

Incorporating deep learning into the analysis of the Cherenkov Telescope Array

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IWAPP - Innovative Workflows in Astro- & Particle Physics (09/03/2021)

This work was conducted in the context of the CTA Analysis & Simulations Working Group.

Outline

Imaging Atmospheric Cherenkov Telescopes (IACTs)

- Cherenkov Telescope Array

- IACT technique

IACT event reconstruction

Incorporating deep learning into the IACT analysis

- Challenges for deep learning & IACT data

 - DL1-Data-Handler

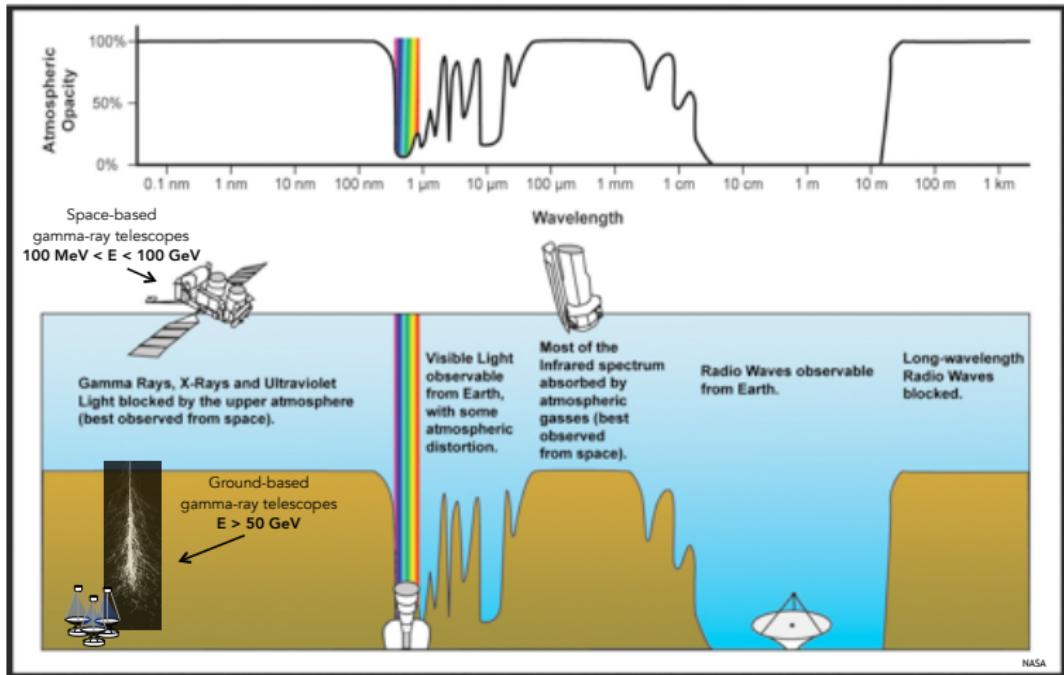
 - ImageMapper

 - IndexedConv

- Deep learning packages for IACT analysis

Results

Windows to the universe



Current-generation Imaging Atmospheric Cherenkov Telescopes



Namibia

- 4+1 telescope array
- Reflectors: 4 x 13 m Ø, 1 x 28 m Ø
- Cameras: 4 x 960 PMT, 5° FoV, 1 x 2048 PMT, 3.2° FoV
- Energy range: 30 GeV - 100 TeV



La Palma Island (Spain)

- Two telescope array
- Reflectors: 2 x 17 m Ø
- Cameras: 1039 PMT, 3.5° FoV
- Energy range: 30 GeV - 30 TeV



Tucson (USA)

- Four telescope array
- Reflectors: 4 x 12 m Ø
- Cameras: 499 PMT, 3.5° FoV
- Energy range: 100 GeV - 30 TeV



- 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:

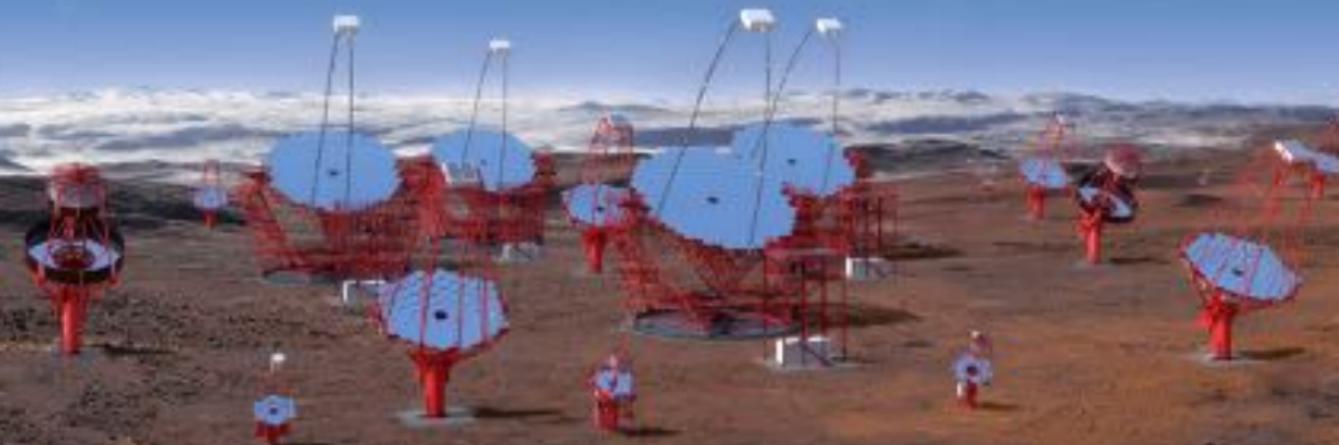
23 m ø
Parabolic reflector
4.3° FoV
Energy threshold 20 GeV

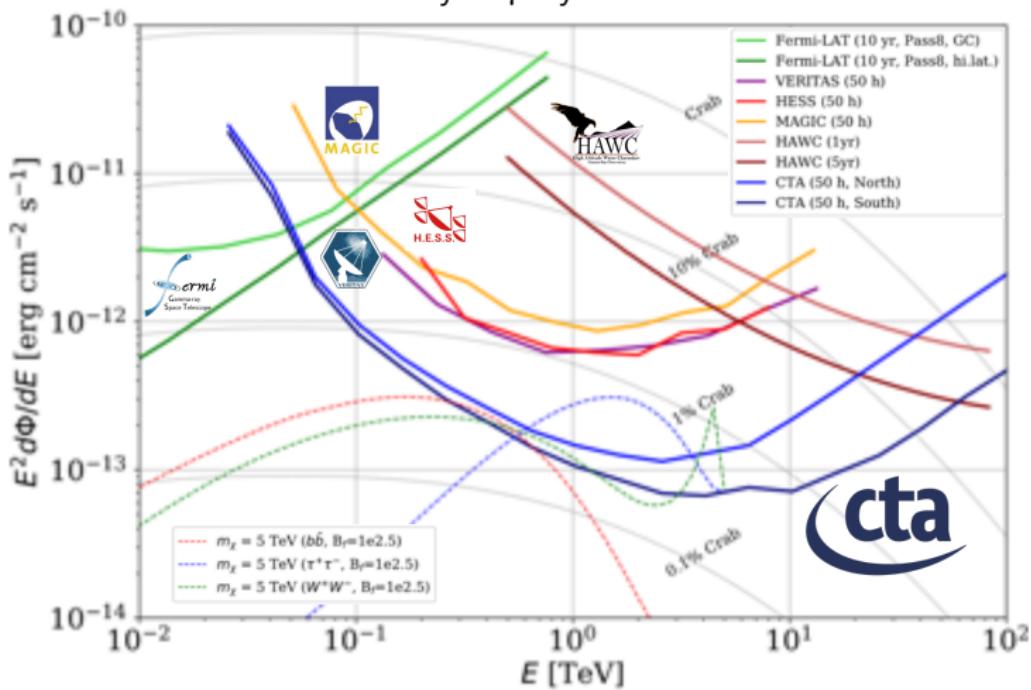
Mid energy-range:

11.5 m ø modified Davies-Cotton reflector
9.7 m ø Schwarzschild-Couder reflector
7.5° - 7.7° FoV
Best sensitivity in the
150 GeV – 5 TeV range

High-energy range:

4.3 m ø Schwarzschild-Couder reflector
10.5° FoV
Several km² area at
multi-TeV energies



Sensitivity of γ -ray observatories

IACT technique

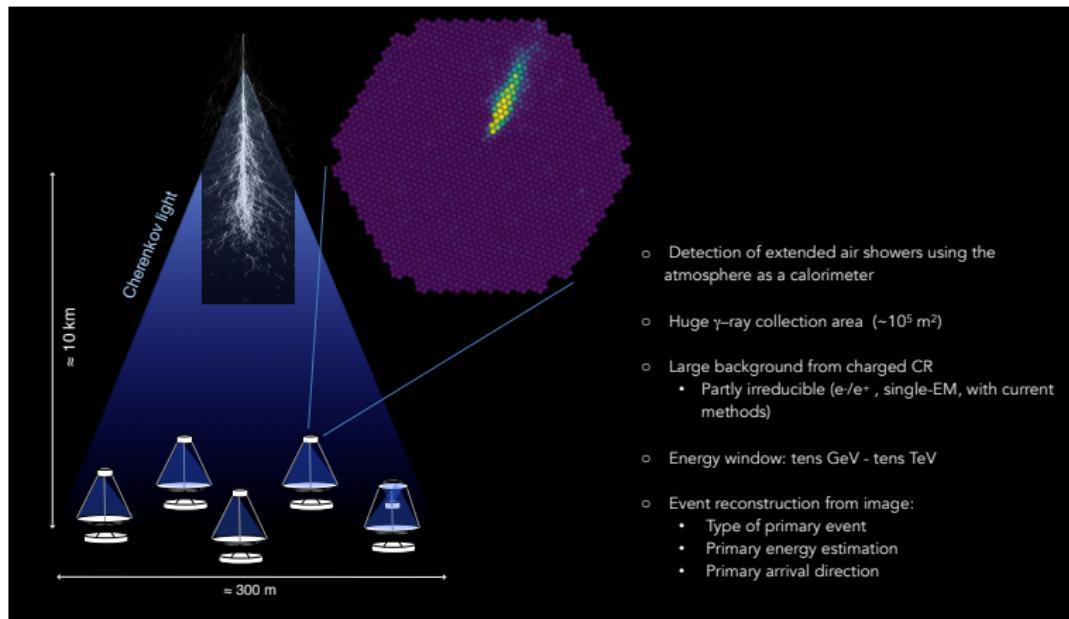


Figure: Imaging atmospheric Cherenkov telescope technique.

