Washington University in St. Louis
Arts & Sciences
ISNET-9

Deep-learning techniques in ground-based imaging gamma-ray observatories

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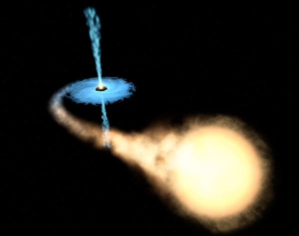
IPARCOS-UCM

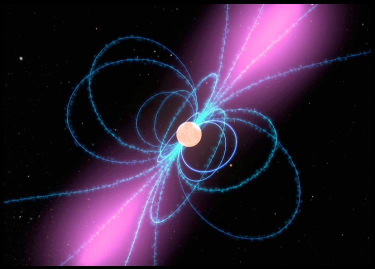
https://apod.nasa.gov/apod/ap200724.html

- Gamma-ray astronomy in a (very-small) nutshell
- Imaging atmospheric Cherenkov telescopes
- Enhancing IACTs with machine learning

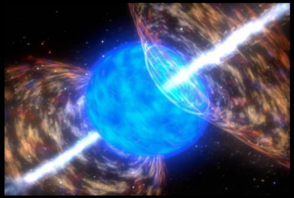
Conventional non-thermal emitters & CR accelerators



Gamma-ray Binaries

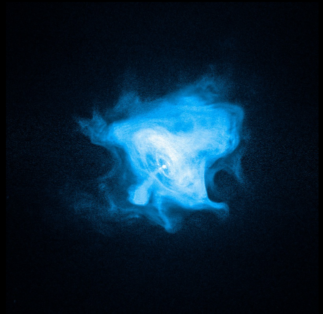


Pulsars

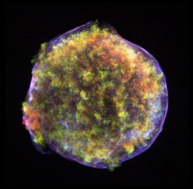


Gamma-ray Bursts

Compact-object mergers



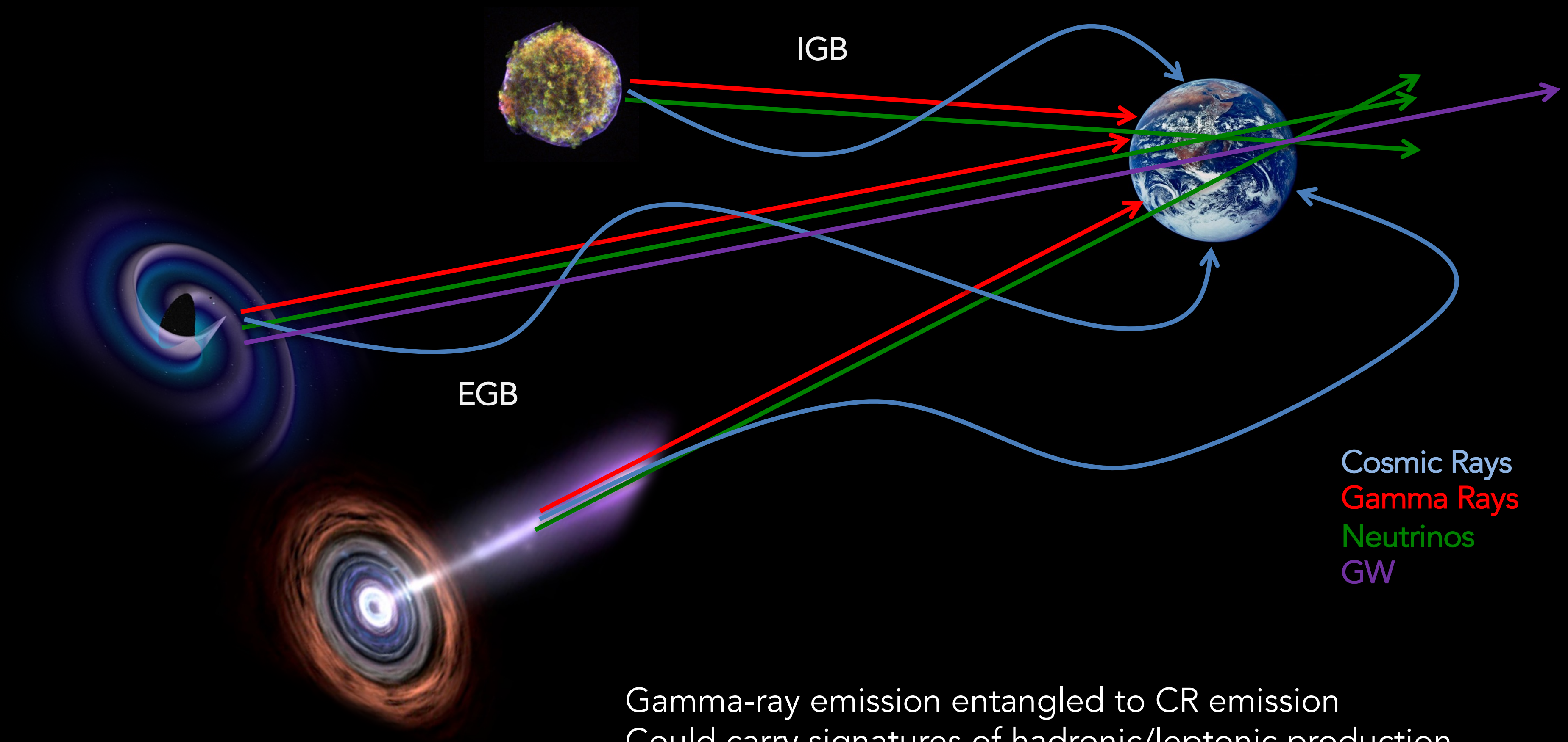
Pulsar Wind Nebulae



Supernova Remnants

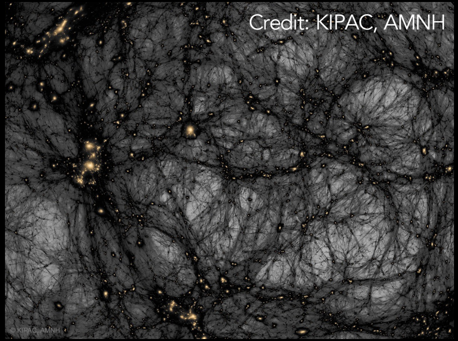
Starburst Galaxies

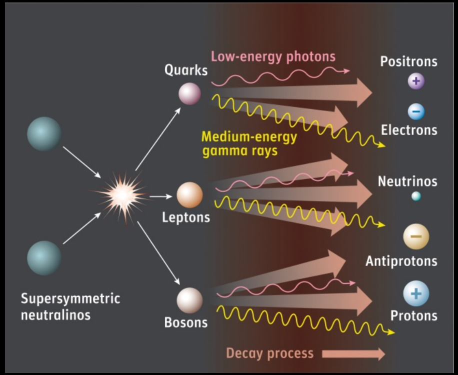
Active Galactic Nuclei



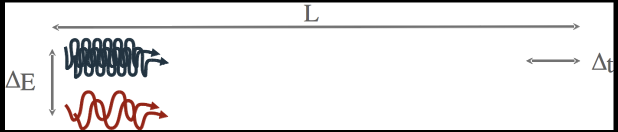
Gamma-ray emission entangled to CR emission
Could carry signatures of hadronic/leptonic production

