Machine learning for very-high-energy gamma-ray astronomy

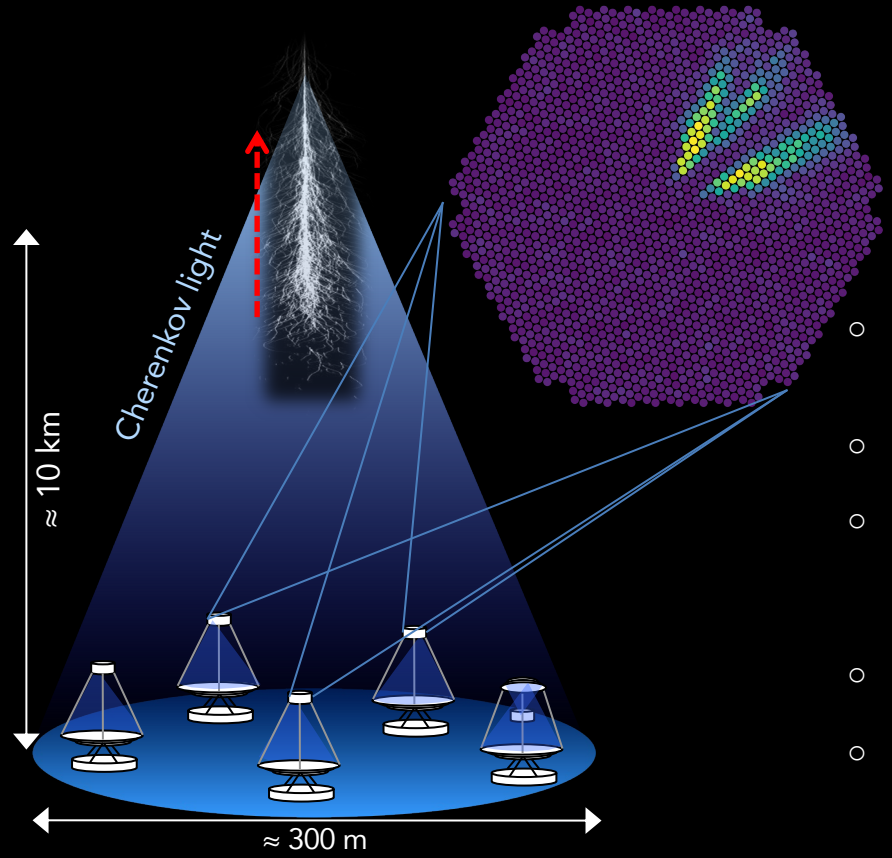
T. Miener (miener@ucm.es)