IACT technique

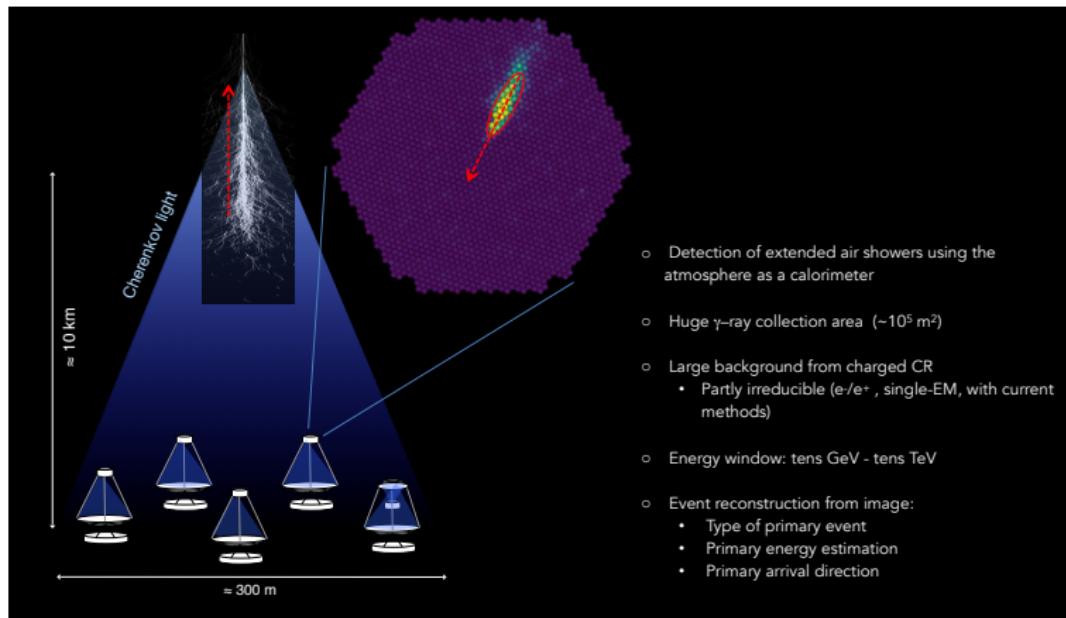


Figure: Imaging atmospheric Cherenkov telescope technique.

IACT technique

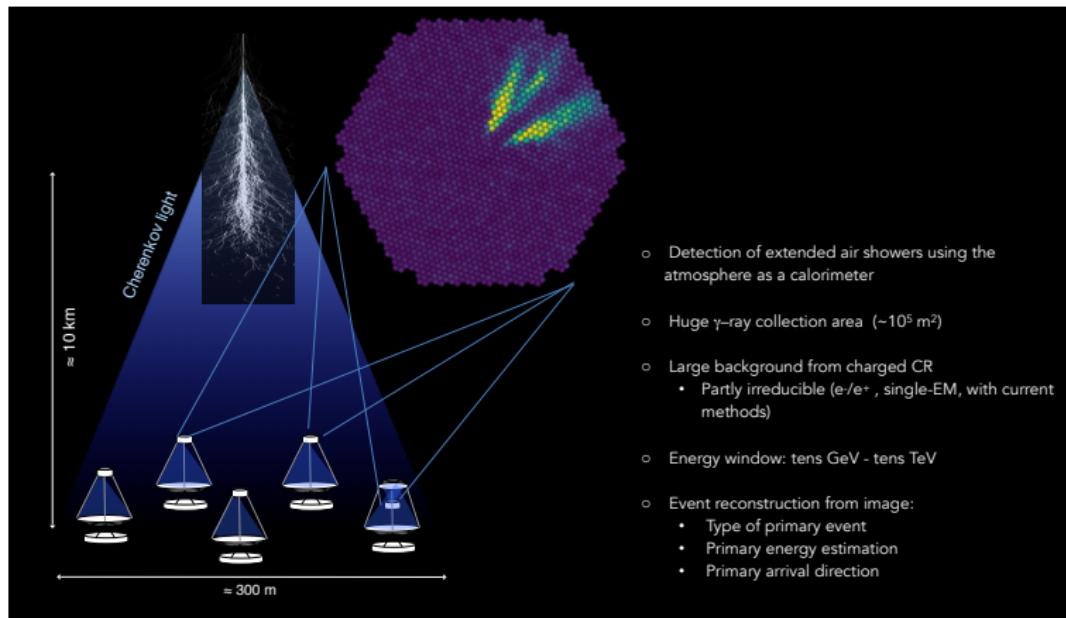


Figure: Imaging atmospheric Cherenkov telescope technique.

IACT technique

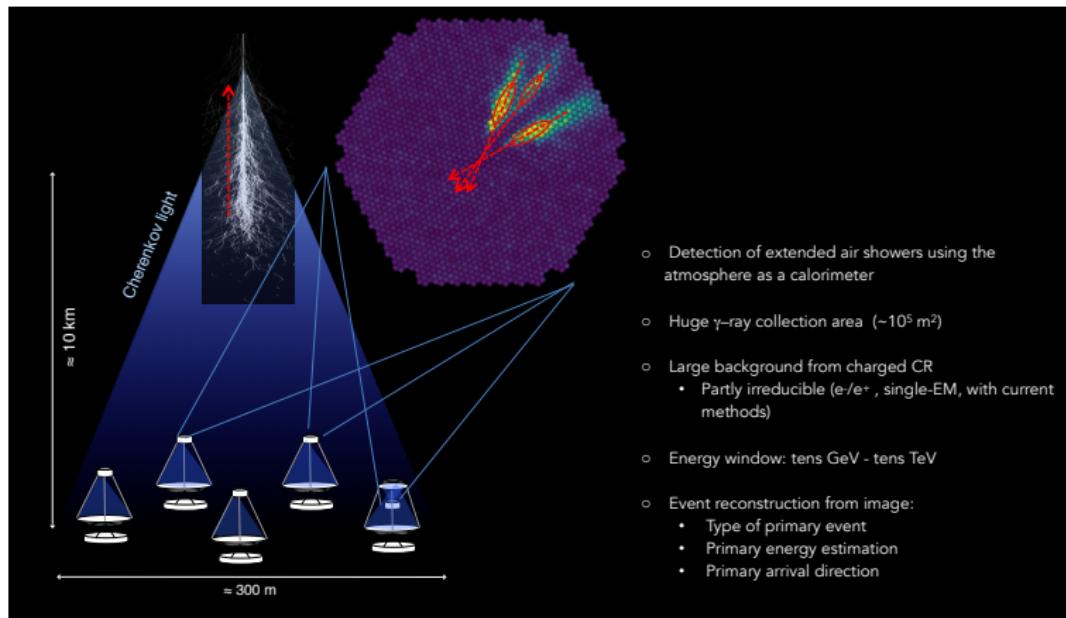


Figure: Imaging atmospheric Cherenkov telescope technique.

IACT technique

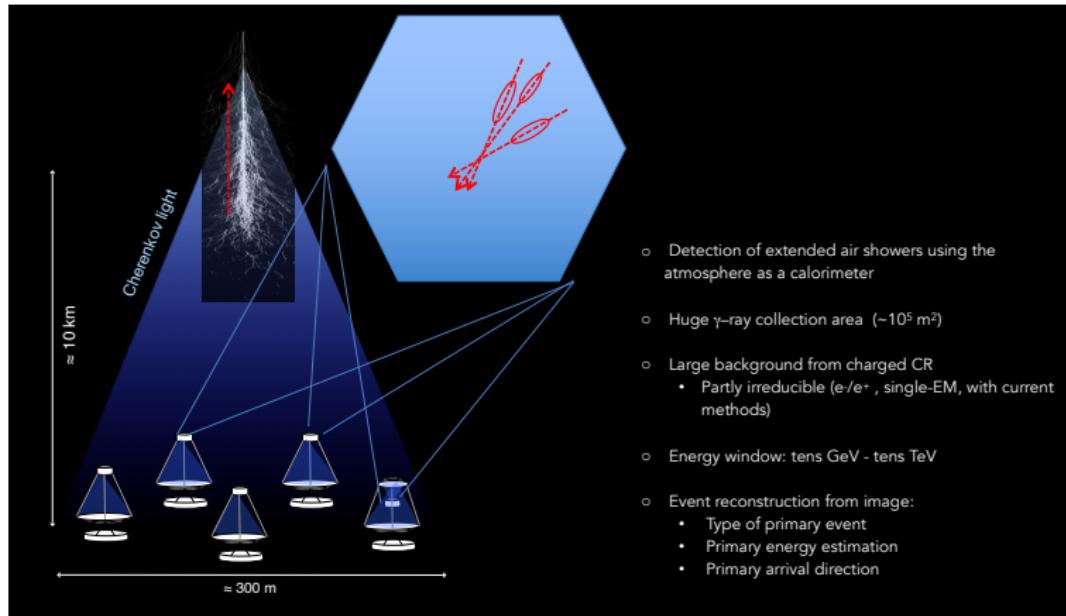


Figure: Imaging atmospheric Cherenkov telescope technique.