Dark matter searches

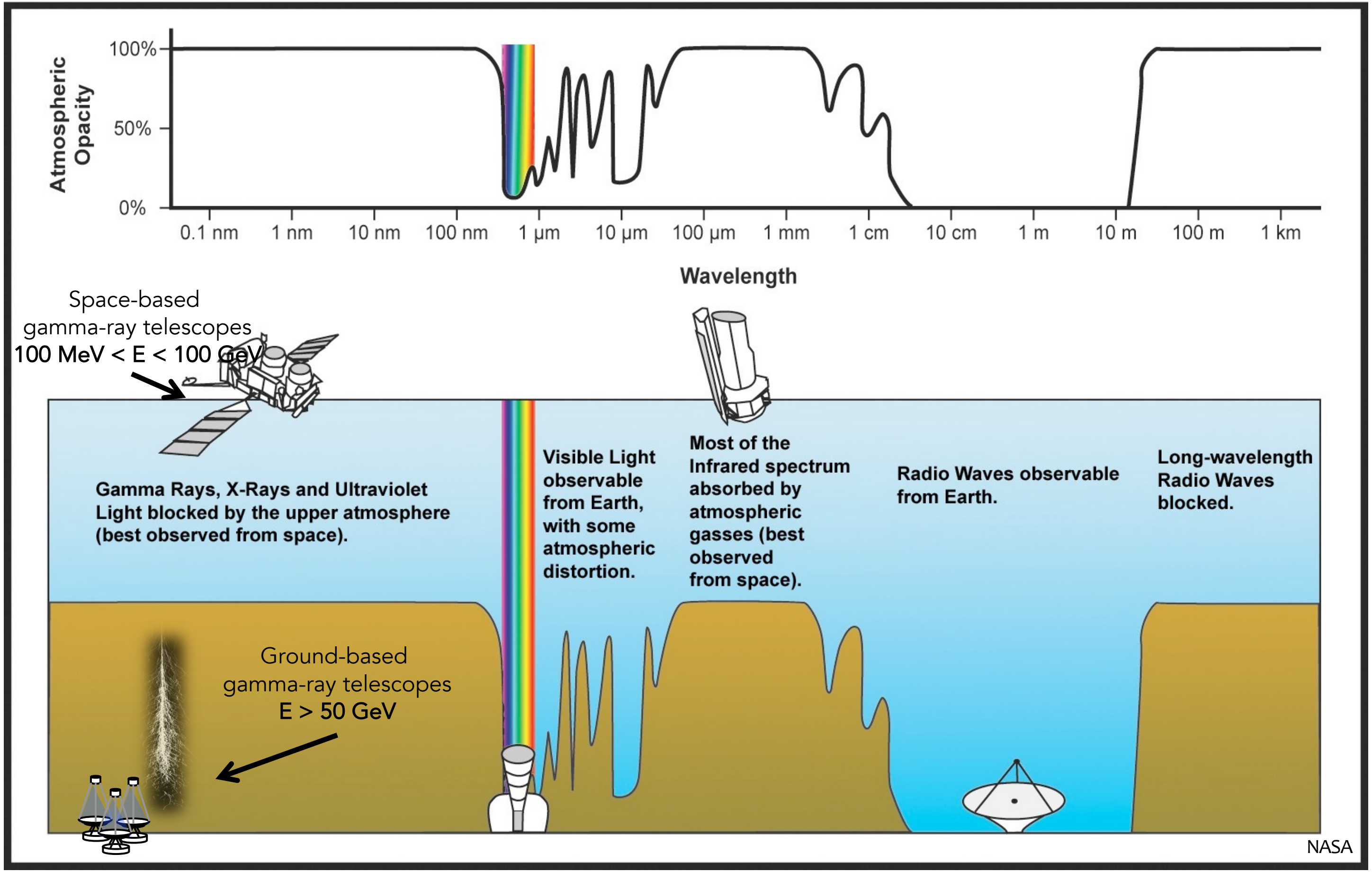




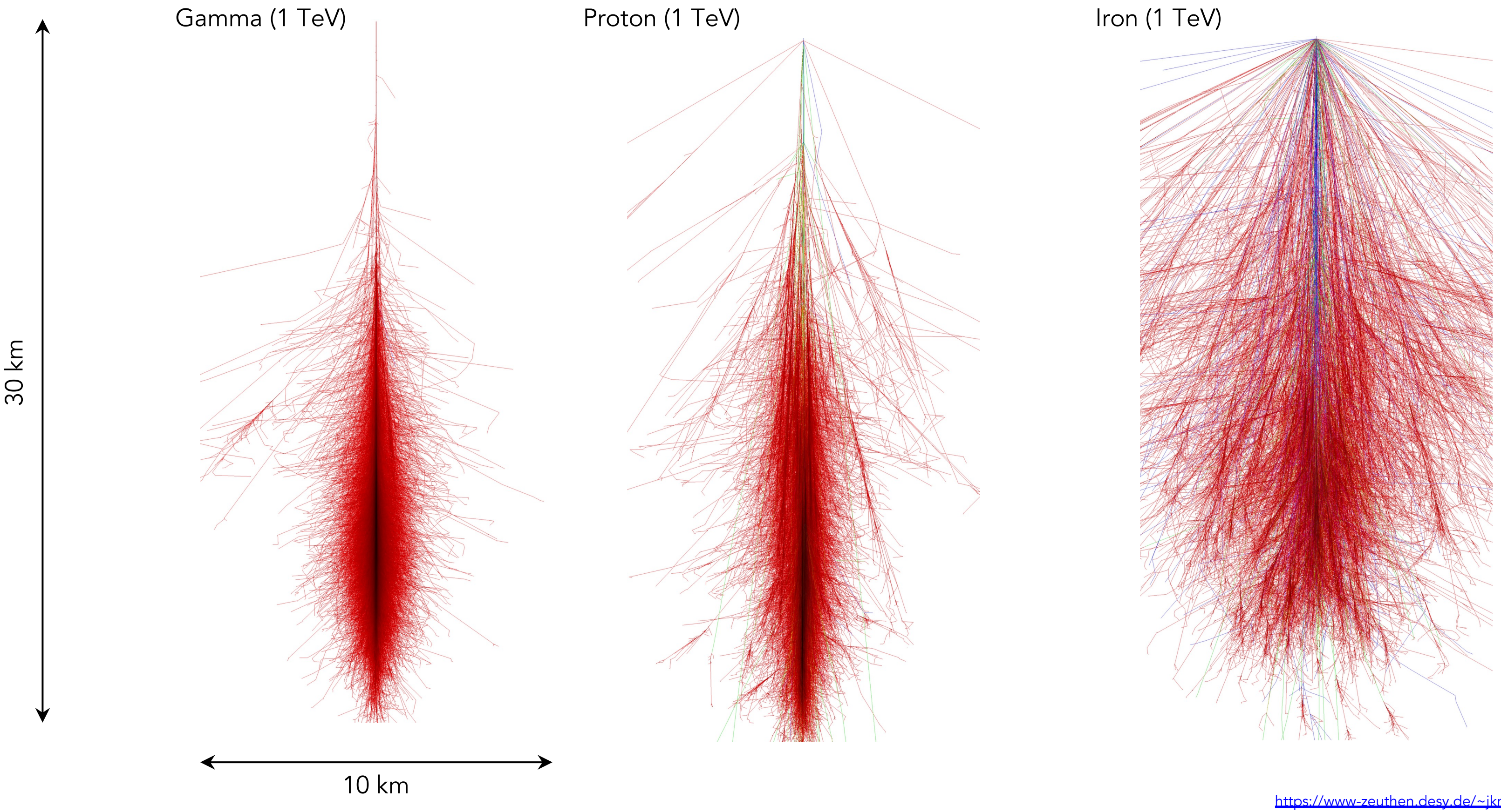
Lorentz invariance



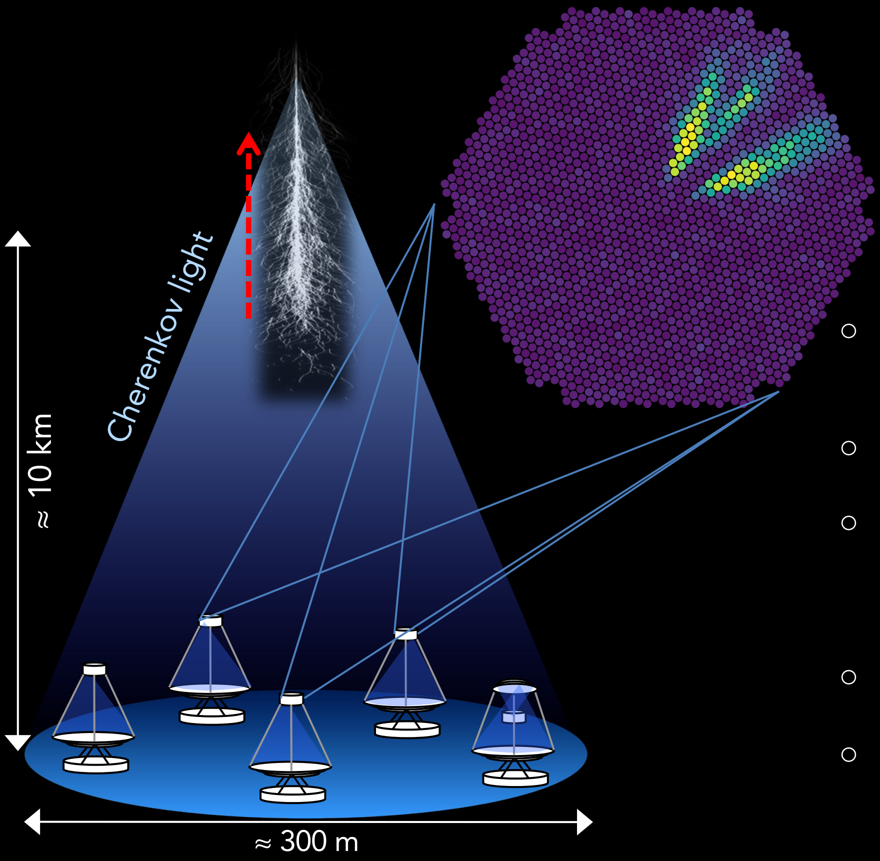
Gamma-ray detectors



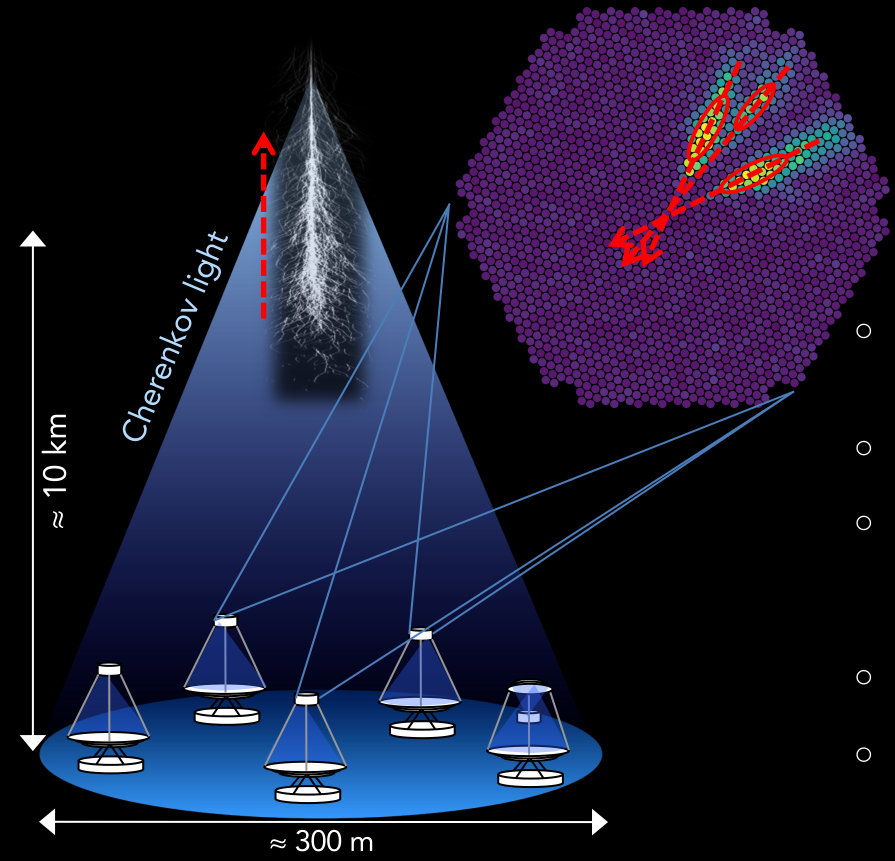
Extended atmospheric showers



https://www-zeuthen.desy.de/~jknapp/fs/showerimages.html



- 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



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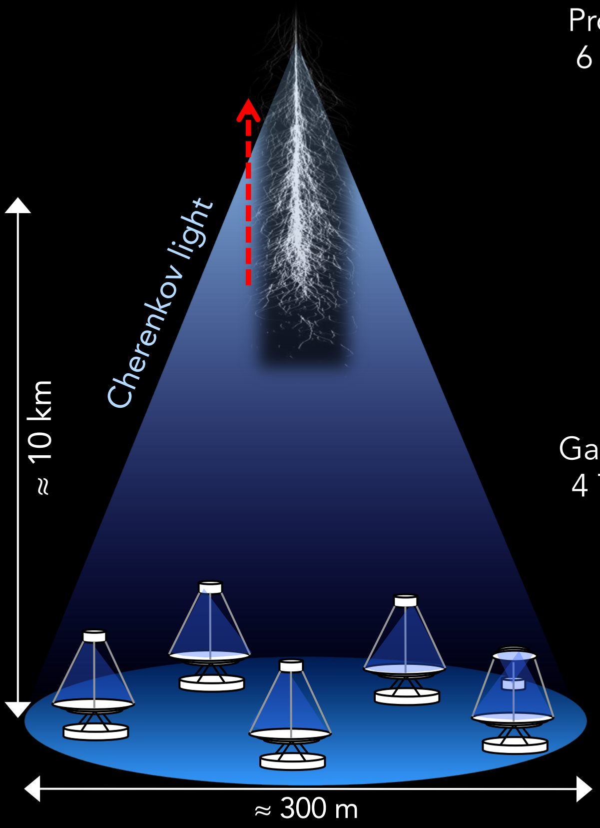
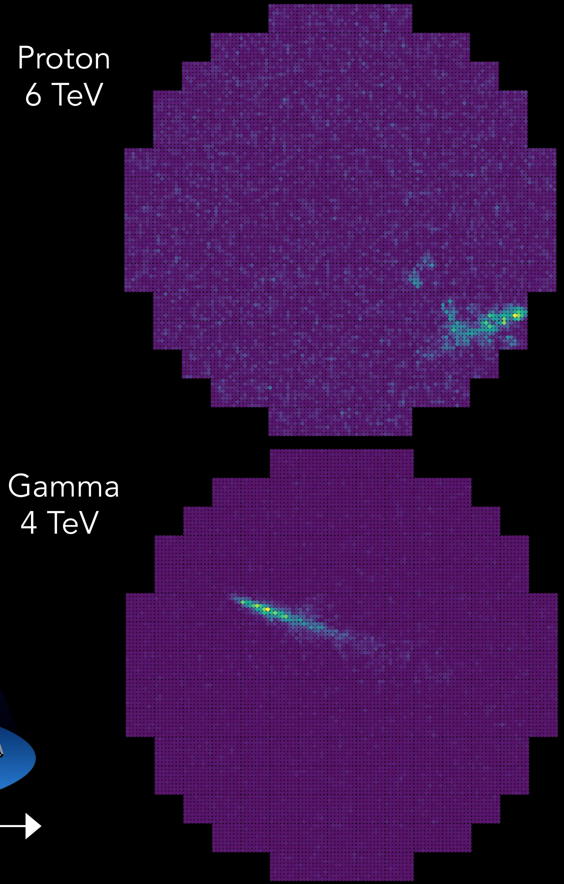
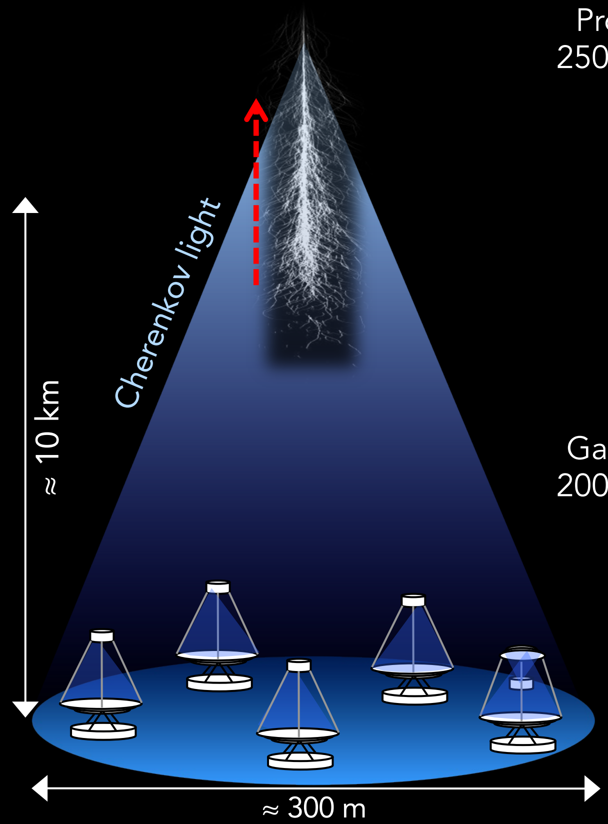

