Application of Machine Learning in Astroparticle Physics

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Saha Institute for Nuclear Physics

Daniel Nieto

(d.nieto@ucm.es)

Institute for Particle and Cosmos Physics

IPARCOS-UCM

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

- Machine learning in a nutshell
- Enhancing IACTs with machine learning
- Applications to other astroparticle physics experiments

Artificial intelligence?

Study of *intelligent agents*: systems that perceive their environment and take actions that maximize their chance to successfully achieving their goals (e.g. solving a problem).

Machine Learning

- System acquires its own knowledge learning from examples
- System achieves its goal without utilizing explicit rules

Problems in AI:

- Abstract and formal:

😎 computers, 😖 humans

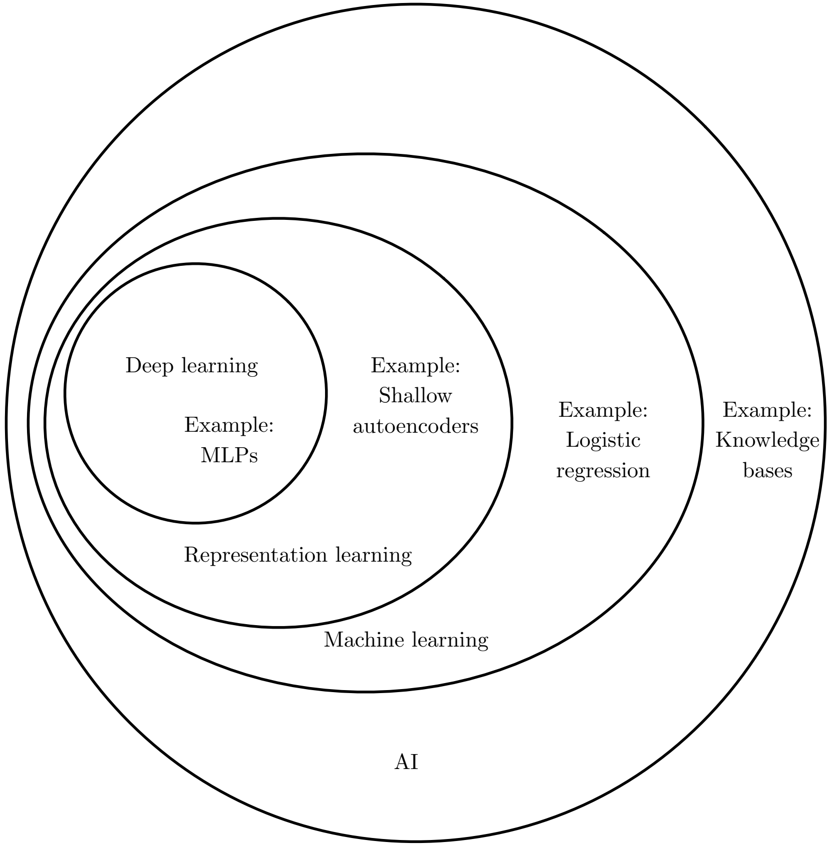
Knowledge-based approach

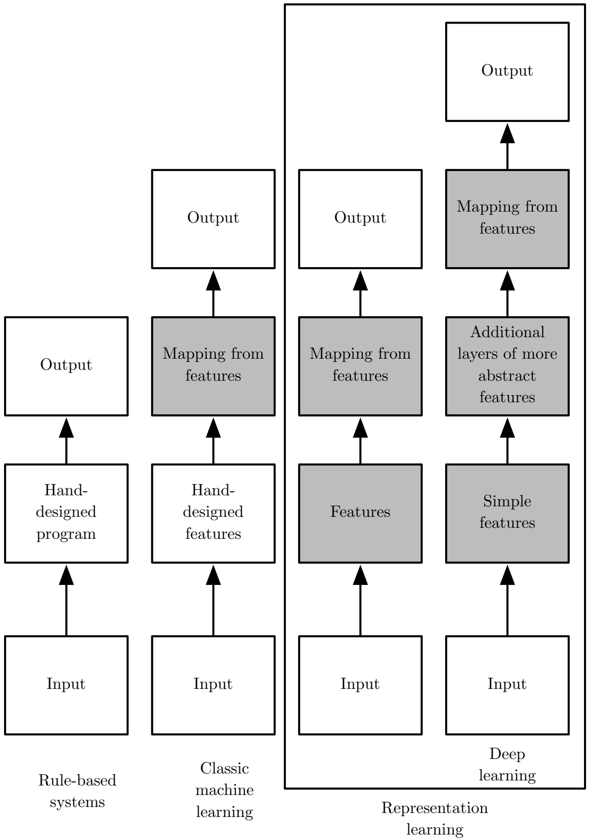
- Intuitive, hard to formalize:

😎 humans, 😖 computers

Concept capture and generalization

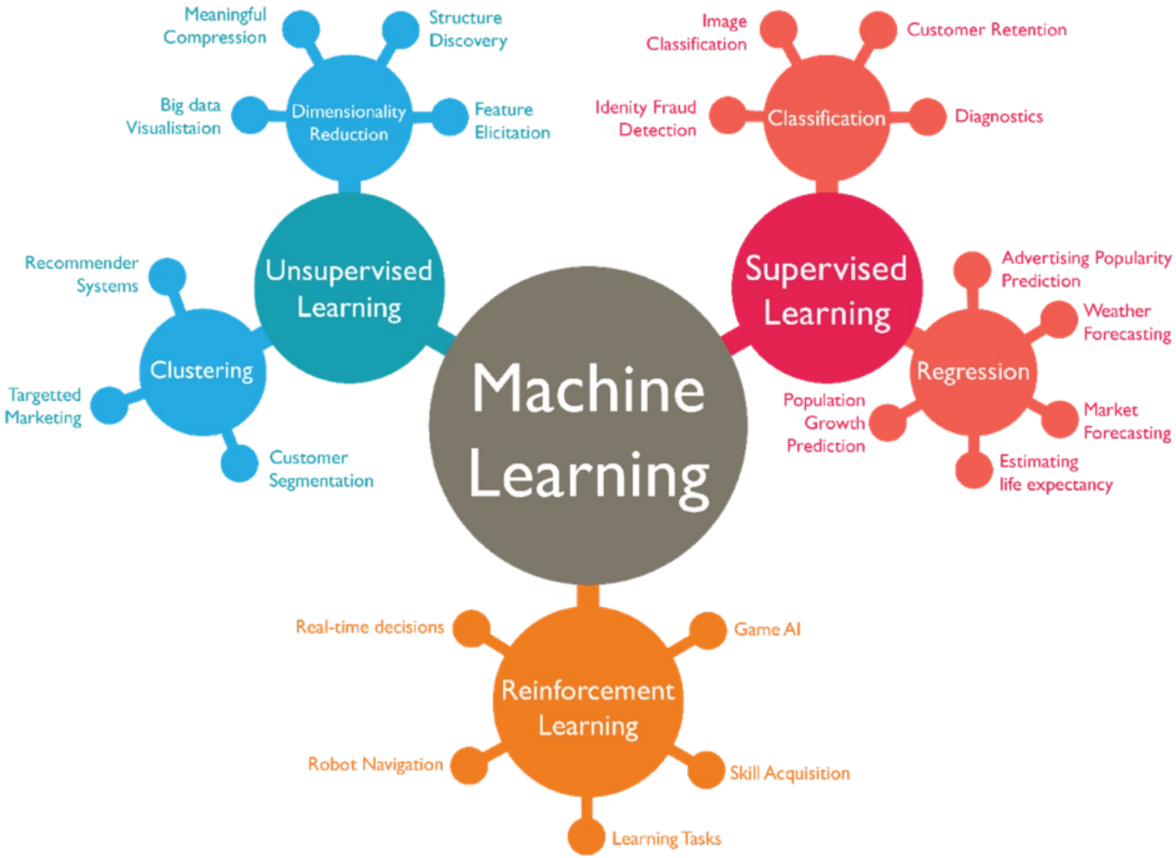
Machine Learning in a nutshell





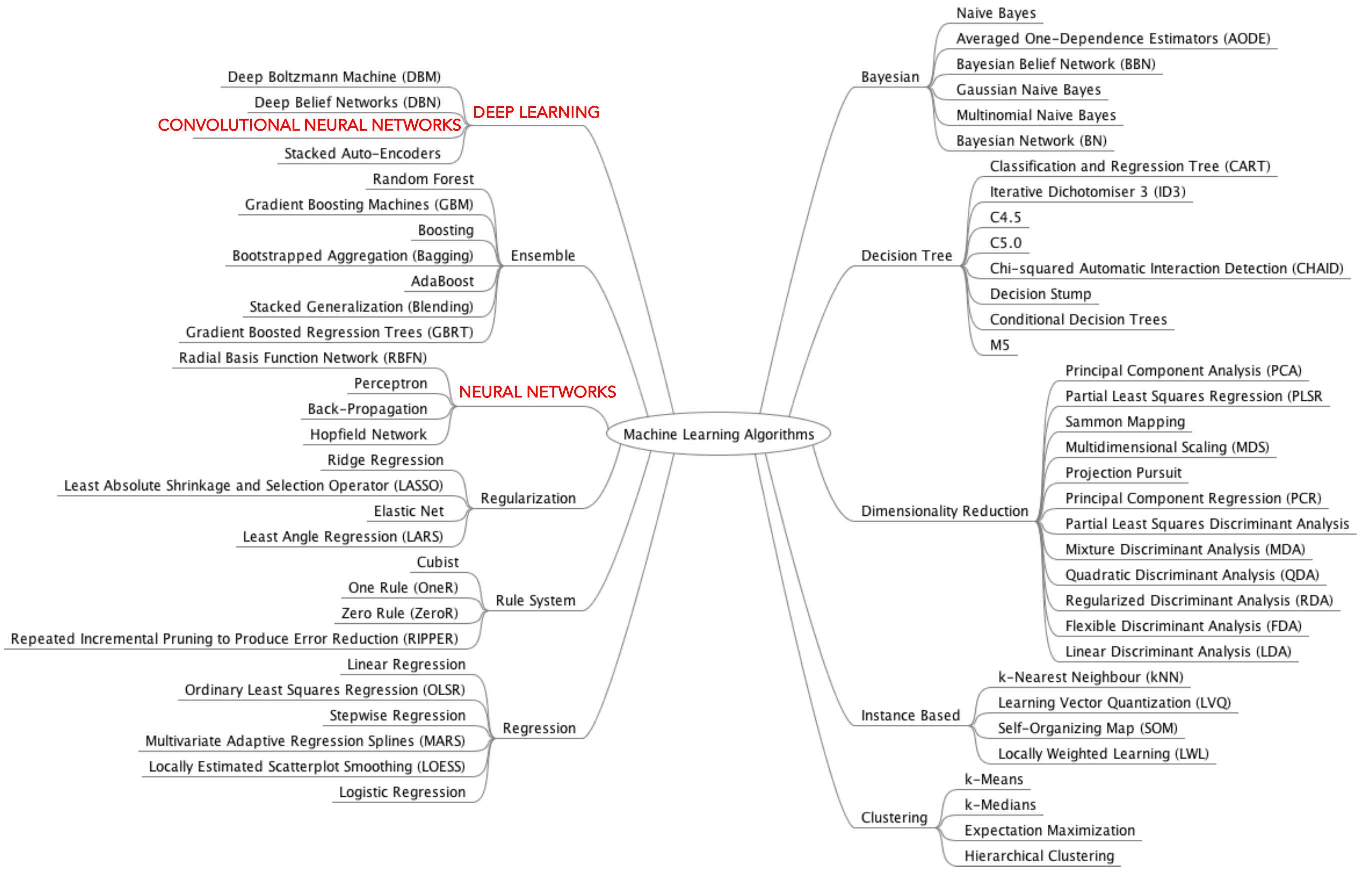
Goodfellow et al. (2016)