Gamma/hadron classification

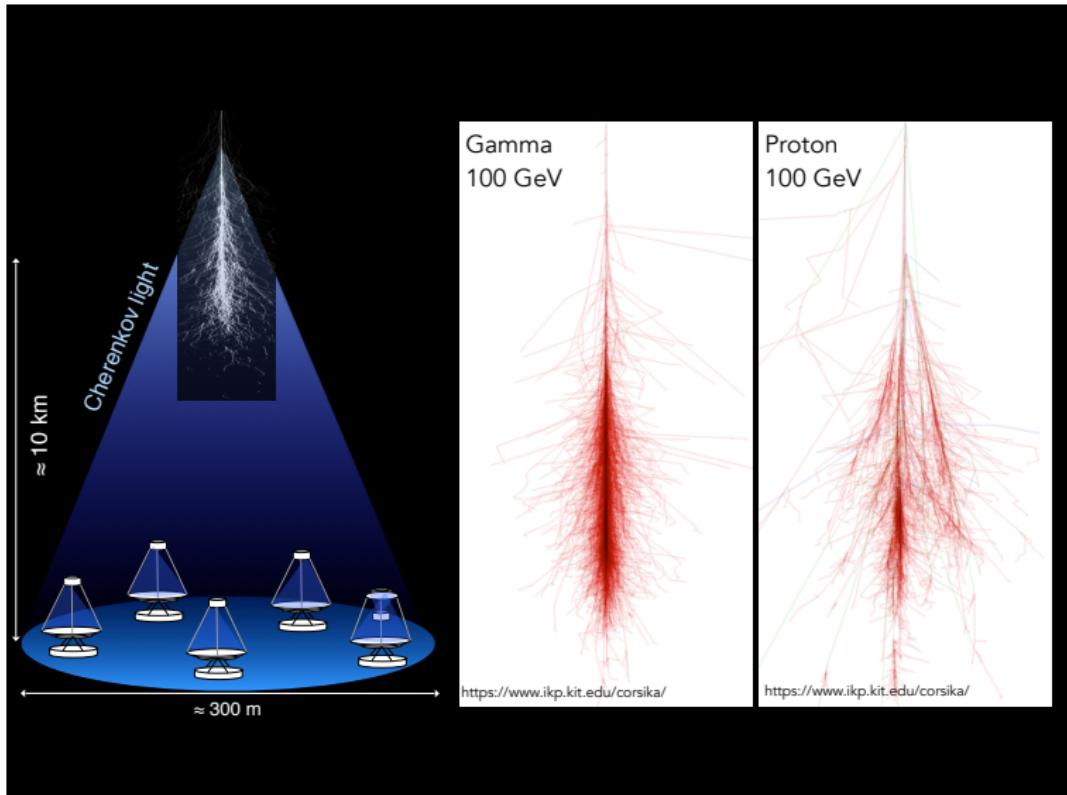


Figure: Simulated events produced with *CORSIKA*.

Gamma/hadron classification

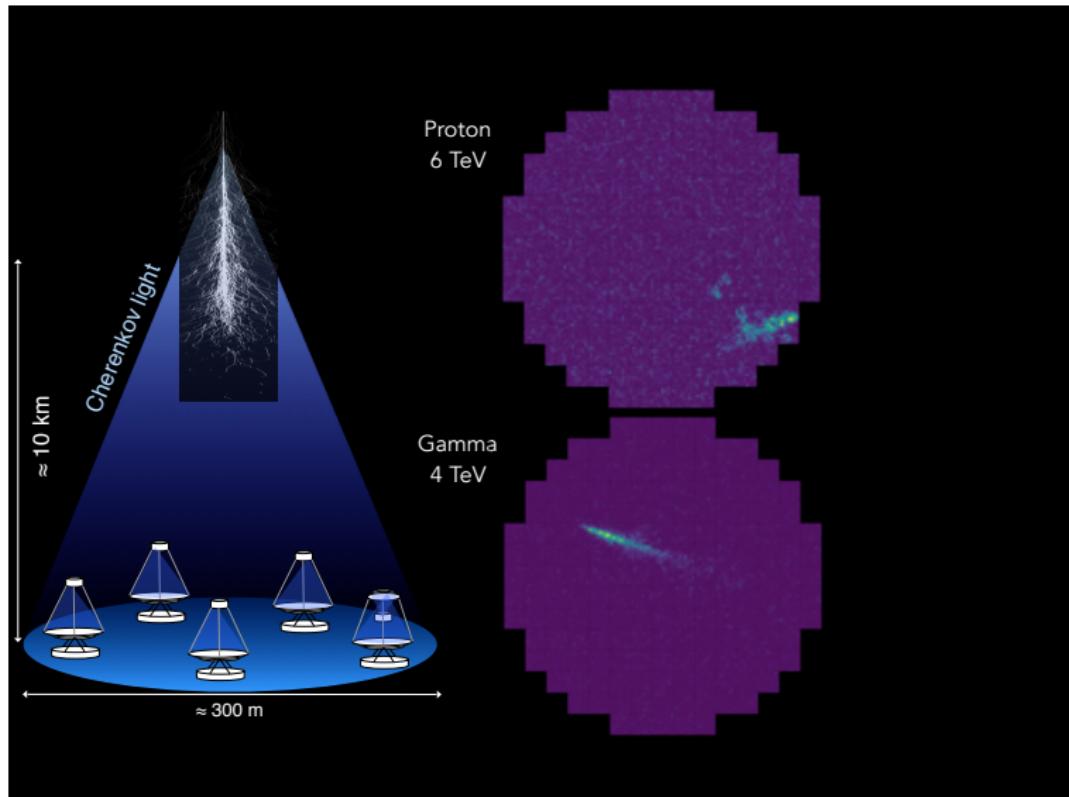


Figure: Bright MC events captured by the SCT-Cam

Gamma/hadron classification

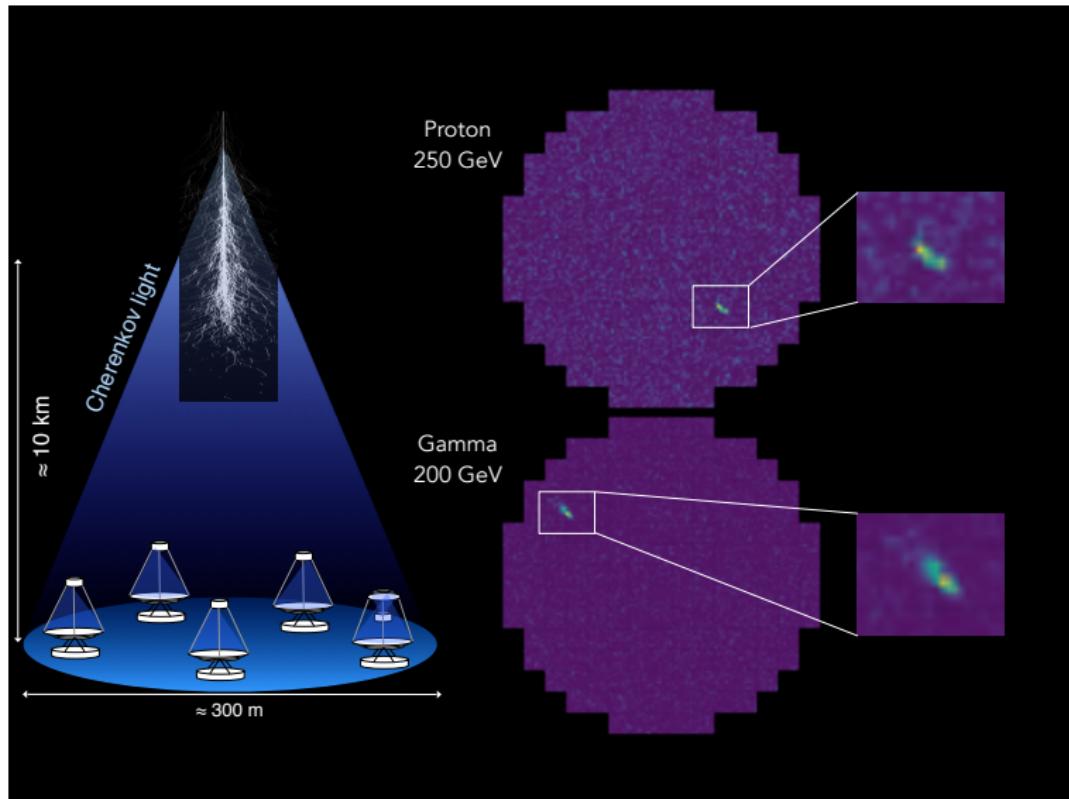
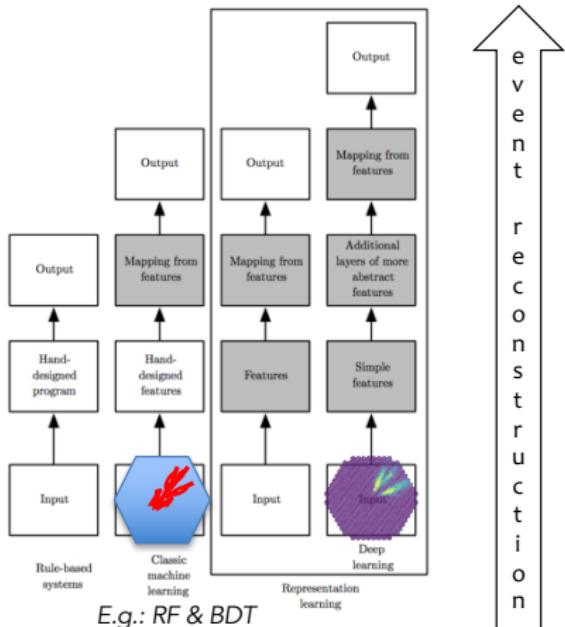


Figure: Faint MC events captured by the SCT-Cam.

