



Second IPARCOS Workshop
on Machine Learning and
Applications to Physics



Deep learning for imaging atmospheric Cherenkov telescopes



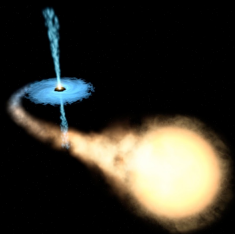
Daniel Nieto

(d.nieto@ucm.es)

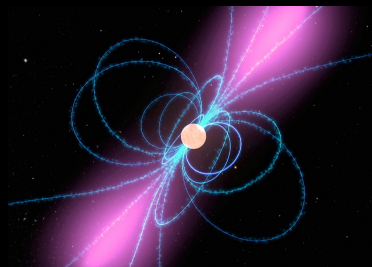
Institute for Particle and Cosmos Physics

IPARCOS-UCM

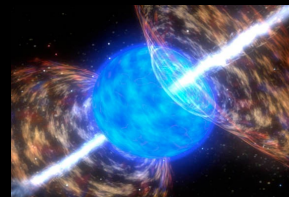
- Very-high-energy astrophysics in a nutshell
- Imaging atmospheric Cherenkov telescopes
- Enhancing IACTs with machine learning
- Applications to other astroparticle physics experiments



Gamma-ray Binaries



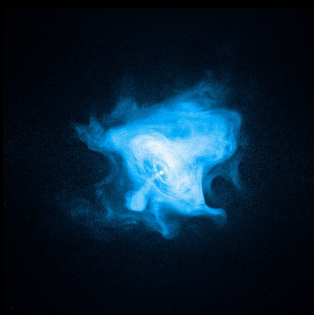
Pulsars



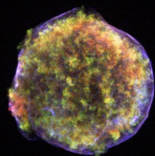
Gamma-ray Bursts



Compact-object mergers



Pulsar Wind Nebulae



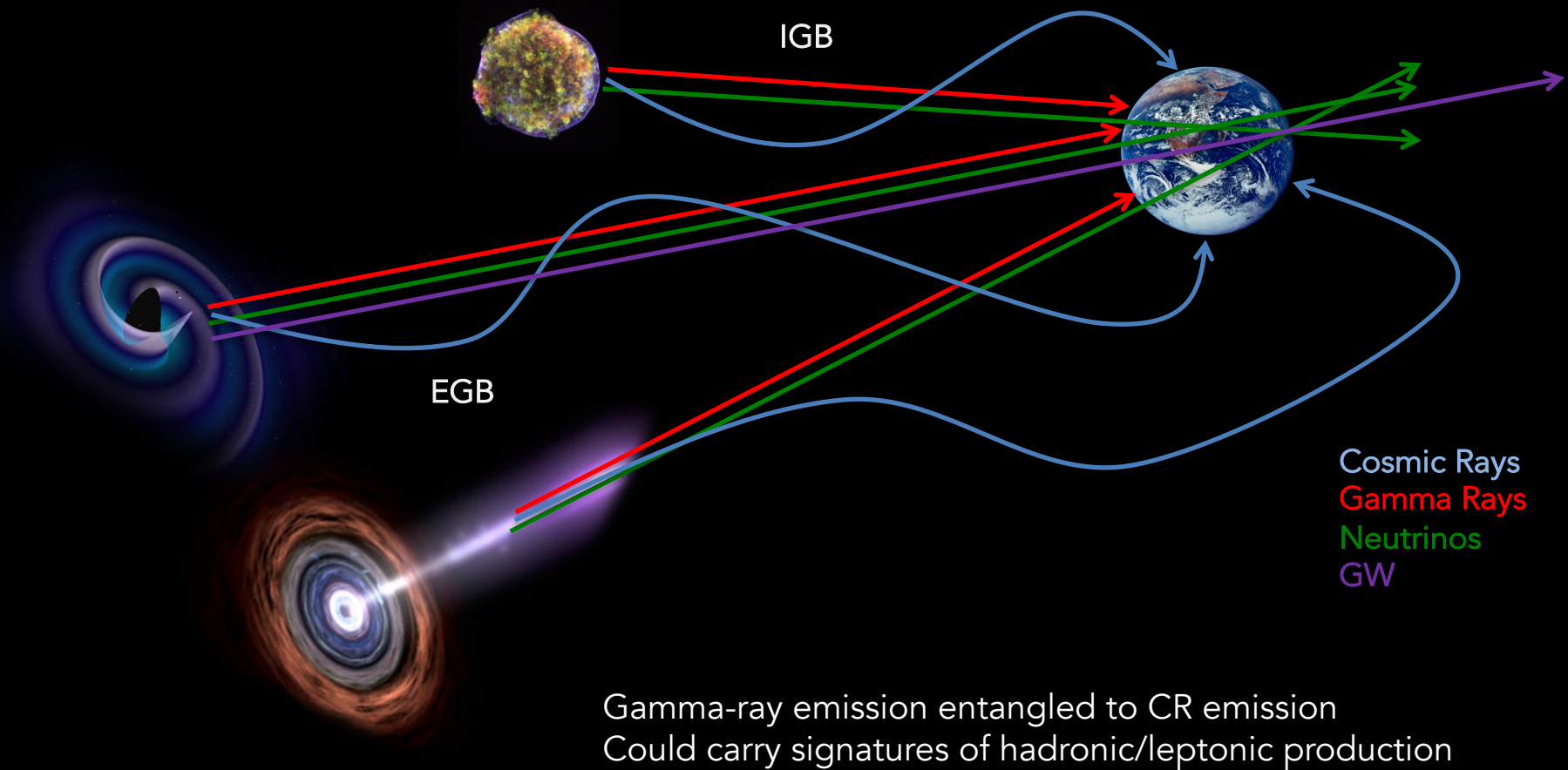
Supernova Remnants



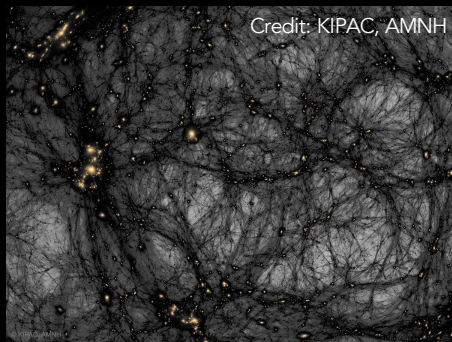
Starburst Galaxies



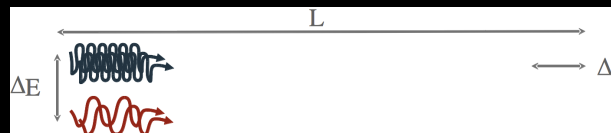
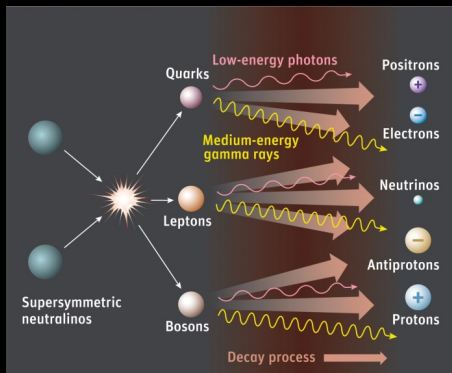
Active Galactic Nuclei