Machine Learning strategies

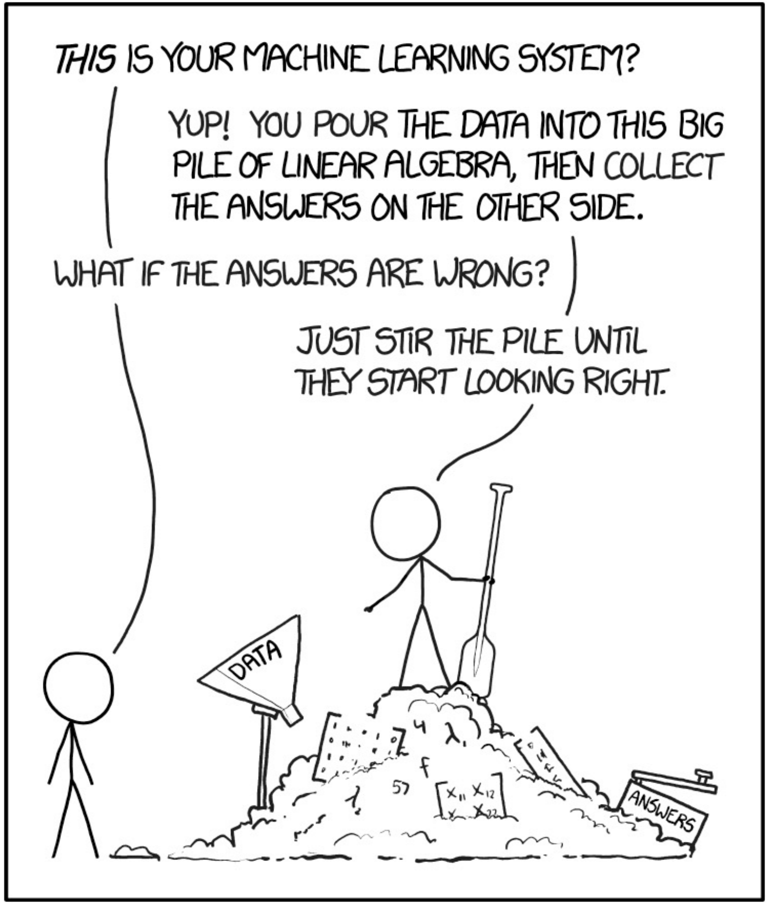


towardsdatascience.com

Machine Learning algorithms

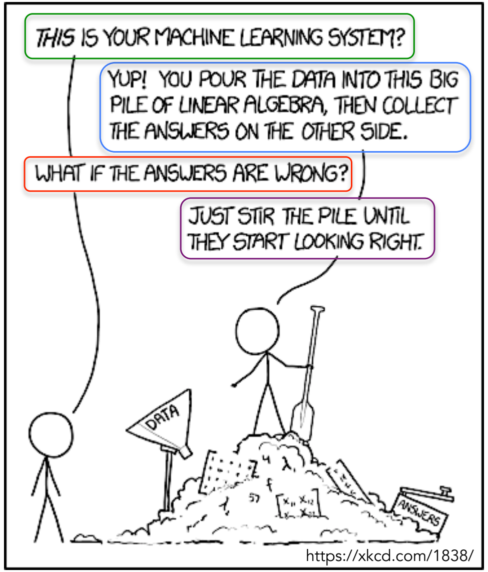


jixta.wordpress.com

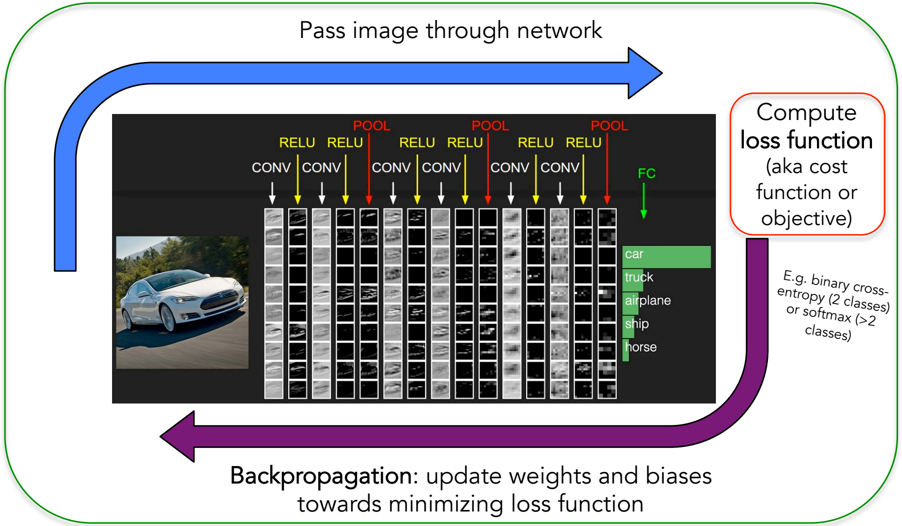


https://xkcd.com/1838/

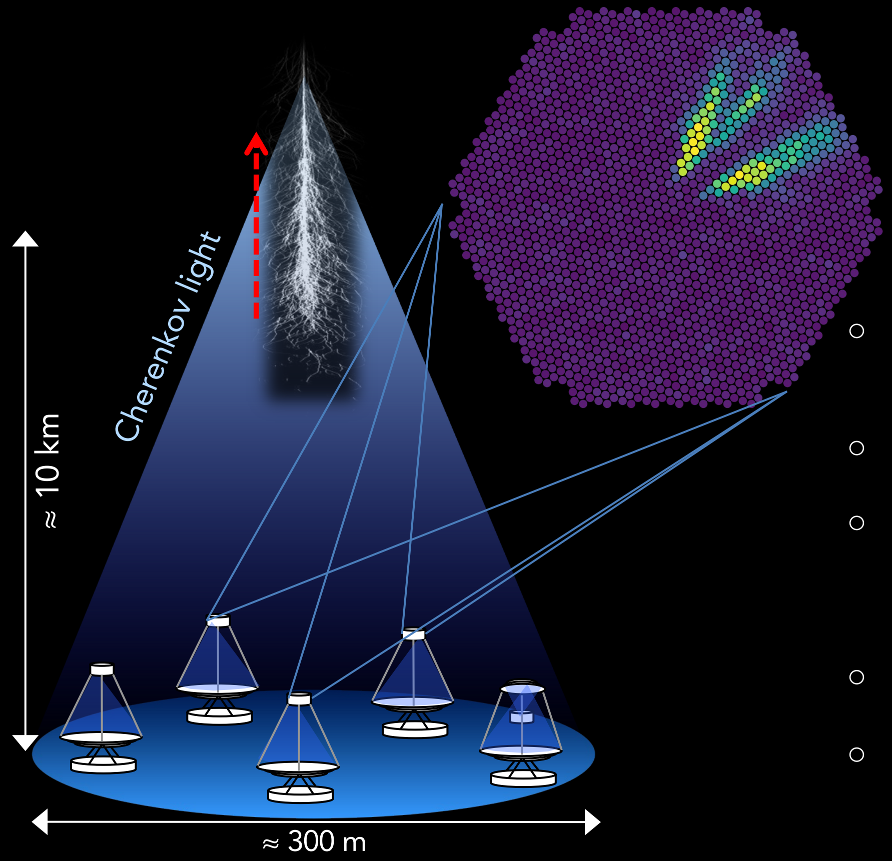
Training ML systems: an example



https://xkcd.com/1838/

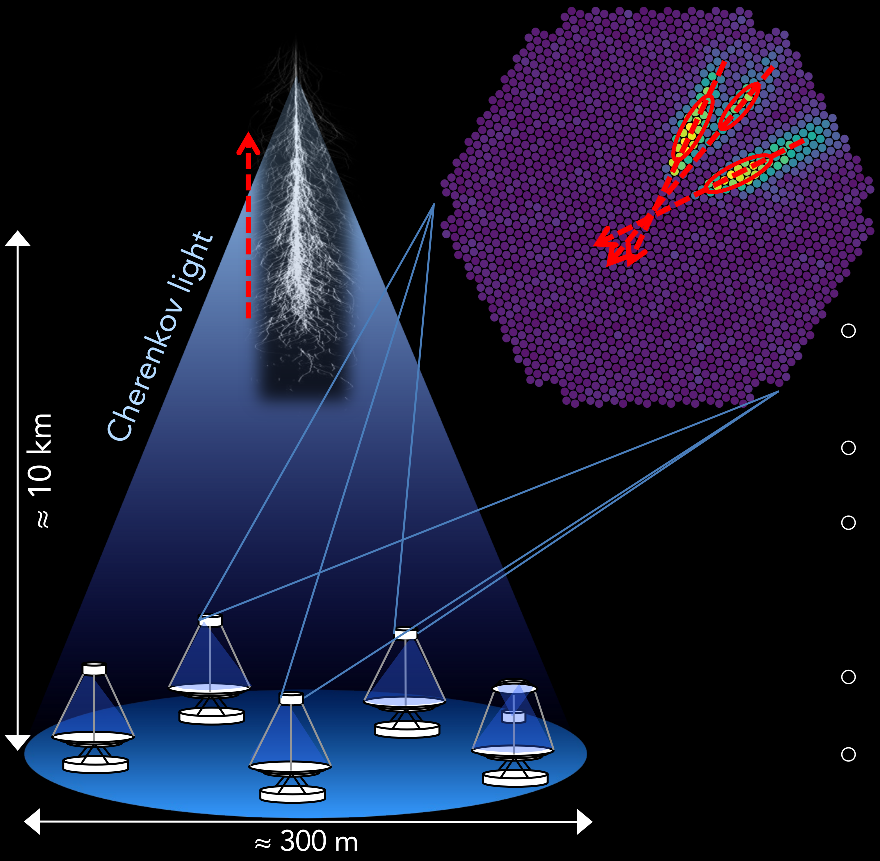


cs231n.github.io



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

Imaging atmospheric Cherenkov technique



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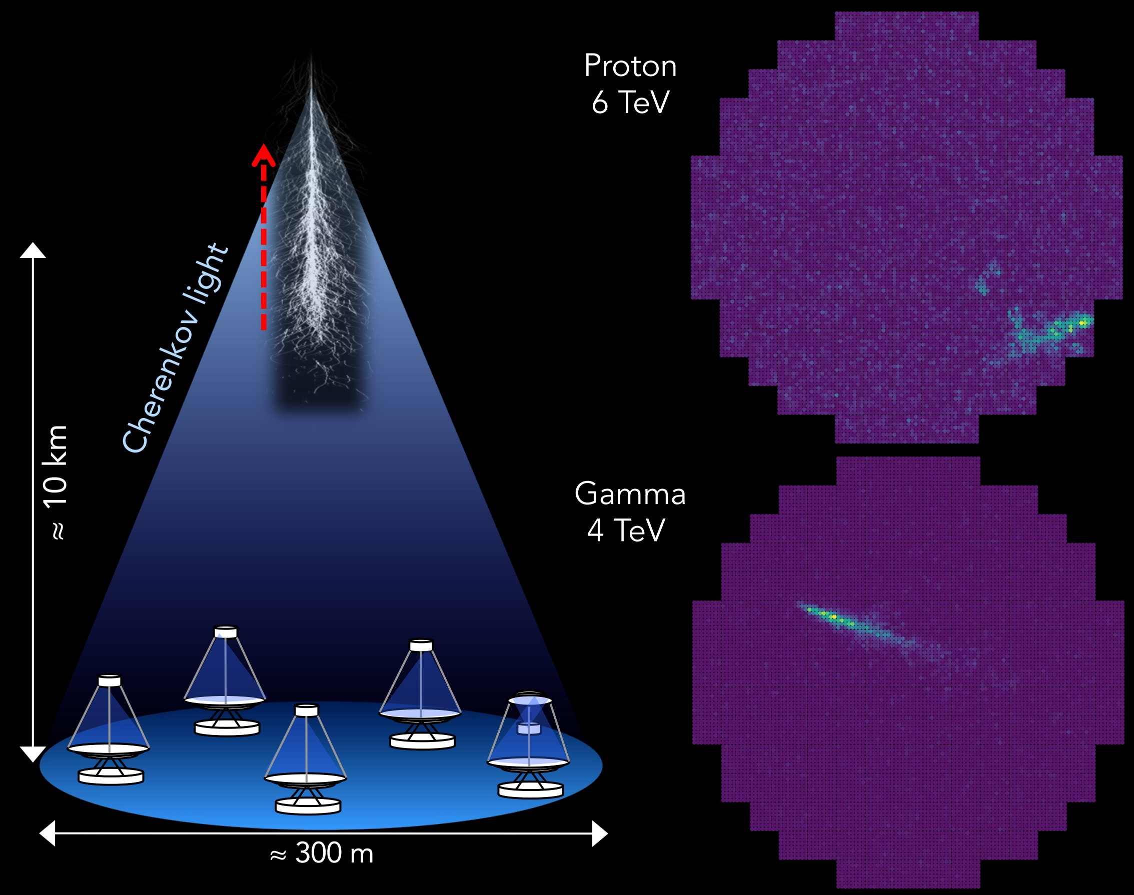
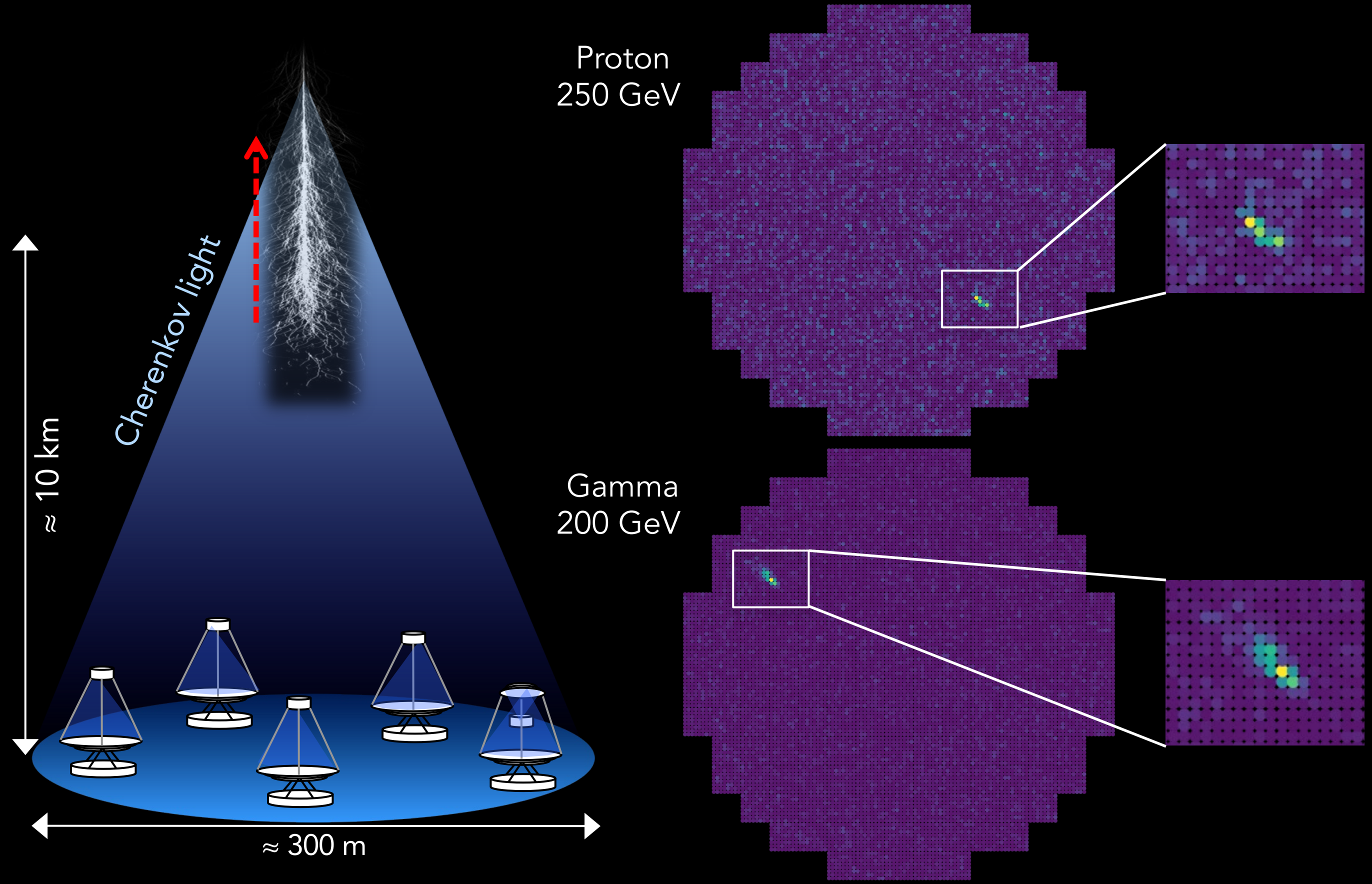
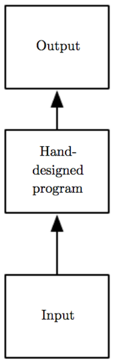

Cherenkov light
≈ 10 km
≈ 300 m
Proton
6 TeV
Gamma
4 TeV

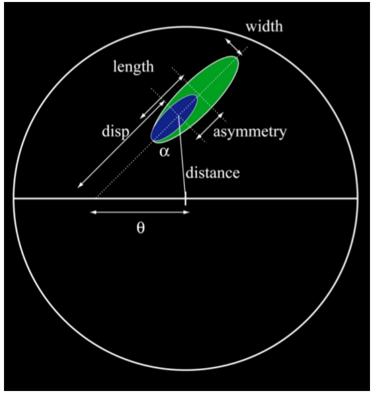

Cherenkov light
≈ 10 km
≈ 300 m
Proton
250 GeV
Gamma
200 GeV

Output: event type, energy, arrival direction

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



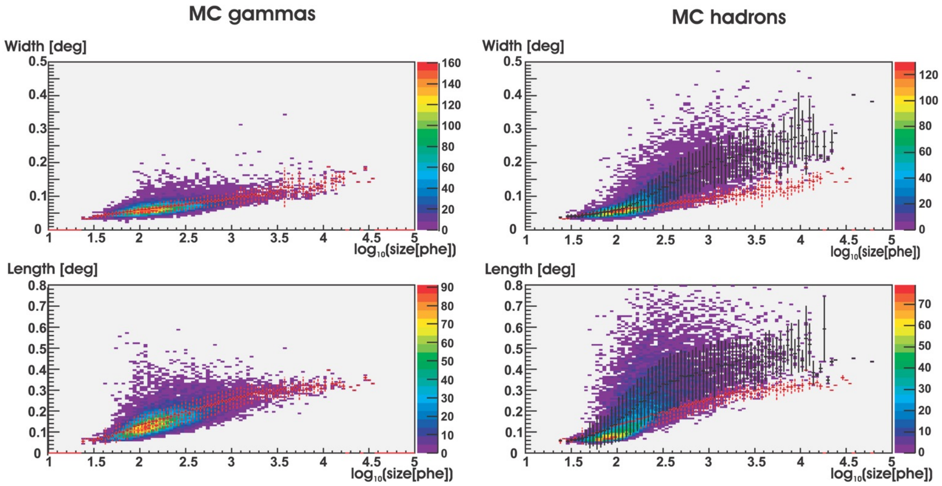
Rule-based systems



event reconstruction

Input: observed events

- Based on image parametrization (Hillas parameters)

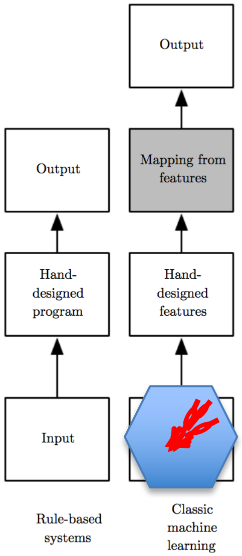


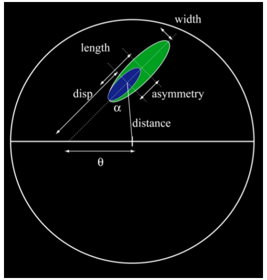
$$E = E(size, distance, h_{max})$$