IACT event reconstruction

Output: event type,
energy, incoming direction



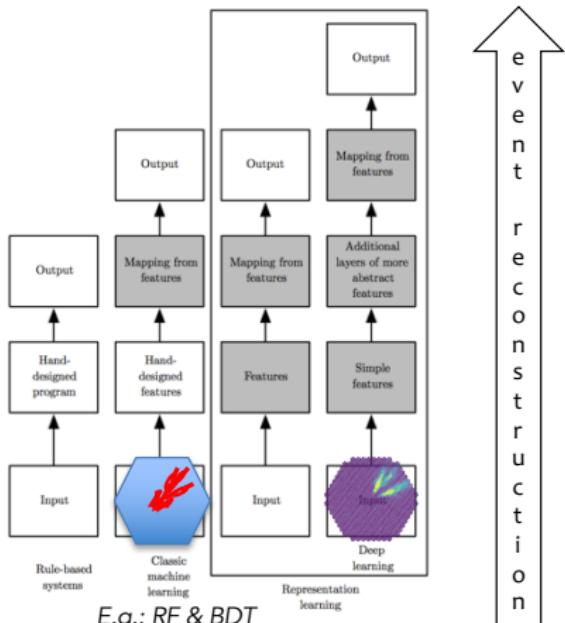
Input: observed events

Problem:
supervised learning requires labelled data

Solution:
?

IACT event reconstruction

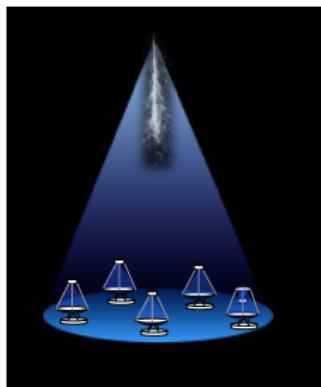
Output: event type,
energy, incoming direction



Input: observed events

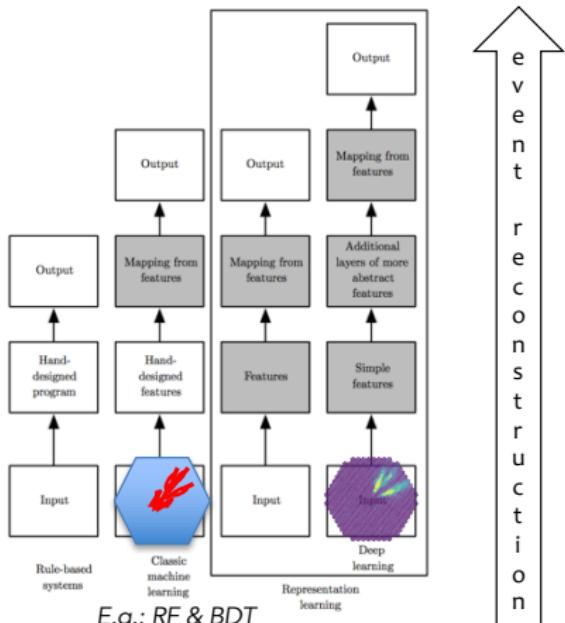
Problem:
supervised learning requires labelled data

Solution:
to simulate your data!



IACT event reconstruction

Output: event type,
energy, incoming direction

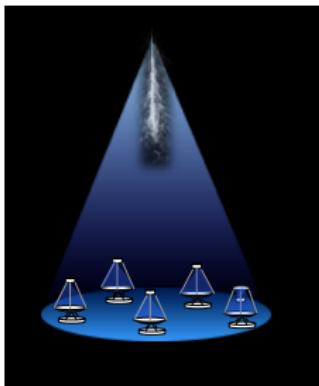


Input: observed events

Problem:
supervised learning requires labelled data

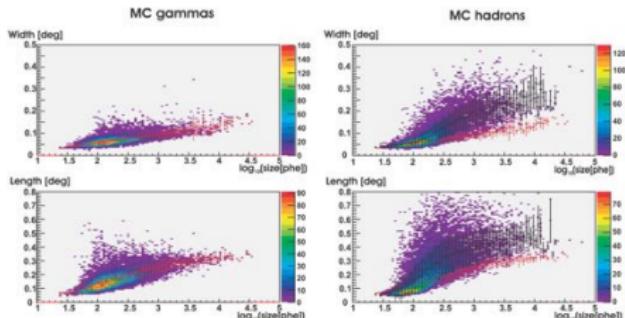
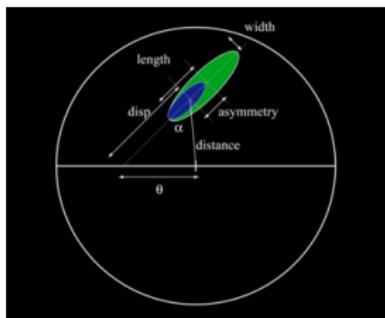
Solution:
to simulate your data!

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



Event reconstruction before machine learning

- Based on image parametrization (Hillas parameters)



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

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

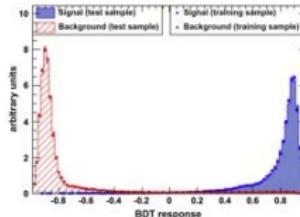
$$\text{DISP} = A(\text{SIZE}) + B(\text{SIZE}) \cdot \frac{\text{WIDTH}}{\text{LENGTH} + \eta(\text{SIZE}) \cdot \text{LEAKAGE}}$$

Albert et al., NIM-A 588:424-432 (2008), JPCS 718(5):052003

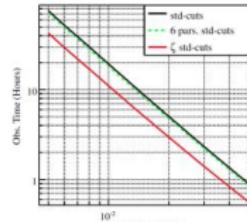
Machine learning & current-generation IACT



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



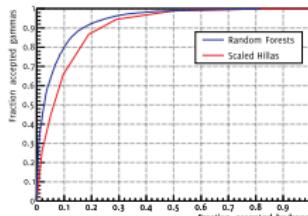
Becherini et al., APP V34-12 P858-870
(2011)



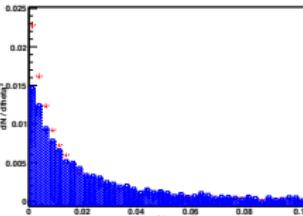
Ohm et al., APP V31-5 P383-391 (2009)
(Results for H.E.S.S. I only)



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



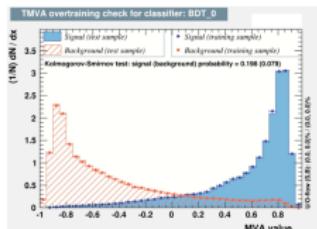
Albert et al., NIM-A 588:424-432 (2008)



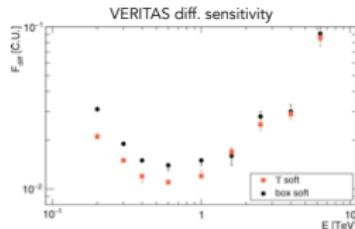
Aleksic et al., A&A 524 A77 (2010)



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



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



E [TeV]

Deep convolutional neural networks (DCNs)

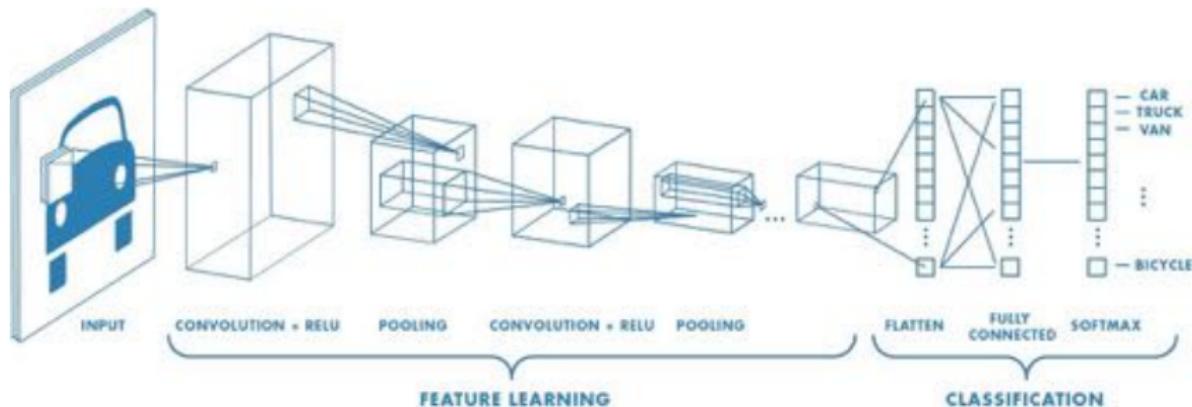
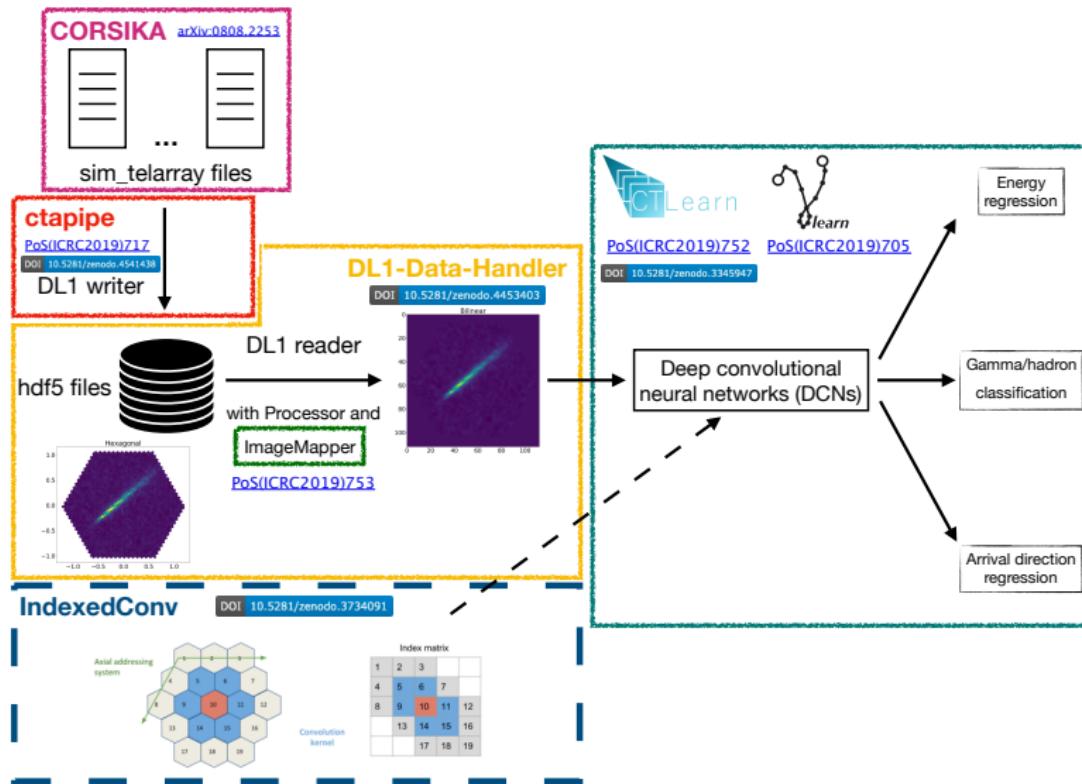


Figure: Concept of deep convolutional neural networks.

