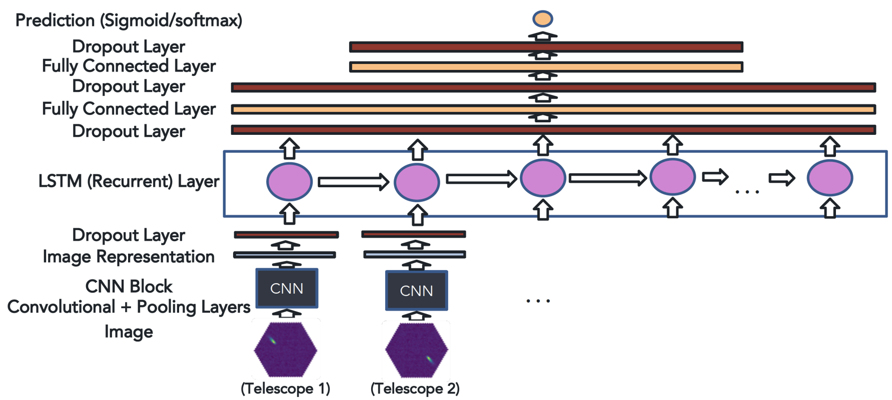
- Tackling the stereo challenge:

CTLearn: *CNN-RNN* model

A. Brill, B. Kim, Q. Feng, D. Nieto, T. Miener, et al.

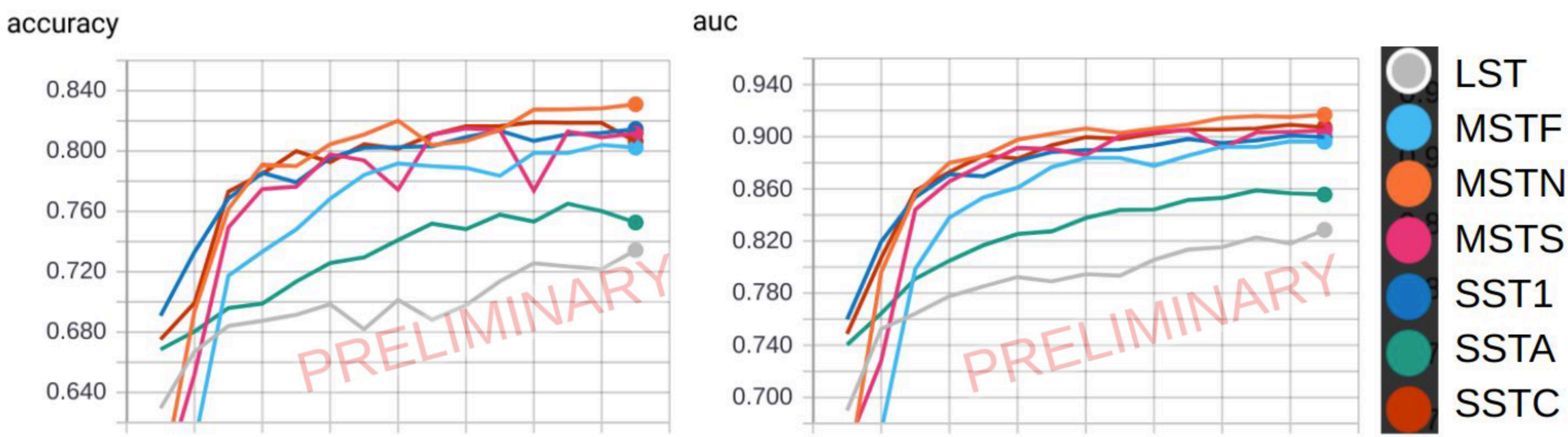
CTLearn

https://github.com/ctlearn-project/



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