D. Nieto (d.nieto@ucm.es)

Facultad de Ciencias Físicas

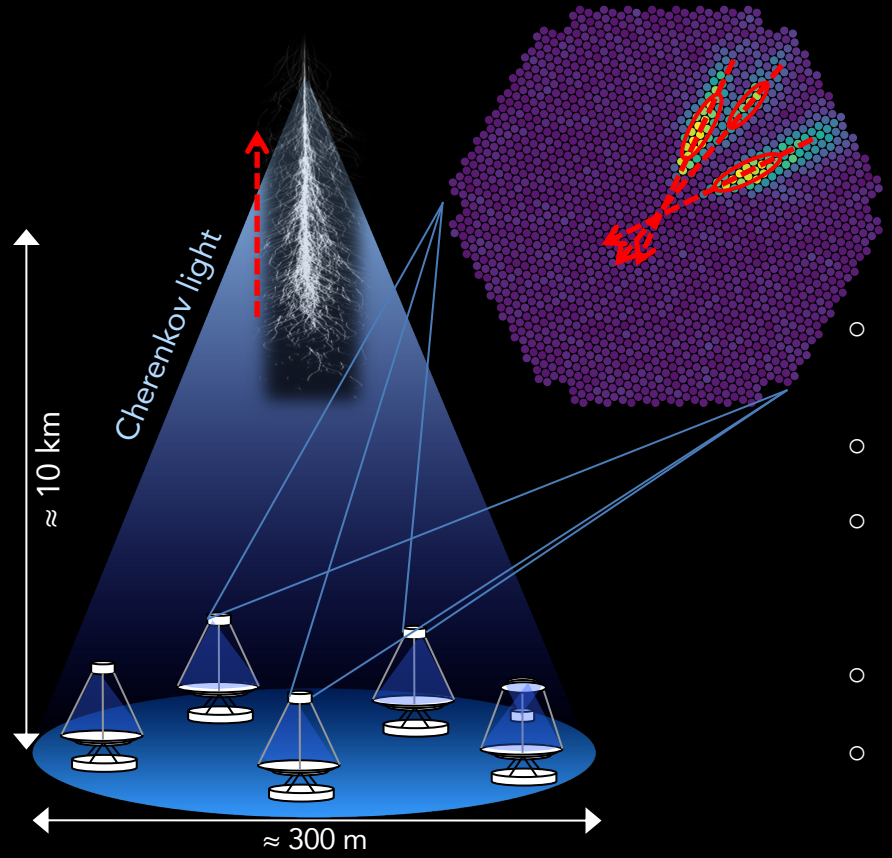
UCM - IPARCOS

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

Imaging atmospheric Cherenkov technique



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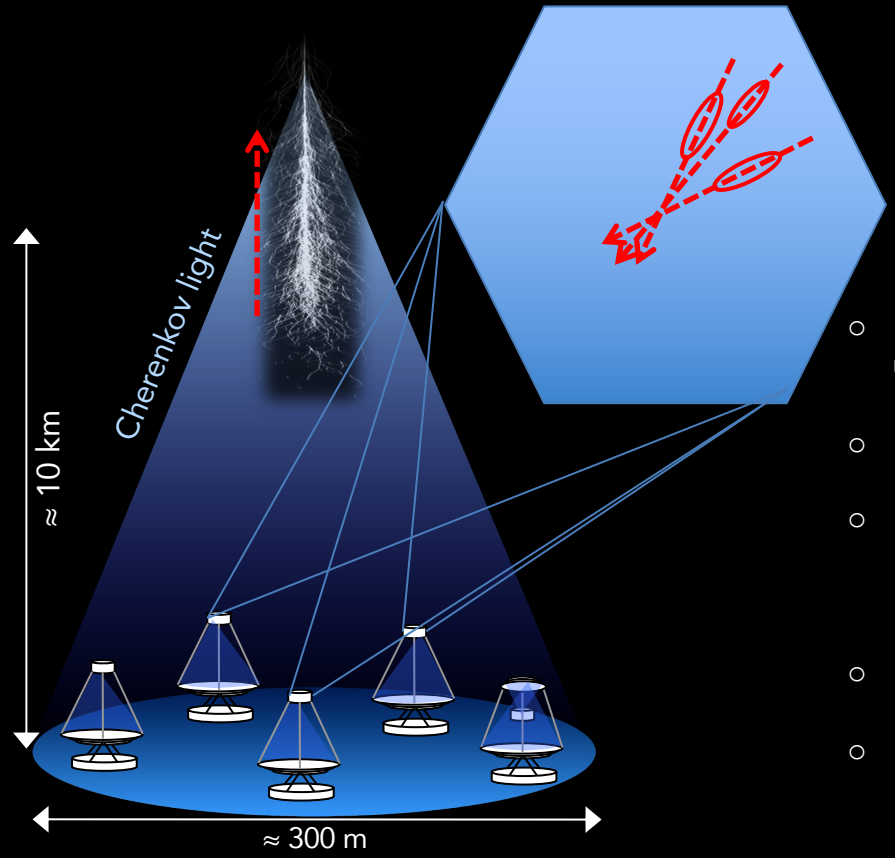

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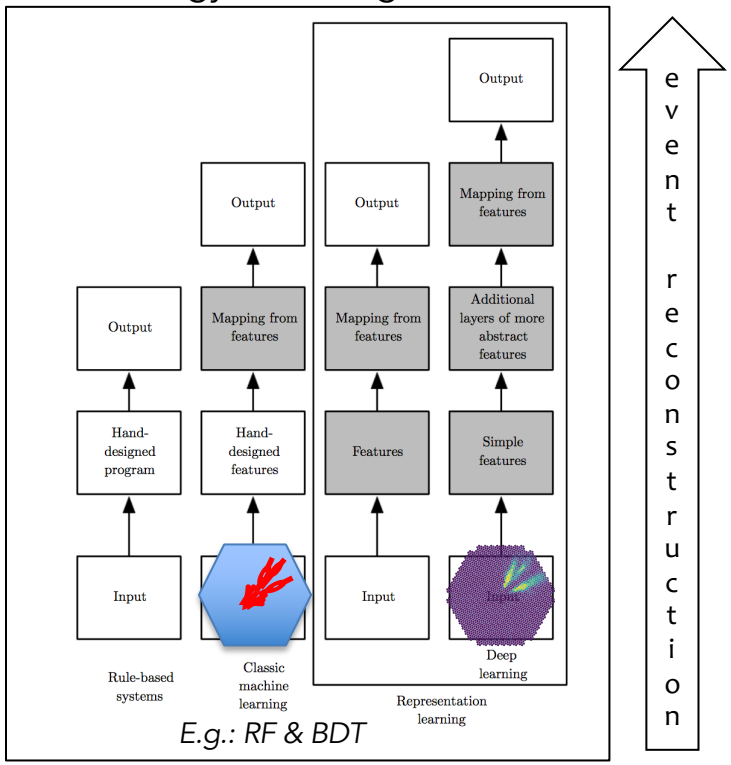
Output: event type, energy, incoming direction



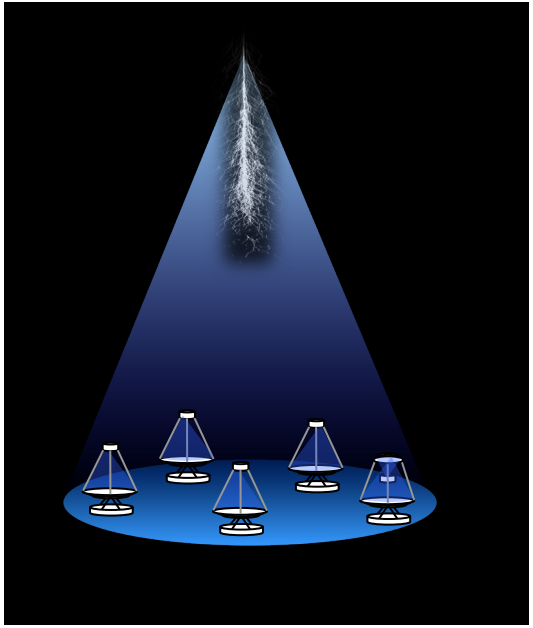
event reconstruction

Input: observed events

Problem:
supervised learning requires labelled data

Solution:
to simulate your data!

Problem:
how well does your simulation represent the real world?



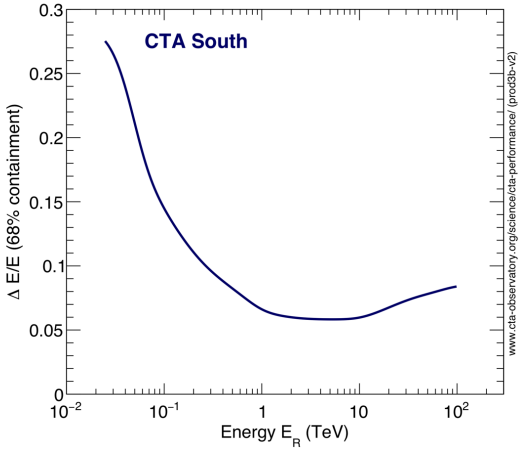
- Stereoscopy:
  - Stereoscopic view of the extended air showers
  - Compact "videos" rather than single snapshots
  - Events effectively recorded in 4D!