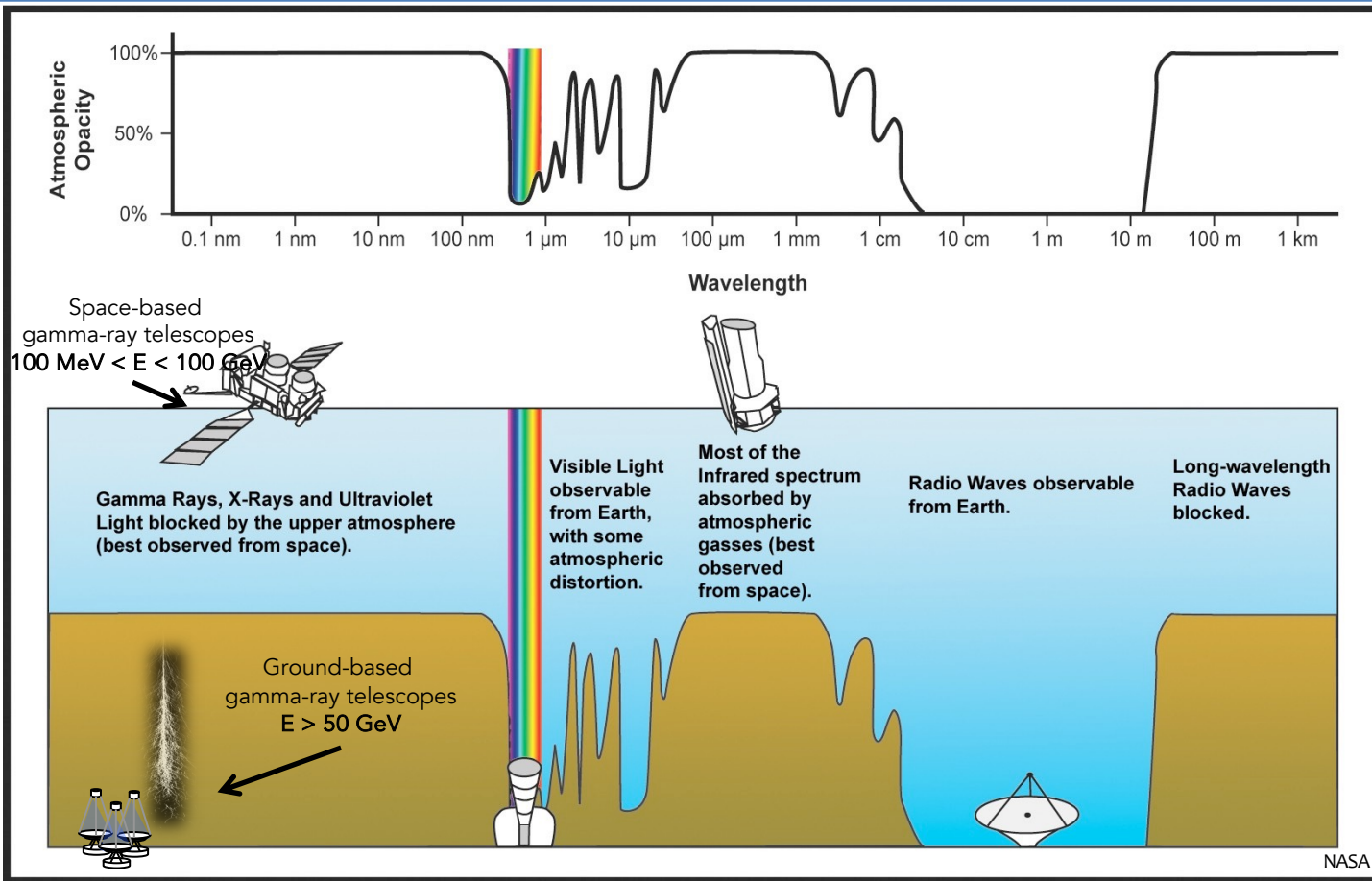


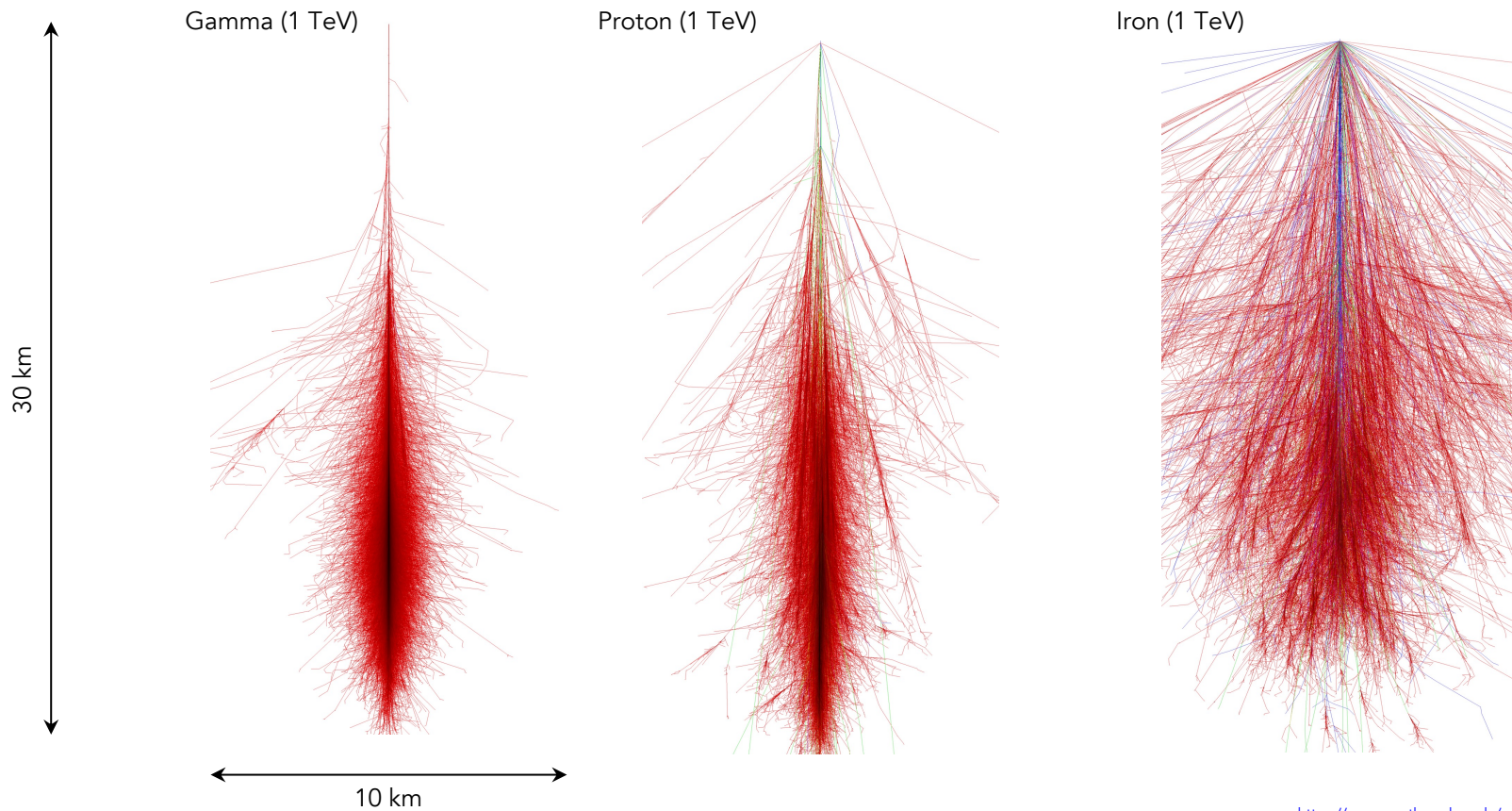
Dark matter searches



Lorentz invariance







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

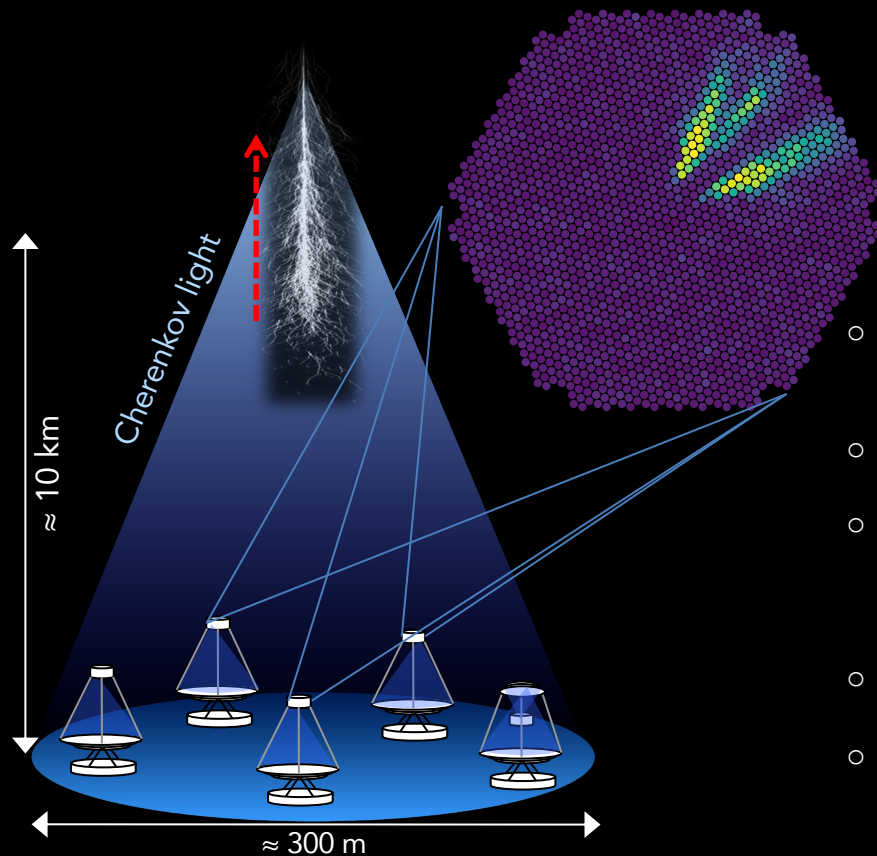
Particle showers produced in Earth's atmosphere by gamma-ray, proton, and carbon-13

-
- Initial particle energy: 400 GeV
 - Animation time: Shower reaching ground
 - **Charged particles: Red dots**
 - **Cherenkov light: Blue dots**
-

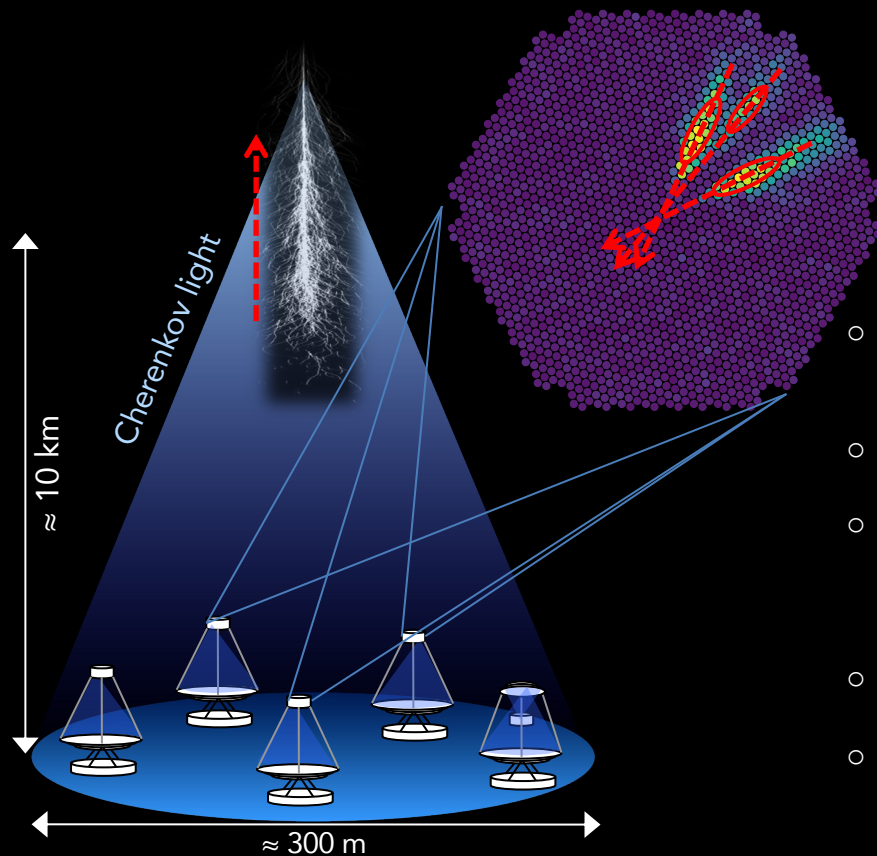
Visit <http://veritas.sao.arizona.edu>

©2012 Martin Schroedter
VERITAS & Harvard Smithsonian Center for Astrophysics

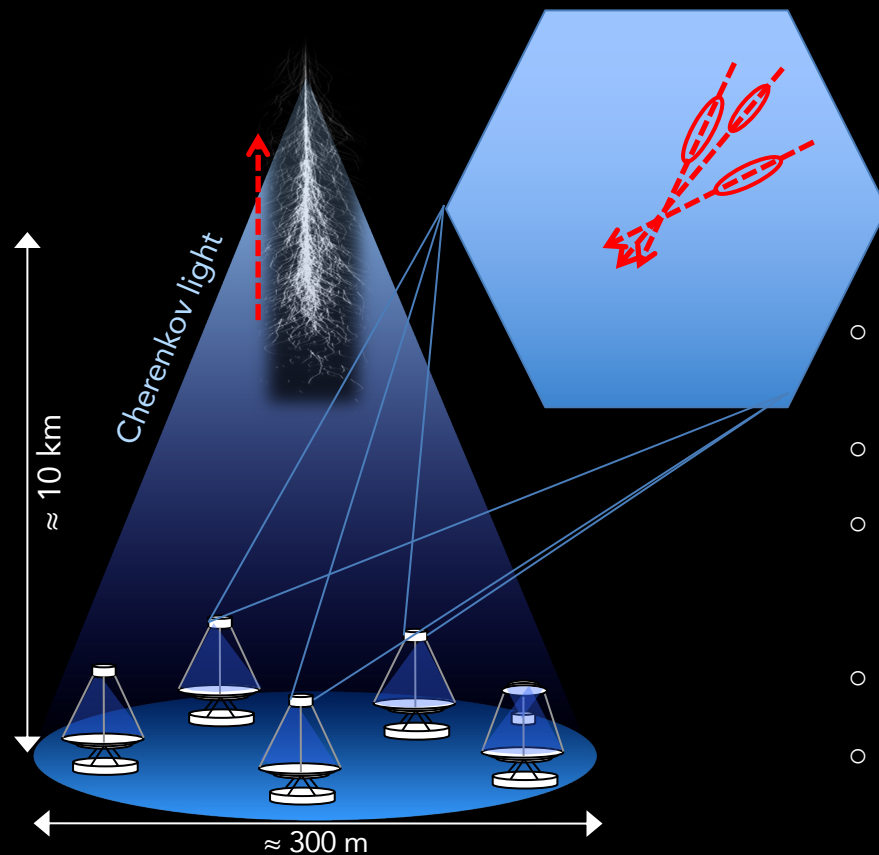
<https://www.youtube.com/watch?v=i-BBzWlOai0>



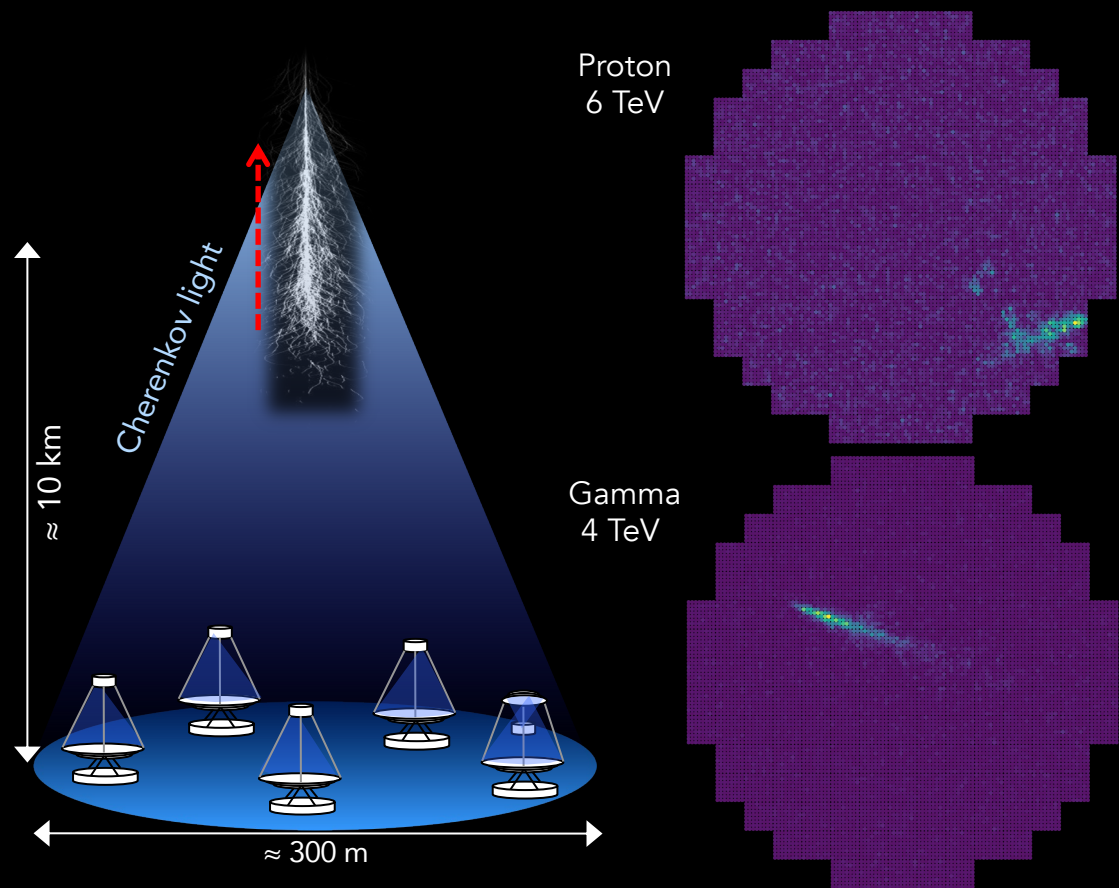
- Detection of extended air showers using the atmosphere as a calorimeter
- Huge γ -ray collection area ($\sim 10^5 \text{ m}^2$)
- Large background from charged CR
 - Partly irreducible (e^-/e^+ , single-EM, with current methods)
- Energy window: tens GeV - tens TeV
- Event reconstruction from image: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