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

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

Output: event type, energy, arrival direction





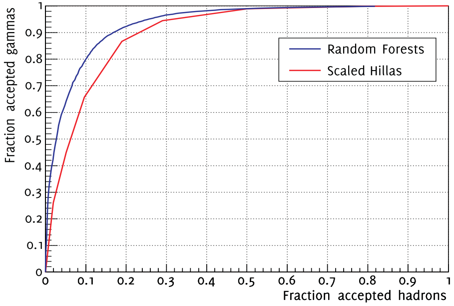
E.g.: RF & BDT

Input: observed events

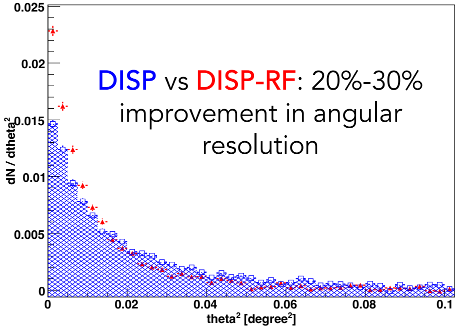
event reconstruction

- Current generation of IACTs: classic ML

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

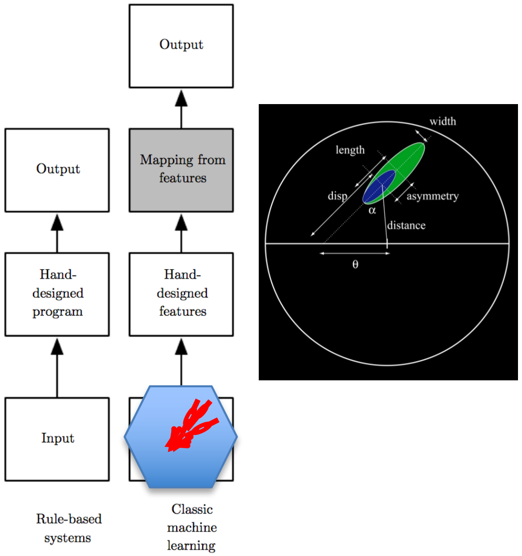


Albert et al., NIM-A 588:424-432 (2008)



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

Output: event type, energy, arrival direction



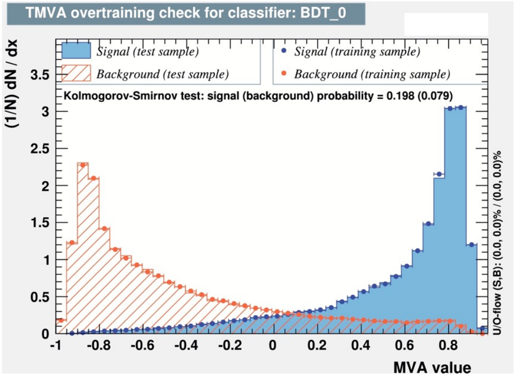
E.g.: RF & BDT

Input: observed events

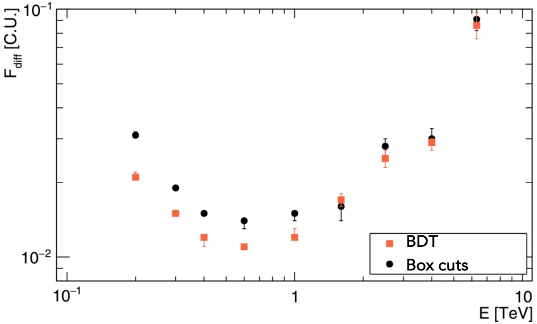
e v e n t r e c o n s t r u c t i o n

- Current generation of IACTs: classic ML

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

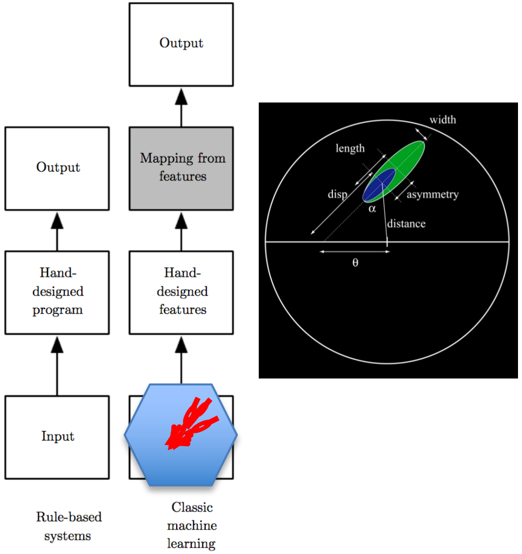


VERITAS diff. sensitivity



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

Output: event type, energy, arrival direction

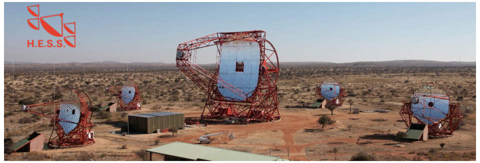


E.g.: RF & BDT

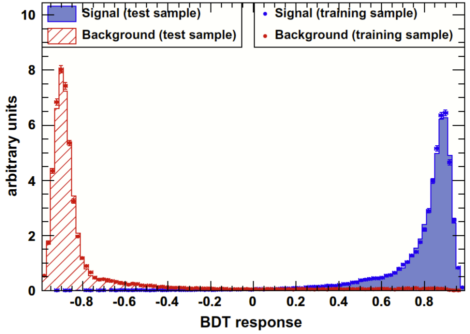
Input: observed events

event reconstruction

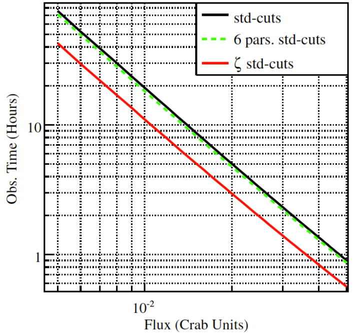
- Current generation of IACTs: classic ML