Cherenkov light
≈ 10 km
≈ 300 m


Proton
6 TeV
Gamma
4 TeV


Cherenkov light
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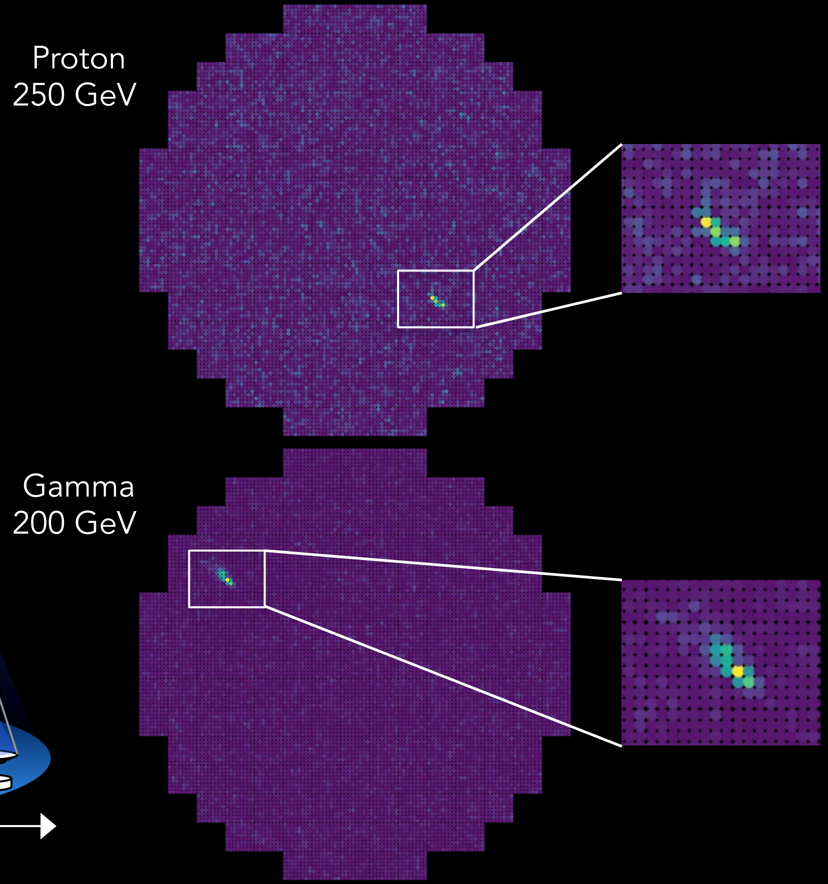
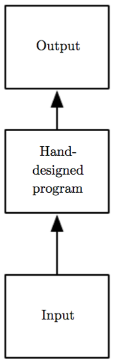
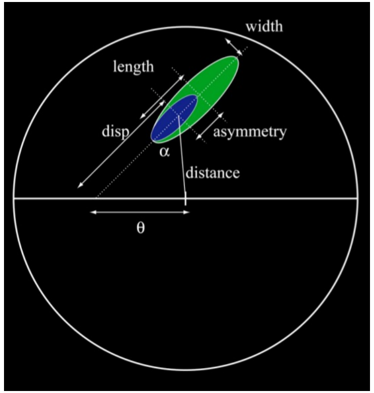

Proton
250 GeV
Gamma
200 GeV

Output: event type, energy, arrival direction

- Event type: box cuts
- Event energy: parametrization
- Event direction: parametrization



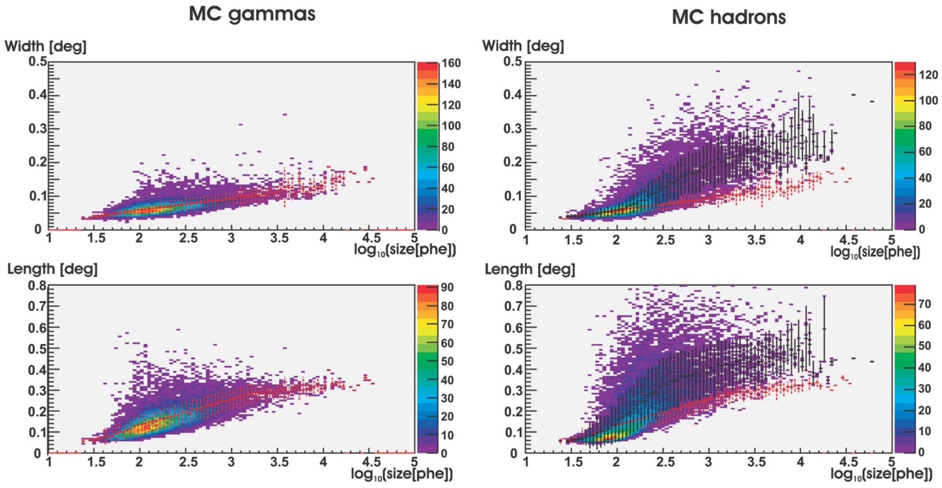
Rule-based systems



Input: observed events

event reconstruction

- Based on image parametrization (Hillas parameters)

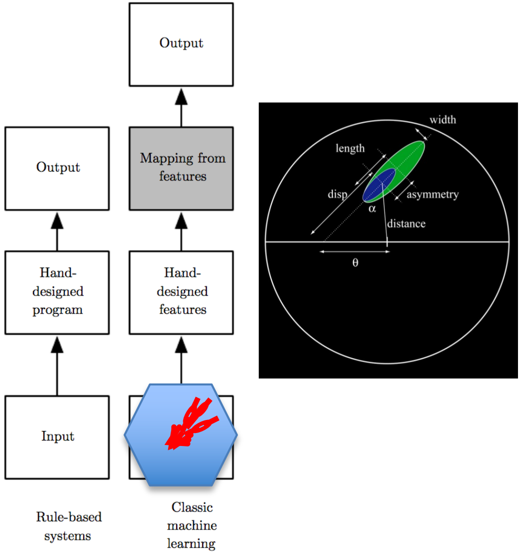


$$E = E(size, distance, h_{max})$$

$$DISP = A(SIZE) + B(SIZE) \cdot \frac{WIDTH}{LENGTH + \eta(SIZE) \cdot LEAKAGE2}$$

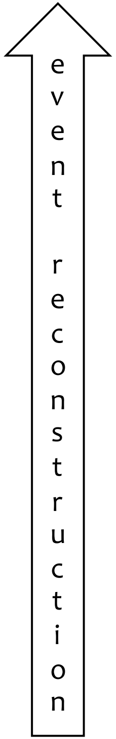
- Instrument calibration with real data not possible
- Strong dependency on Montecarlo simulations

Output: event type, energy, arrival direction



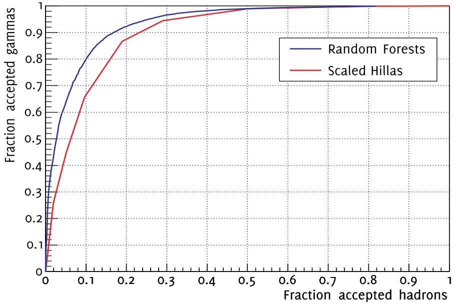
E.g.: RF & BDT

Input: observed events

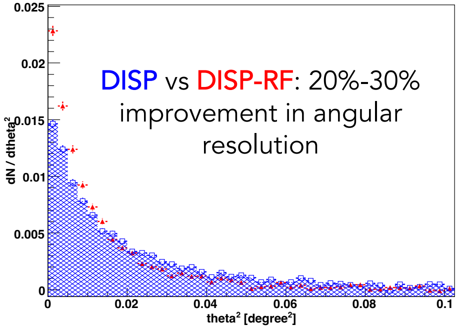


- Current generation of IACTs: classic ML

- ML method:
  - Random Forest (RF)
- Applied to:
  - Background rejection
  - Arrival direction



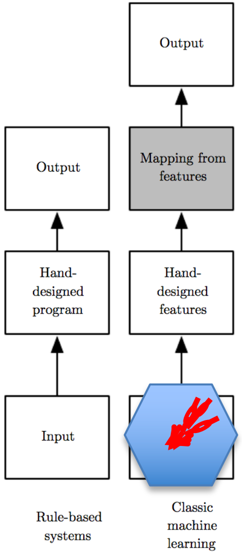
Albert et al., NIM-A 588:424-432 (2008)

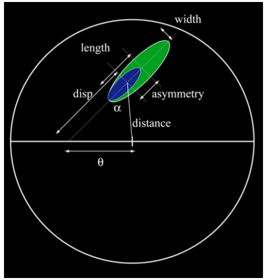


Aleksic et al., A&A 524 A77 (2010)

Event reconstruction in IACTs with machine learning

Output: event type, energy, incoming direction





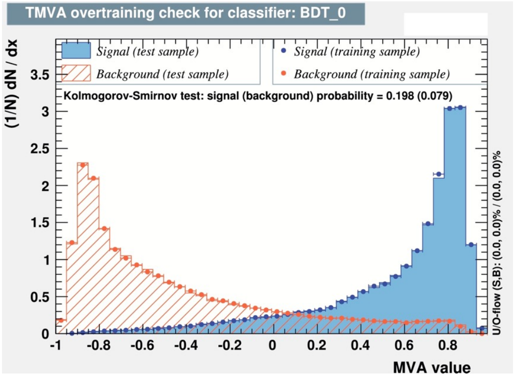
E.g.: RF & BDT

Input: observed events

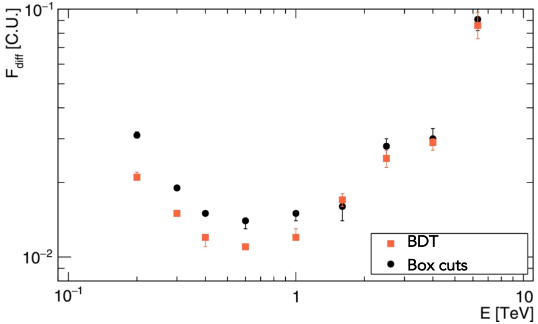
event reconstruction

- Current generation of IACTs: classic ML

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

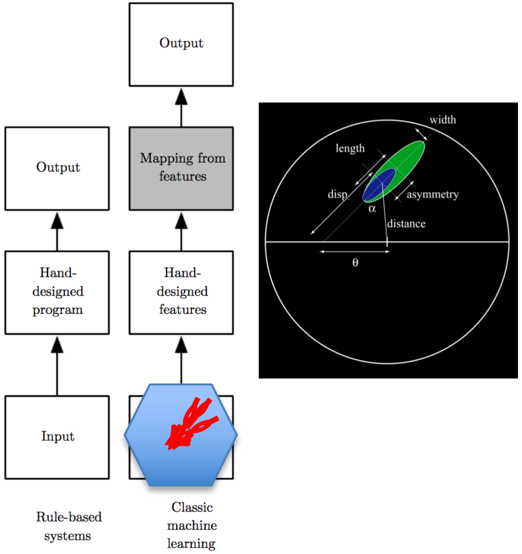


VERITAS diff. sensitivity



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

Output: event type, energy, incoming direction

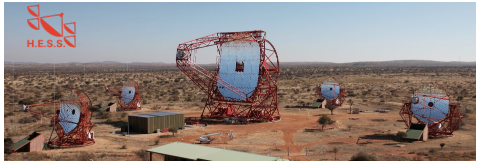


E.g.: RF & BDT

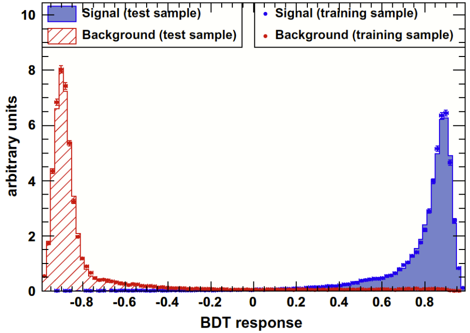
Input: observed events

event reconstruction

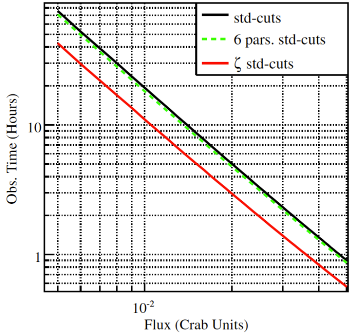
- Current generation of IACTs: classic ML