CREDIT: DESY/Milde Science Communication

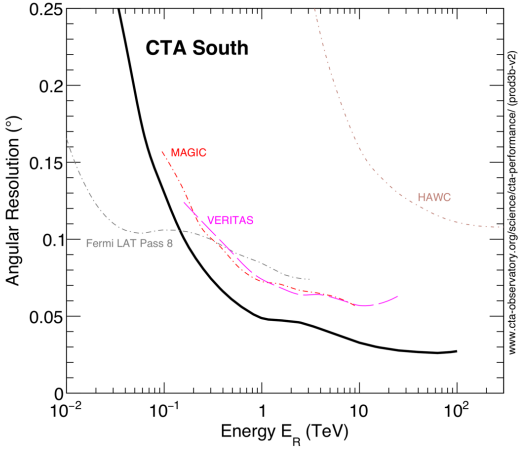
- Heterogeneity of instruments:

- Final metrics are far from trivial and entangled

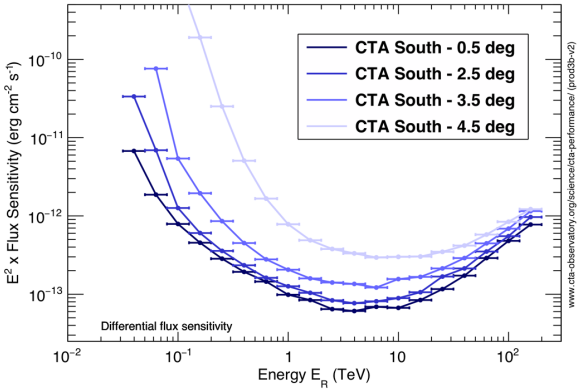
Energy resolution

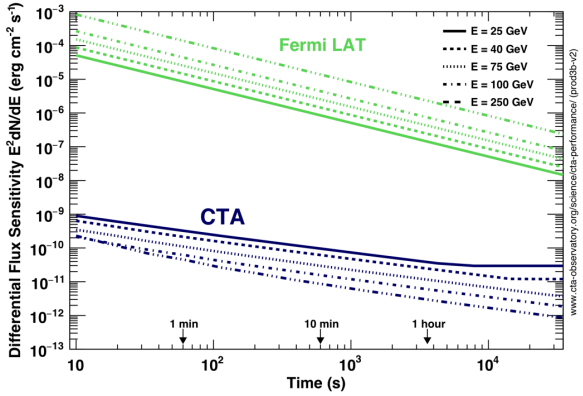


Angular resolution



Flux sensitivity

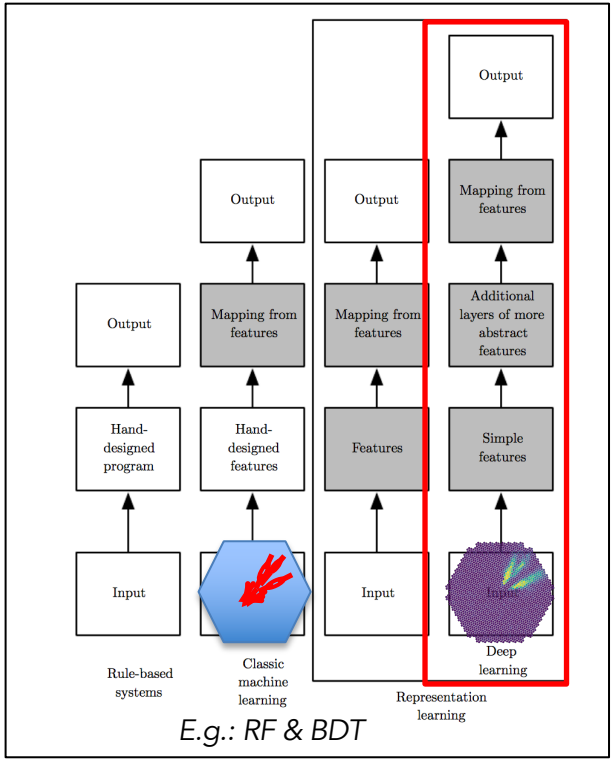




Credit: www.cta-observatory.org

Enhancing IACT performance with deep learning?

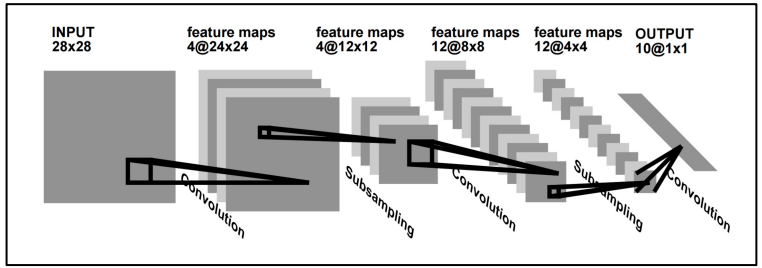
Output: event type, energy, incoming direction



Input: observed events

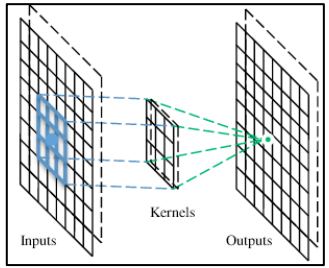
event reconstruction

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…

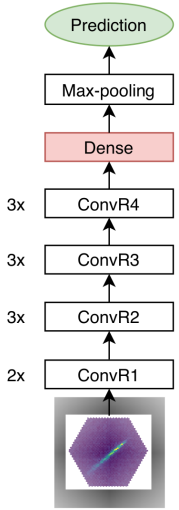
- MC reliability (e.g. network selecting some features from your MC not present in real data)

- 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:

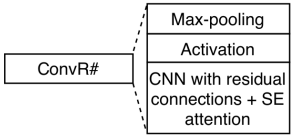
https://github.com/ctlearn-project/ctlearn
https://pos.sissa.it/358/752
DOI 10.5281/zenodo.3345947
(Latest release: **CTLearn v0.5.2**, 02/02/22)