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



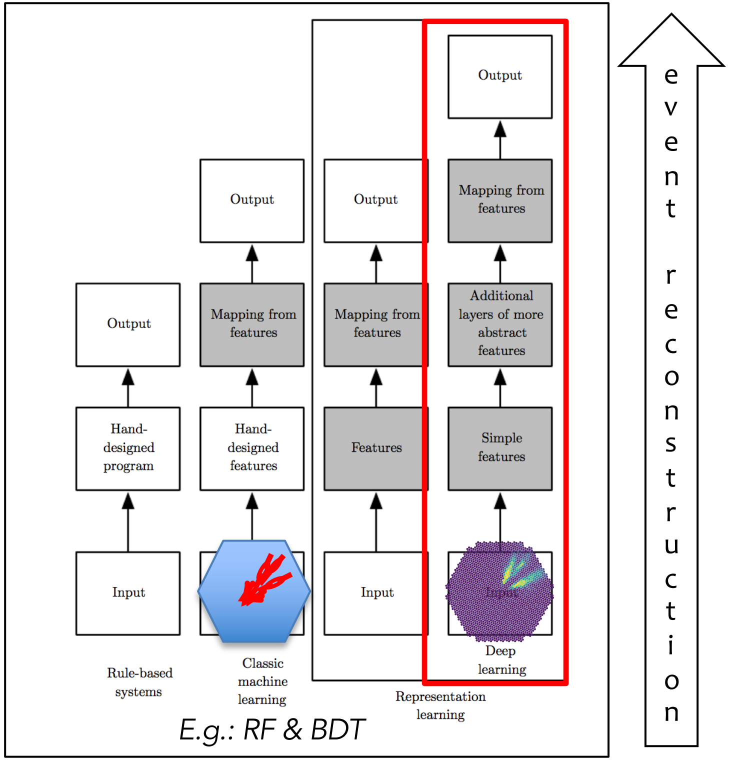
Becherini et al., APP V34-12 P858-870 (2011)



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

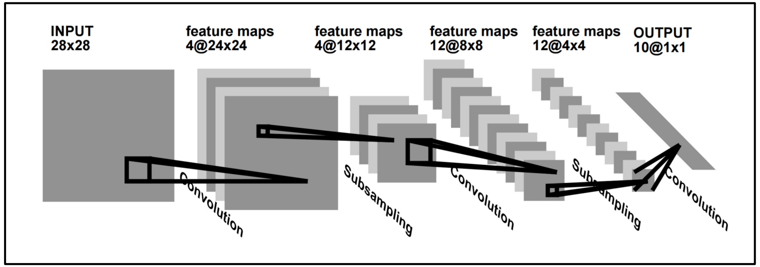
(Results for H.E.S.S. I only)

Output: event type, energy, incoming direction



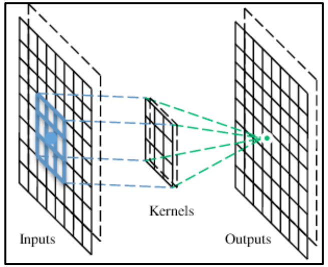
Input: observed events

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 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)

Next-generation IACT: The Cherenkov Telescope Array

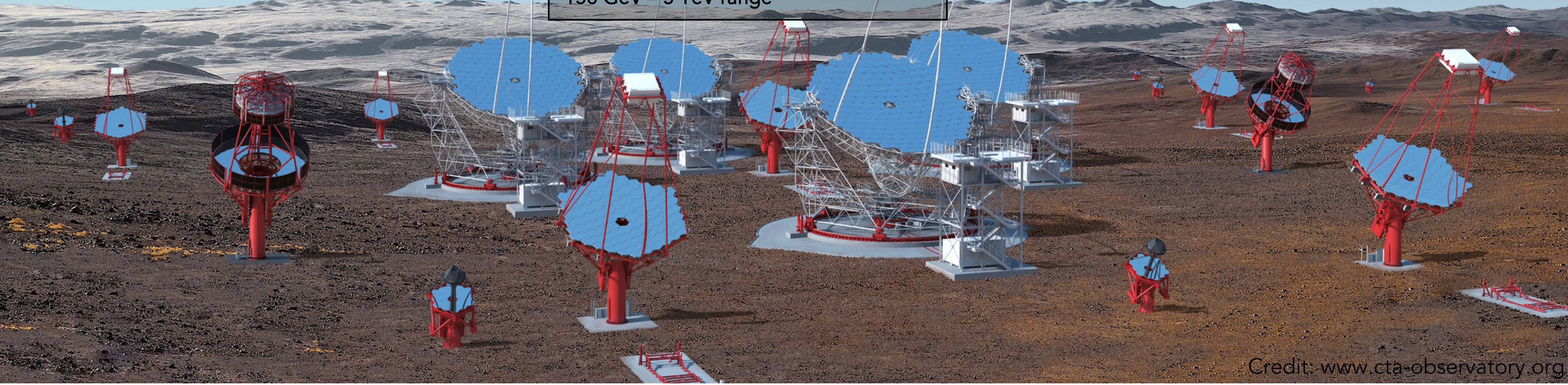
- 5-20 fold better sensitivity w.r.t. current IACTs
- 4 decades of energy coverage: 20 GeV to 300 TeV
- Improved angular and energy resolution
- Two arrays (North/South)

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



www.cta-observatory.org

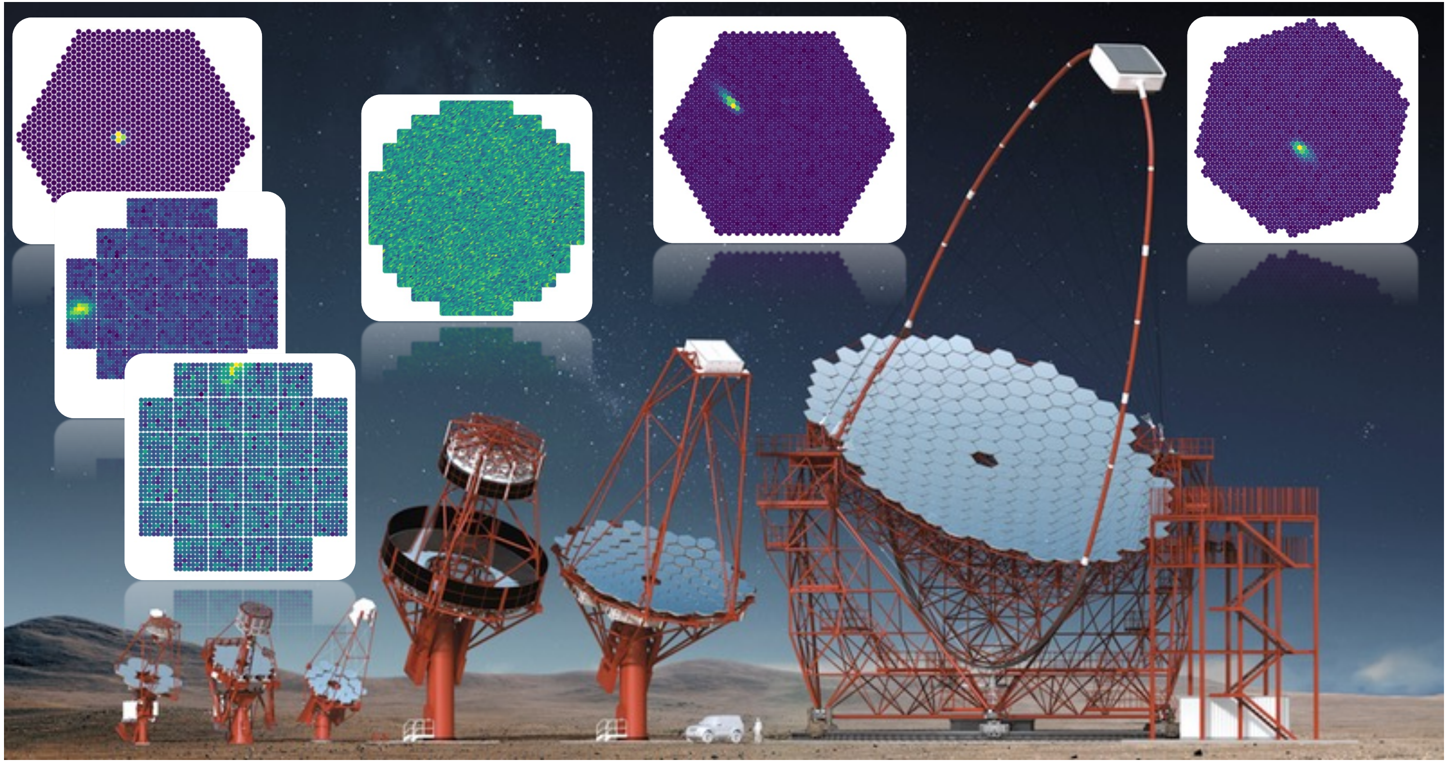
Science with CTA, arXiv:1709.07997

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

CREDIT: DESY/Milde Science Communication

- Heterogeneity of instruments:

Camera images courtesy of T. Vuillaume

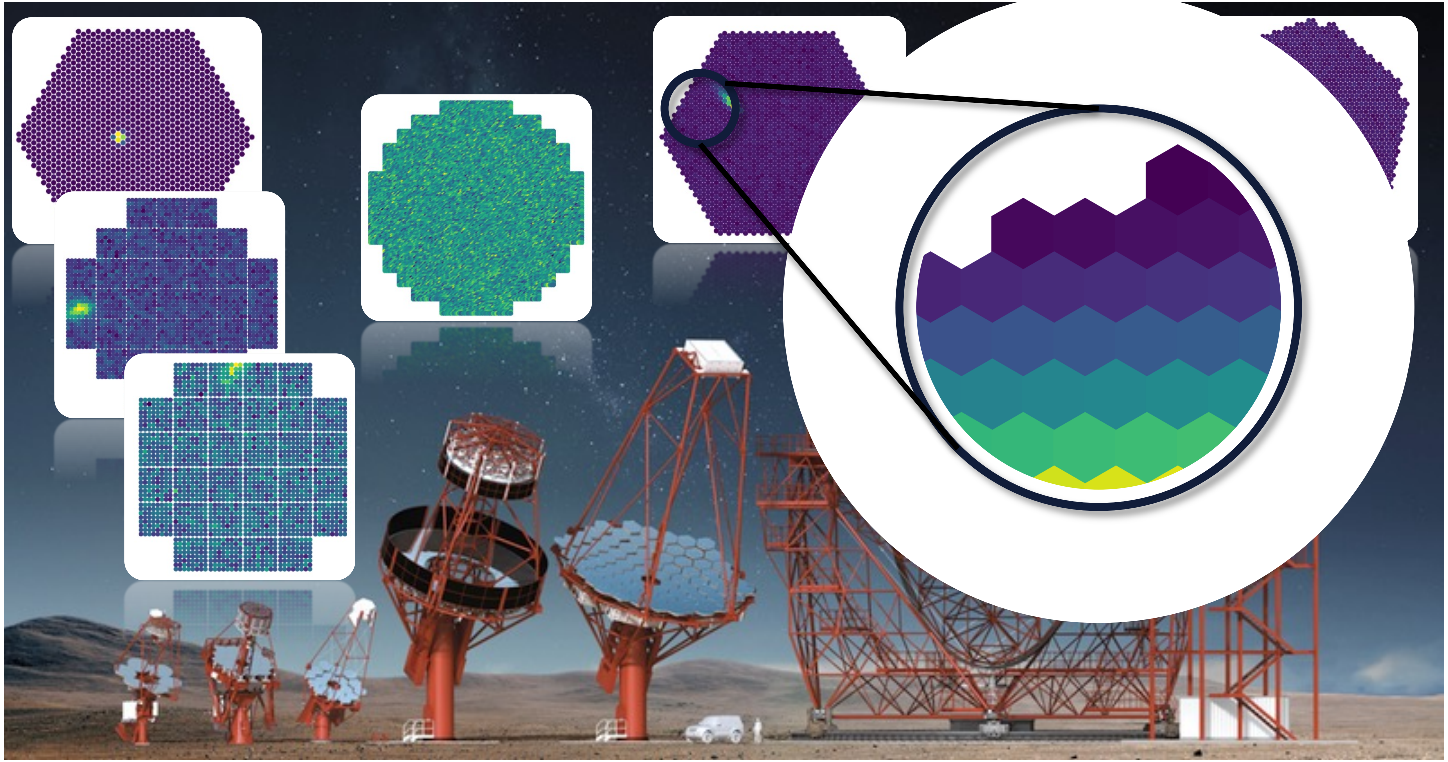


Challenges for deep learning & IACT data

- Heterogeneity of instruments:

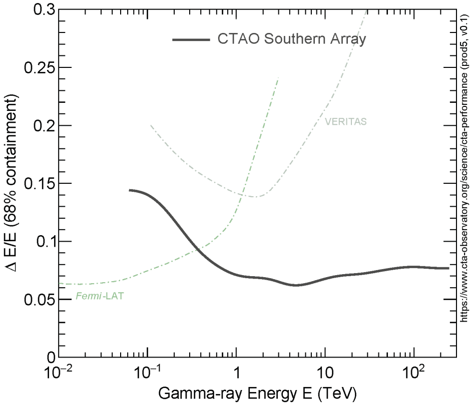
Hexagonal pixels

Camera images courtesy of T. Vuillaume

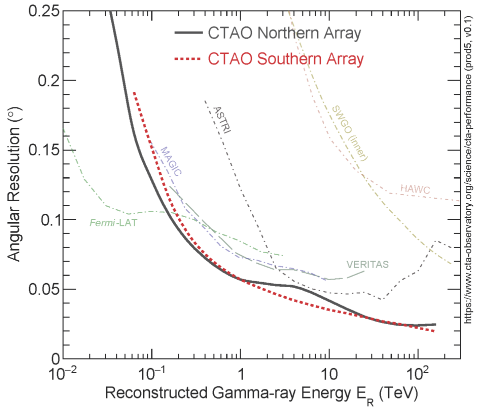


- Final metrics are far from trivial and entangled

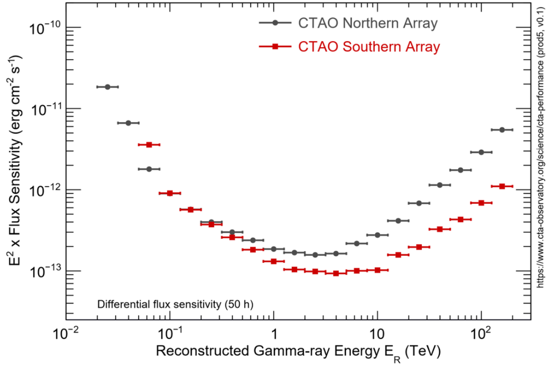
Energy resolution

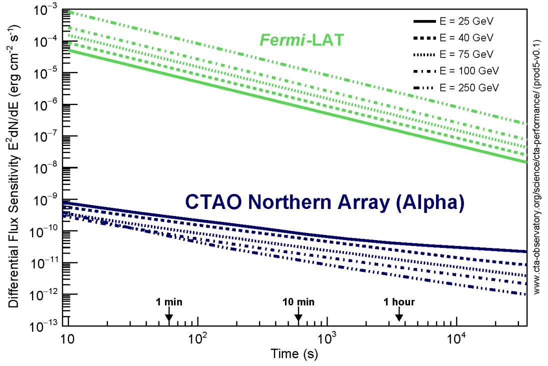


Angular resolution



Flux sensitivity

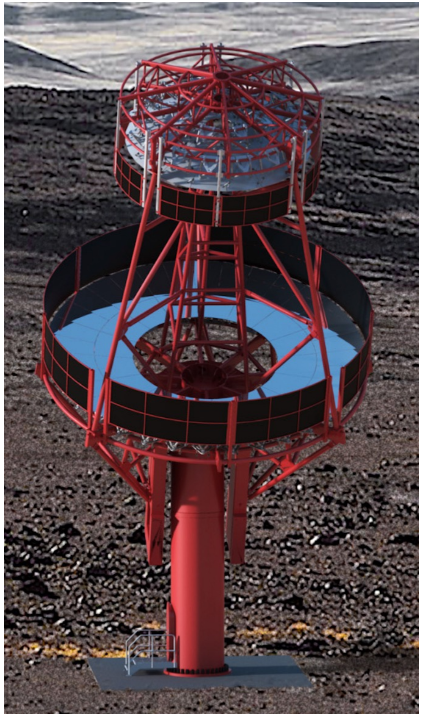




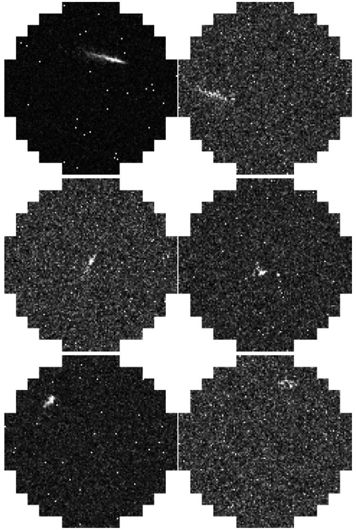
cherenkov telescope array
the observatory for ground-based gamma-ray astronomy

Credit: www.cta-observatory.org

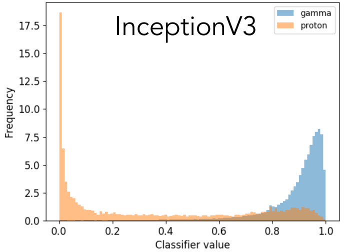
Proof of concept: gamma/hadron classification in SC-MST

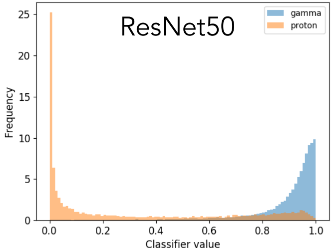


- Single telescope
- Square pixels
- Only signal charge (no timing)
- Single task: classification



Medium energies
(0.3 TeV < E < 1 TeV)





AUC

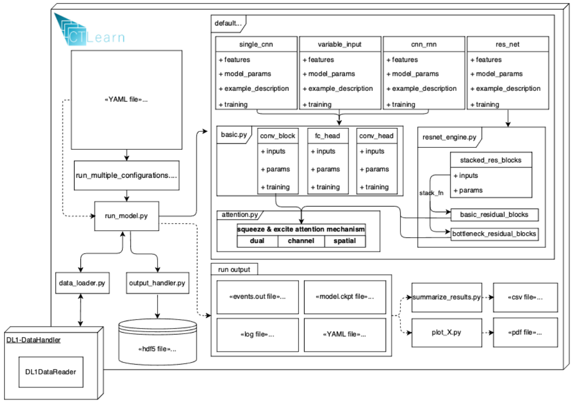
Model/Energy	Low E.	Med. E.	High E.
InceptionV3	84.7%	91.1%	92.0%
ResNet50	84.8%	91.4%	90.2%

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**)

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



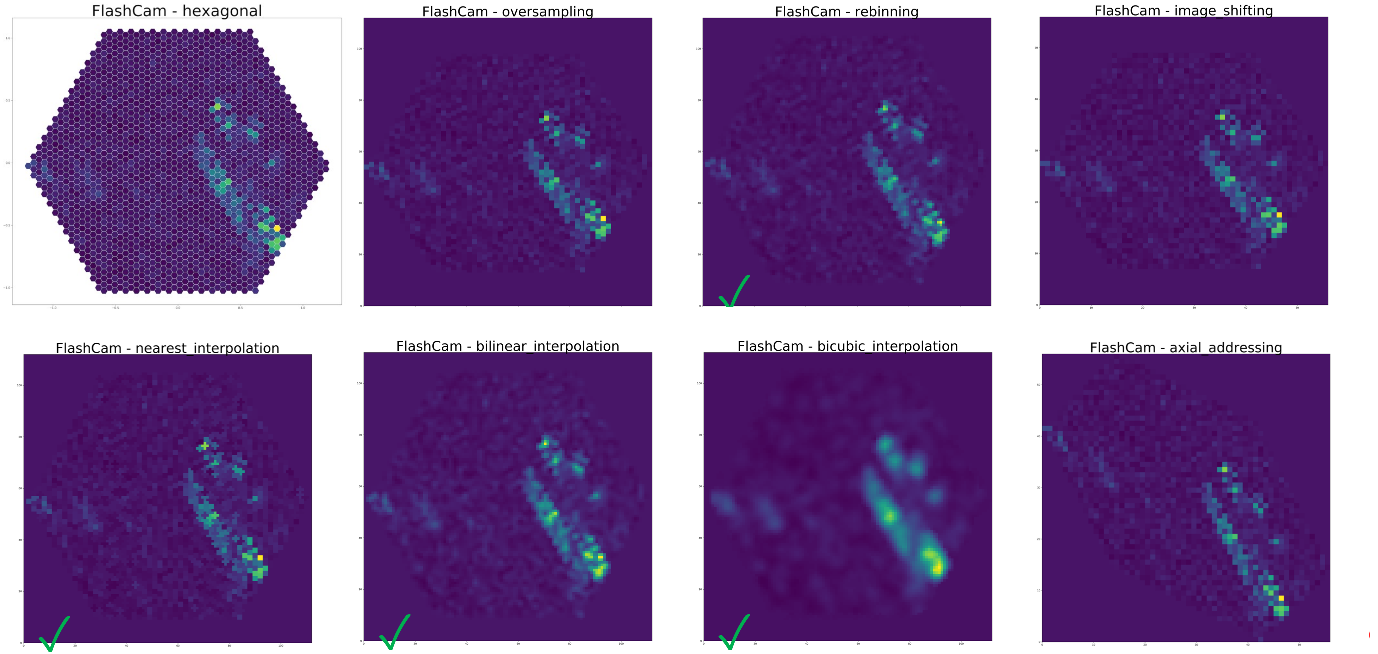
Tackling the hexagonal-pixel challenge

- Image mapping (preprocessing)