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



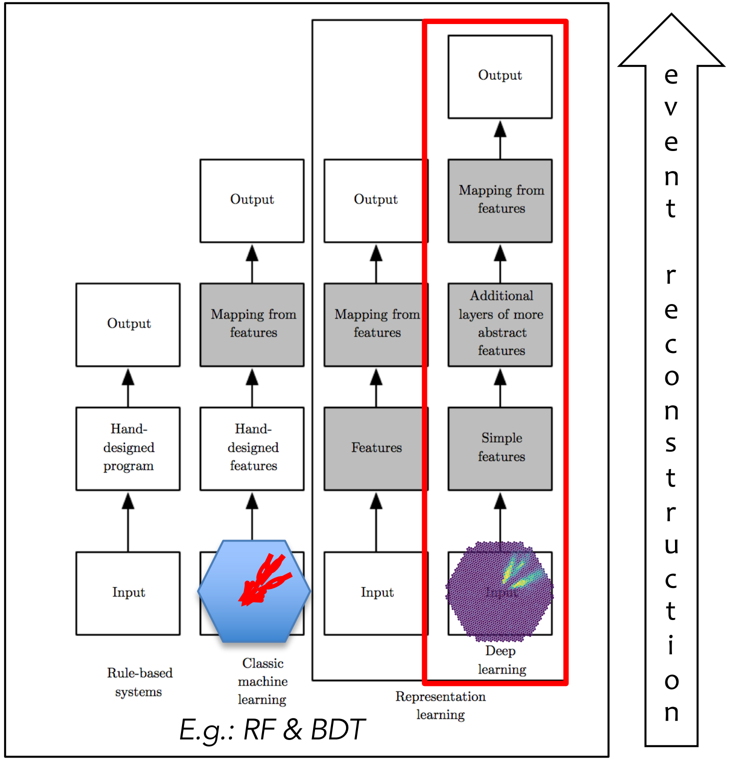
Becherini et al., APP V34-12 P858-870 (2011)



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

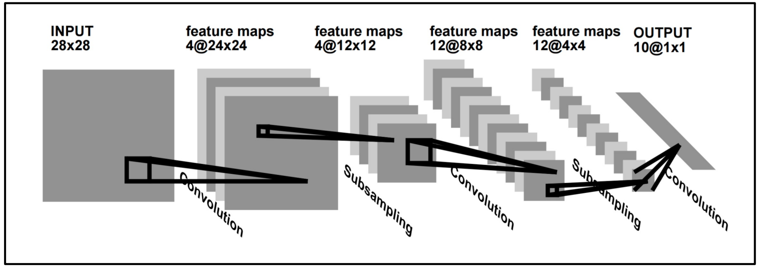
(Results for H.E.S.S. I only)

Output: event type, energy, incoming direction



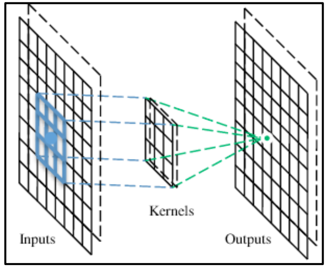
Input: observed events

Convolutional Neural Network (CNN)



LeCunn et al.

Convolution



Guo 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

But there are risk…

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

- 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)

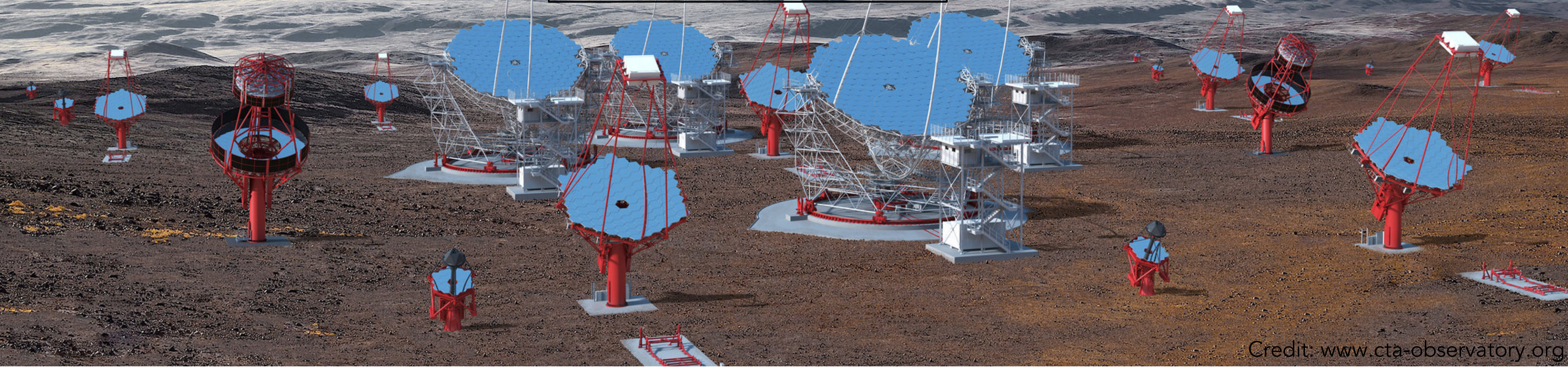
cta cherenkov telescope array

the observatory for ground-based gamma-ray astronomy

Low-energy range:
23 m ø
Parabolic reflector
4.3° FoV
Energy threshold 20 GeV

Mid energy-range:
12 m ø modified Davies-Cotton reflector
9.7 m ø Schwarzschild-Couder reflector
7.5° FoV
Full system sensitivity in the 150 GeV – 5 TeV range

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



Credit: www.cta-observatory.org

www.cta-observatory.org

Science with CTA, arXiv:1709.07997

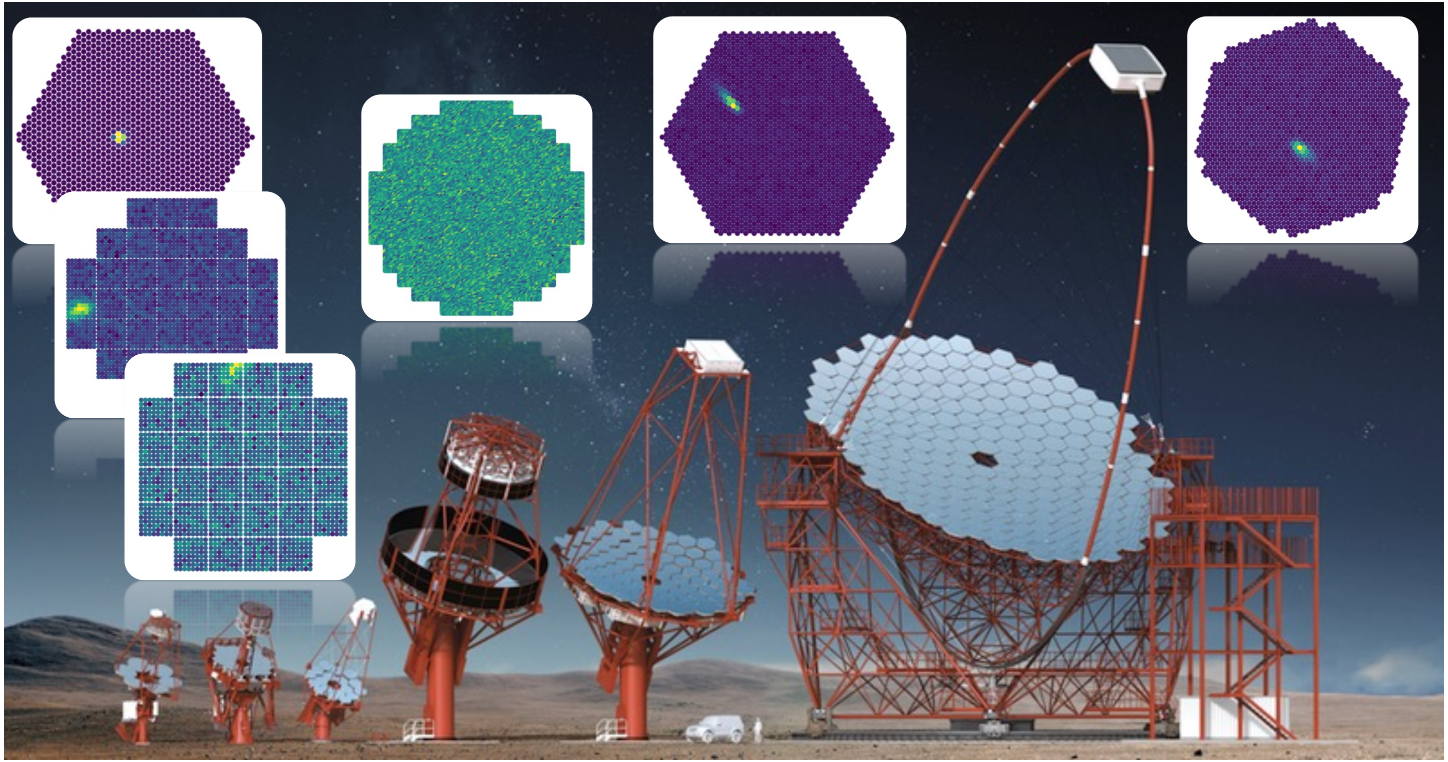
- Stereoscopy:
  - Stereoscopic view of the extended air showers
  - Compact "videos" rather than single snapshots
  - Events effectively recorded in 4D!

CREDIT: DESY/Milde Science Communication

Challenges for deep learning & IACT data

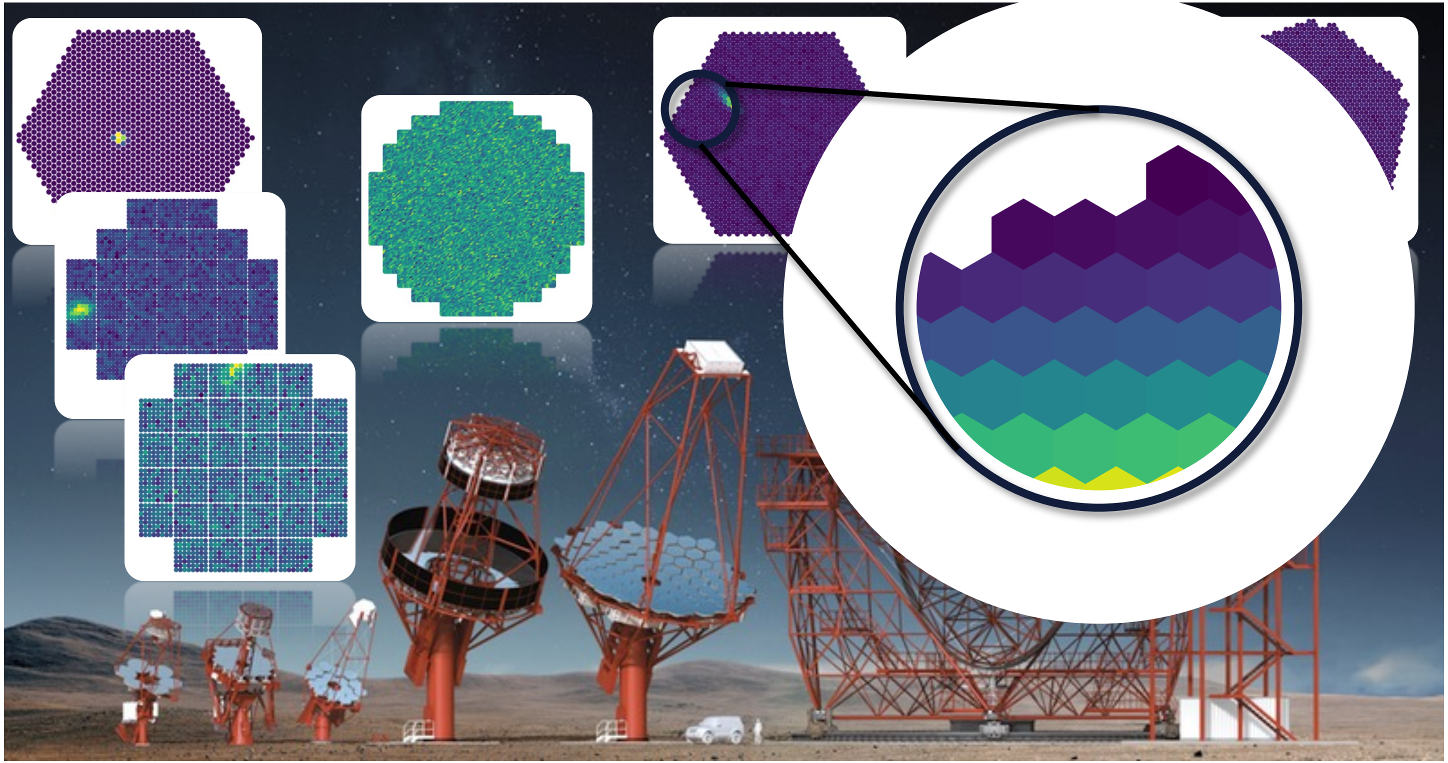
- Heterogeneity of instruments:

Camera images courtesy of T. Vuillaume



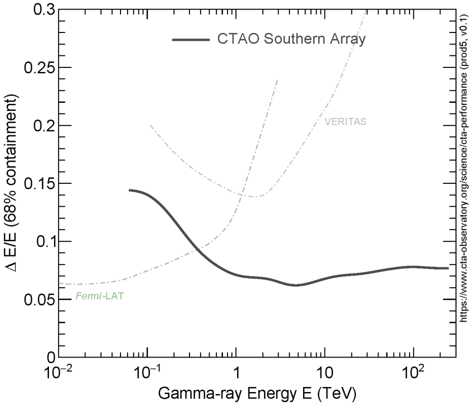
- Heterogeneity of instruments:

Camera images courtesy of T. Vuillaume

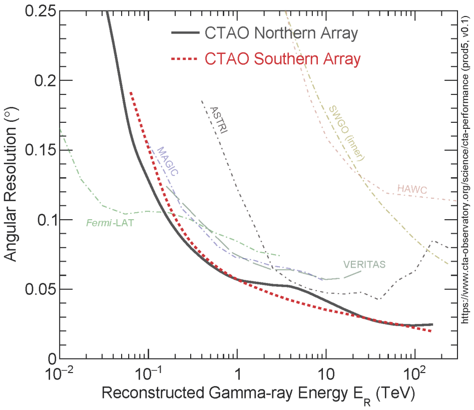


- Final metrics are far from trivial and entangled

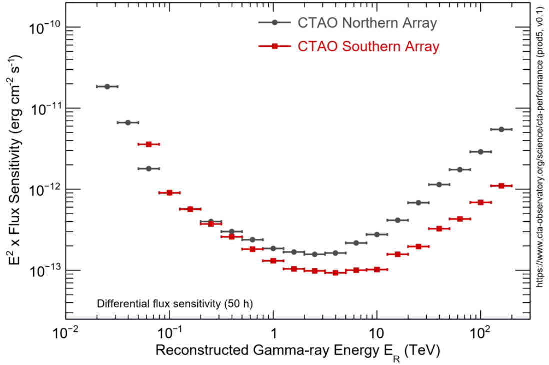
Energy resolution

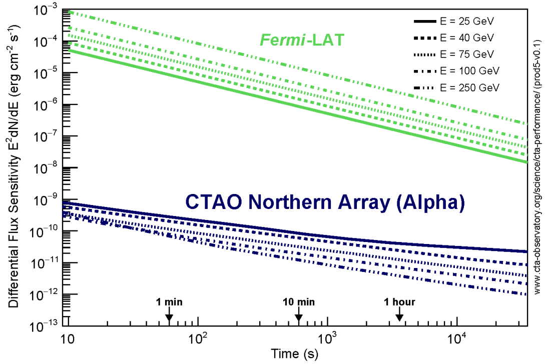


Angular resolution



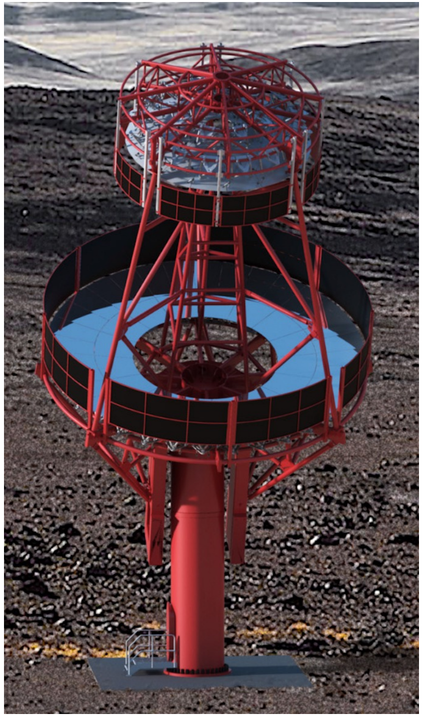
Flux sensitivity



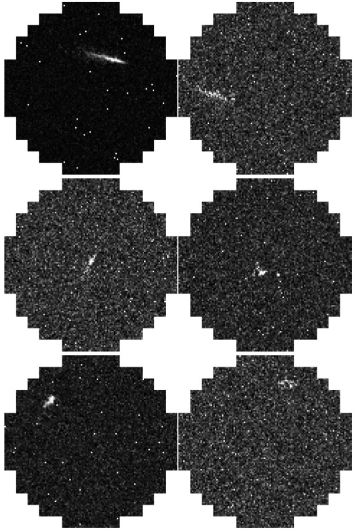


cta cherenkov telescope array — the observatory for ground-based gamma-ray astronomy

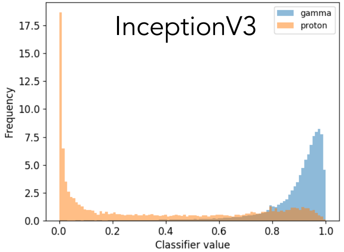
Credit: www.cta-observatory.org

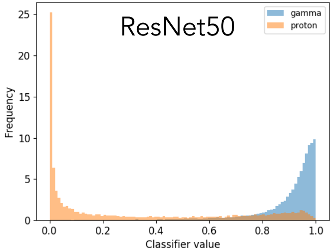


- Single telescope
- Square pixels
- Only signal charge (no timing)
- Single task: classification



Medium energies
(0.3 TeV < E < 1 TeV)





AUC

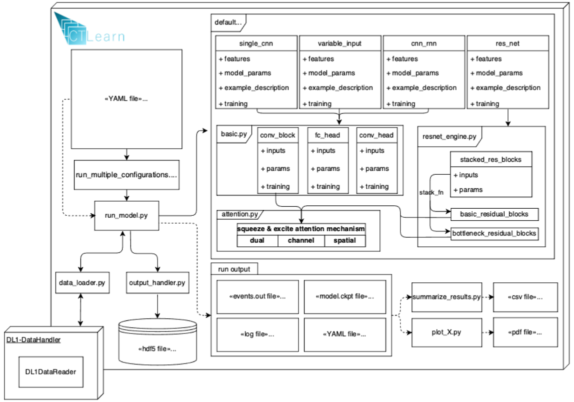
Model/Energy	Low E.	Med. E.	High E.
InceptionV3	84.7%	91.1%	92.0%
ResNet50	84.8%	91.4%	90.2%

Nieto et al., PoS(ICRC2017)809

- 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
  https://pos.sissa.it/358/752
  DOI 10.5281/zenodo.3345947
  (Latest release: **CTLearn v0.6.2**, 09/22)

Core developers
Tjark Miener, DN (**IPARCOS-UCM**)
Ari Brill, Qi Feng (Columbia)
Bryan Kim (UCLA, now at Stanford)
(See contributors here)

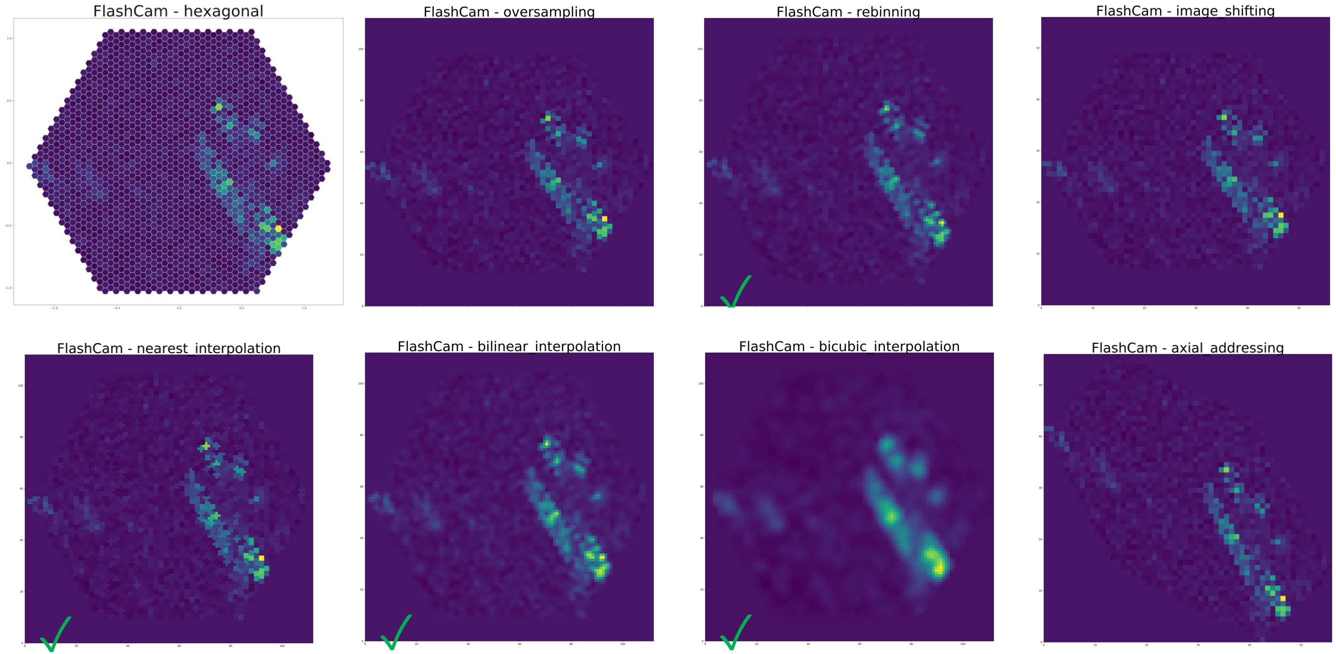


- Image mapping (preprocessing)

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

CTLearn

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

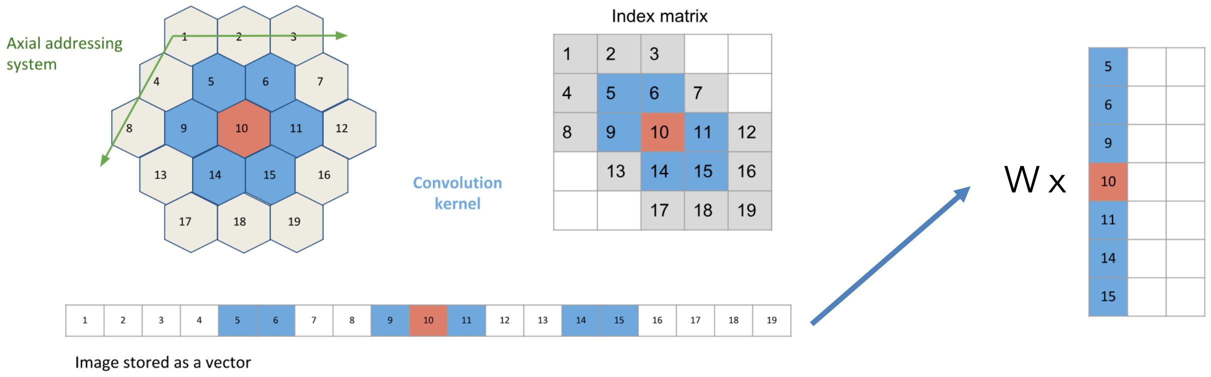


✓ Angles and distances preserved

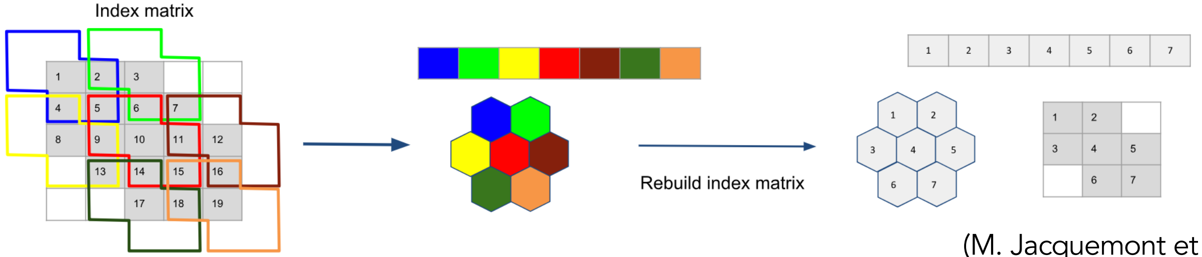
T. Vuillaume,
M. Jaquemont, et al.