PRELIMINARY

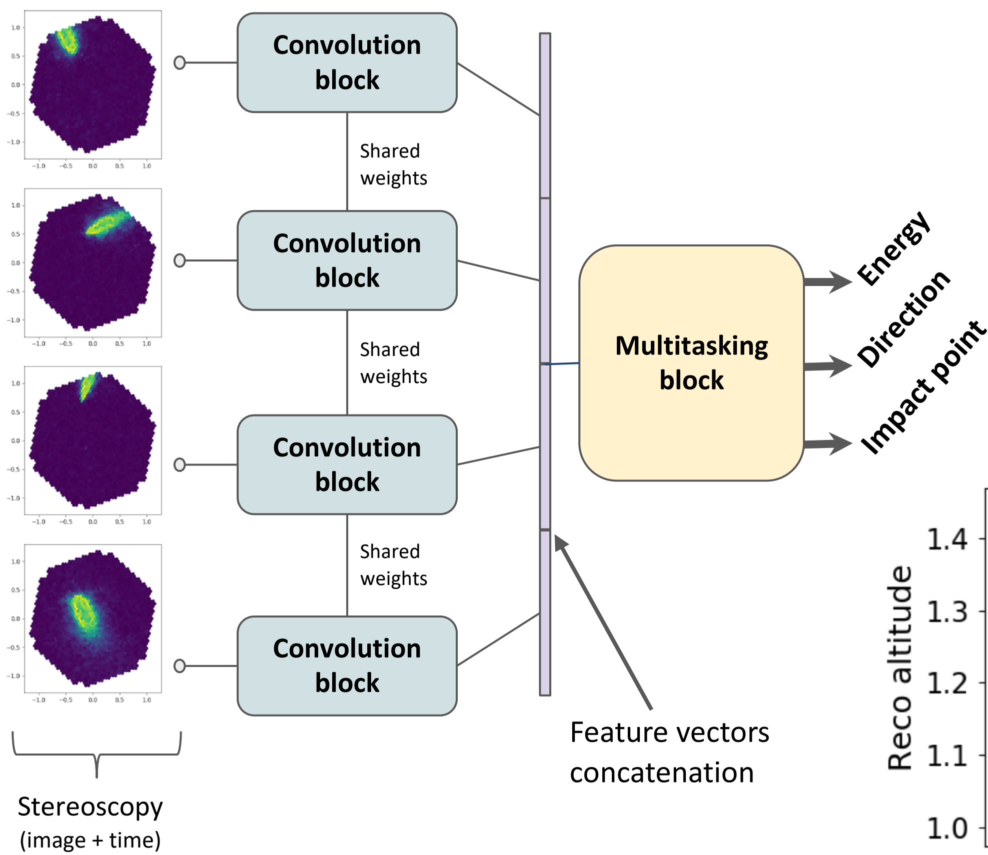


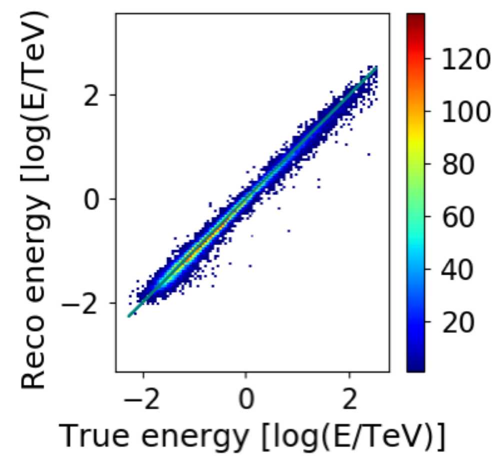
Courtesy of A. Brill

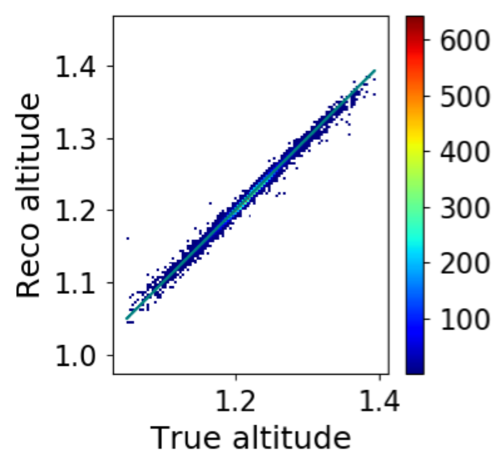
- Tackling the stereo challenge:

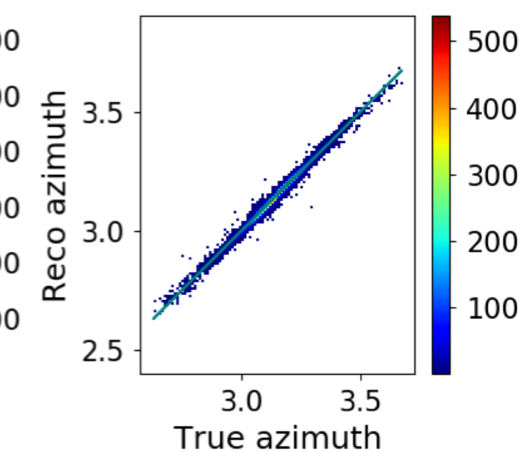
T. Vuillaume,
M. Jaquemont, et al.