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

CTLearn

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

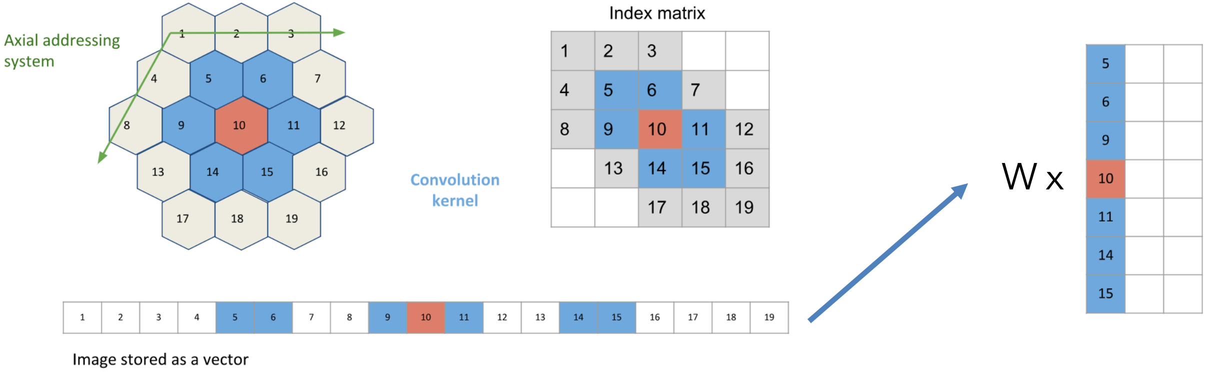


✓ Angles and distances preserved

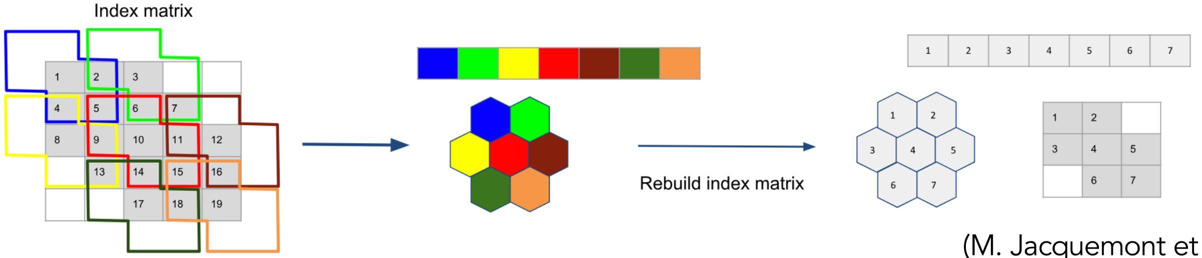
T. Vuillaume,
M. Jaquemont, et al.

https://github.com/IndexedConv

- Hexagonal convolution
  - Convolution

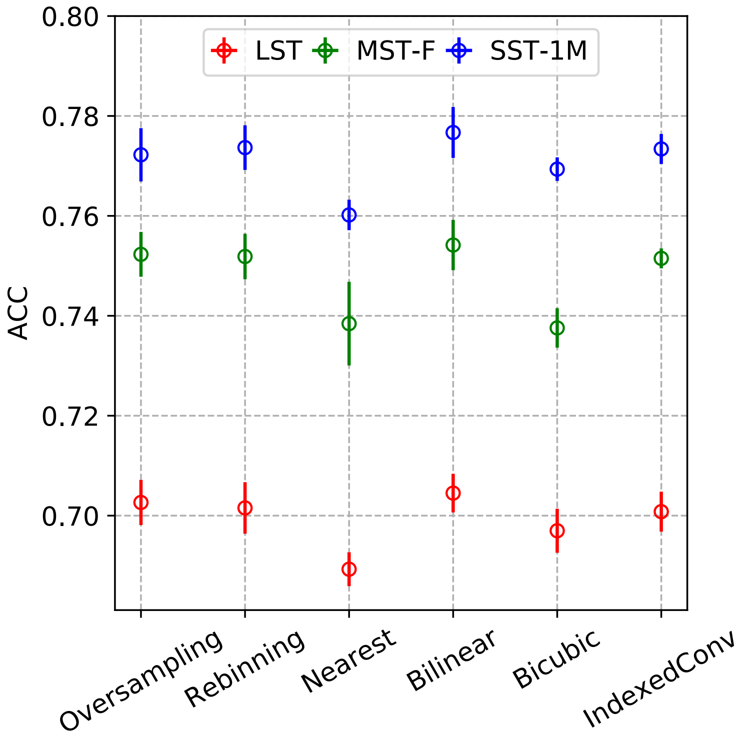


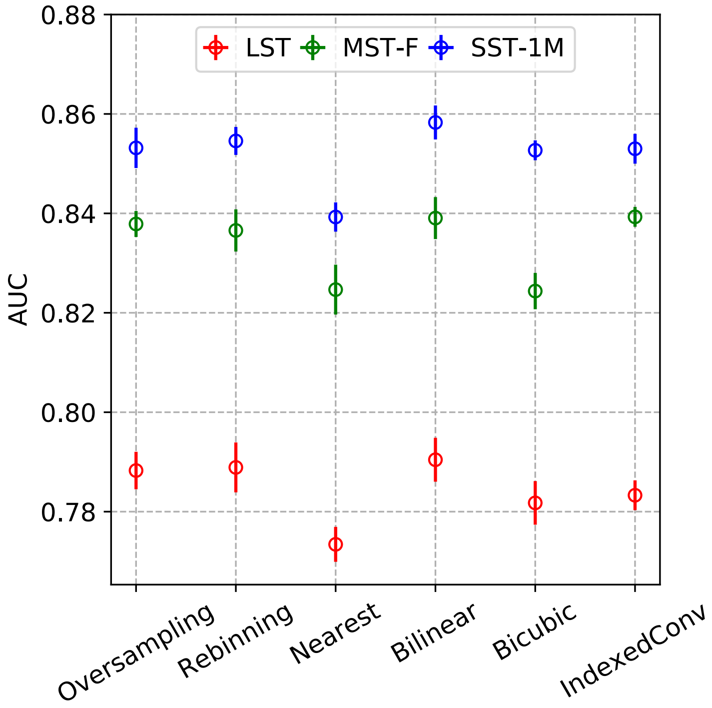
  - Pooling



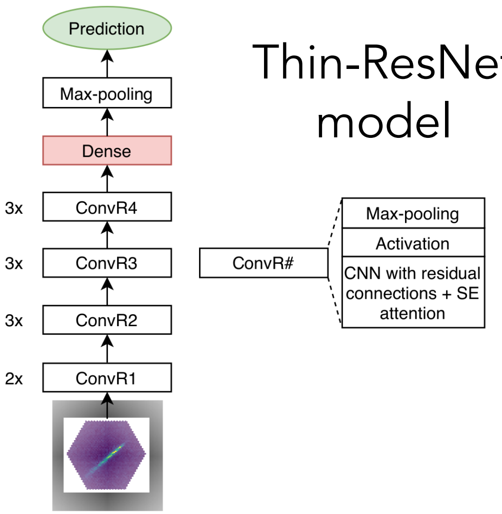
(M. Jacquemont et al. 2019)

- Comparison of methods for classification task

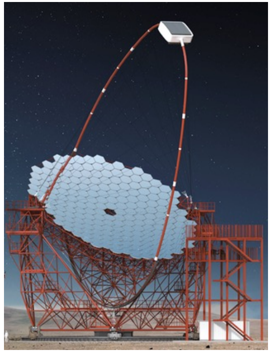




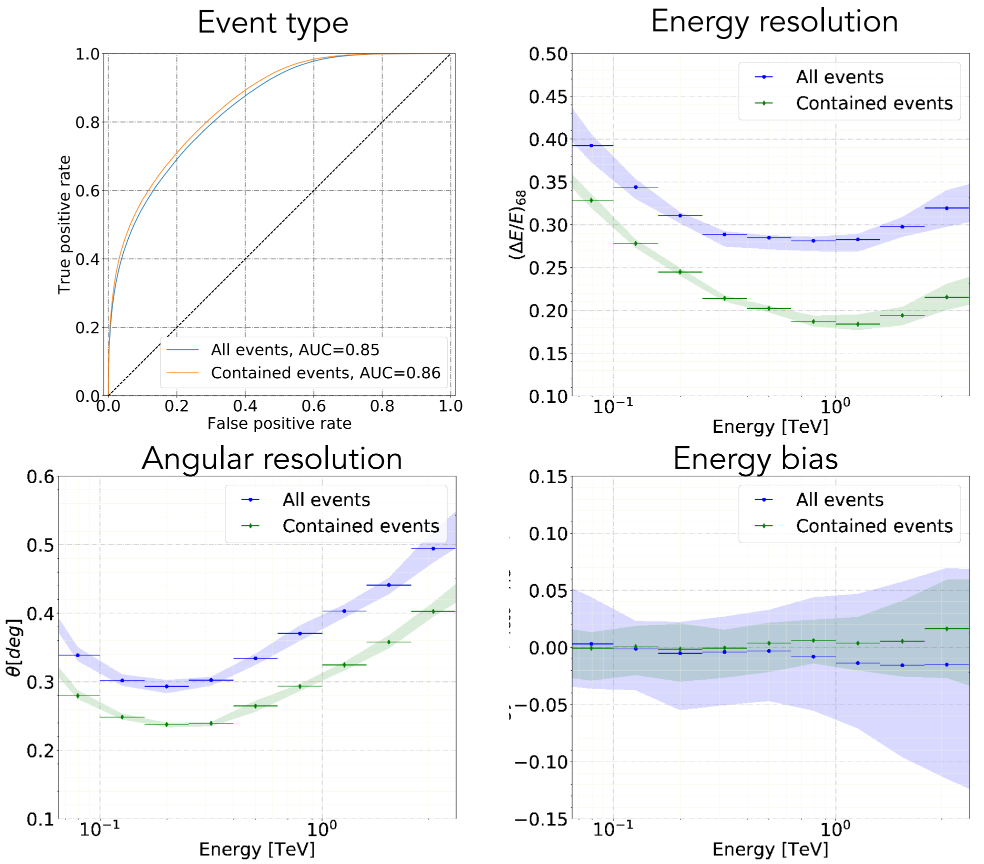
[D. Nieto et al. PoS(ICRC2019)753]



Thin-ResNet model



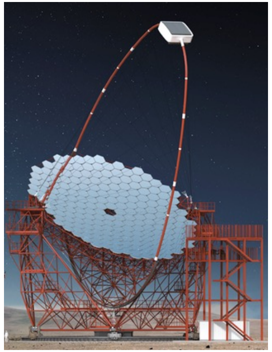
Full-event reconstruction for single-telescope data achieved!