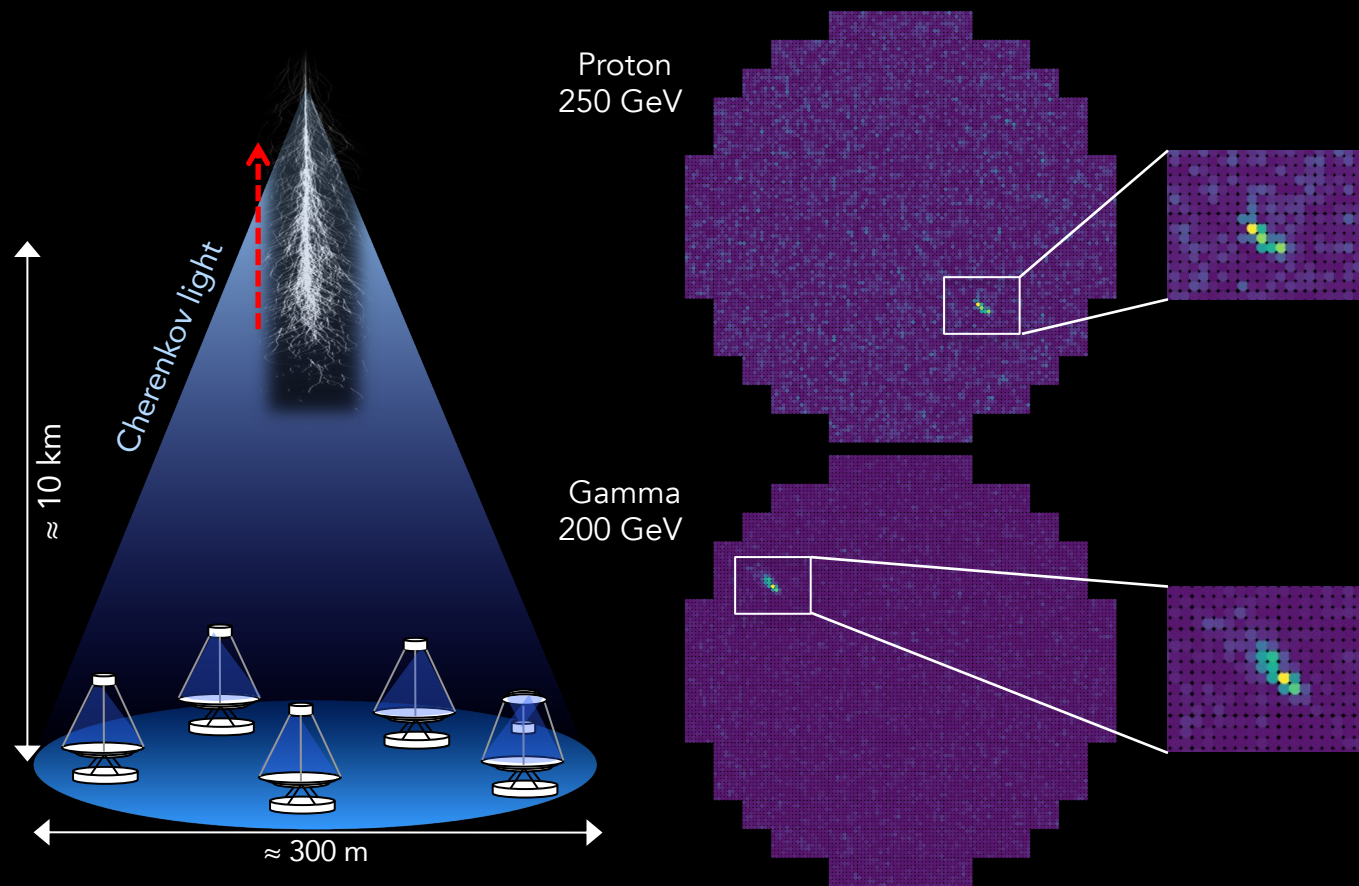


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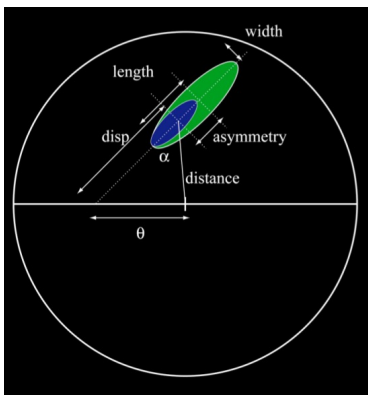
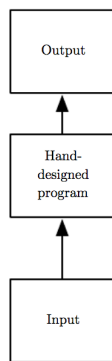
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- Energy window: tens GeV - tens TeV
- Event reconstruction from image:
 - Type of primary event
 - Primary energy estimation
 - Primary arrival direction





Output: event type,
energy, arrival direction

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

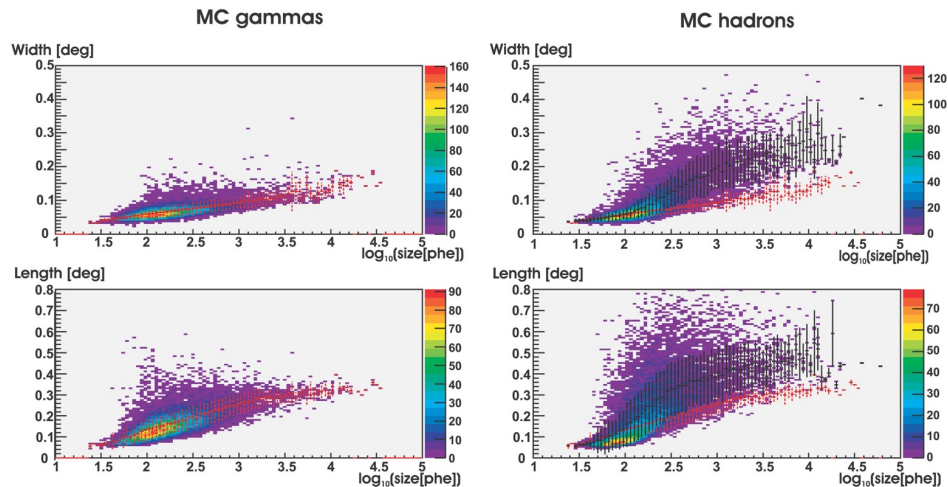


Rule-based
systems

Input: observed events

event reconstruction

- Based on image parametrization (Hillas parameters)

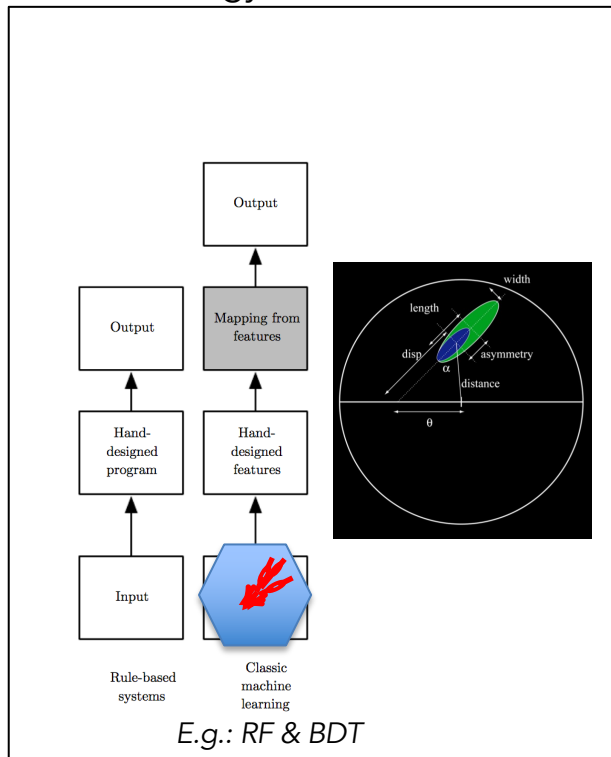


$$E = E(\text{size}, \text{distance}, h_{max})$$

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

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

Output: event type,
energy, arrival direction

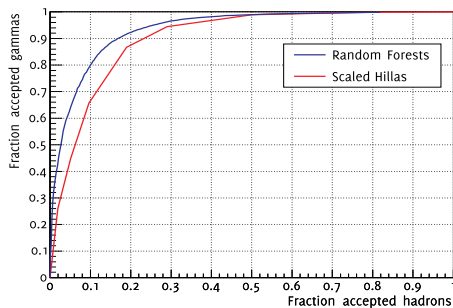


Input: observed events

e
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e
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t

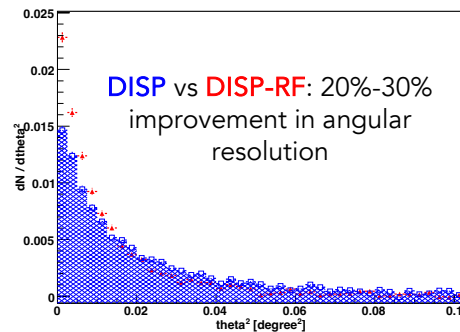
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○ Current generation of IACTs: classic ML



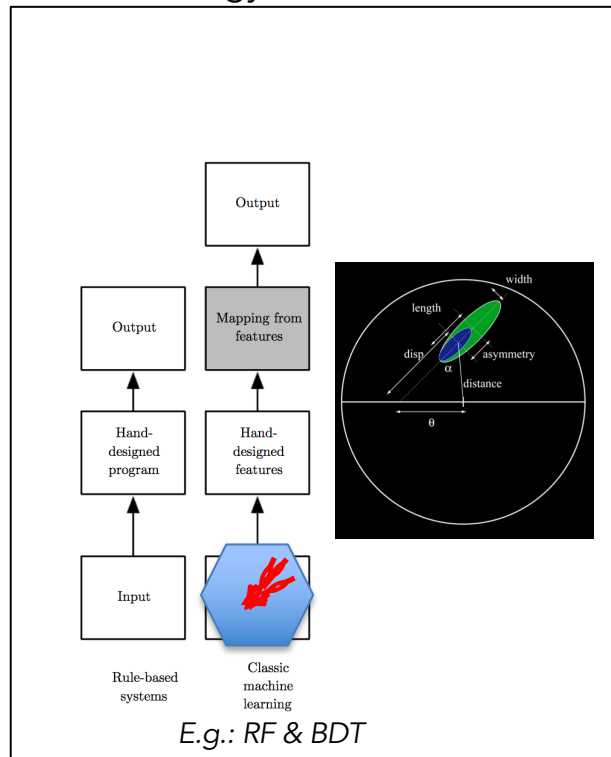
Albert et al., NIM-A 588:424-432 (2008)

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



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

Output: event type,
energy, arrival direction



Input: observed events

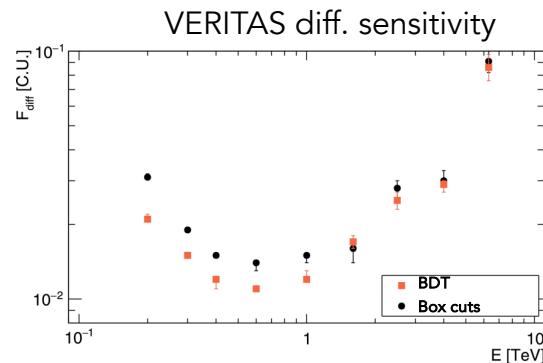
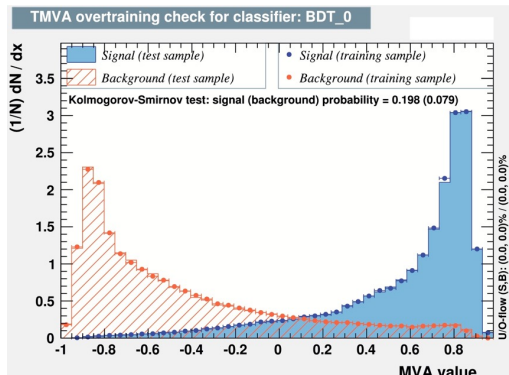
e
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○ Current generation of IACTs: classic ML

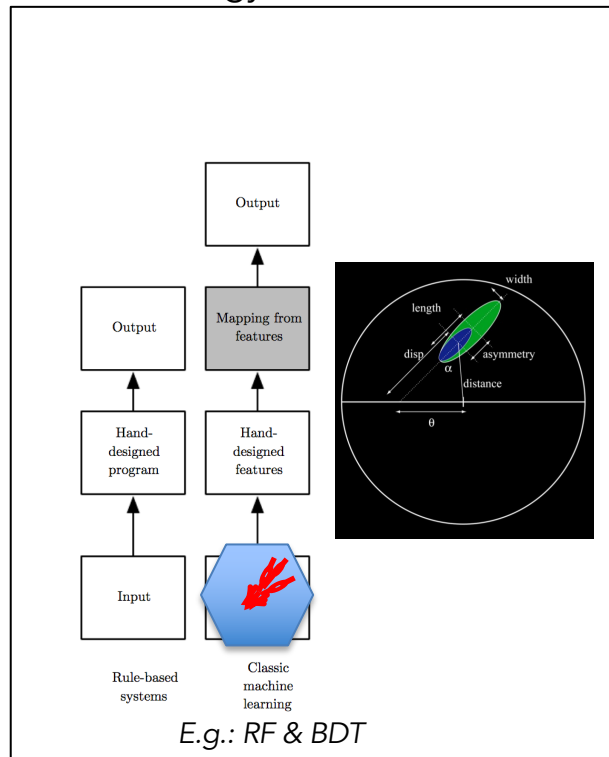


- ML method:
 - Boosted Decision Trees (BDT)
- Applied to:
 - Background rejection



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

Output: event type,
energy, arrival direction

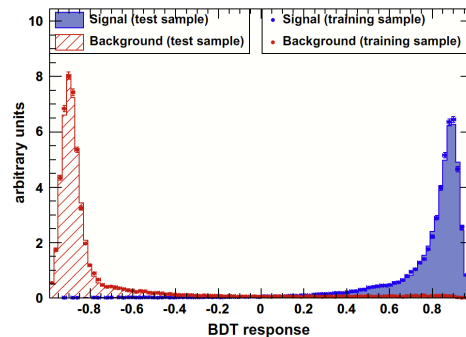


Input: observed events

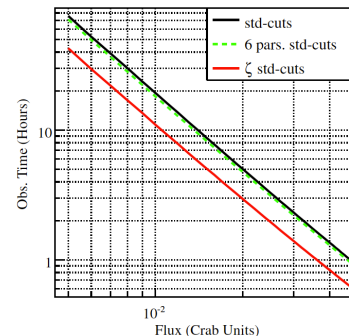
○ Current generation of IACTs: classic ML



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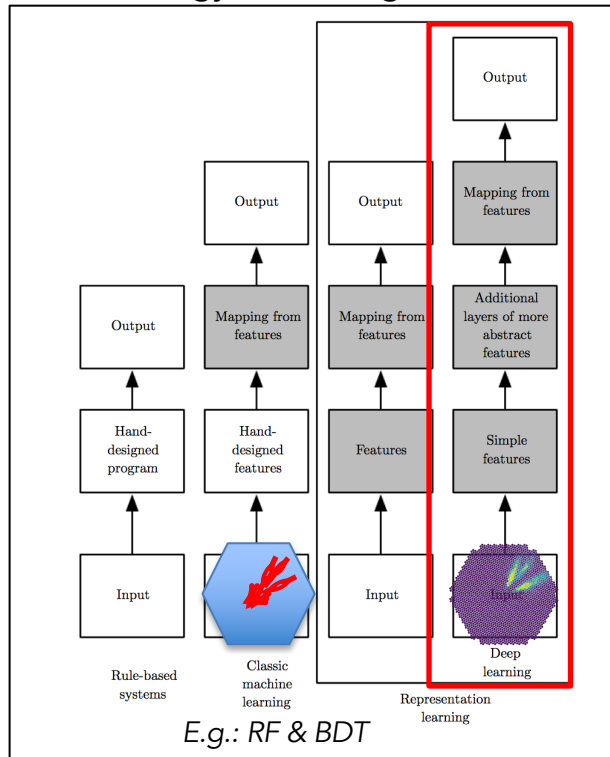
Becherini et al., APP V34-12 P858-870 (2011)



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

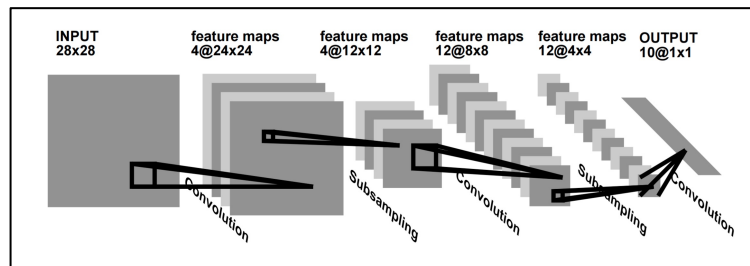
(Results for H.E.S.S. I only)