https://github.com/IndexedConv

- Hexagonal convolution
  - Convolution

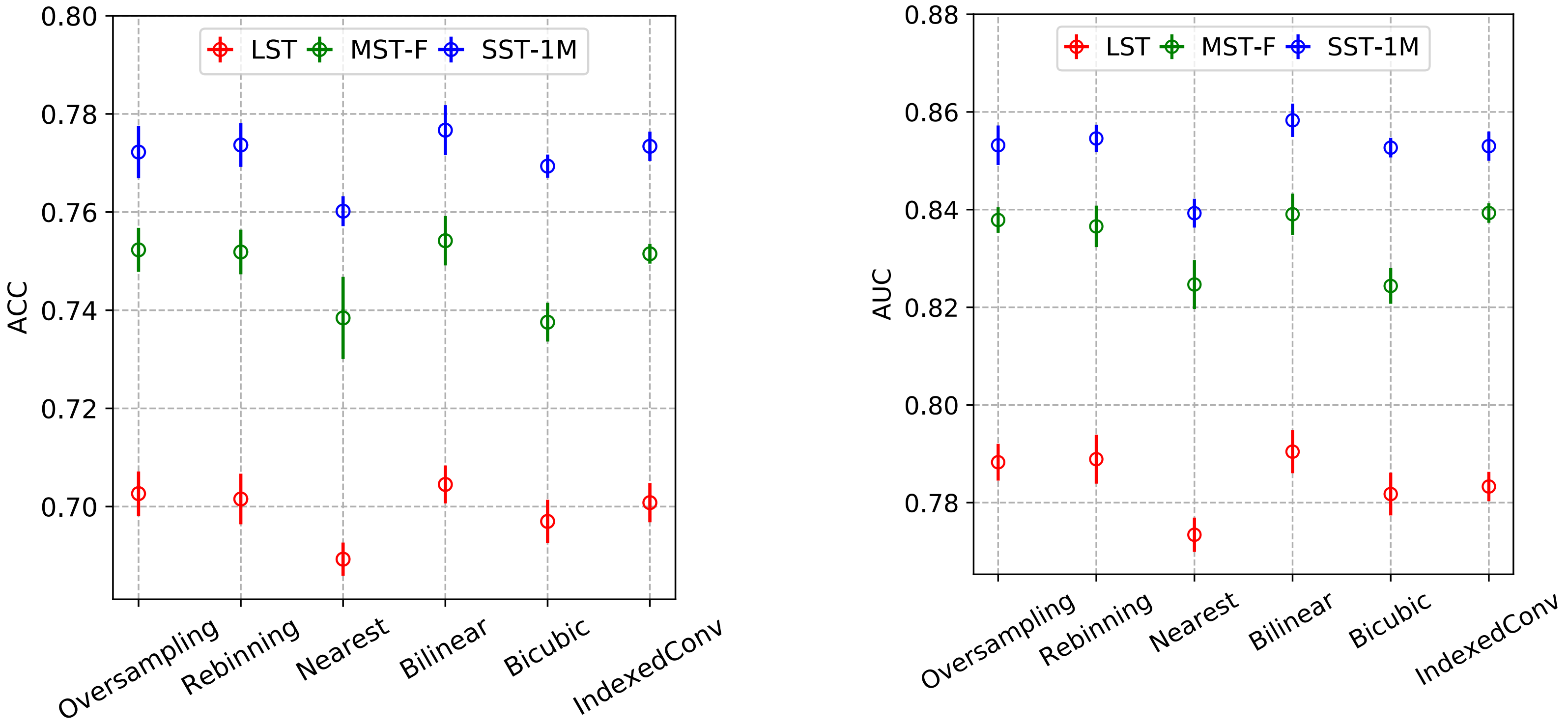


  - Pooling



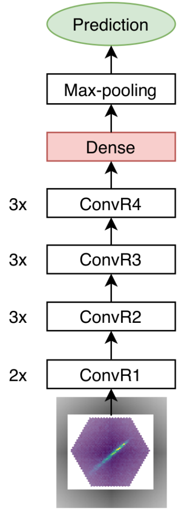
(M. Jacquemont et al. 2019)

- Comparison of methods for classification task

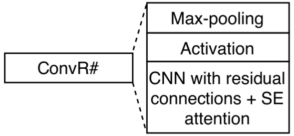


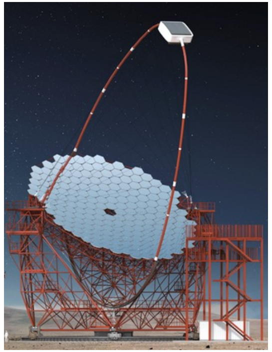
D. Nieto et al. PoS(ICRC2019)753

CTLearn: single-telescope full-event reconstruction

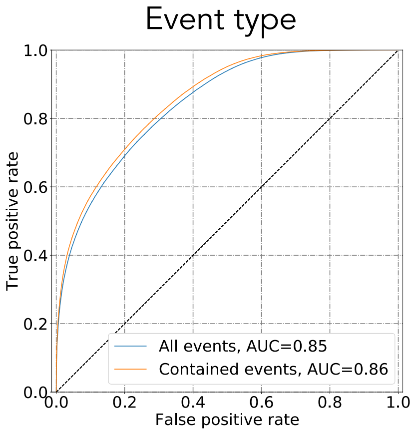


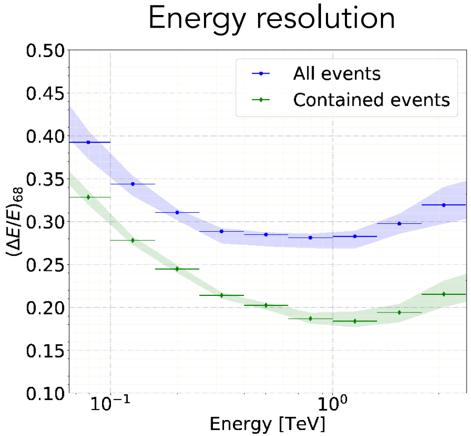
Thin-ResNet model

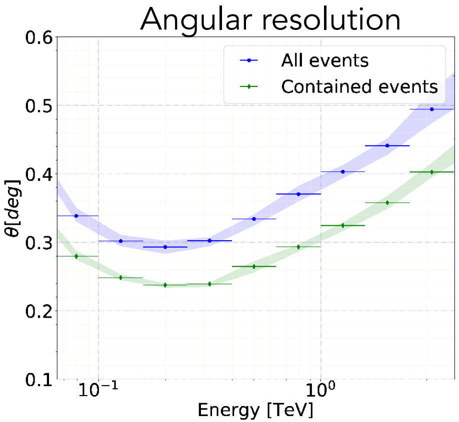


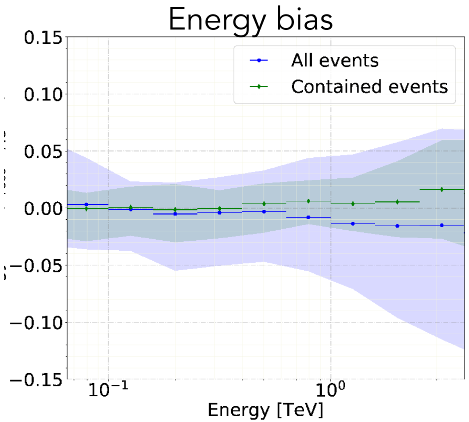


Full-event reconstruction for single-telescope data achieved!



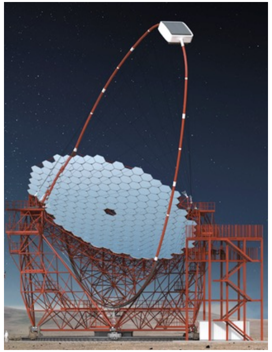




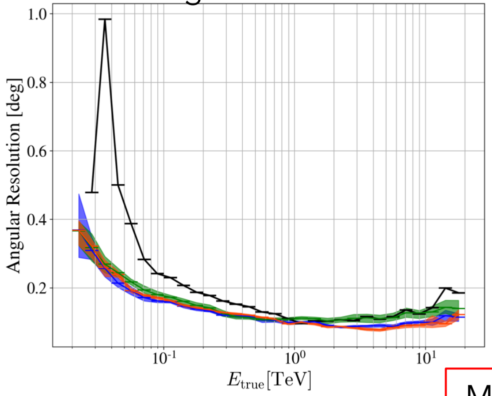


[D. Nieto et al. ADASS XXX 2020]

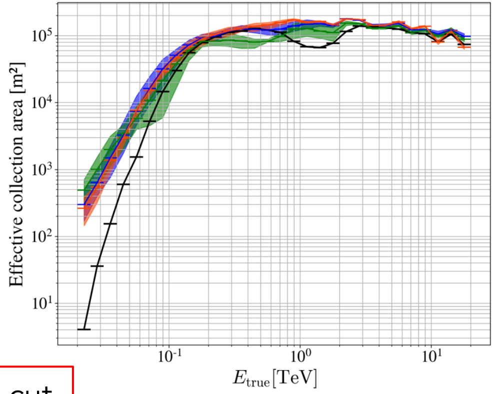
- Crosschecking three different implementations
- Same datasets, same cuts
- Different models
- Comparison against standard analysis (RF)