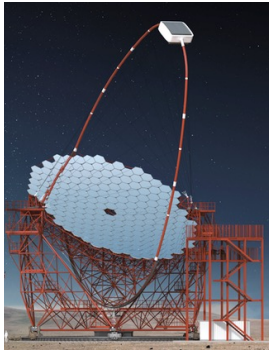
Core developers
Tjark Miener, DN (IPARCOS-UCM)
Ari Brill, Qi Feng (Columbia)
Bryan Kim (UCLA, now at Stanford)
(See contributors here)

CTLearn: single-telescope full-event reconstruction



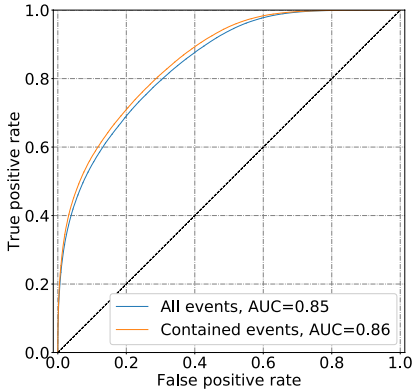
Thin-ResNet model



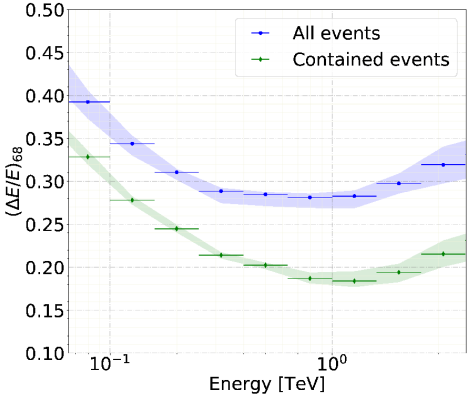


Full-event reconstruction for single-telescope data achieved!

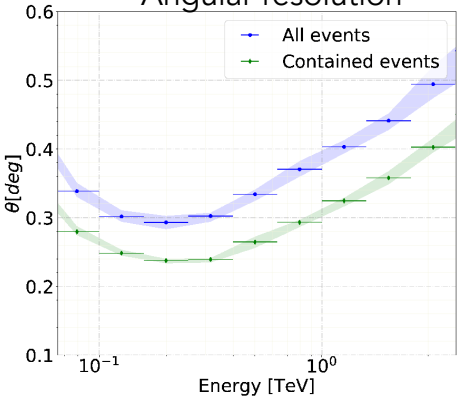
Event type



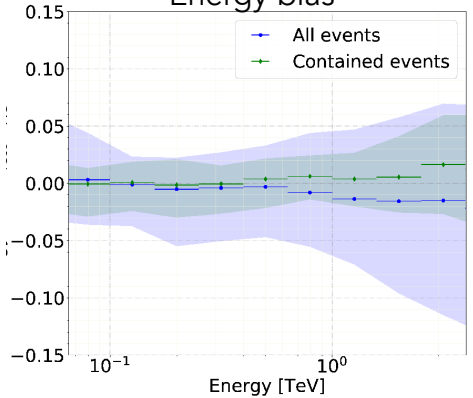
Energy resolution



Angular resolution



Energy bias



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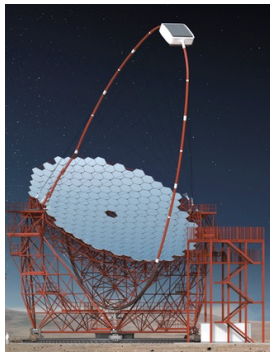
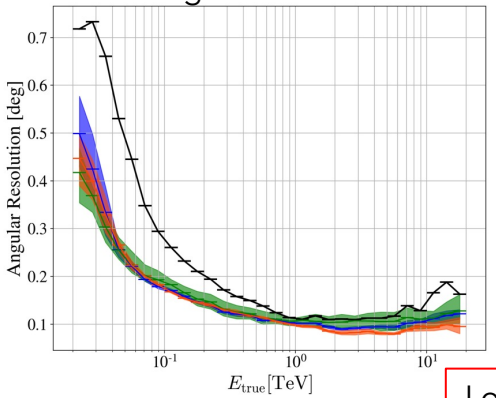
CTLearn: crosschecking results

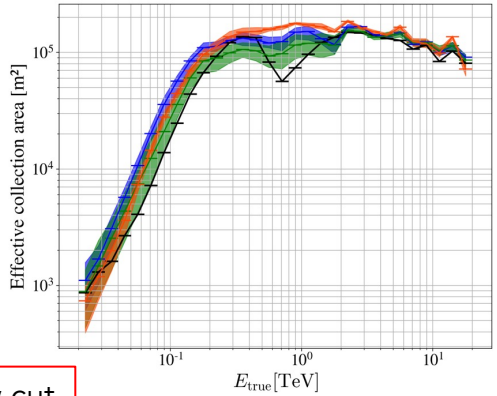
- Crosschecking three different implementations
- Same datasets, same cuts
- Different models
- Comparison against standard analysis (RF)