Output: event type,
energy, incoming direction



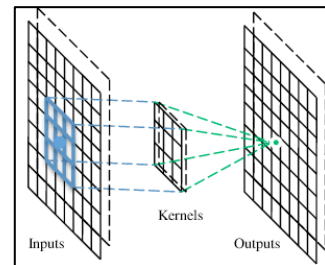
Input: observed events

Convolutional Neural Network (CNN)



LeCun 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 IACT 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)



ch
erenkov
telescope
array

the observatory for
ground-based
gamma-ray astronomy

Low-energy range:

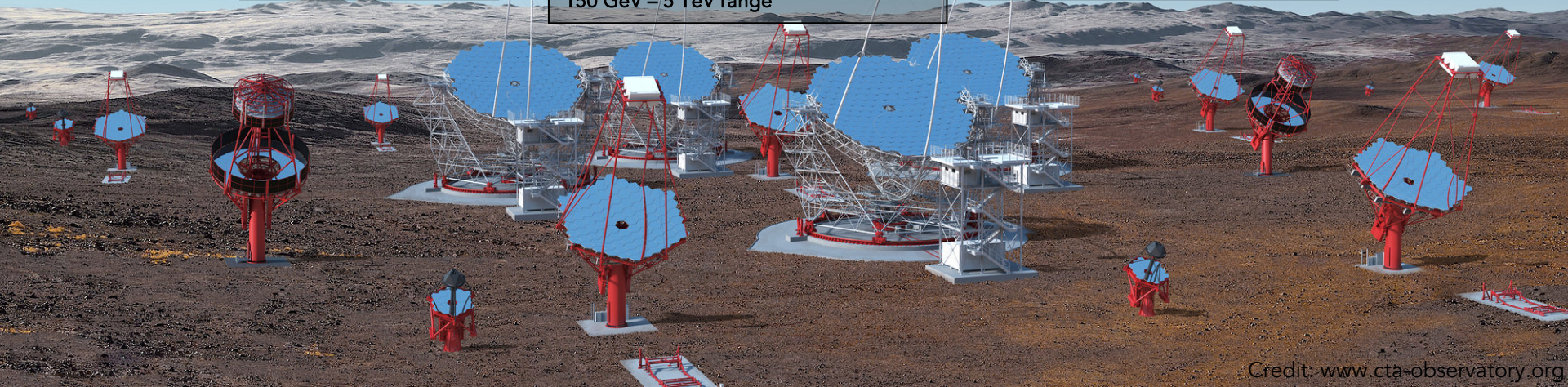
23 m $\varnothing$
Parabolic reflector
4.3° FoV
Energy threshold 20 GeV

Mid energy-range:

12 m $\varnothing$ modified Davies-Cotton reflector
9.7 m $\varnothing$ Schwarzschild-Couder reflector
7.5° FoV
Full system sensitivity in the
150 GeV – 5 TeV range

High-energy range:

4 m $\varnothing$ Schwarzschild-Couder reflector
10° FoV
Several km² area at
multi-TeV energies



Credit: www.cta-observatory.org

www.cta-observatory.org

Science with CTA, [arXiv:1709.07997](https://arxiv.org/abs/1709.07997)

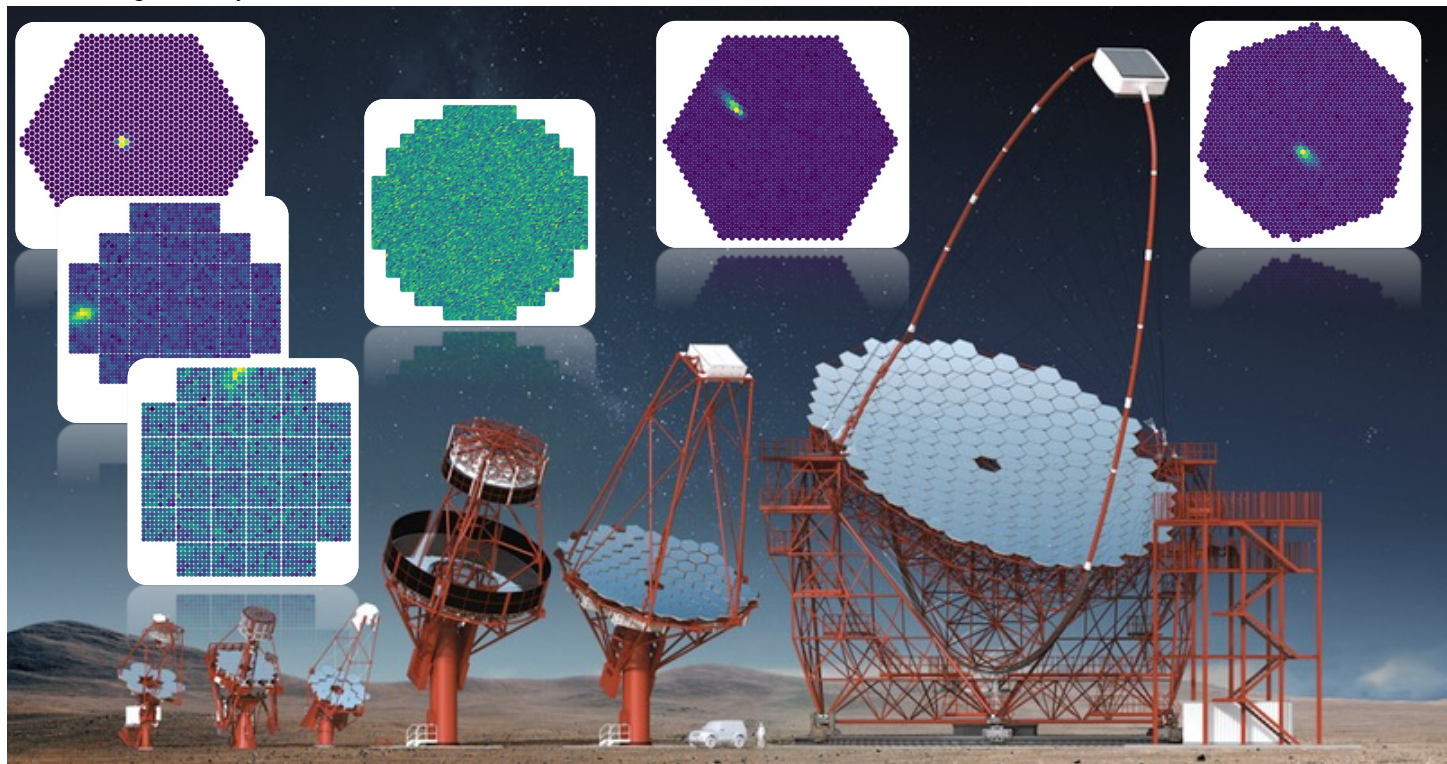
- Stereoscopy:
 - Stereoscopic view of the extended air showers
 - Compact “videos” rather than single snapshots
 - Events effectively recorded in 4D!



CREDIT: DESY/Milde Science Communication

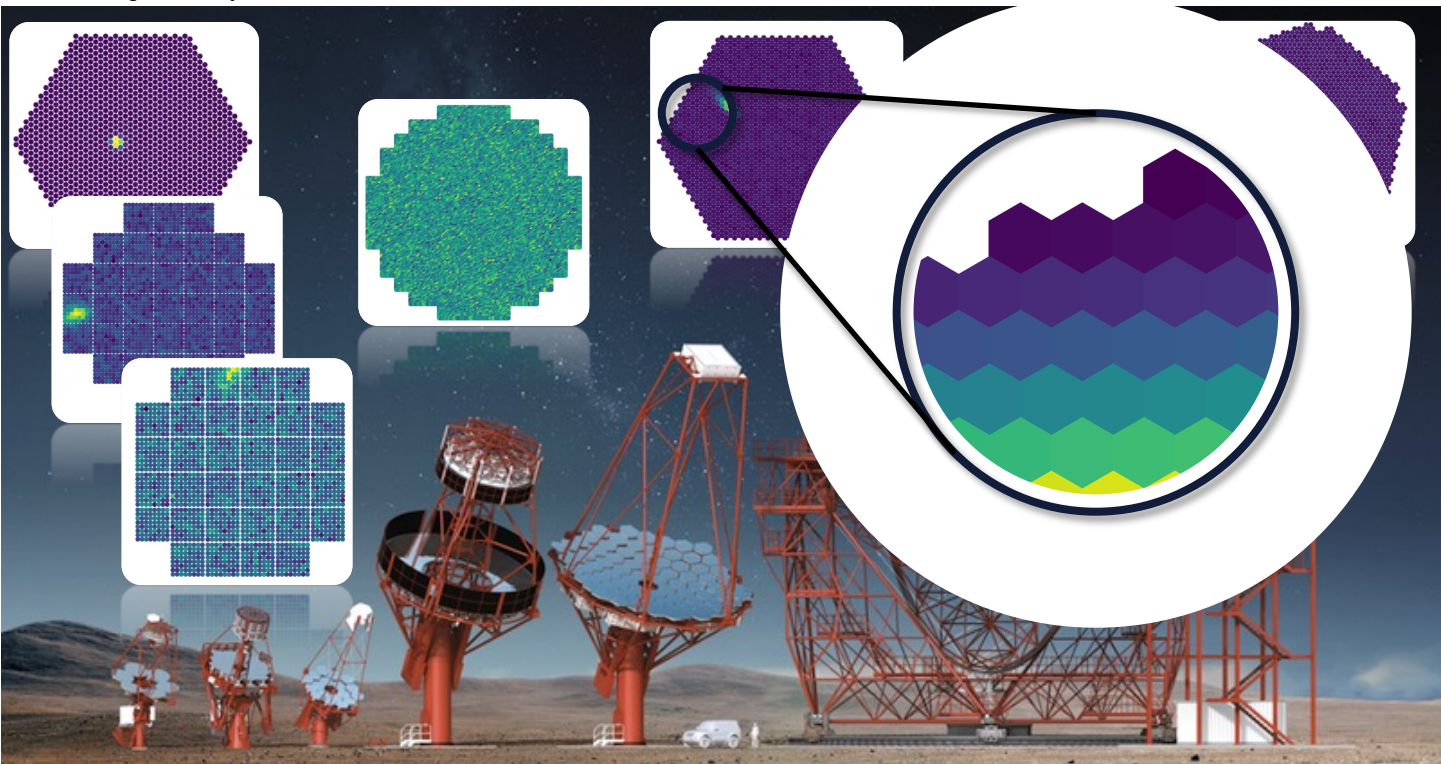
- Heterogeneity of instruments:

Camera images courtesy of T. Vuillaume



- Heterogeneity of instruments:

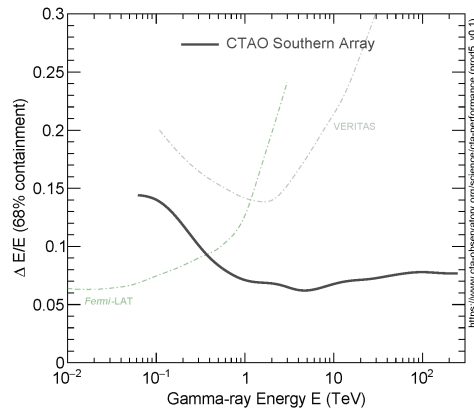
Camera images courtesy of T. Vuillaume



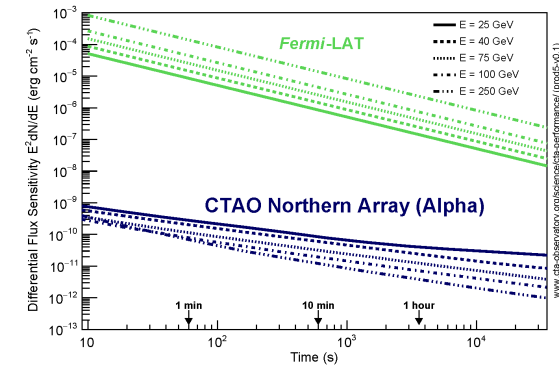
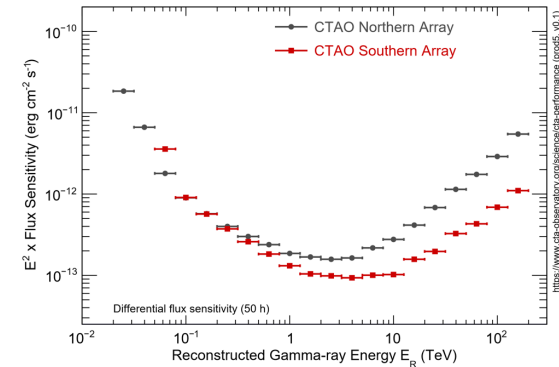
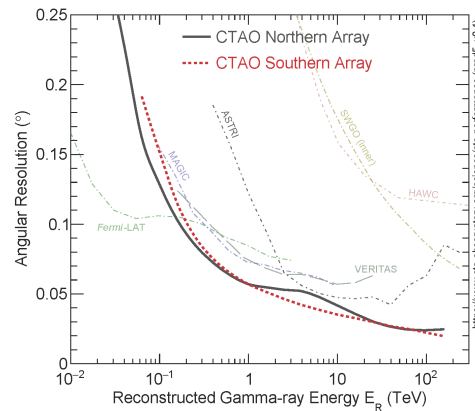
- Final metrics are far from trivial and entangled