Angular resolution

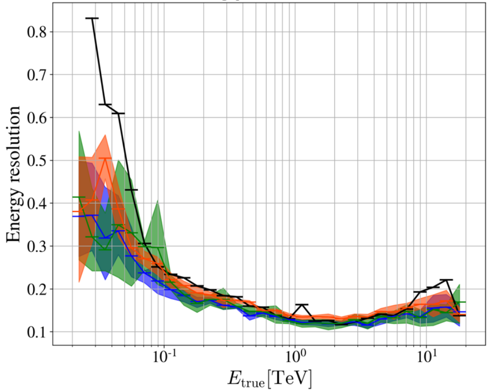


Effective area

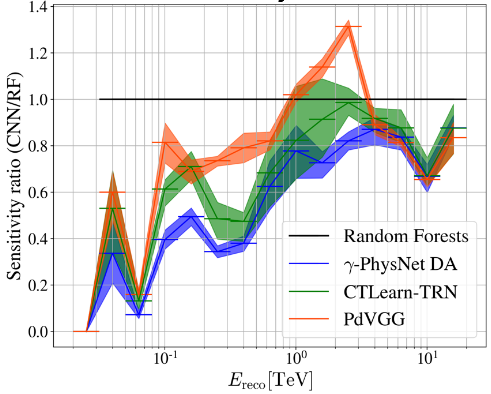


Mid cut

Energy resolution

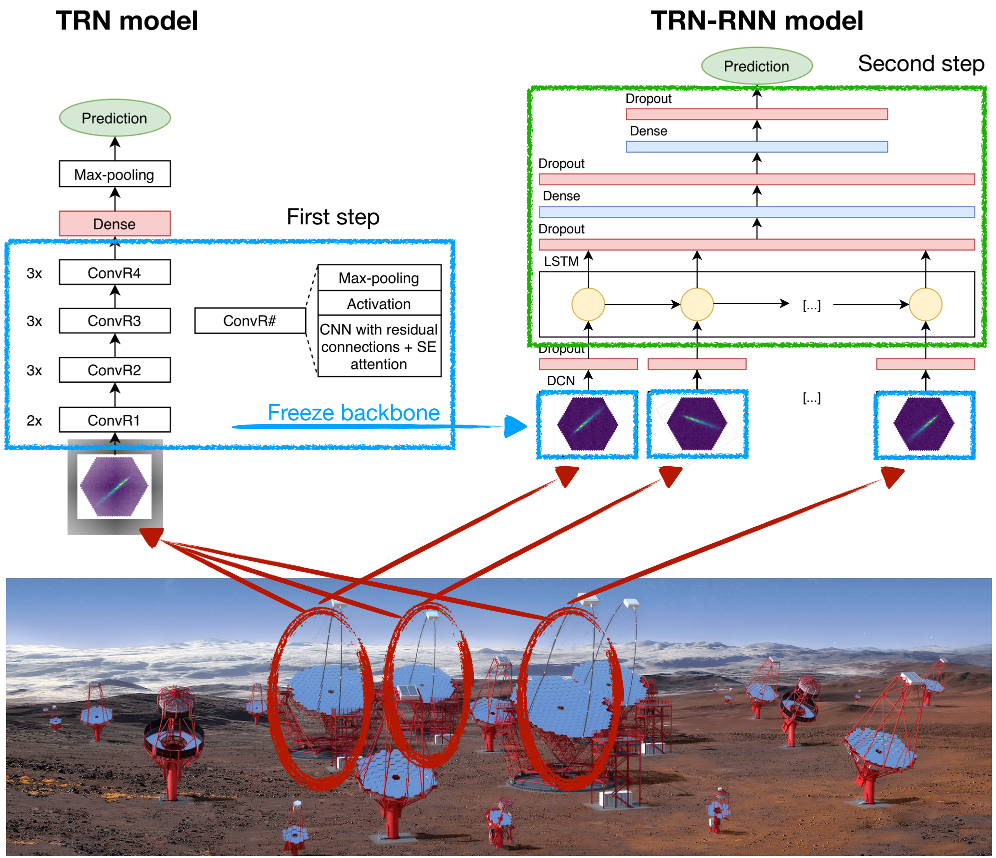


Sensitivity ratio



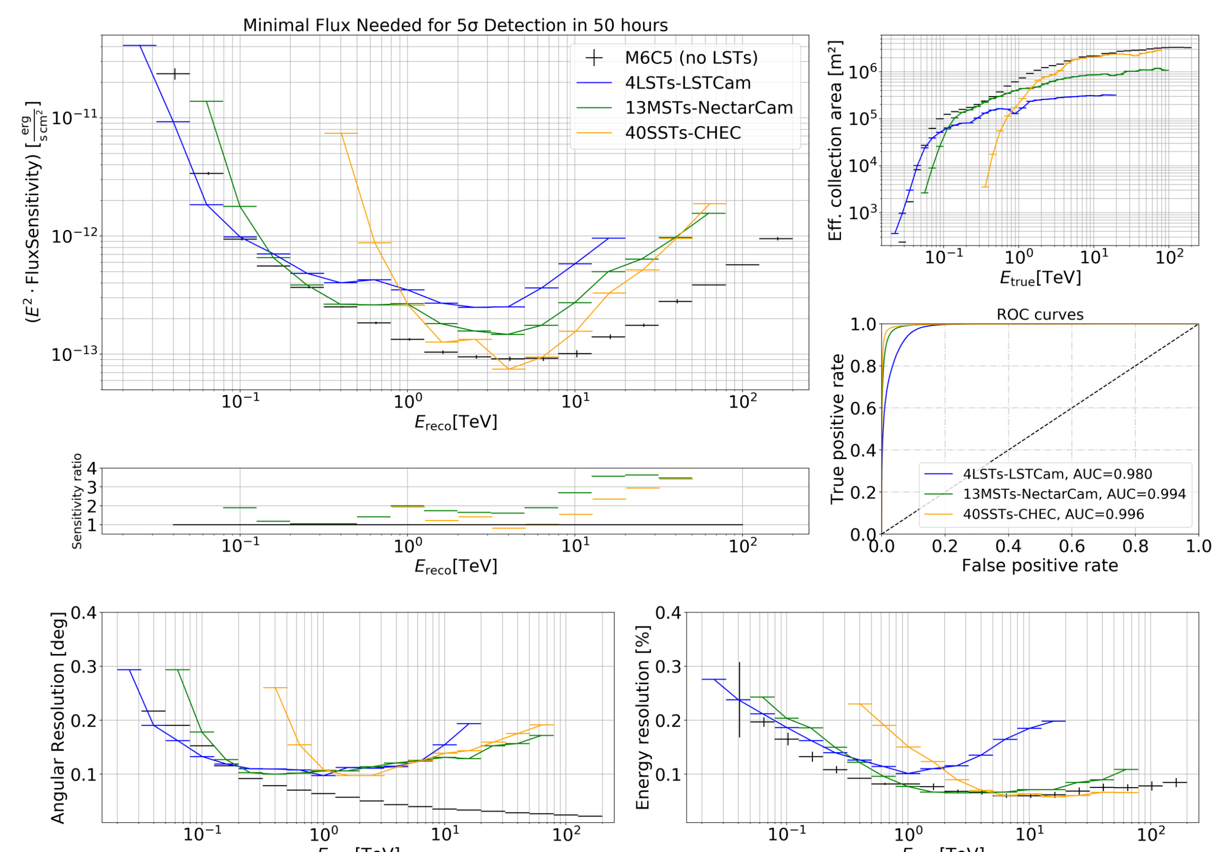
[P. Grespan et al. PoS(ICRC2021) 771]

CTLearn: multiple-telescope full-event reconstruction

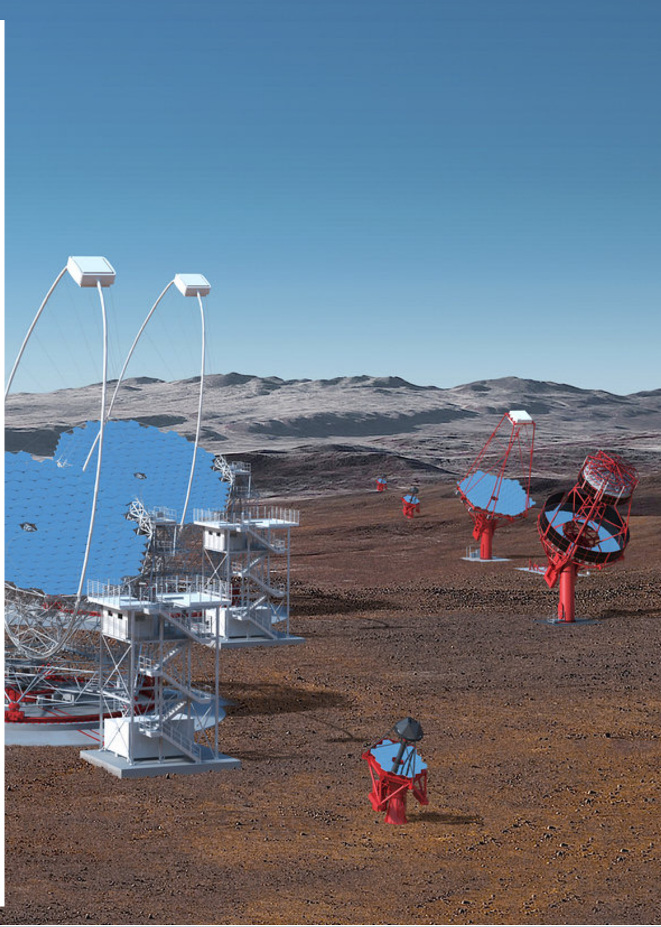


[T. Miener et al., PoS(ICRC2021) 730]()

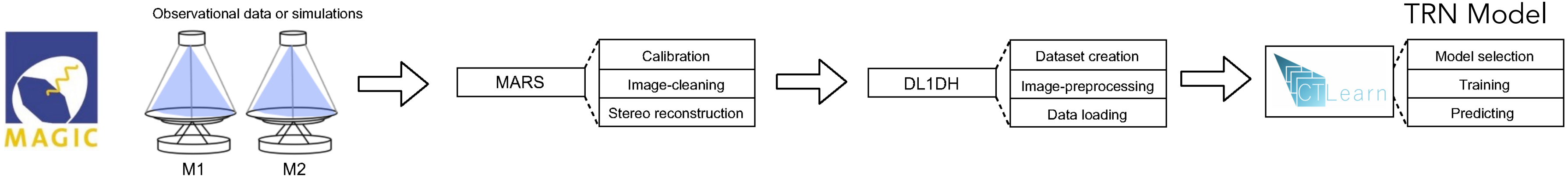
CTLearn: multiple-telescope full-event reconstruction

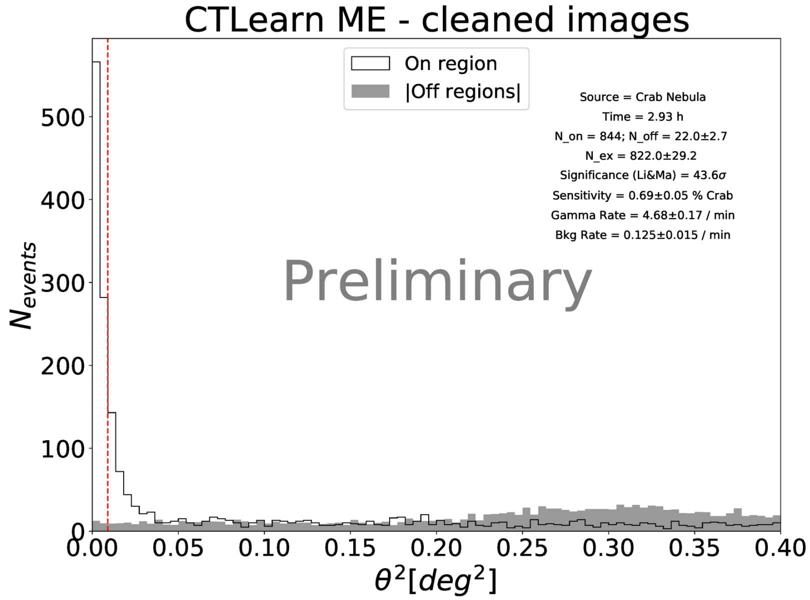


[T. Miener et al., PoS(ICRC2021) 730]()



CTLearn: application to real data





Analysis	γ rate [/min]	bkg rate [/min]	Sen. [% Crab]	Sig. (Li&Ma)
MARS – ME	4.54 ± 0.16	0.119 ± 0.015	0.70 ± 0.05	43.0σ
CTLearn – ME (raw)	3.45 ± 0.14	0.133 ± 0.018	0.97 ± 0.08	36.5σ
CTLearn – ME (cleaned)	4.68 ± 0.17	0.125 ± 0.015	0.69 ± 0.05	43.6σ
MARS – LE	16.49 ± 0.35	3.861 ± 0.086	1.09 ± 0.03	61.1σ
CTLearn – LE (raw)	11.70 ± 0.32	3.832 ± 0.114	1.53 ± 0.05	47.5σ
CTLearn – LE (cleaned)	16.24 ± 0.35	3.872 ± 0.086	1.11 ± 0.03	60.4σ