CTA analysis workflow with deep learning



CTA dataflow

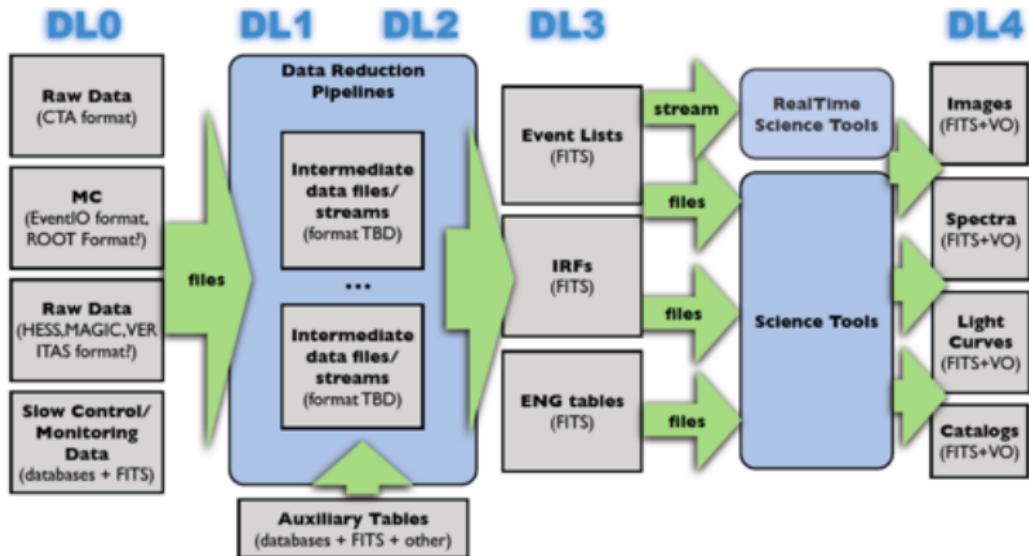


Figure: Courtesy of K. Kosack.

CTA low-level dataflow

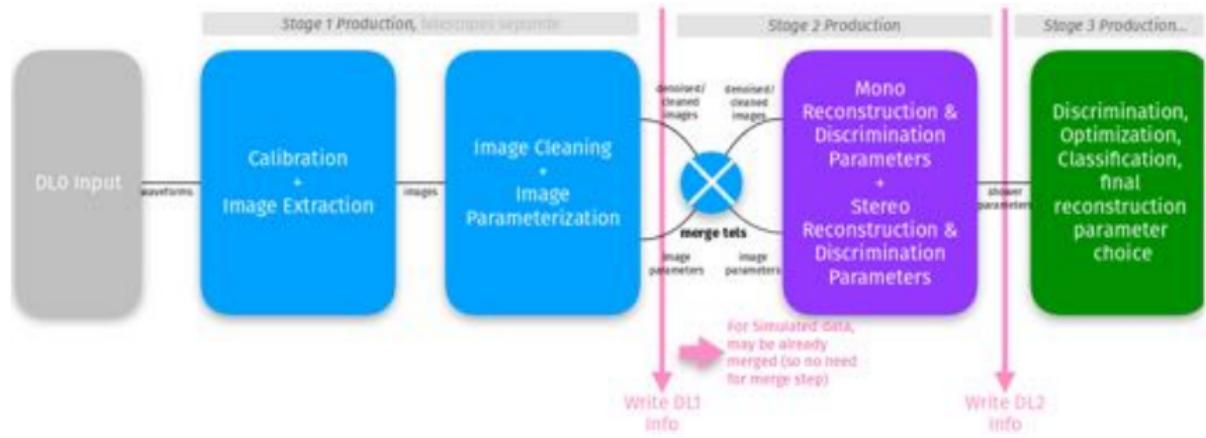


Figure: Courtesy of K. Kosack.

CTA low-level dataflow

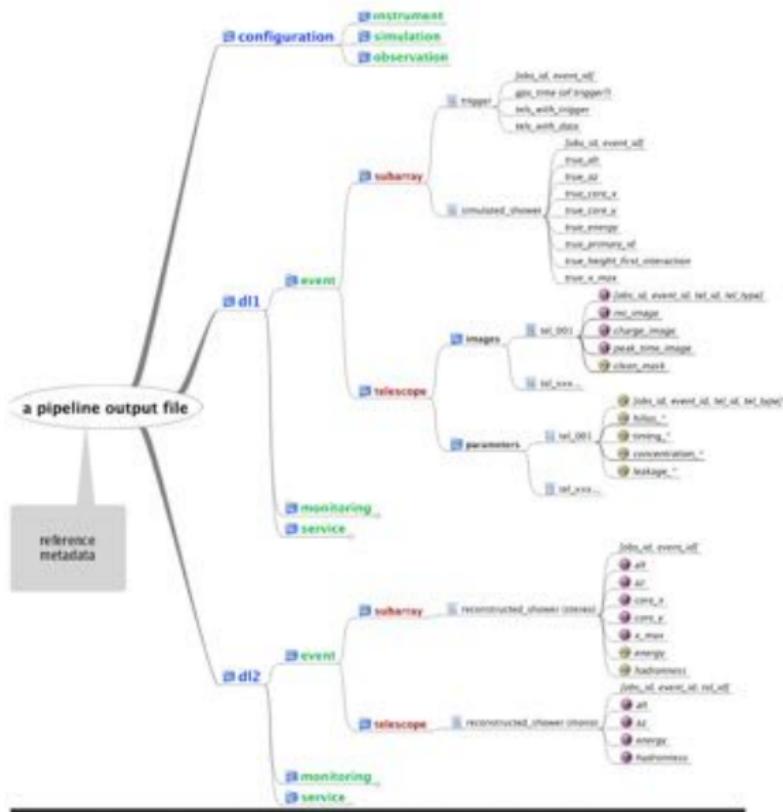


Figure: Courtesy of K. Kosack.

Challenges for deep learning & IACT data

Camera images courtesy of T. Vuillaume

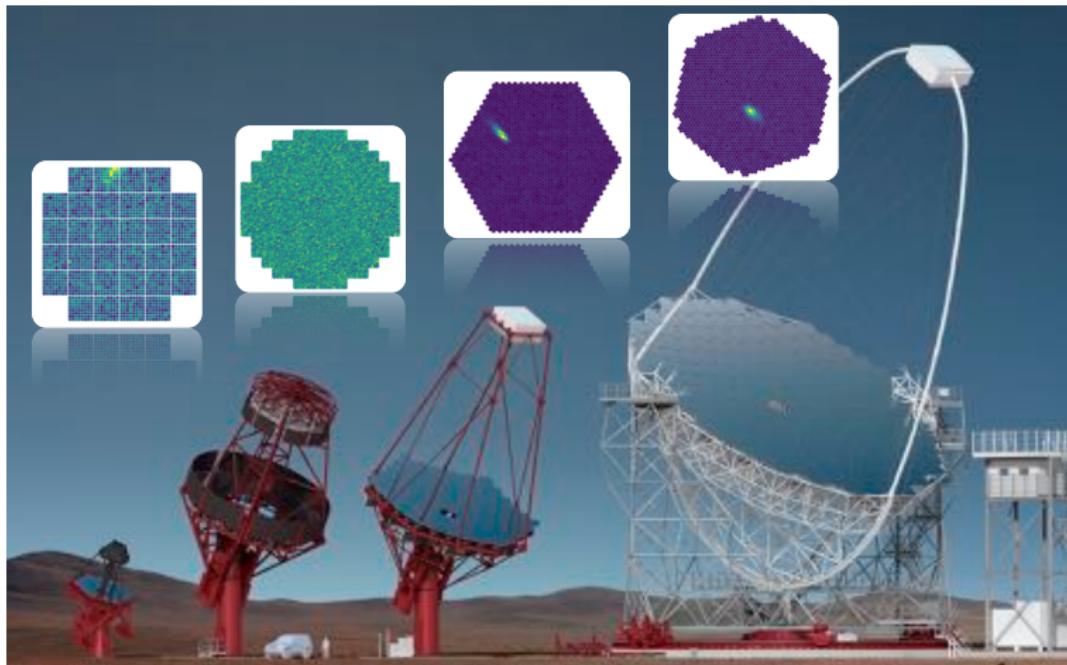


Figure: Heterogeneity of instruments & big data.