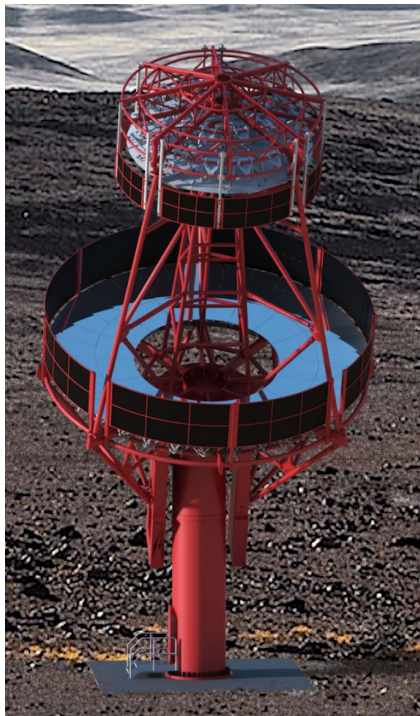
Flux sensitivity

Energy resolution

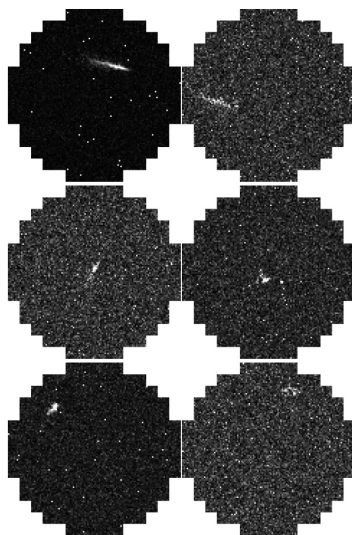


Angular resolution

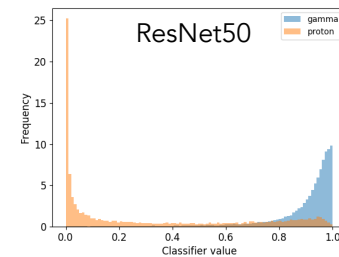
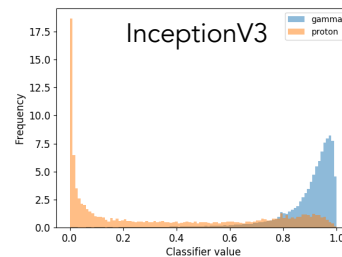




- Single telescope
- Square pixels
- Only signal charge (no timing)
- Single task: classification



Medium energies
($0.3 \text{ TeV} < E < 1 \text{ TeV}$)



AUC

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

- 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**)



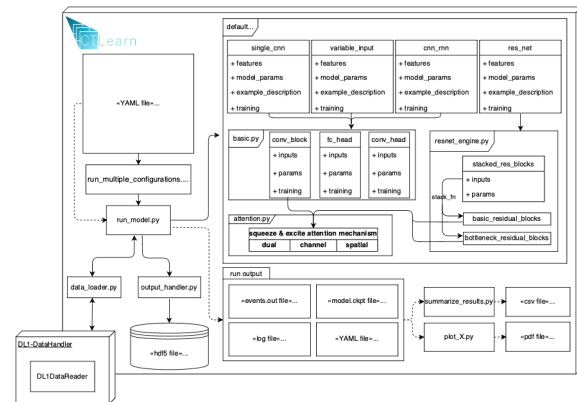
Core developers

Tjark Miener, DN (IPARCOS-UCM)

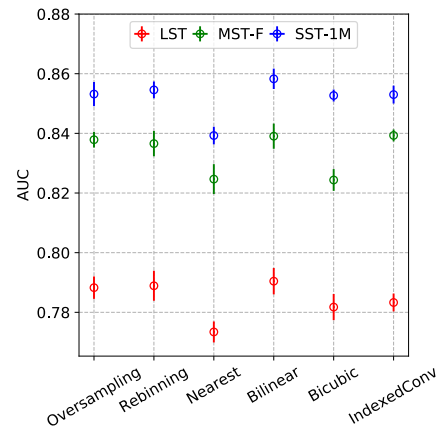
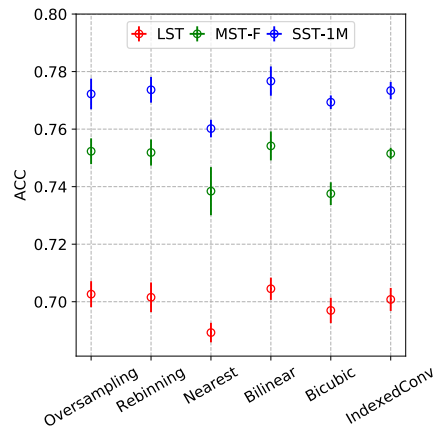
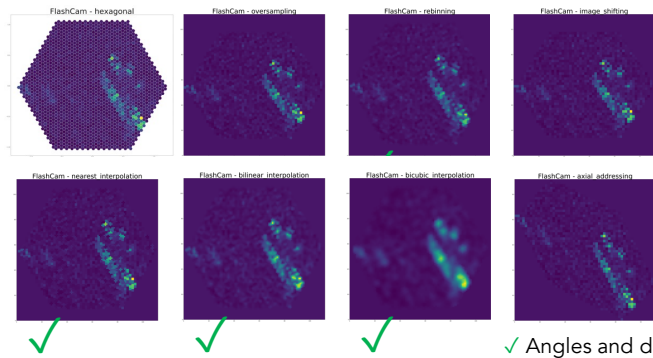
Ari Brill, Qi Feng (Columbia)

Bryan Kim (UCLA, now at Stanford)

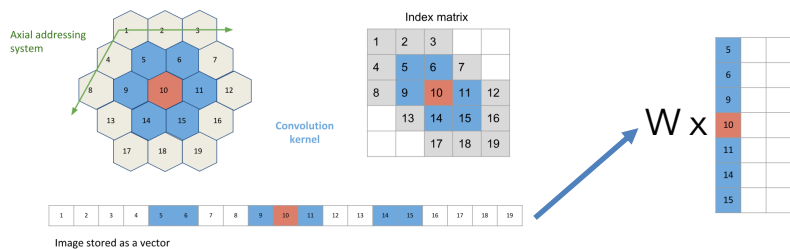
(See contributors [here](#))



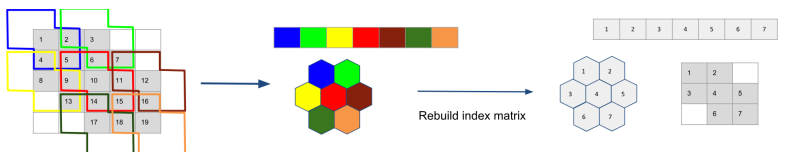
Comparison of methods for classification task



Hex. Convolution

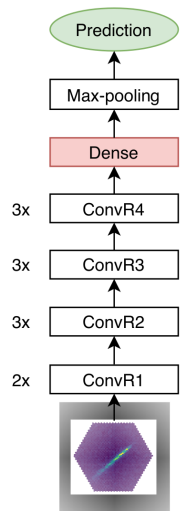


Hex. Pooling

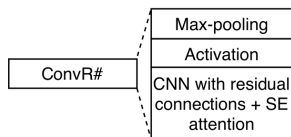


[D. Nieto et al. PoS\(ICRC2019\)753](#)

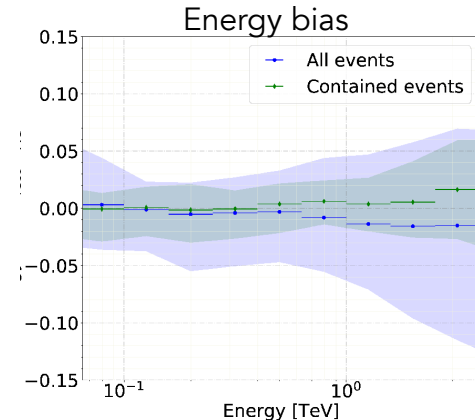
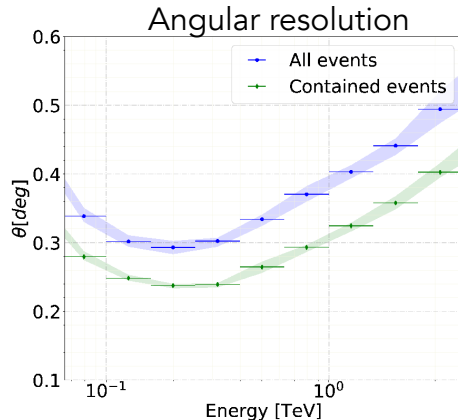
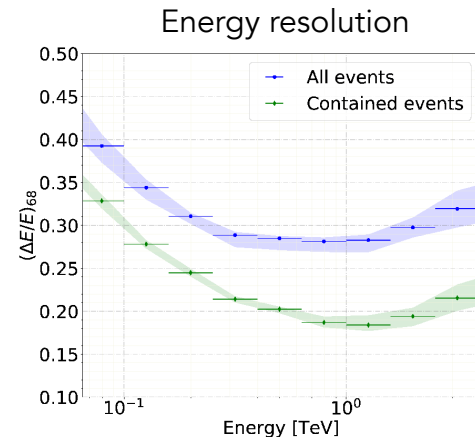
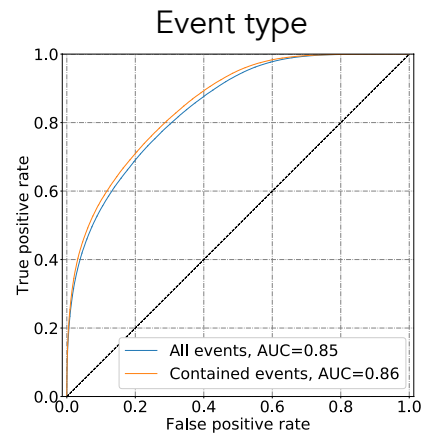
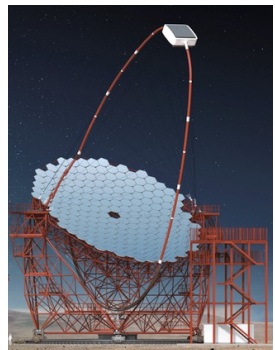
(M. Jacquemont
et al. 2019)



Thin-ResNet
model

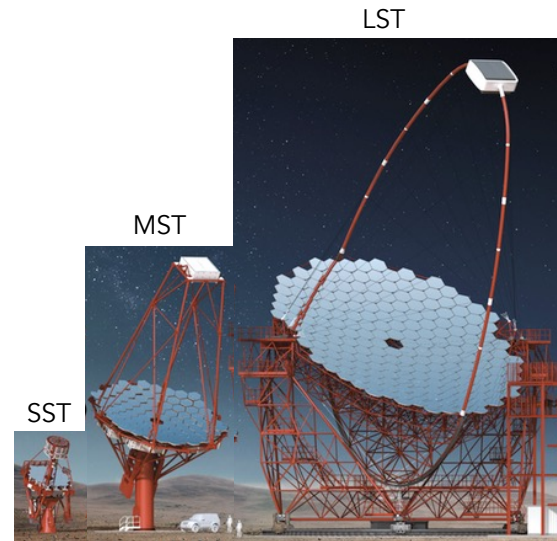
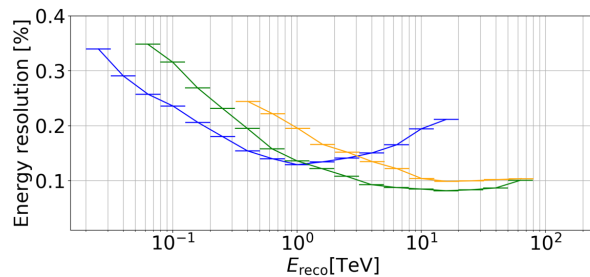
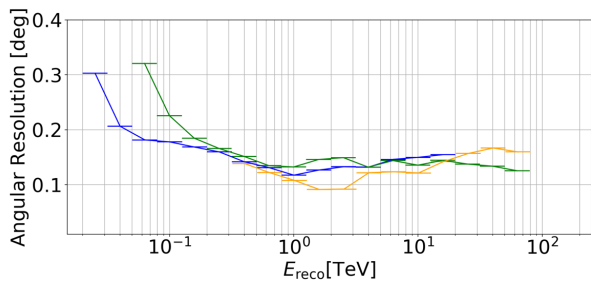
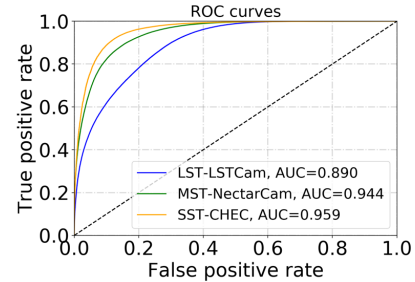
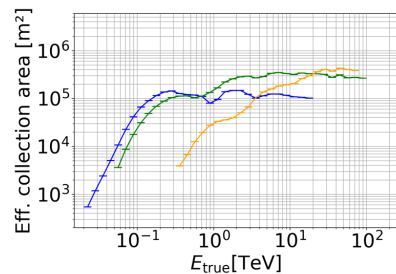
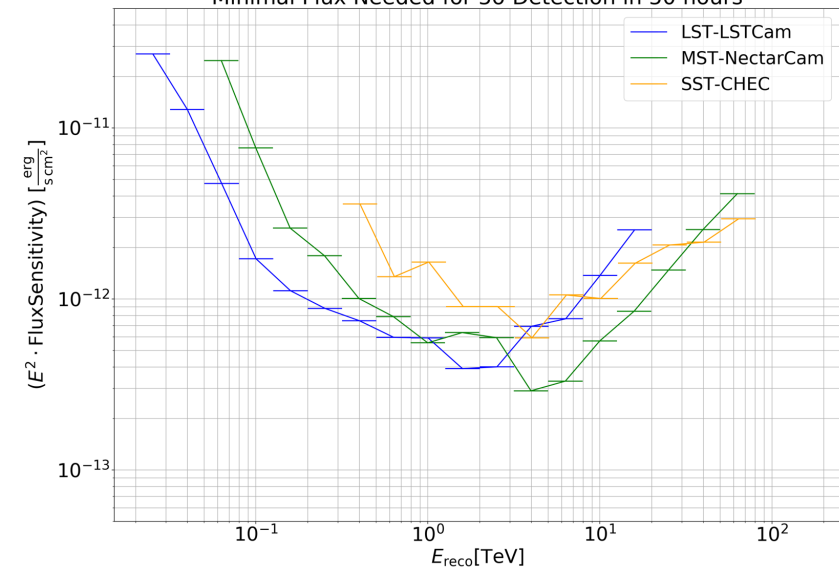


Full-event reconstruction
for single-telescope data
achieved!