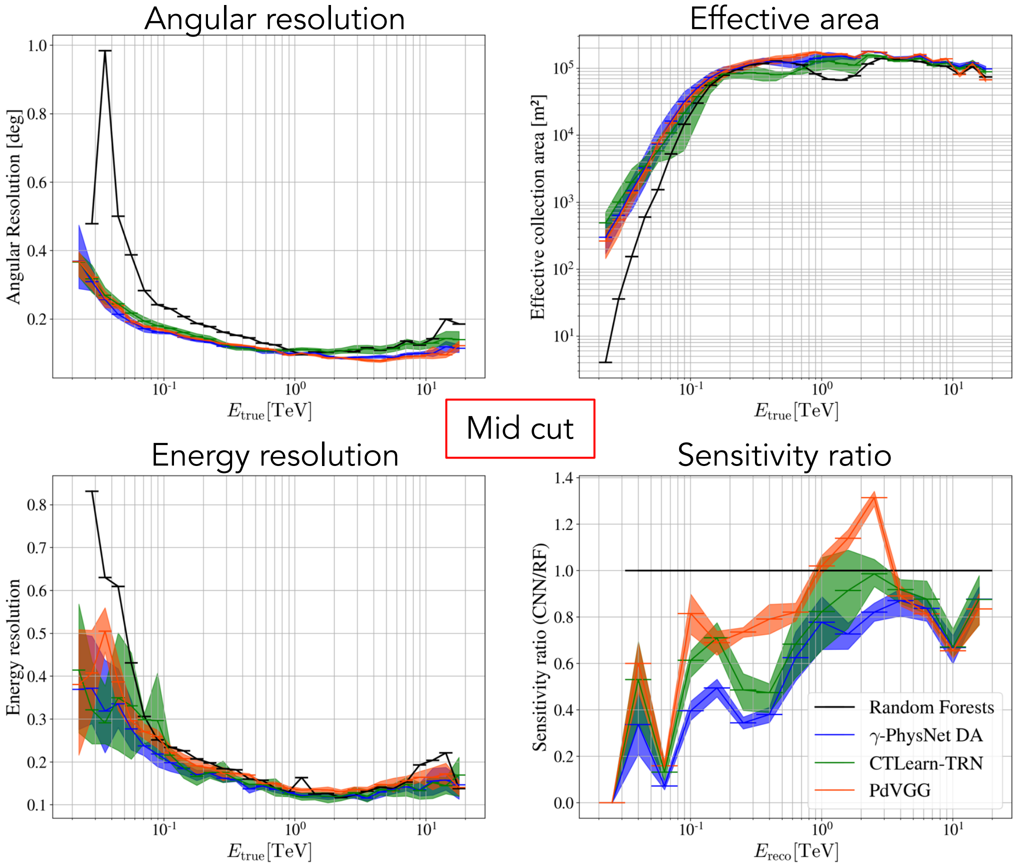


D. Nieto et al. ADASS XXX 2020

CTLearn: crosschecking results

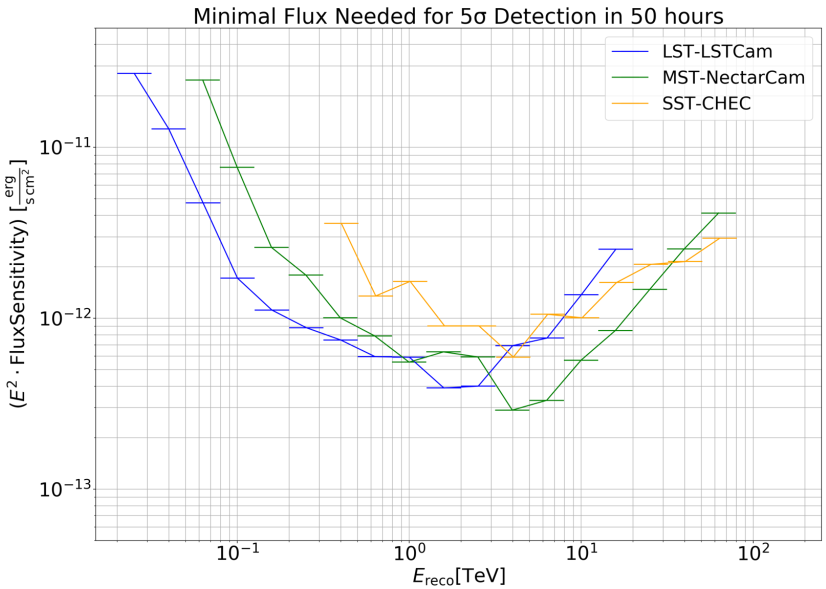
- Crosschecking three different implementations
- Same datasets, same cuts
- Different models
- Comparison against standard analysis (RF)

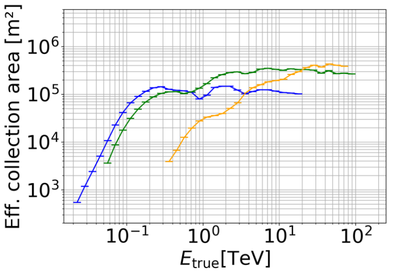


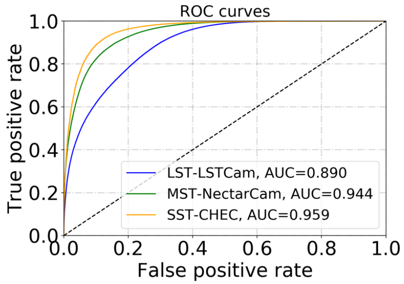


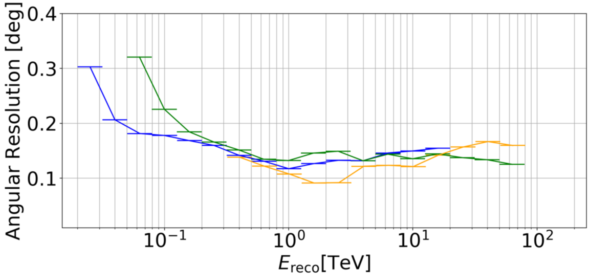
P. Grespan et al. PoS(ICRC2021) 771

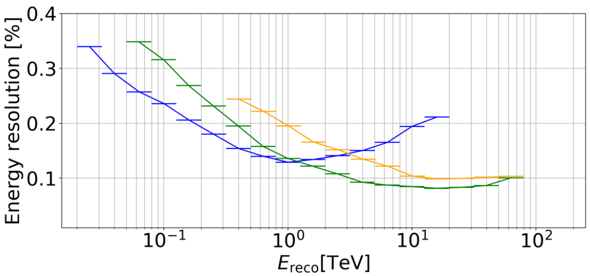
CTLearn: single-telescope full-event reconstruction