Challenges for deep learning & IACT data

Camera images courtesy of T. Vuillaume



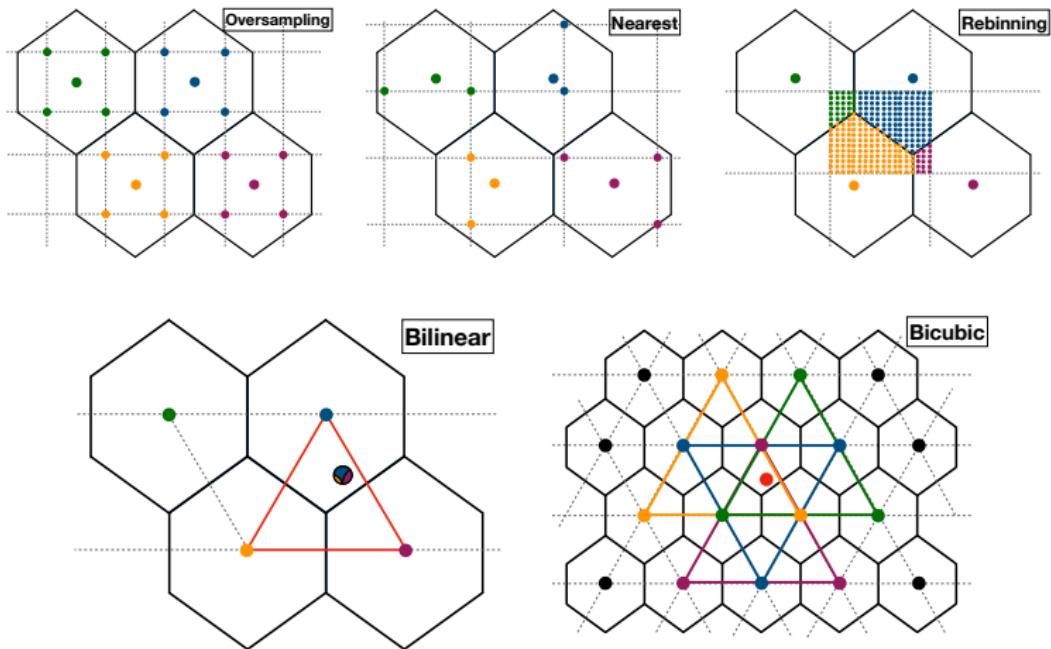
Figure: Hexagonal pixels.

- ▶ A package of utilities for writing (deprecated), reading, and applying image processing to Cherenkov Telescope Array (CTA) & MAGIC DL1 data (calibrated images) in a standardized format
- ▶ Installation via pip/setuptools from source or as a conda package.
- ▶ Event-wise image reading using generators to handle big data.
- ▶ Open source on GitHub:
<https://github.com/cta-observatory/dl1-data-handler>

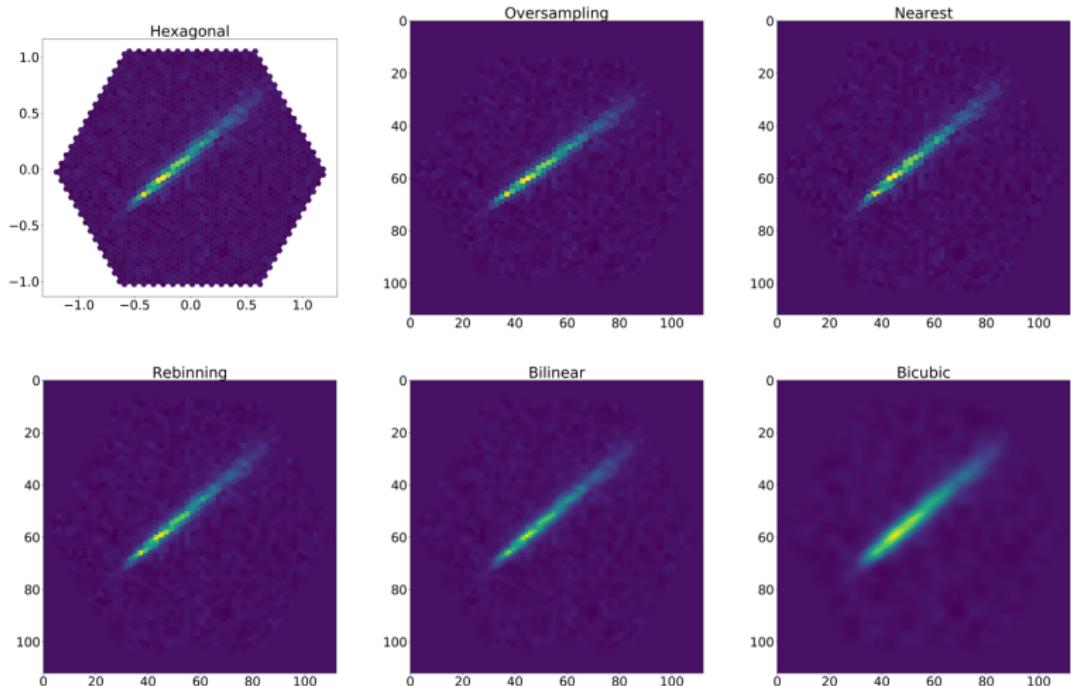
Contributors

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Sahil Yadav, Lukas Gutiérrez

ImageMapper: Hexagonal pixel charges → 2D image



ImageMapper: Hexagonal pixel charges → 2D image



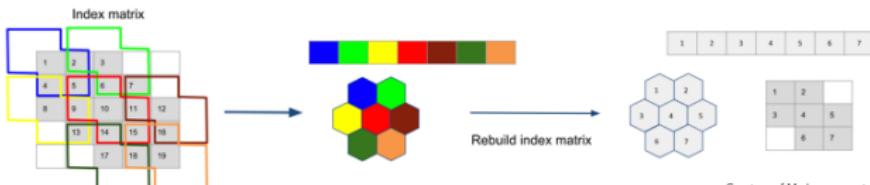
IndexedConv

- ▶ Well described in M. Jacquemont, L. Antiga & T. Vuillaume et al. (doi:10.5220/0007364303620371)
- ▶ Open source: doi:10.5281/zenodo.2542664
- ▶ Ongoing work: Making IndexedConv compatible with tensorflow models (Issue #21)

Convolution:



Pooling:



CTLearn & GammaLearn

- ▶ High-level Python packages for using deep learning for IACT event reconstruction
- ▶ Configuration-file-based workflow and installation with conda to drive reproducible training and prediction
- ▶ Supports any TensorFlow (CTLearn) & PyTorch (GammaLearn) model that obeys a generic signature
- ▶ Open source:
<https://github.com/ctlearn-project/ctlearn>
<https://gitlab.lapp.in2p3.fr/GammaLearn>



Primary developers

Ari Brill, Qi Feng (Columbia)

Bryan Kim (Stanford)

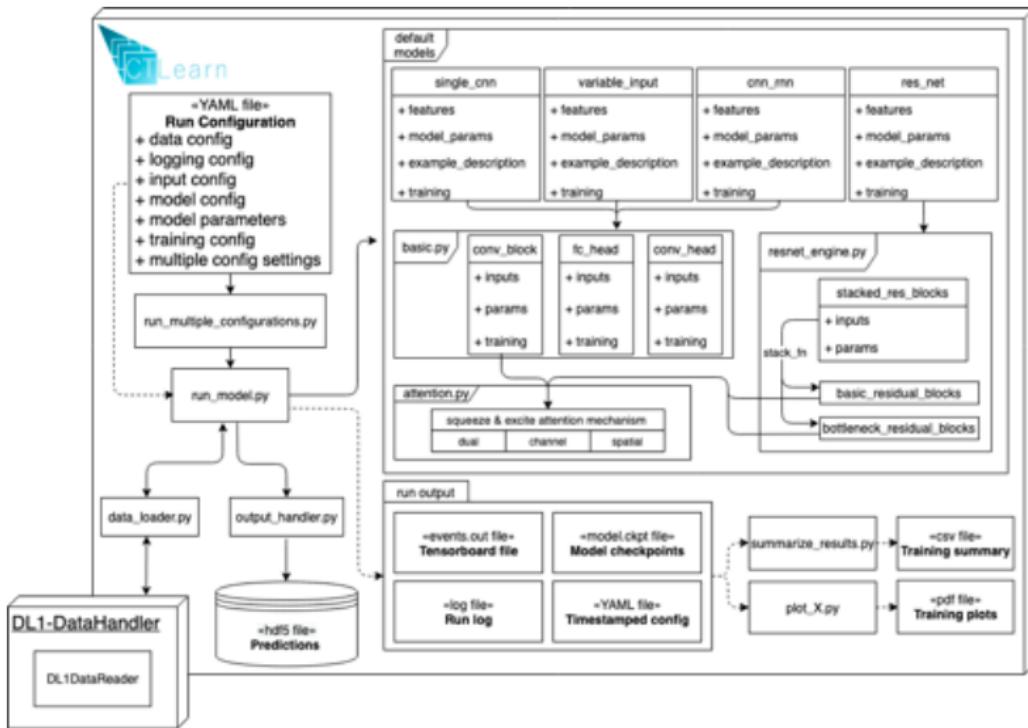
Tjark Miener, Daniel Nieto (UCM)