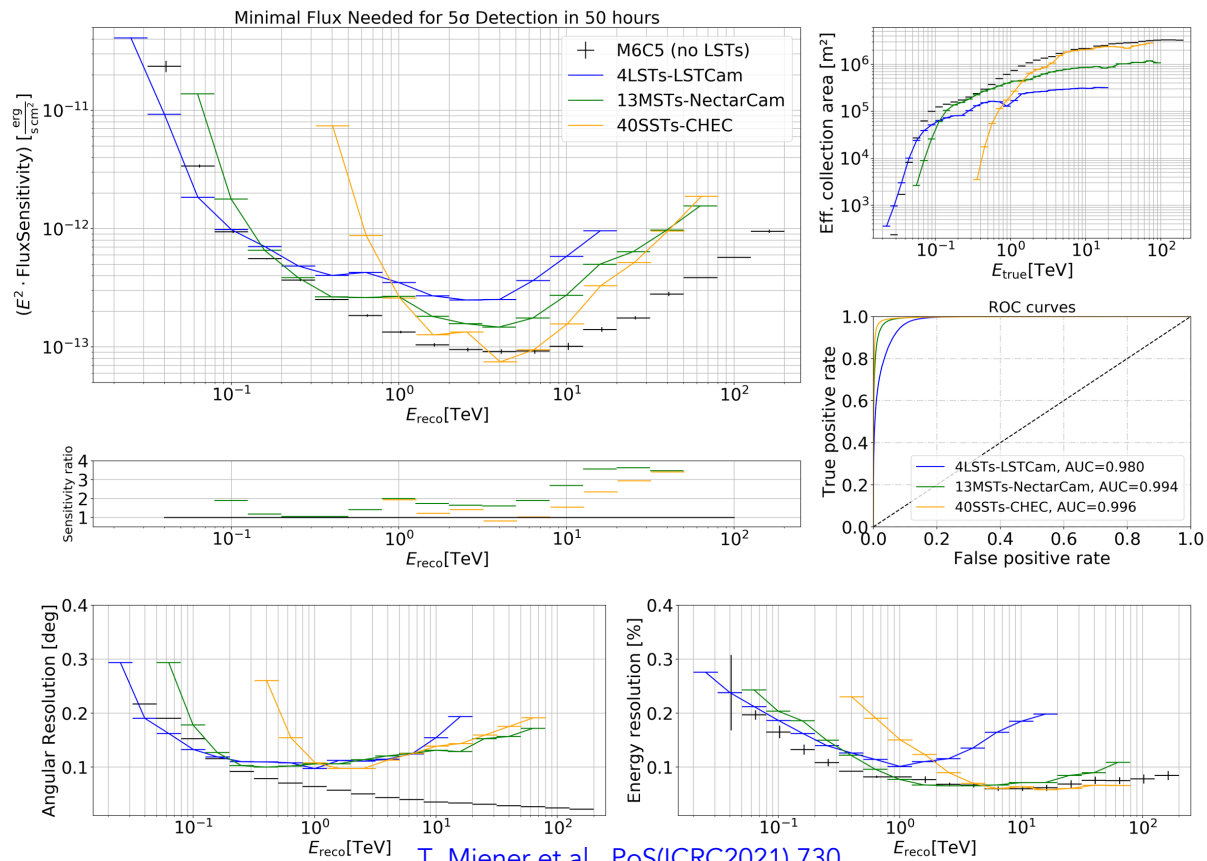
[D. Nieto et al. ADASS XXX 2020](#)

Minimal Flux Needed for 5σ Detection in 50 hours

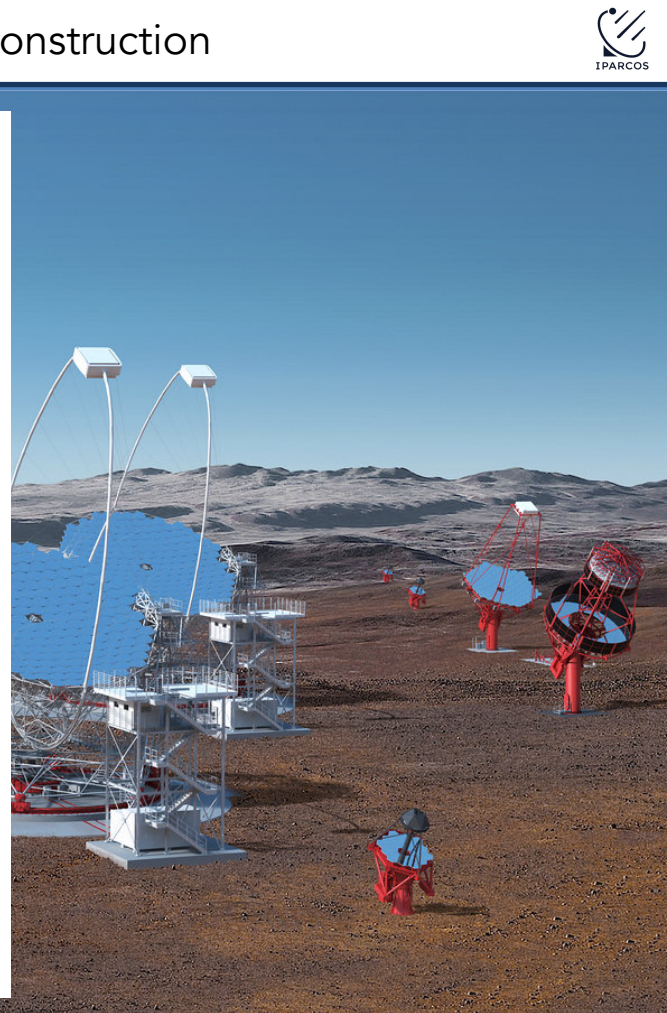


[T. Miener et al., PoS\(ICRC2021\) 730](#)



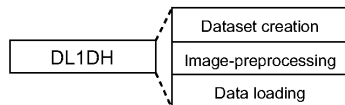
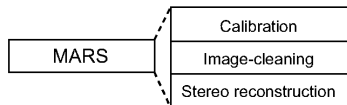
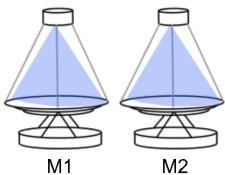


[T. Miener et al., PoS\(ICRC2021\) 730](#)

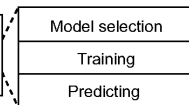




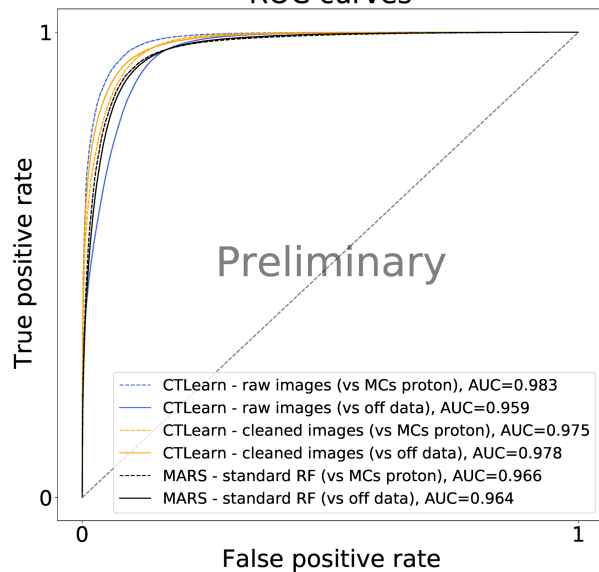
Observational data or simulations



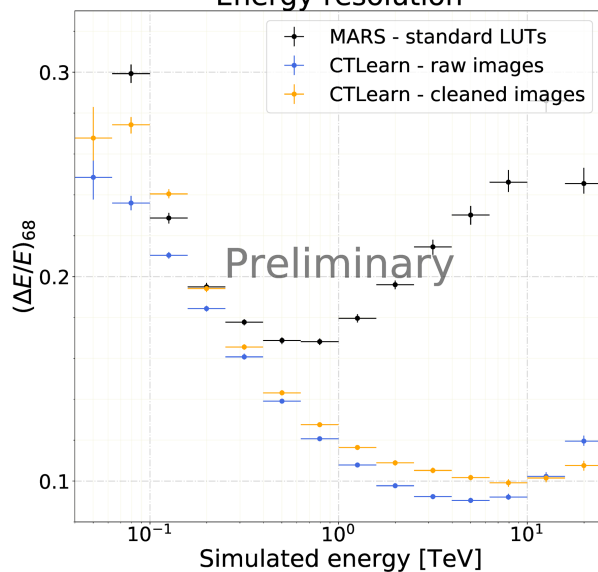
TRN Model



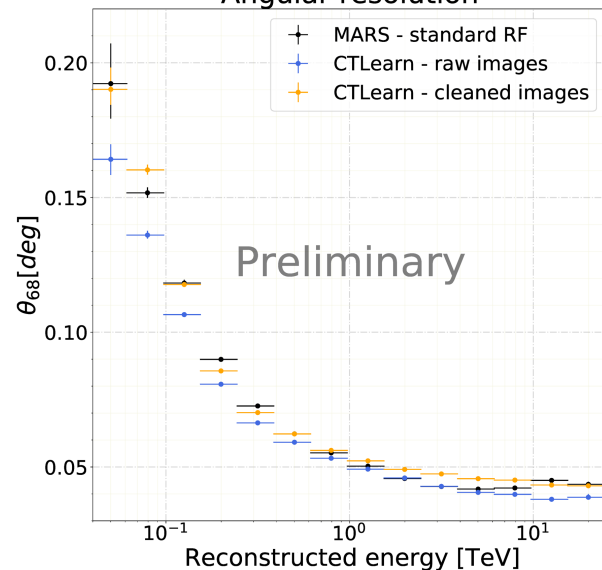
ROC curves



Energy resolution



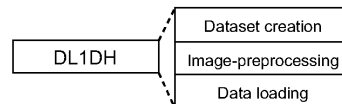
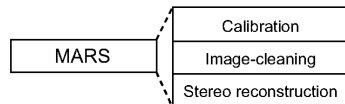
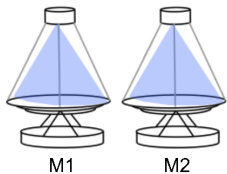
Angular resolution



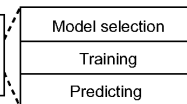
[T. Miener et al. 2021 \(ADASS XXXI\)](#)



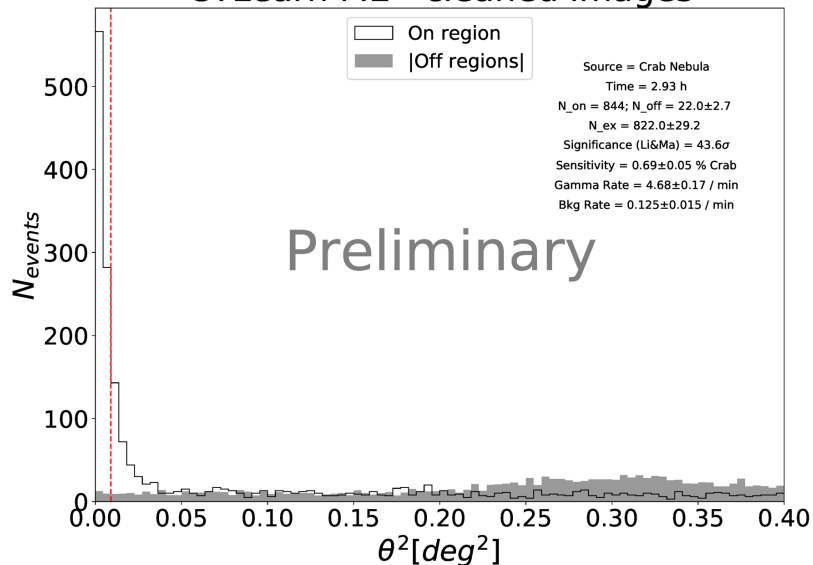
Observational data or simulations



TRN Model



CTLearn ME - cleaned images



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

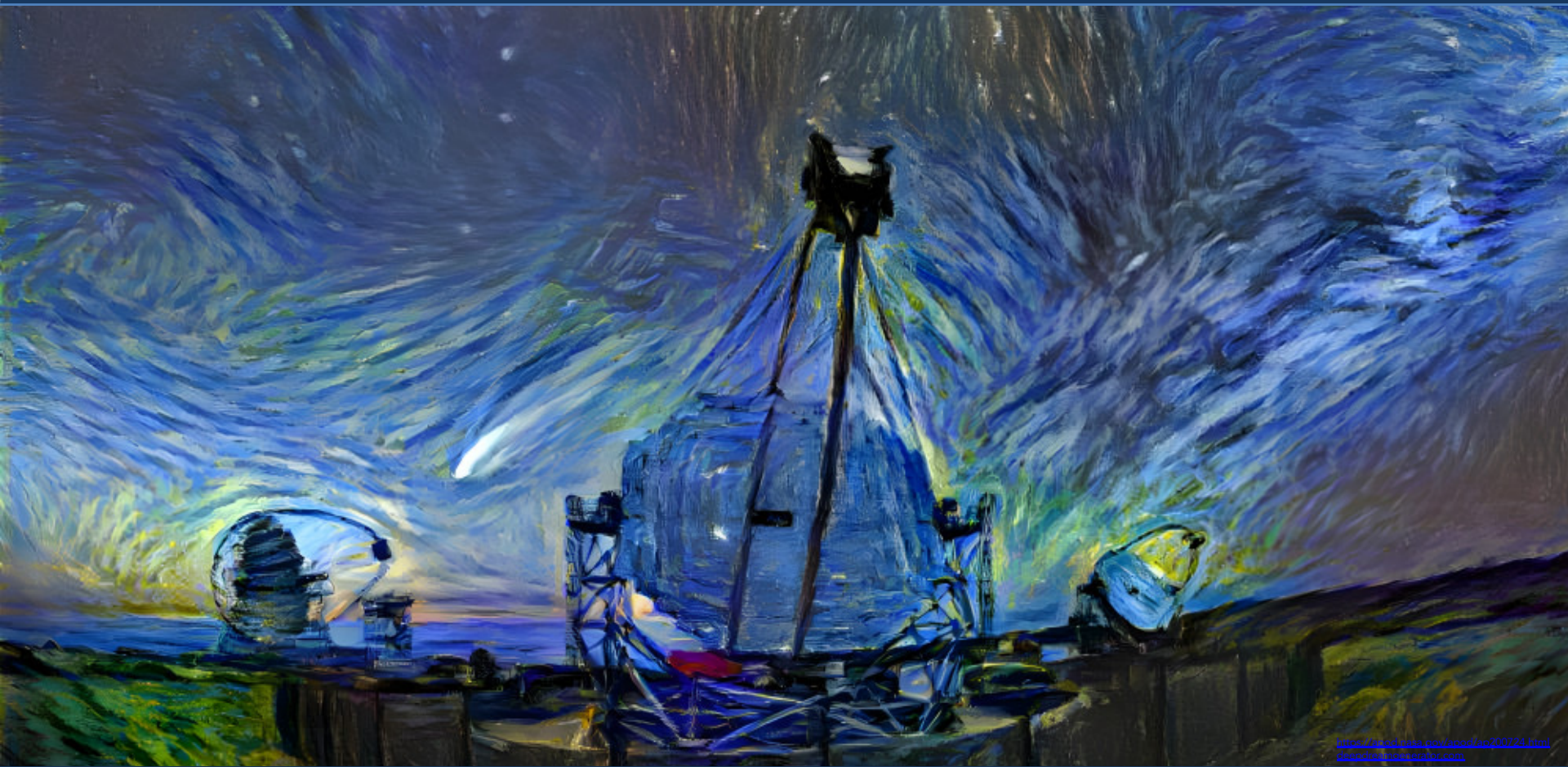
Analysis	N_{on}	N_{off}	N_{ex}
MARS – ME	819	21.0 ± 2.6	798.0 ± 28.7
CTLearn – ME (raw)	629	23.3 ± 3.1	605.7 ± 25.3
CTLearn – ME (cleaned)	844	22.0 ± 2.7	822.0 ± 29.2
MARS – LE	3579	679.0 ± 15.0	2900.0 ± 61.7
CTLearn – LE (raw)	2730	673.7 ± 20.0	2056.3 ± 56.0
CTLearn – LE (cleaned)	3536	680.7 ± 15.1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