https://gitlab.lapp.in2p3.fr/GammaLearn









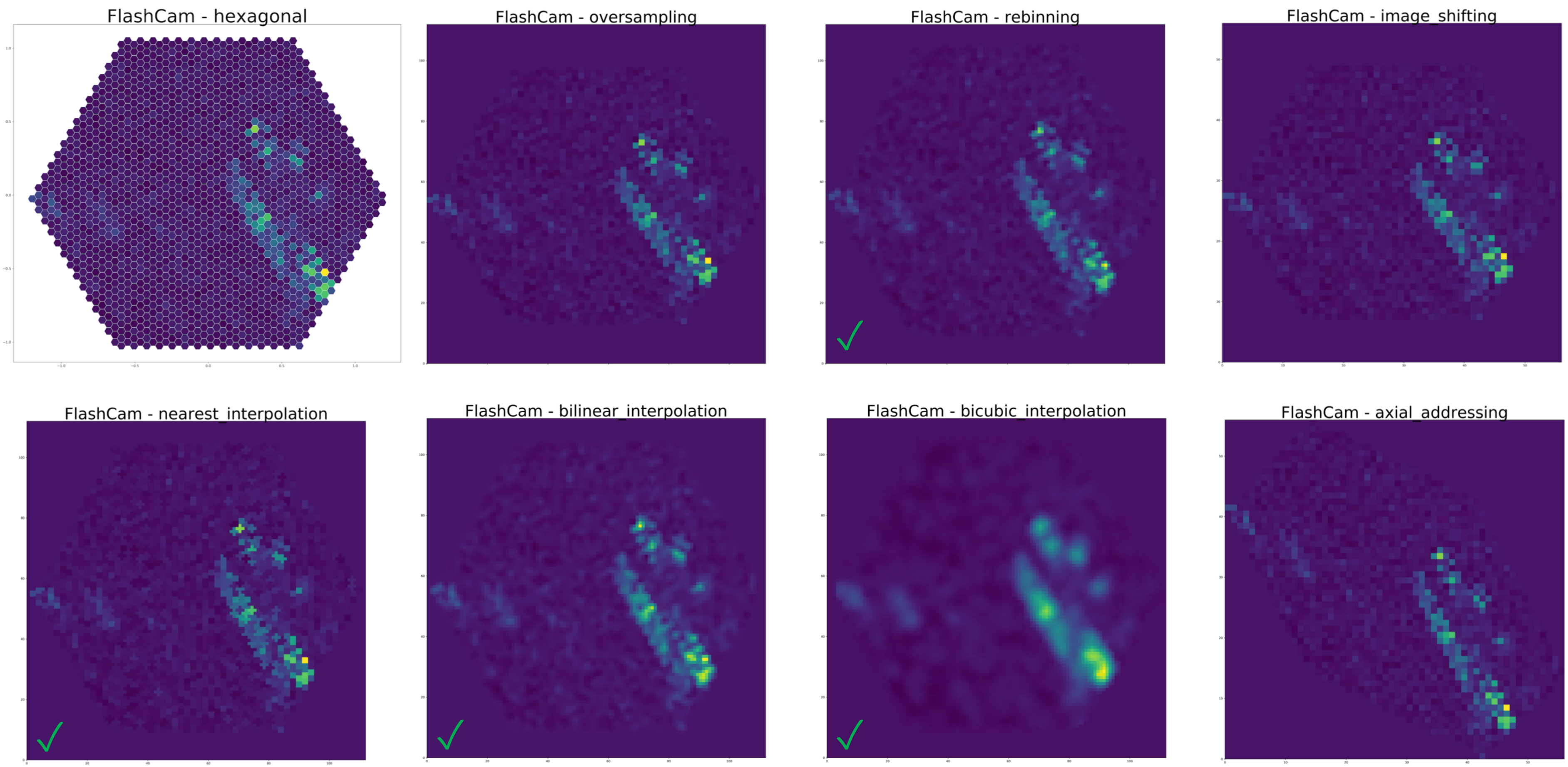
Enhancing CTA’s performance with deep learning

- Tackling the hexagonal-pixel challenge:

A. Brill, B. Kim, Q. Feng
D. Nieto, T. Miener,
et al.

CTLearn

https://github.com/ctlearn-project/



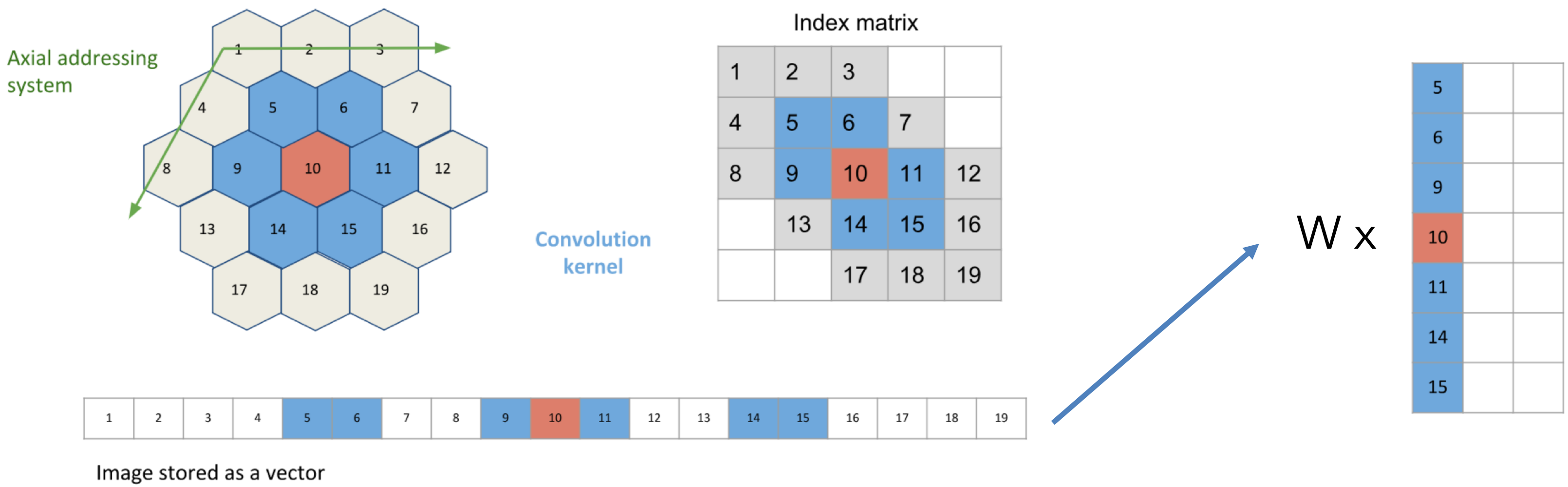
✓ Angles and distances preserved

Enhancing CTA's performance with deep learning

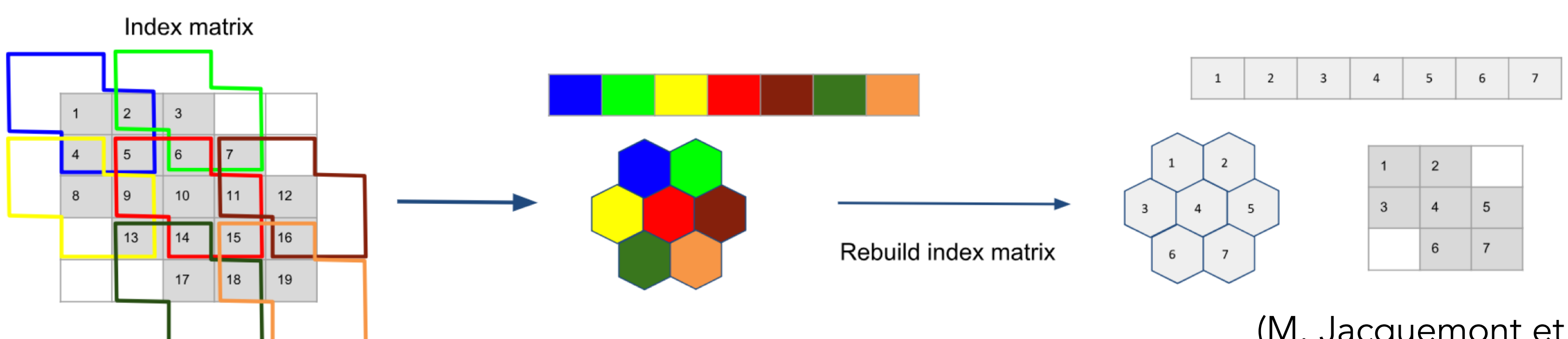
T. Vuillaume,
M. Jaquemont, et al.