Angular resolution

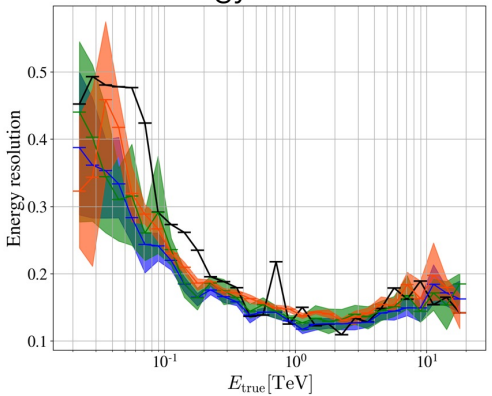


Effective area

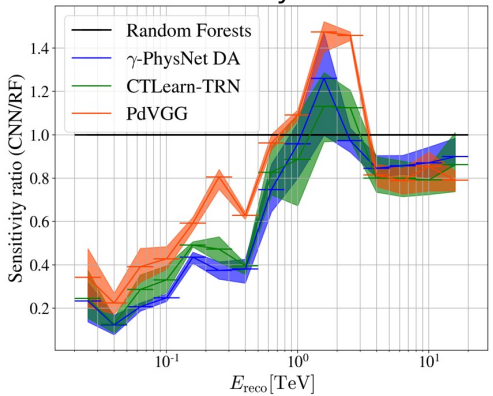


Low cut

Energy resolution

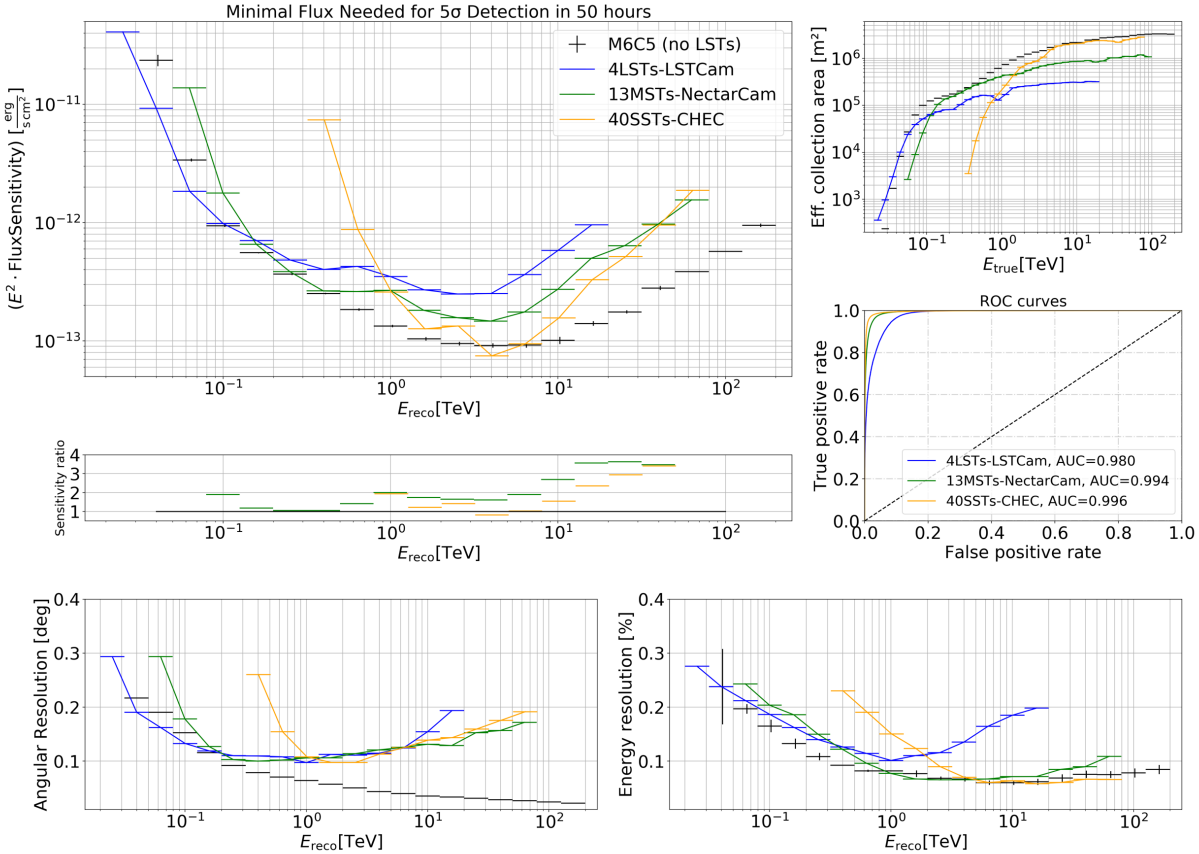


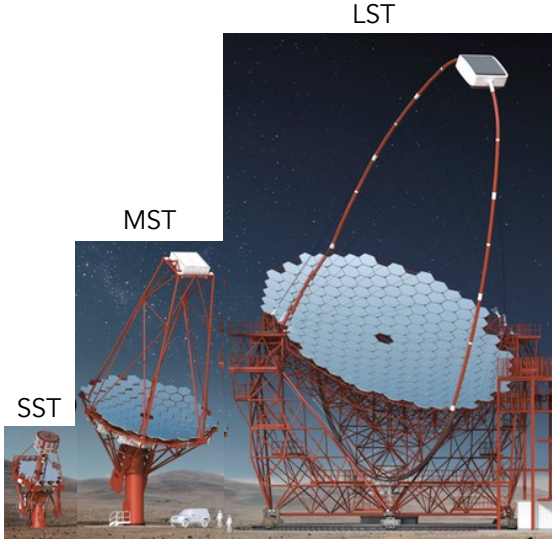
Sensitivity ratio



P. Grespan et al. PoS(ICRC2021) 771

CTLearn: multiple-telescope full-event reconstruction