Summary of all performed analyses of the same Crab Nebula sample

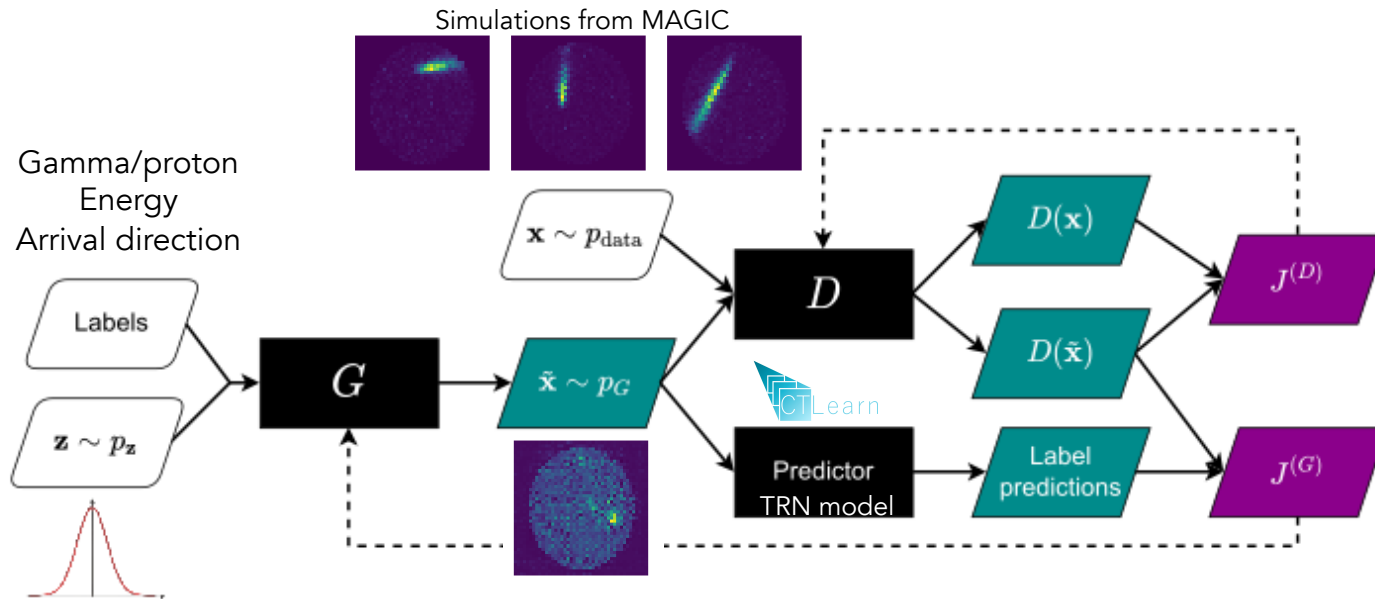
[T. Miener et al. 2021 \(ADASS XXXI\)](#)



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

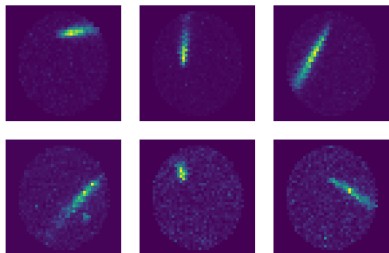


- Auxiliary conditional generative adversarial networks (AC-GANs)

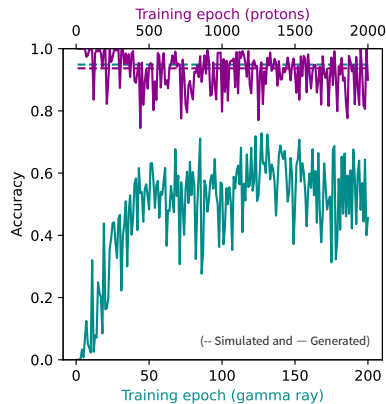
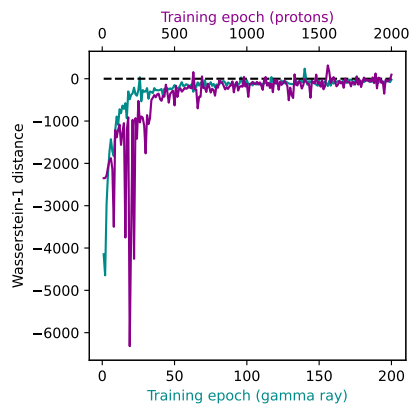
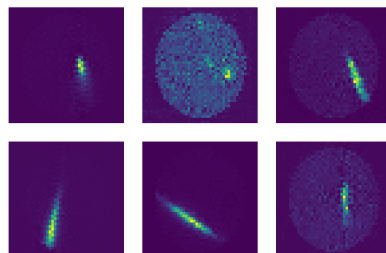


GAMMA RAYS

Simulated

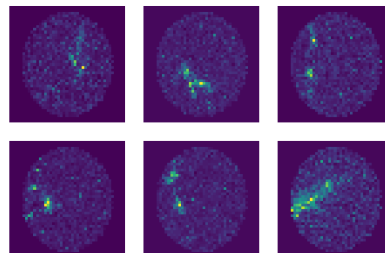


Generated

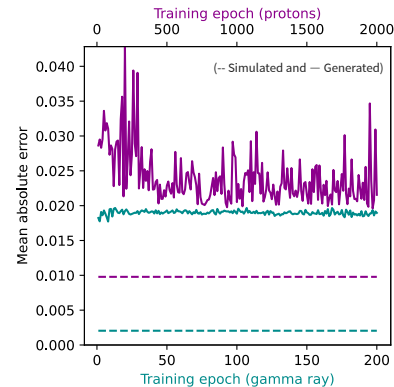
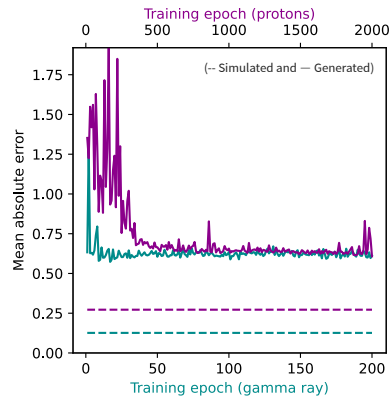
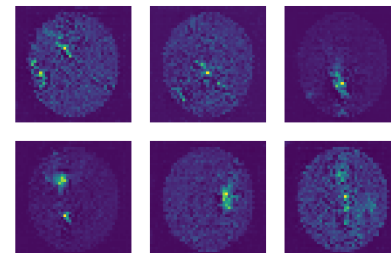


PROTONS

Simulated



Generated



S. García-Heredia et al.

Next step -> find the **best** performing **model** for event **reconstruction**

The **curse of dimensionality** haunts us here too!

- Hyperparameter space for deep learning architecture design

- Number of CNN layers
- Kernel size
- Activation function
- Dropout rate
- Number of FC layers
- Batch size
- Learning rate
- Optimizer
- ...

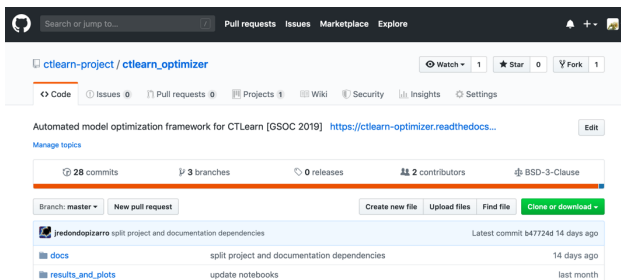
- Optimization strategies

- Grid searches
- Random searches
- Bayesian optimization
- Evolutionary algorithms
- Reinforcement learning
- ...

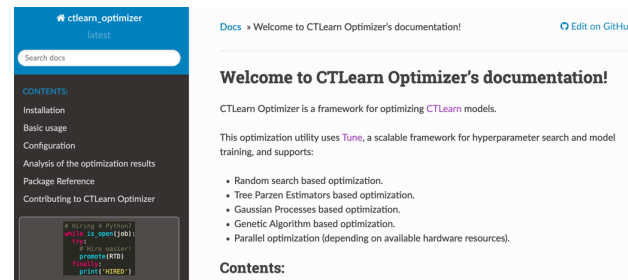
- Framework for hyperparameter optimization of CTFlearn models
(Although can be adapted to any config-file based DCN framework)
- Based on Tune: a scalable hyperparameter tuning library
- Supported optimization strategies:
 - Random search
 - Tree Parzen Estimators
 - Gaussian Processes
 - Genetic Algorithms
 - Parallel optimization (depending on available hardware)

Bayesian optimization

github.com/ctlearn-project/ctlearn_optimizer

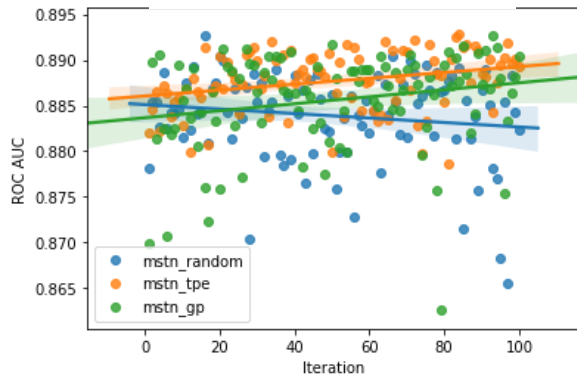


ctlearn-optimizer.readthedocs.io

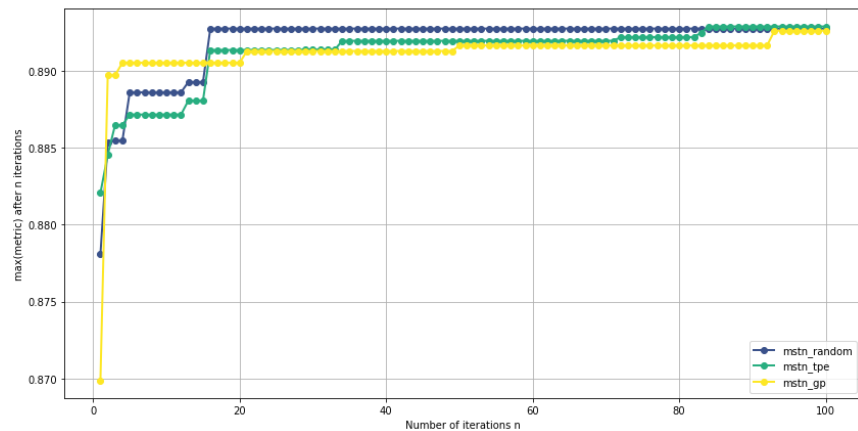


Visualization

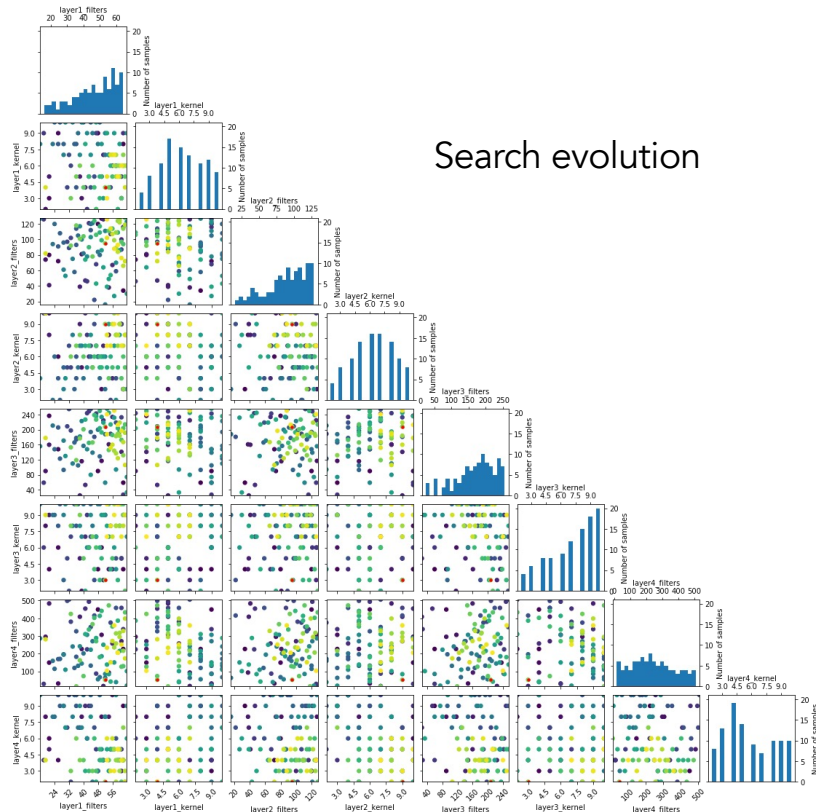
Evolution of the metric

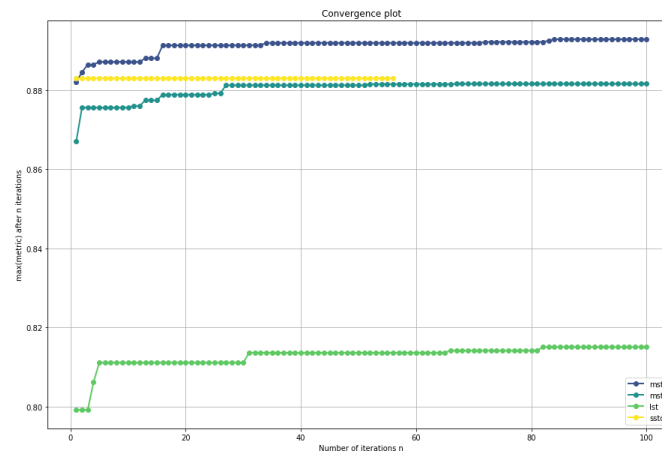
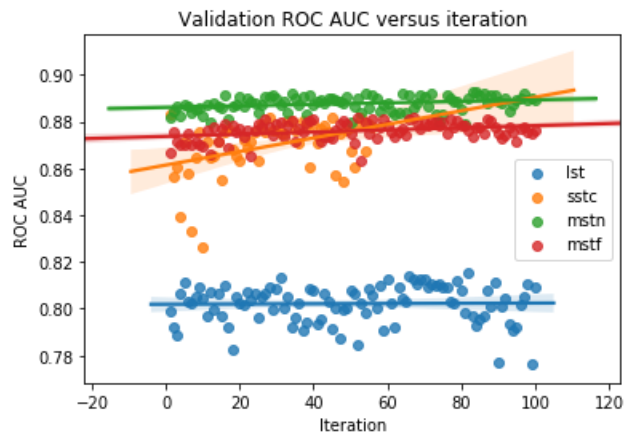