https://github.com/IndexedConv

- Tackling the hexagonal-pixel challenge:
  - Convolution



  - Pooling



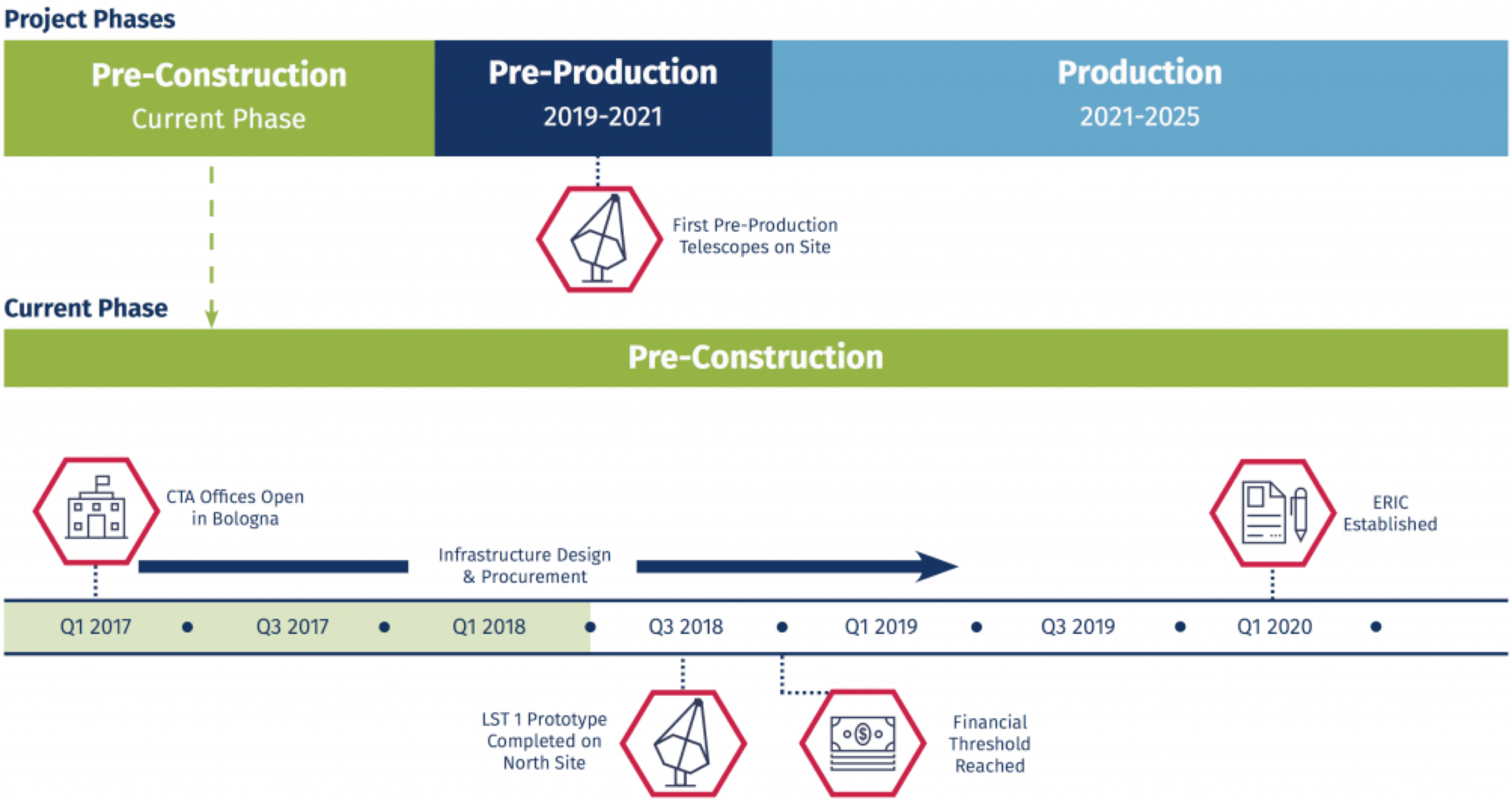
(M. Jacquemont et al. 2019)

Conclusions & Outlook

- Gamma-ray telescopes and IACTs in particular are competitive DM probes
- Current-generation IACTs have enhanced their performances through ML
- Next-generation IACT may profit from latest developments in ML
  - Any gain in performance can be translated into better sensitivity to DM
- Ongoing efforts to exploit deep learning as an event reconstruction method for CTA
  - Event reconstruction over non-parametrized single images demonstrated!
  - Working on optimizing architectures

Backup

Backup



- 2022: Beginning of observatory operations
- 2025: Construction project completion

- Hexagonal convolutions:

T. Vuillaume,
M. Jaquemont, et al.

https://github.com/IndexedConv

Comparison of the loss for regression task with hexagonal and standard kernels