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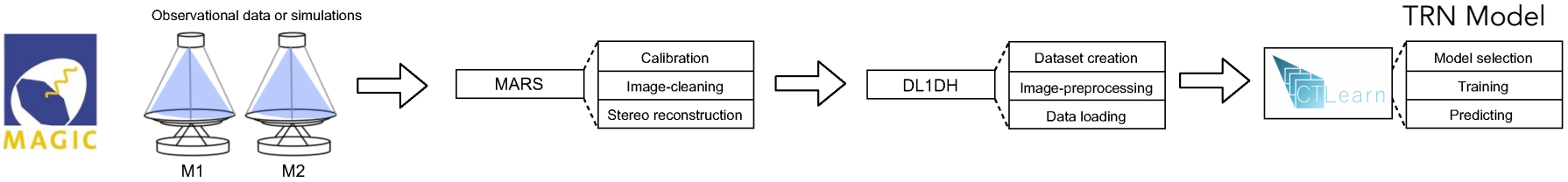
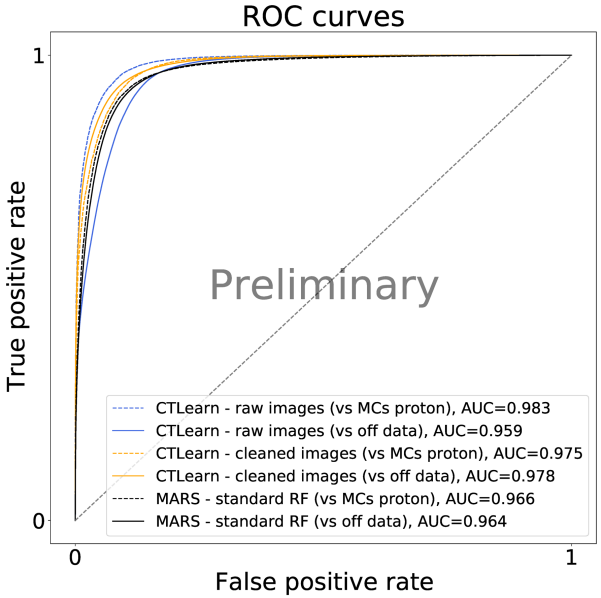
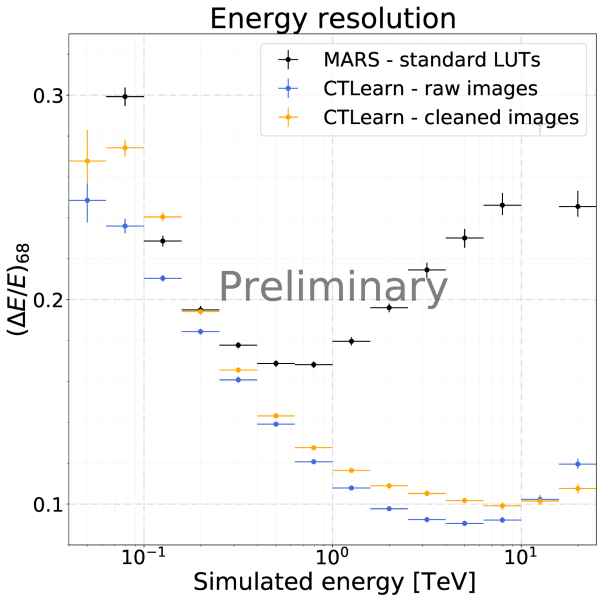
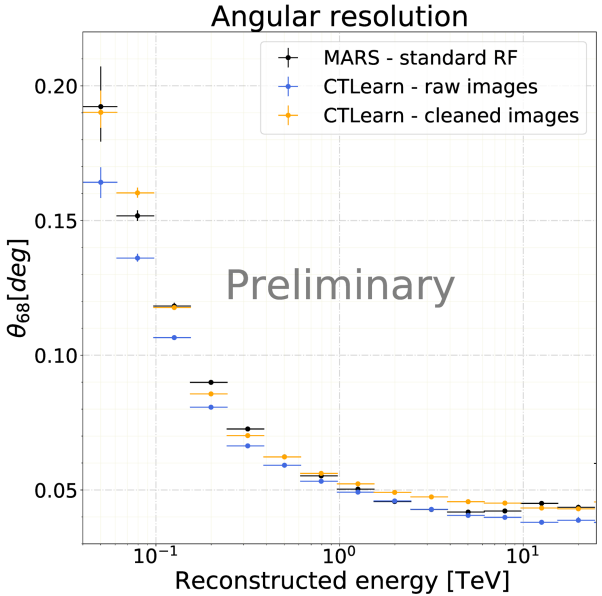
CTLearn: application to real data









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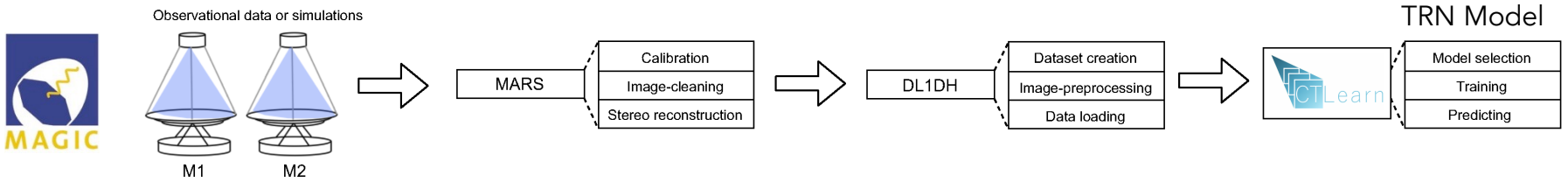
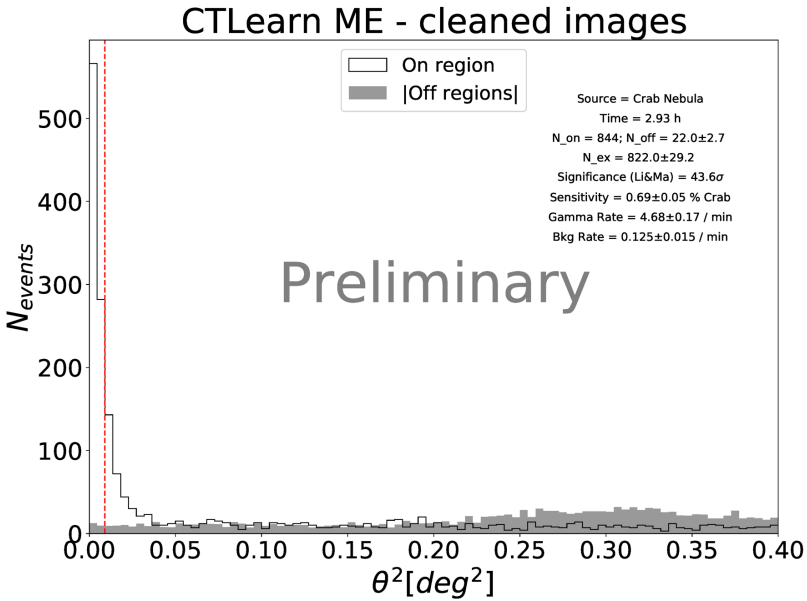
CTLearn: application to real data