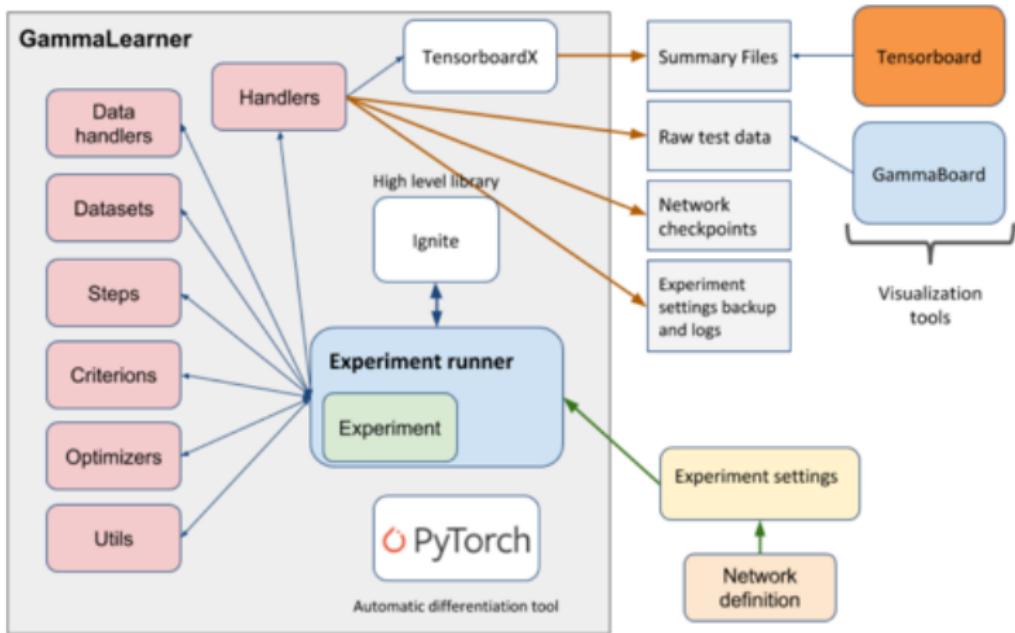
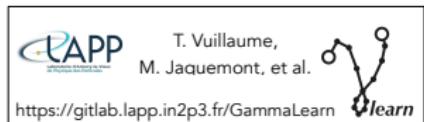
Primary developers

Mikaël Jacquemont, Thomas Vuillaume (LAPP)

CTLearn workflow

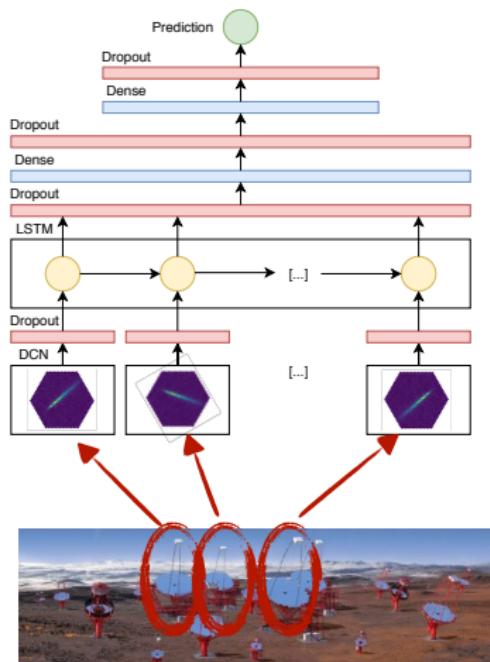


GammaLearn workflow

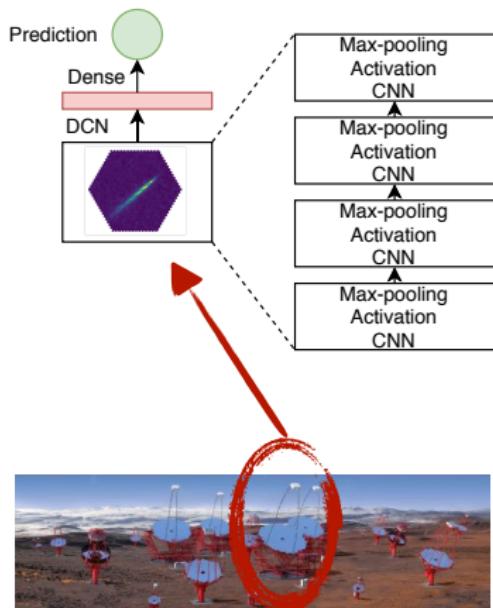


CTLearn - default models

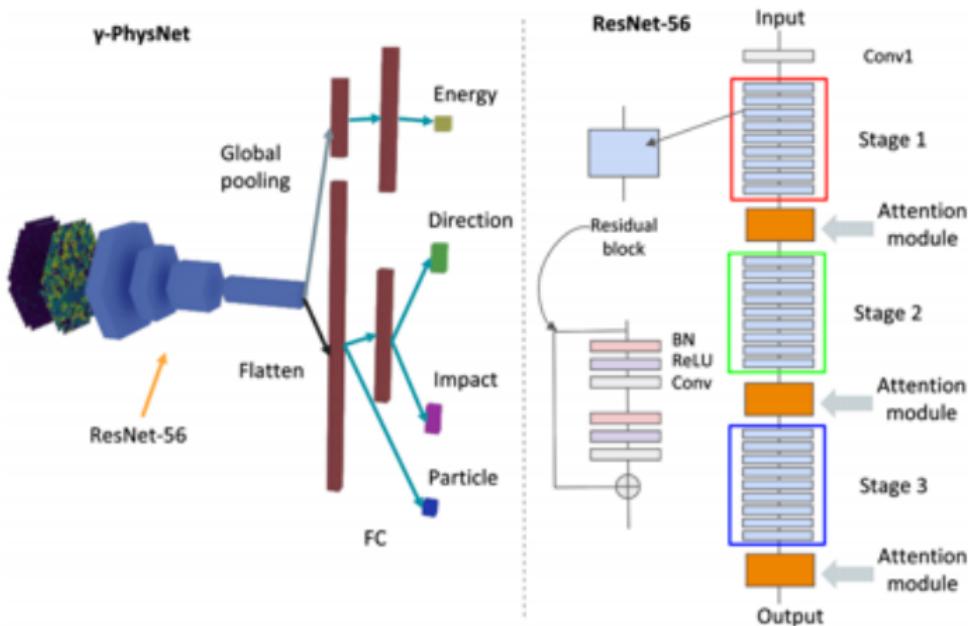
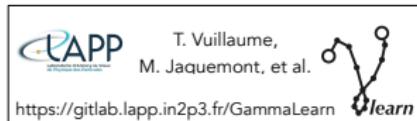
CNN-RNN model



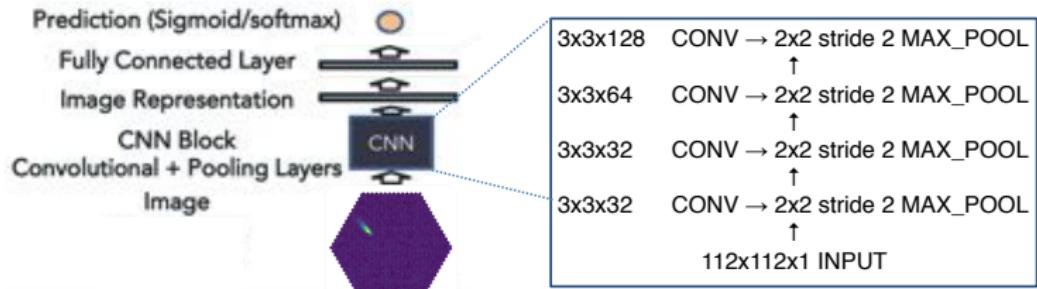
Single CNN model



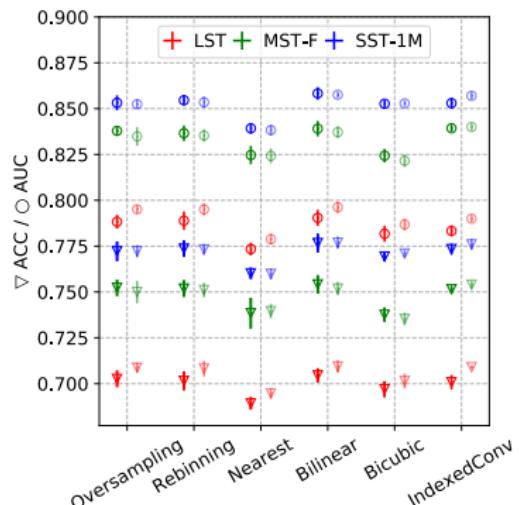
GammaLearn - GammaPhysNet



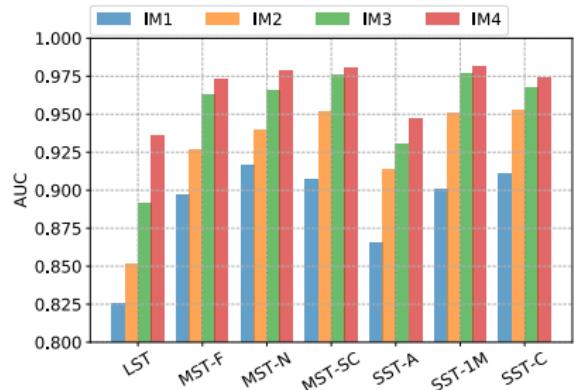
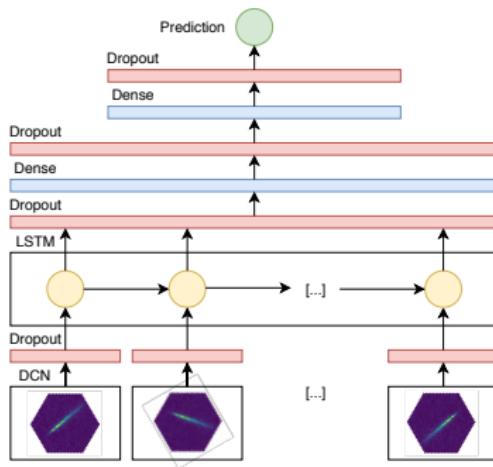
CTLearn & GammaLearn: Tackling the hexagonal-pixel challenge