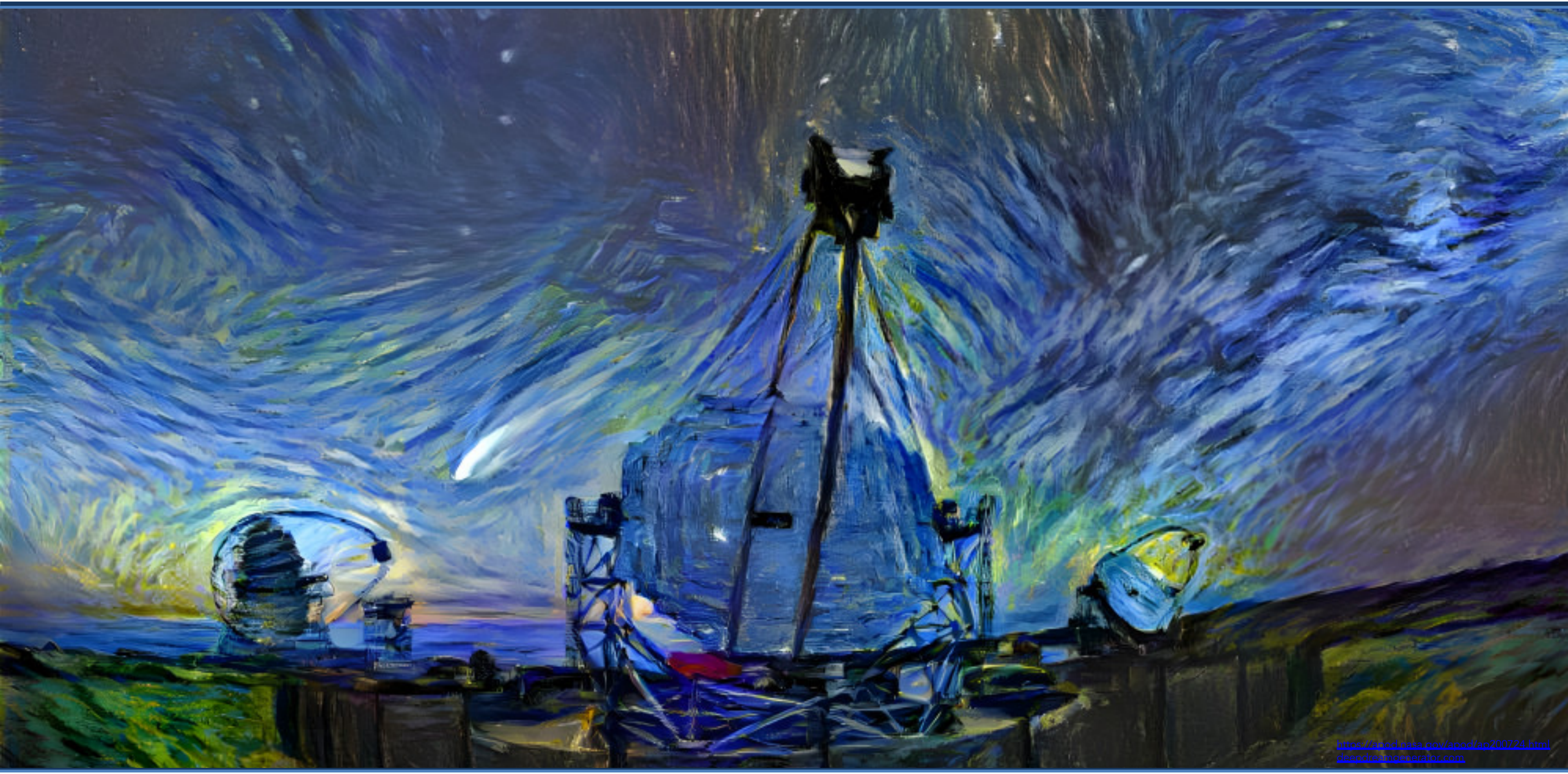
Analysis	N_{on}	N_{off}	N_{ex}
MARS – ME	819	21.0 ± 2.6	798.0 ± 28.7
CTLearn – ME (raw)	629	23.3 ± 3.1	605.7 ± 25.3
CTLearn – ME (cleaned)	844	22.0 ± 2.7	822.0 ± 29.2
MARS – LE	3579	679.0 ± 15.0	2900.0 ± 61.7
CTLearn – LE (raw)	2730	673.7 ± 20.0	2056.3 ± 56.0
CTLearn – LE (cleaned)	3536	680.7 ± 15.1	2855.3 ± 61.3

Summary of all performed analyses of the same Crab Nebula sample

T. Miener et al. 2021 (ADASS XXXI)

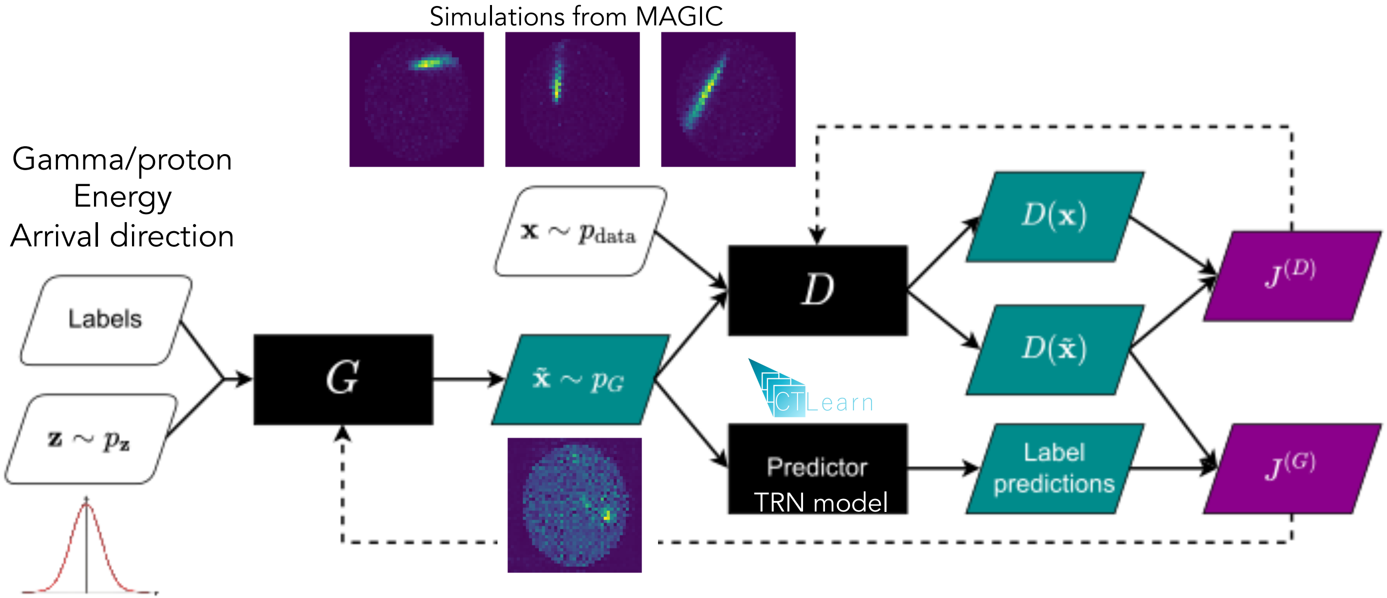
Dreaming of IACTs

Dreaming of IACTs



https://apod.nasa.gov/apod/ap200724.html
deepdreamgenerator.com

- Auxiliary conditional generative adversarial networks (AC-GANs)



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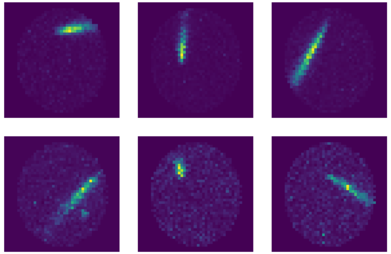
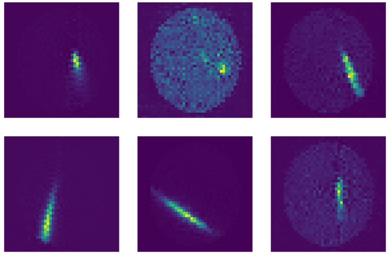
GAMMA RAYS

Simulated

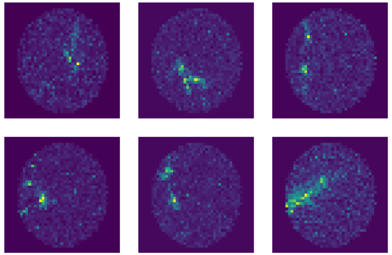


Generated

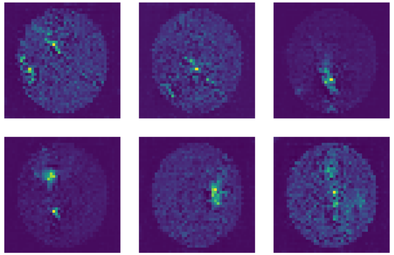


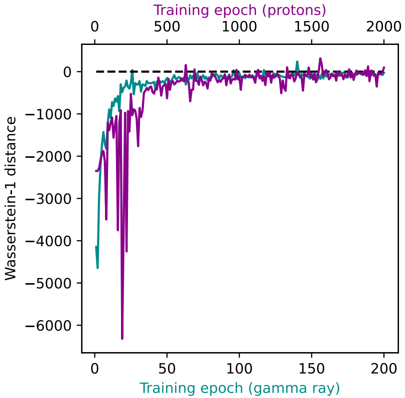
PROTONS

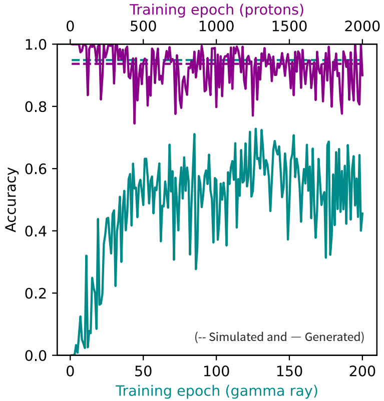
Simulated

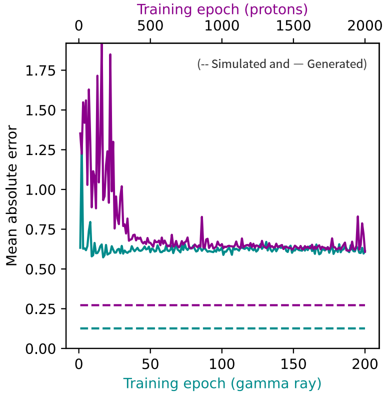


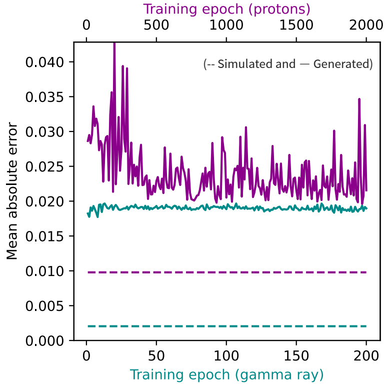
Generated





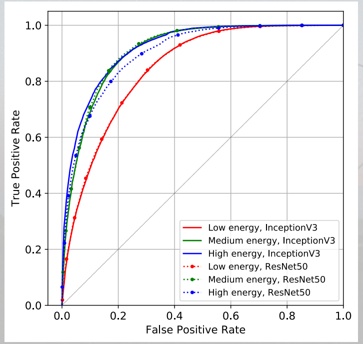


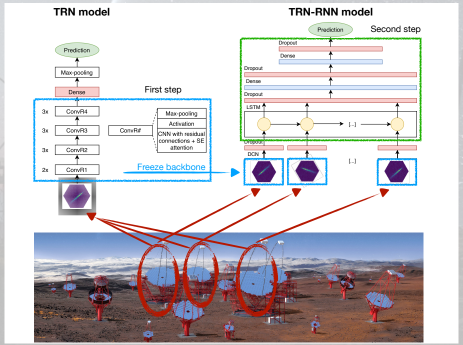


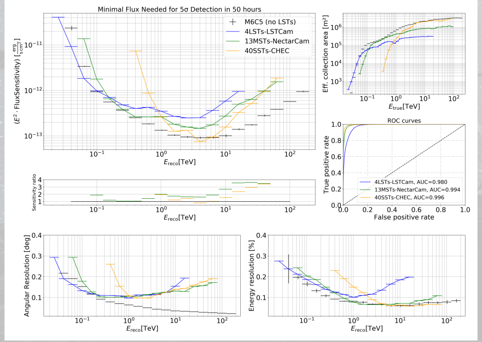


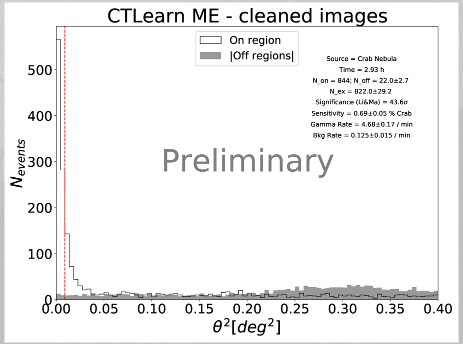
S. García-Heredia et al.

- Current-generation IACTs have enhanced their performances through ML
- Next-gen (even current-gen!) IACT may profit from latest developments in ML
- Ongoing efforts to exploit deep learning as an event reconstruction method for IACTs
  - Full-event reconstruction over simulated IACT events demonstrated
  - Application to real observations works!
  - Working on optimizing architectures & multi-task learning
  - Using AC-GANs as pseudosimulators
  - Tackling the real-data problem









Acknowledgment

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