Convergence of the metric

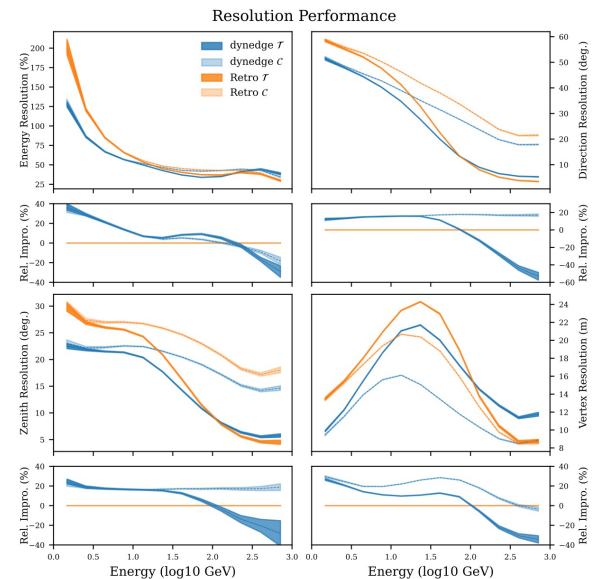
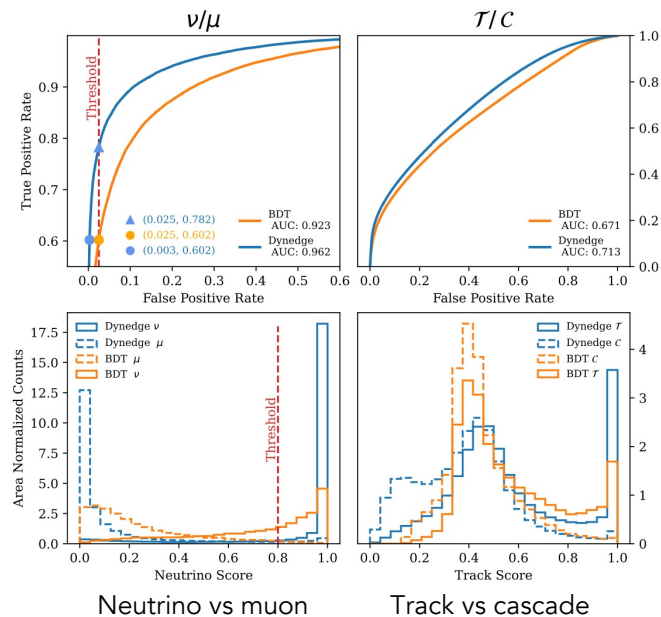


Search evolution



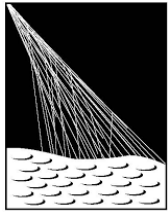


Hyperparameters	Telescope Type	Validation Accuracy	Validation AUC	Training Time	Telescope Type	Metric	Improvement
Base	LST	70.38%	0.7887	0h 41m 22s	LST	Validation Accuracy	2.07%
Optimized	LST	72.45%	0.8150	0h 39m 14s	LST	Validation AUC	2.63%
Base	SSTC	73.90%	0.8118	0h 42m 4s	SSTC	Validation Accuracy	5.97%
Optimized	SSTC	79.87%	0.8830	1h 16m 4s	SSTC	Validation AUC	7.12%
Base	MSTN	78.04%	0.8659	0h 58m 10s	MSTN	Validation Accuracy	2.07%
Optimized	MSTN	80.11%	0.8929	0h 52m 48s	MSTN	Validation AUC	2.70%
Base	MSTF	74.60%	0.8360	0h 55m 0s	MSTF	Validation Accuracy	4.41%
Optimized	MSTF	79.01%	0.8816	0h 48m 37s	MSTF	Validation AUC	4.56%



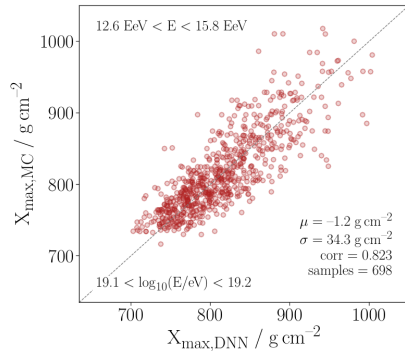
- Graph Neural Networks for low-energy events
- Classification: signal/bkg, neutrino types
- Signal eff. +18%, bkg suppression /8
- Energy, arrival direction ~20% improv
- Processing rate 2x IceCube trigger rate (GPU)

[JINST 17 P11003 \(2022\)](#)

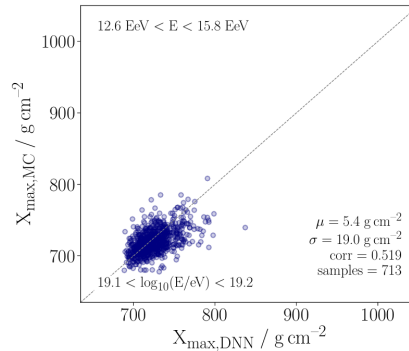


**PIERRE
AUGER**
OBSERVATORY

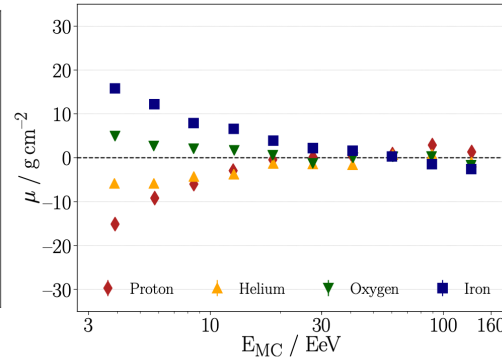
- $X_{\max}$ from Fluorescence Det. ($\sim 15\%$ duty cycle) $\rightarrow X_{\max}$ from Surface Det. ($\sim 99\%$ duty cycle)
($X_{\max}$: air shower maximum, nuclear mass from UHCR)
- CNN with hexagonal convolution kernels



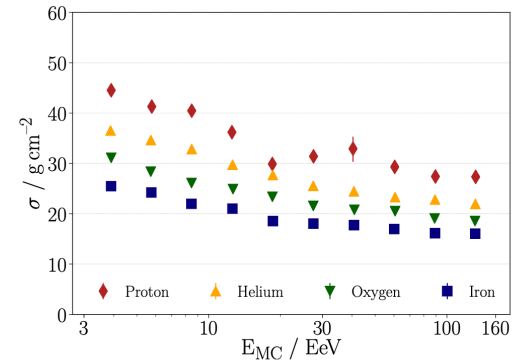
(a) Proton



(b) Iron



(a) $X_{\max}$ reconstruction bias



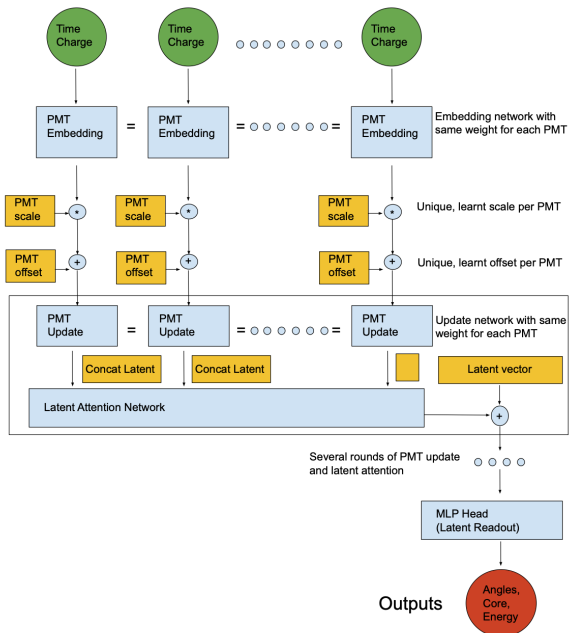
(b) $X_{\max}$ resolution

[JINST 16 P07019 \(2021\)](#)

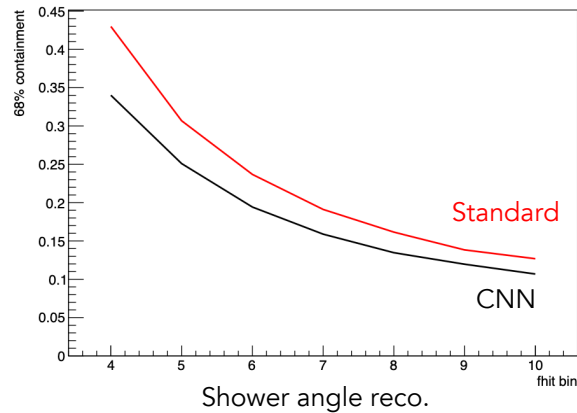


- Attention-based CNN architecture
- Determination of arrival direction
- Best performing than standard analysis on simulation, but not on real observations yet

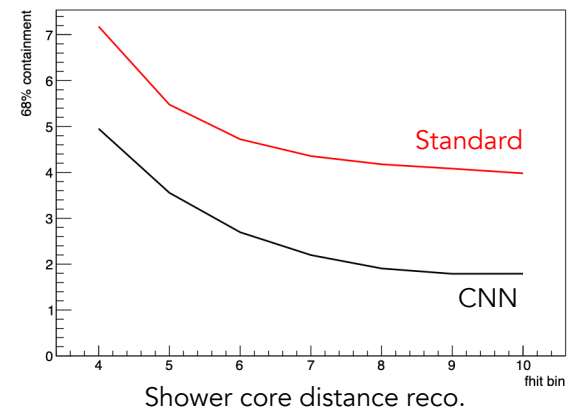
Inputs



Δ Angle (Rec., MC) [deg.] C0



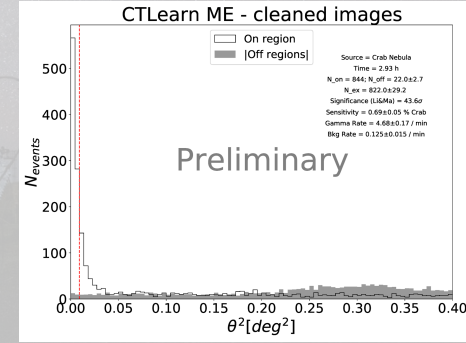
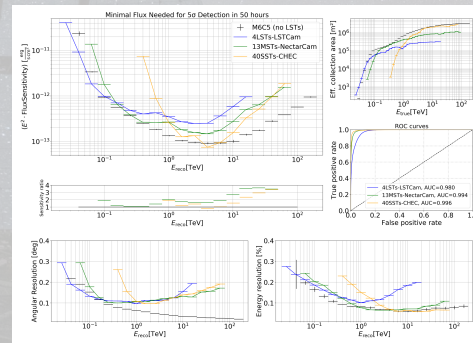
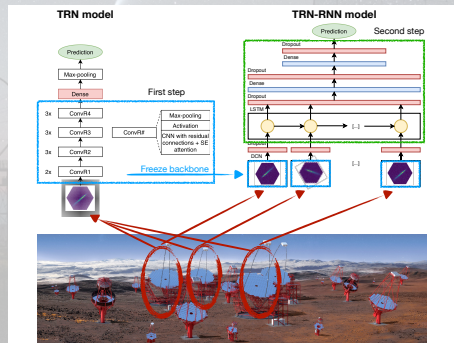
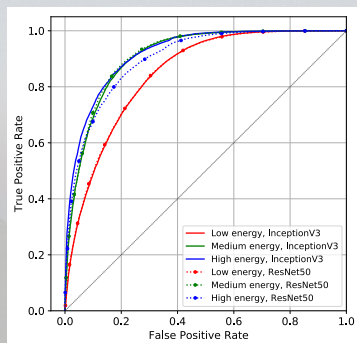
Δ Core (Rec., MC) [m] C0



[PoS ICRC \(2023\) 297](#)

Conclusions & Outlook

- 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



The research here presented has been partially supported by the former Spanish Ministry of Economy, Industry, and Competitiveness / ERDF grants FPA2015-73913-JIN and FPA2017-82729-C6-3-R, the Spanish Ministry of Science and Innovation grant PID2019-104114RB-C32, NSF awards PHY-1229205, 1229792, and 1607491, and the European Science Cluster of Astronomy & Particle Physics ESFRI Research Infrastructures funded by the European Union's Horizon 2020 research and innovation program under Grant Agreement no. 824064. The authors acknowledge support from Google LLC through the Google Summer of Code program and NVIDIA Corporation with the donation of a Titan X Pascal GPU used for part of this research.