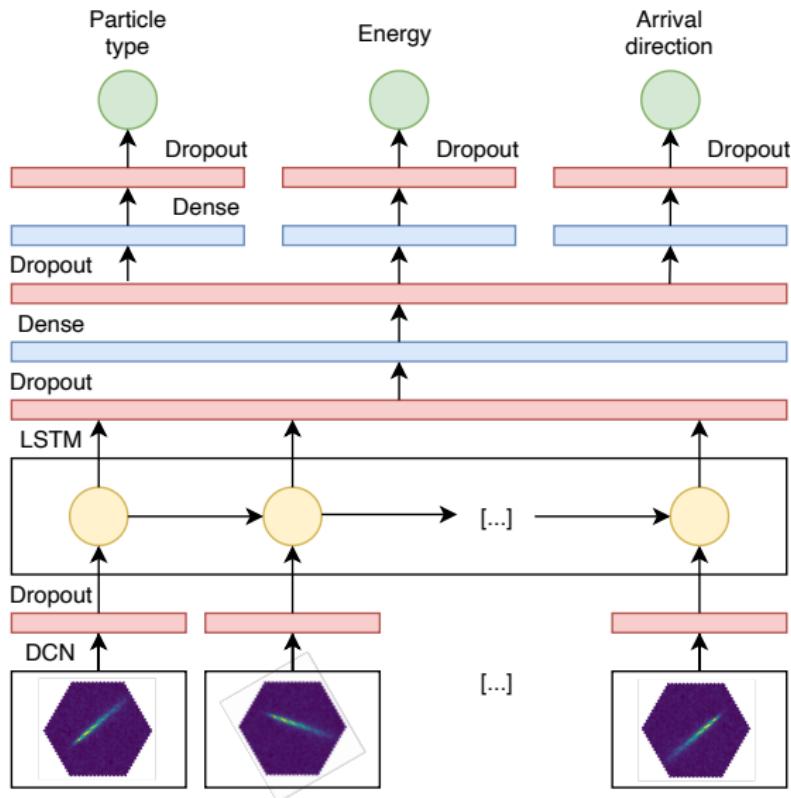
Courtesy of A. Brill



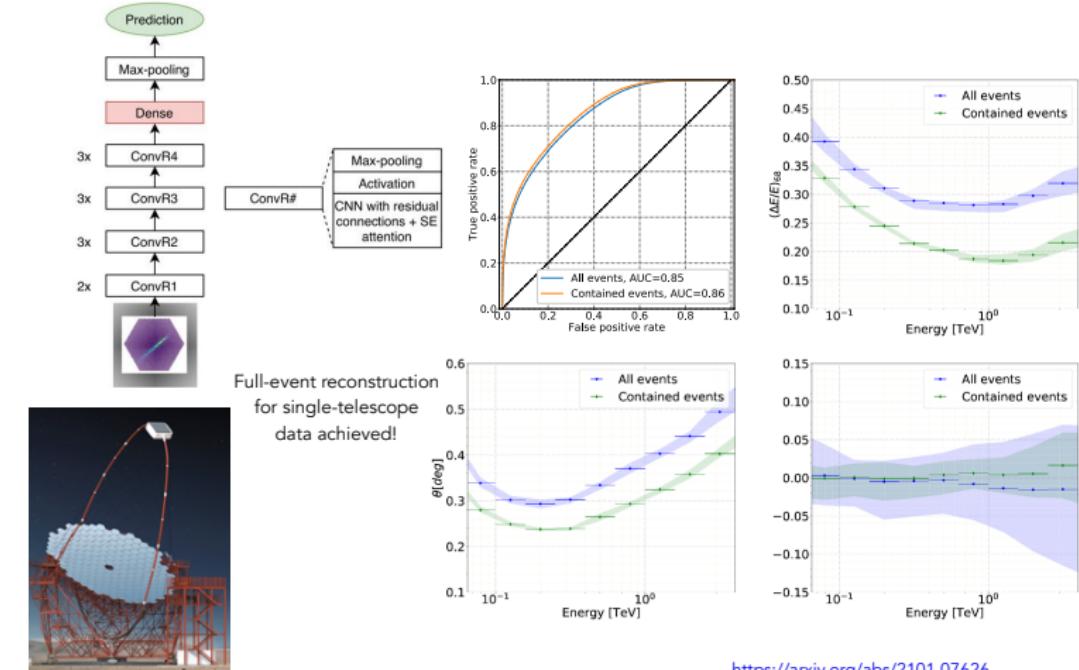
CTLearn: Gamma/hadron classification with stereoscopic models



Future work: Stereo multitask learning architecture



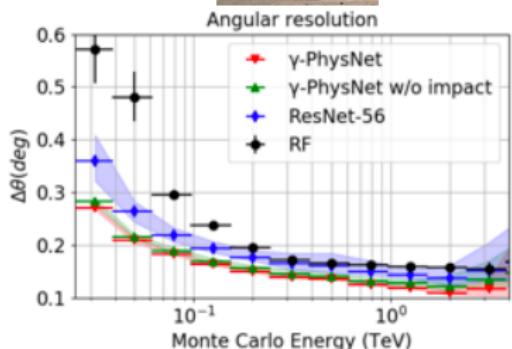
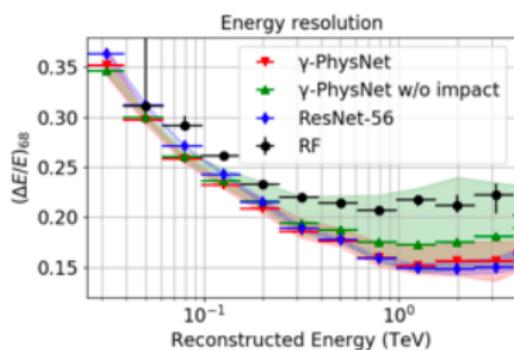
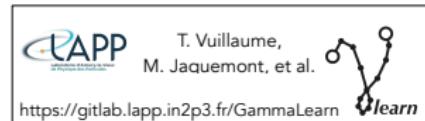
CTLearn: Full-event reconstruction for single-telescope (diffuse) data



GammaLearn: Full-event reconstruction for single-telescope data

Table 1: AUC and F1 score of the gamma/proton classification task for the different models

Model	AUC	F1 score
Hillas + RF	0.898	0.732
ResNet-56	0.954±0.001	0.949±0.001
γ -PhysNet	0.960±0.002	0.956±0.002
γ -PhysNet w/o Impact	0.961±0.002	0.955±0.001



<https://hal.archives-ouvertes.fr/hal-03043188>

Summary & outlook

- ▶ We explored the ground-based IACT technique and the conventional IACT event reconstruction.
- ▶ We learned how deep learning can be incorporated into the analysis workflow of the Cherenkov Telescope Array.
- ▶ We showed what challenges we had faced so far and how we solved them.
- ▶ There are still open questions and challenges, which we have to tackle in the future, like the MC simulation/real data discrepancy and stereoscopic full-event reconstruction.

¡Gracias por su atención!



Acknowledgments

- ▶ This work was conducted in the context of the CTA Analysis & Simulations Working Group.
- ▶ TM acknowledges support from FPA2017-82729-C6-3-R.
- ▶ CTLearn was founded with the support of Spanish MINECO /ERDF grant FPA2015-73913-JIN.
- ▶ GammaLearn acknowledges support from the European Union's Horizon 2020 research and innovation programme under grant agreement No 653477.
- ▶ DN, JLC, TV acknowledge support from the ESCAPE project funded by the European Union's Horizon 2020 research and innovation program under Grant Agreement no. 824064.

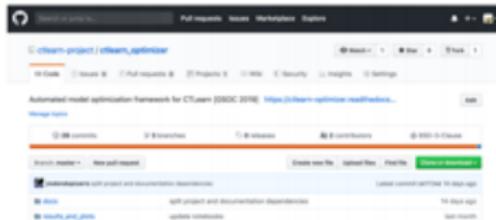
Back up

CTLearn optimizer

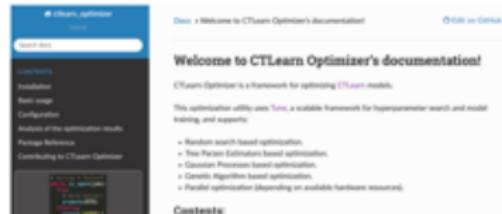
- Framework for hyperparameter optimization of CLearn models
(Although can be adapted to any config-file based DCN framework)
- Based on Tune: a scalable hyperparameter tuning library
- Supported optimization strategies:
 - Random search
 - Tree Parzen Estimators
 - Gaussian Processes
 - Genetic Algorithms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

Main author:
Juan Redondo (UCM)
GSOC '19 Student

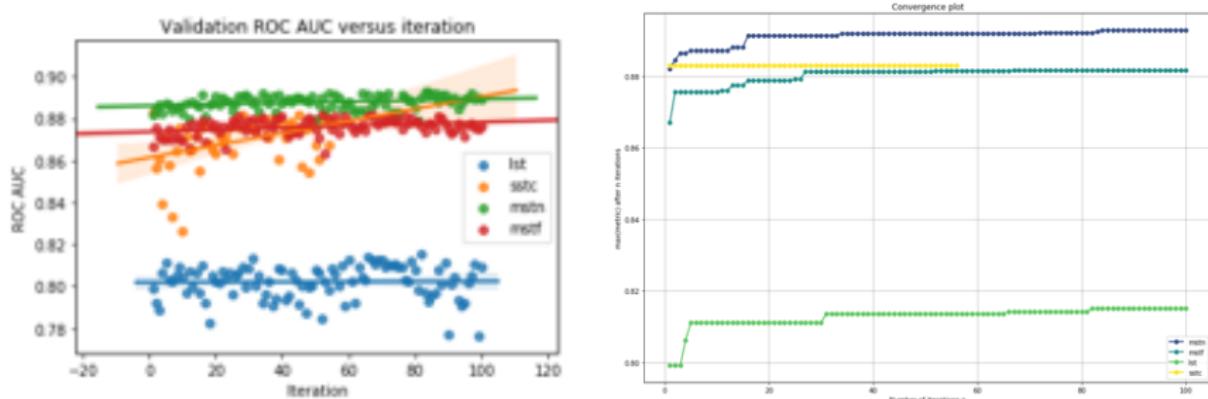
github.com/ctlearn-project/ctlearn_optimizer



ctlearn-optimizer.readthedocs.io



CTLearn optimizer



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%