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

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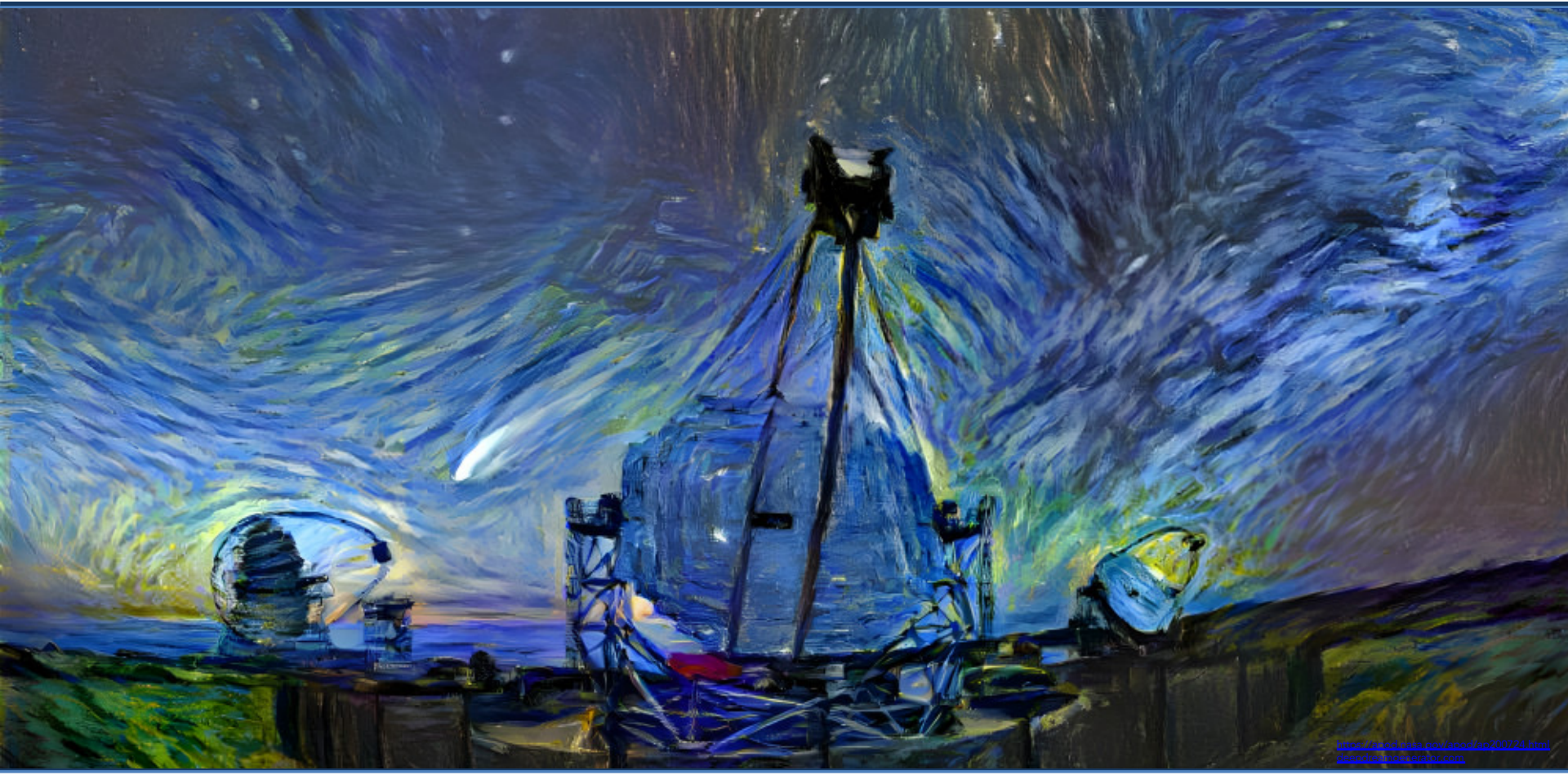
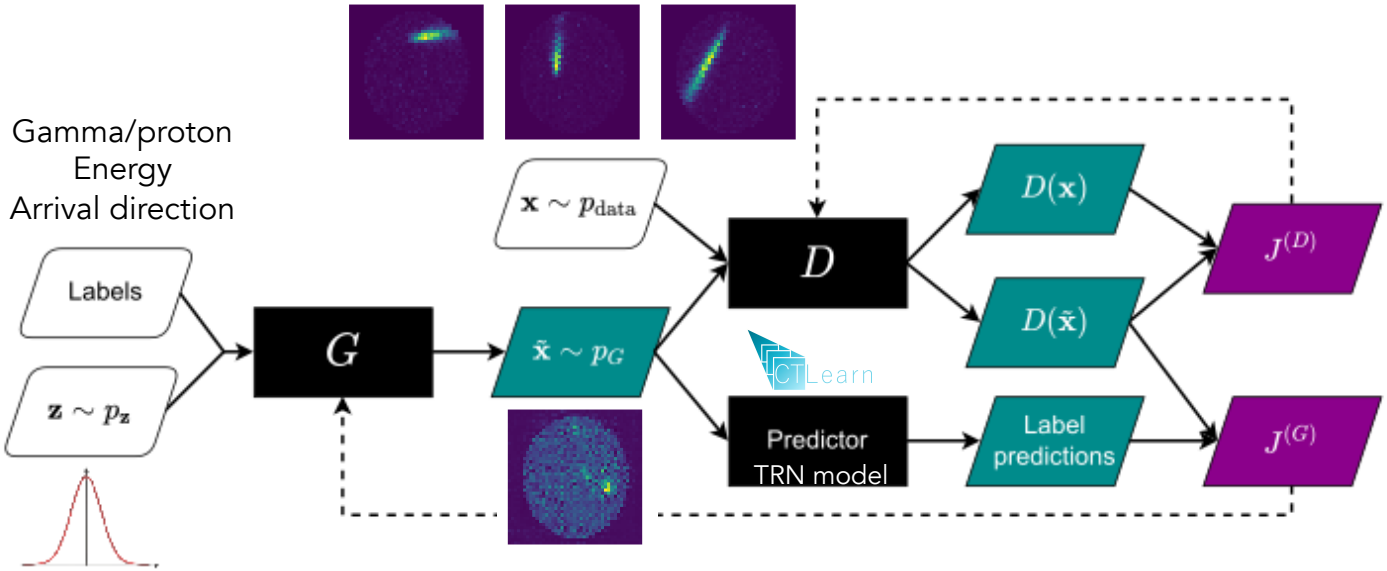
Dreaming of IACTs

Dreaming of IACTs



- Auxiliary conditional generative adversarial networks (AC-GANs)



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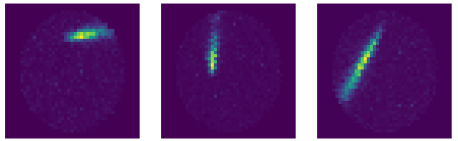
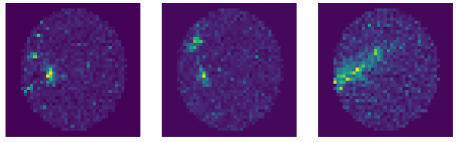
Generating IACT events with GANs

Gamma-rays

Protons

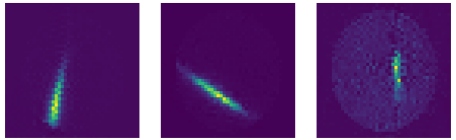
Simulated

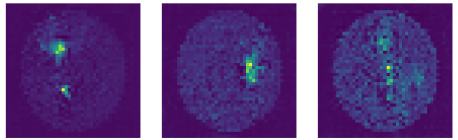




Simulated

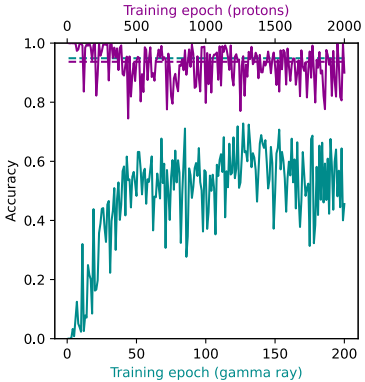
Generated



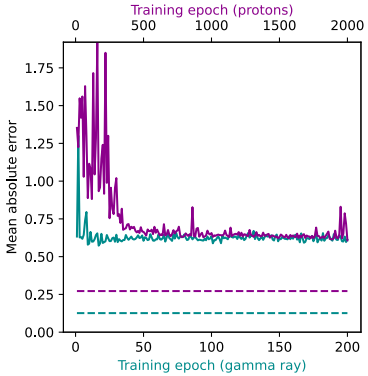


Generated

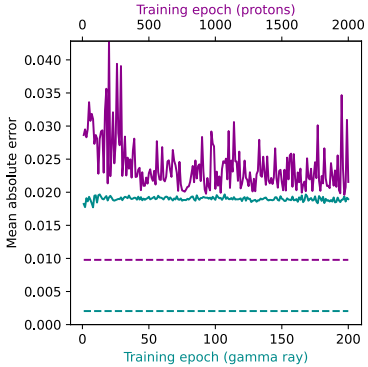
PARTICLE TYPE



ENERGY

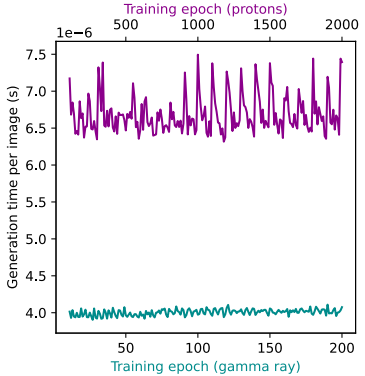


ARRIVAL DIRECTION



(-- Simulated and — Generated)

Using a GPU Nvidia 3090:



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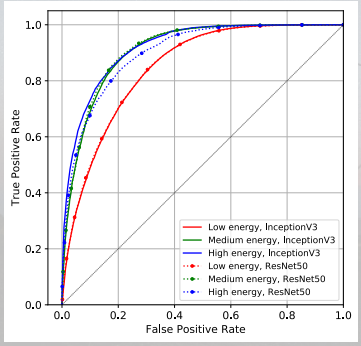
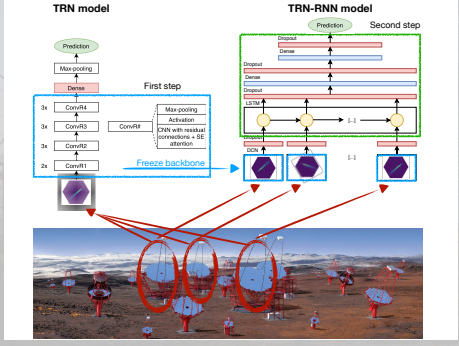
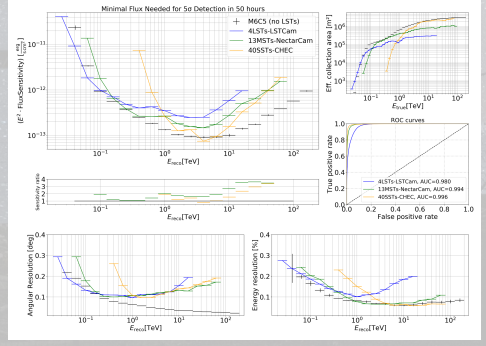
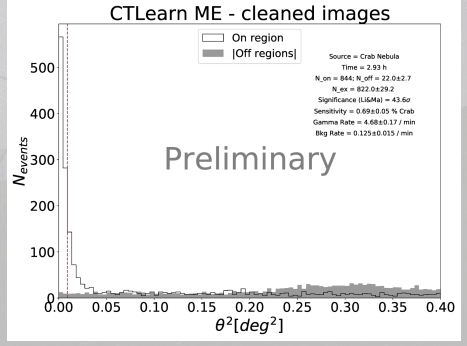
Conclusions & Outlook

- 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









Acknowledgment

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