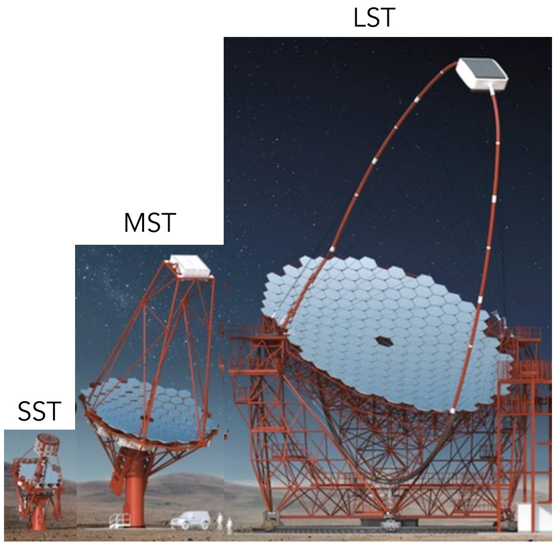






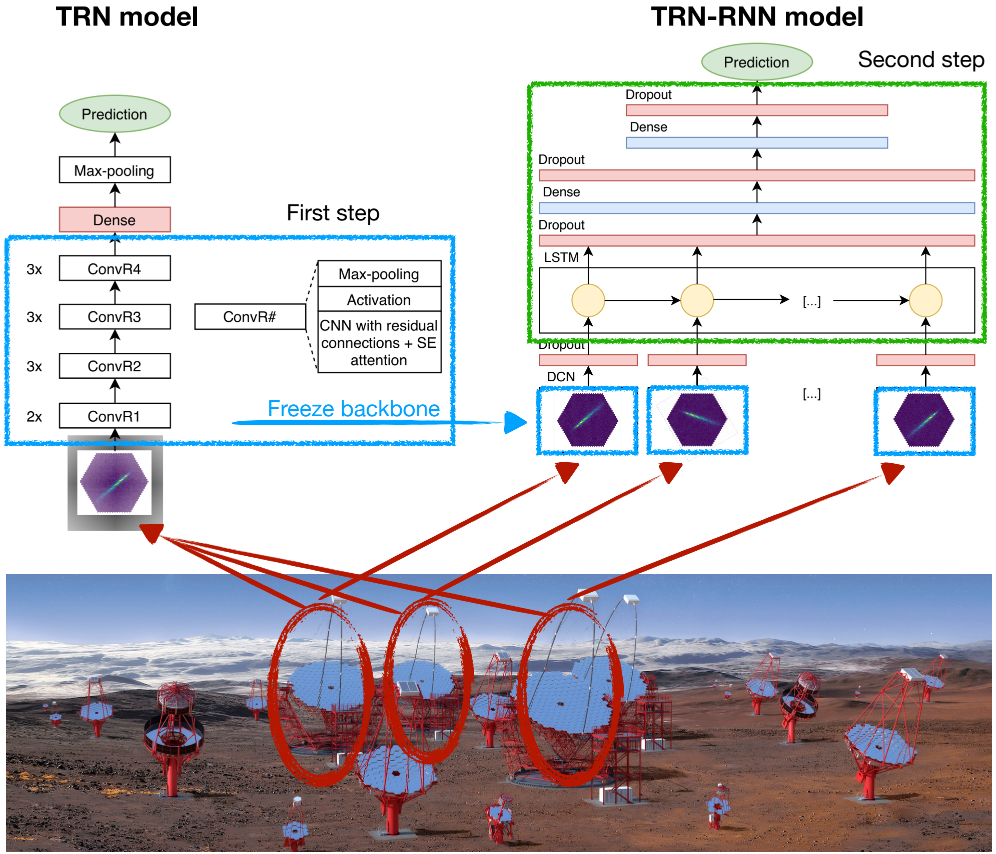






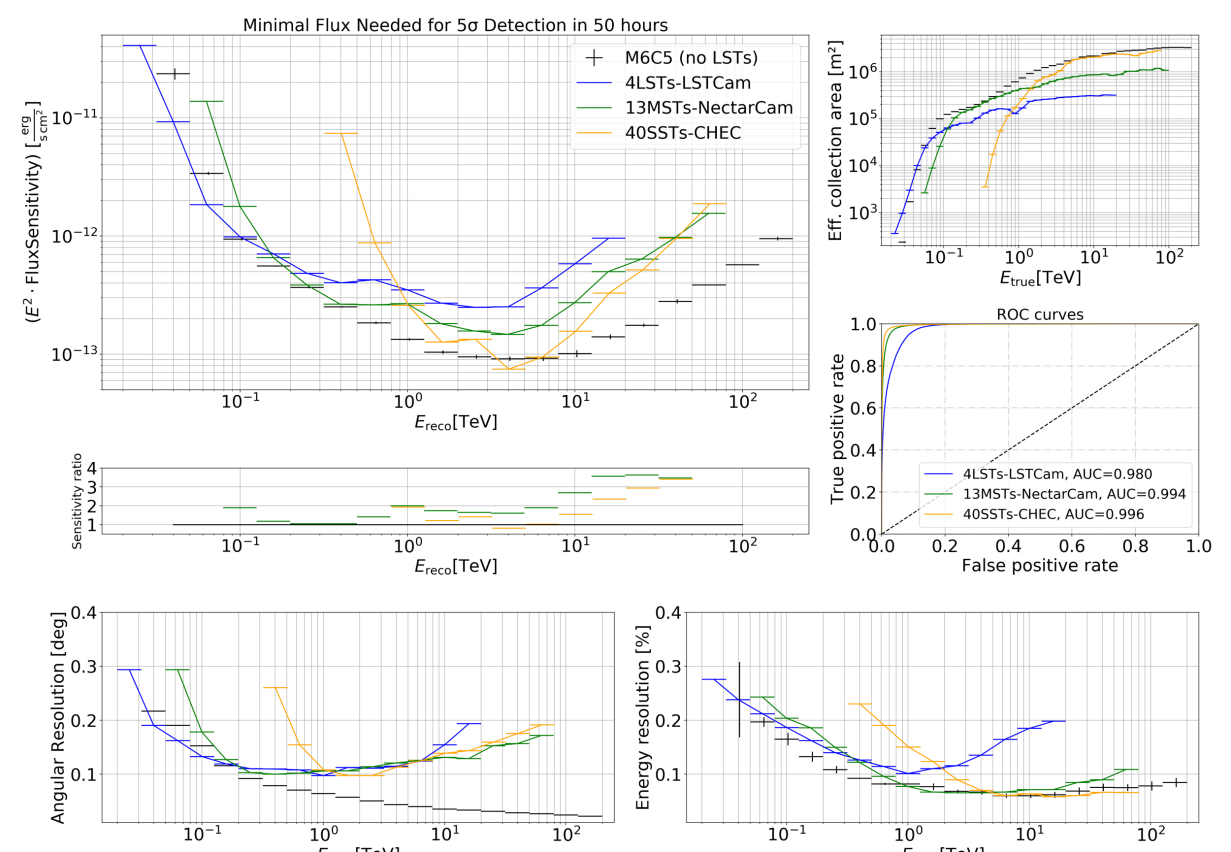
T. Miener et al., PoS(ICRC2021) 730

CTLearn: multiple-telescope full-event reconstruction

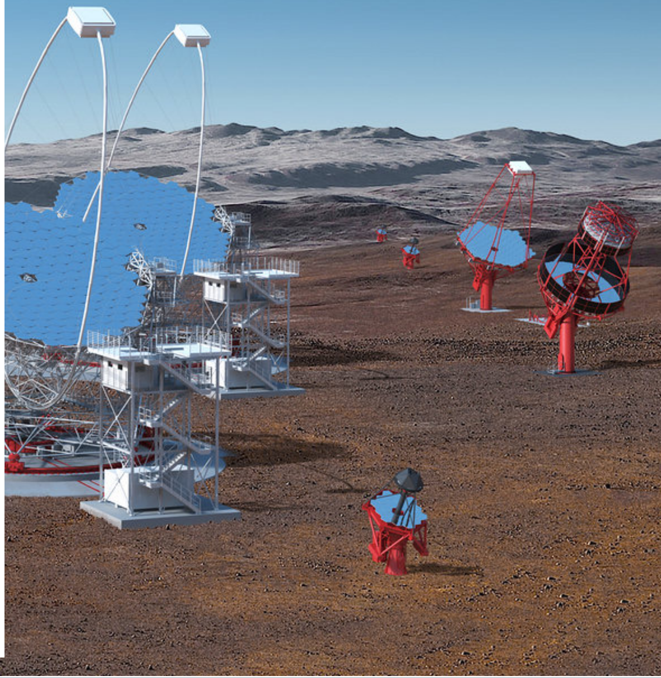


T. Miener et al., PoS(ICRC2021) 730

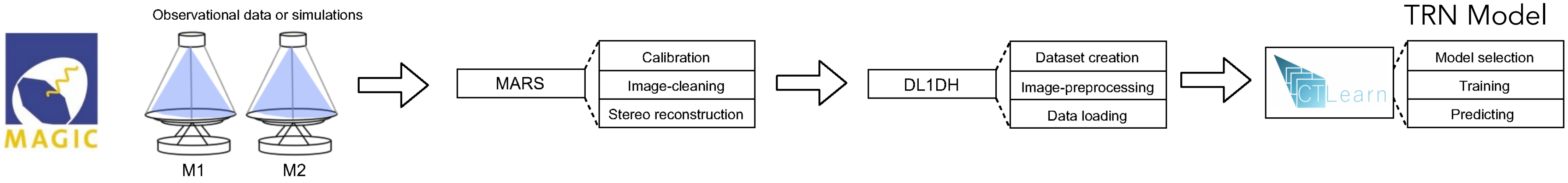
CTLearn: multiple-telescope full-event reconstruction



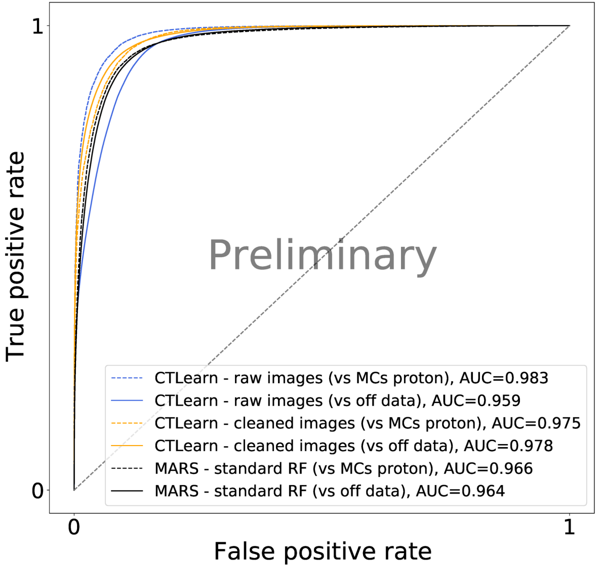
[T. Miener et al., PoS(ICRC2021) 730]



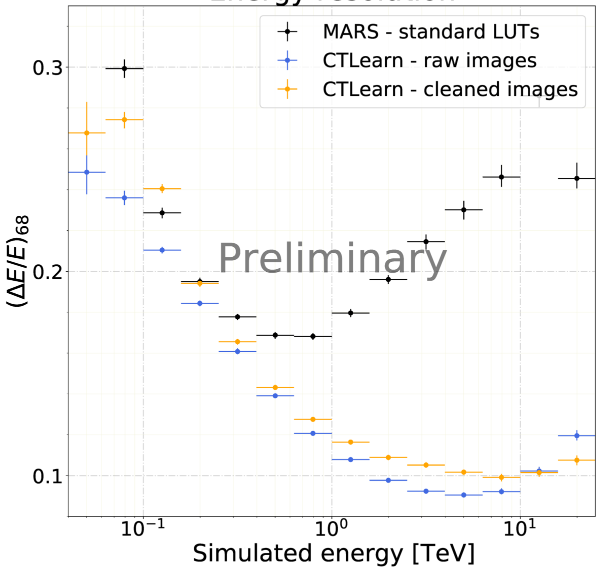
CTLearn: application to real data



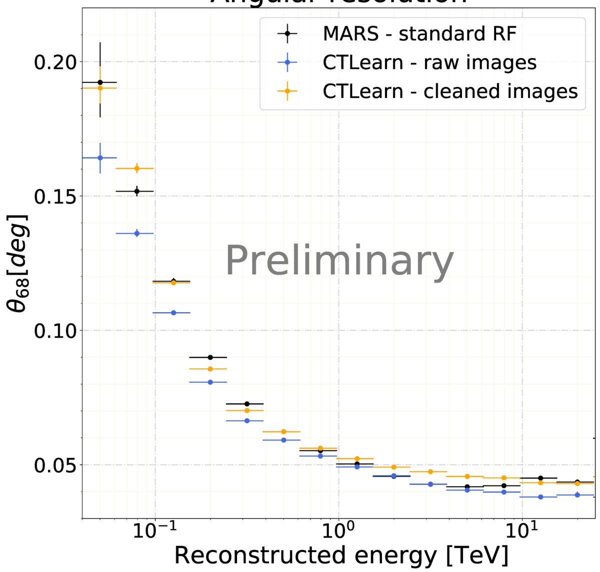
ROC curves



Energy resolution

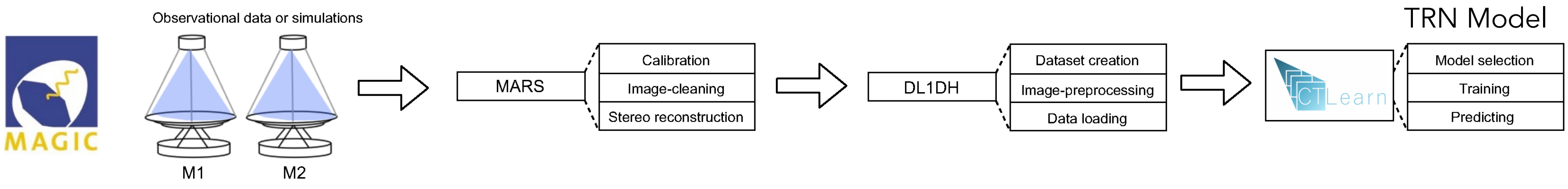


Angular resolution

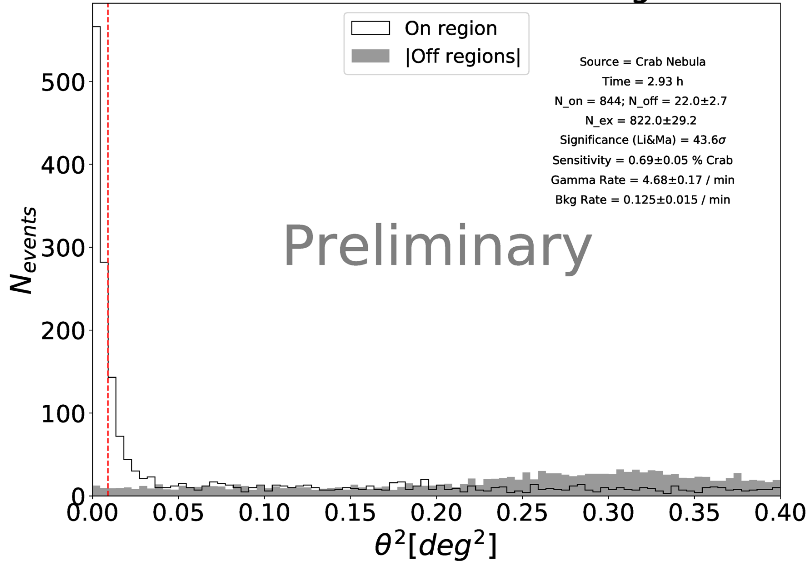


T. Miener et al. 2021 (ADASS XXXI)

CTLearn: application to real data



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

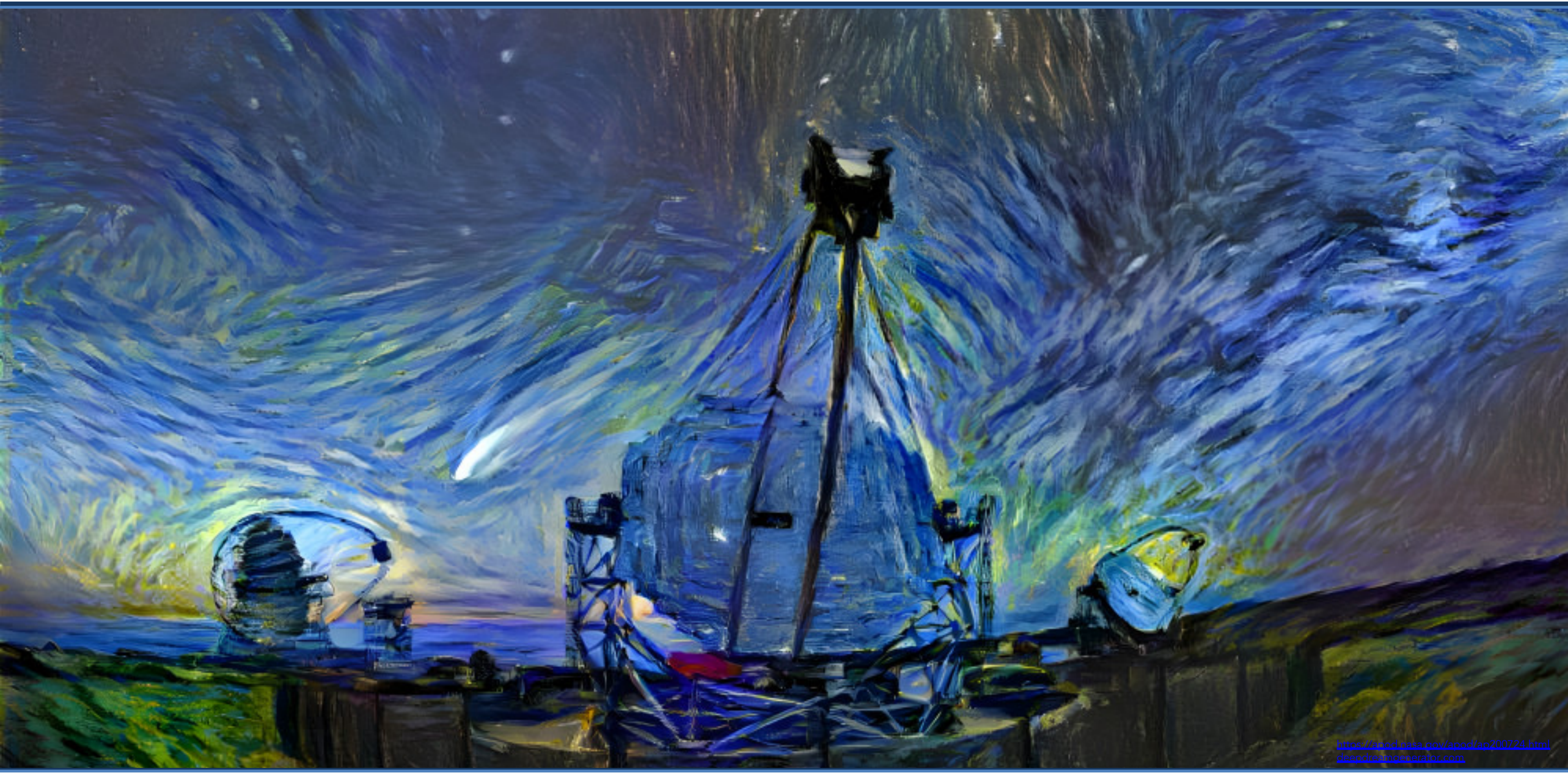
Summary of all performed analyses of the same Crab Nebula sample

T. Miener et al. 2021 (ADASS XXXI)

Dreaming of IACTs

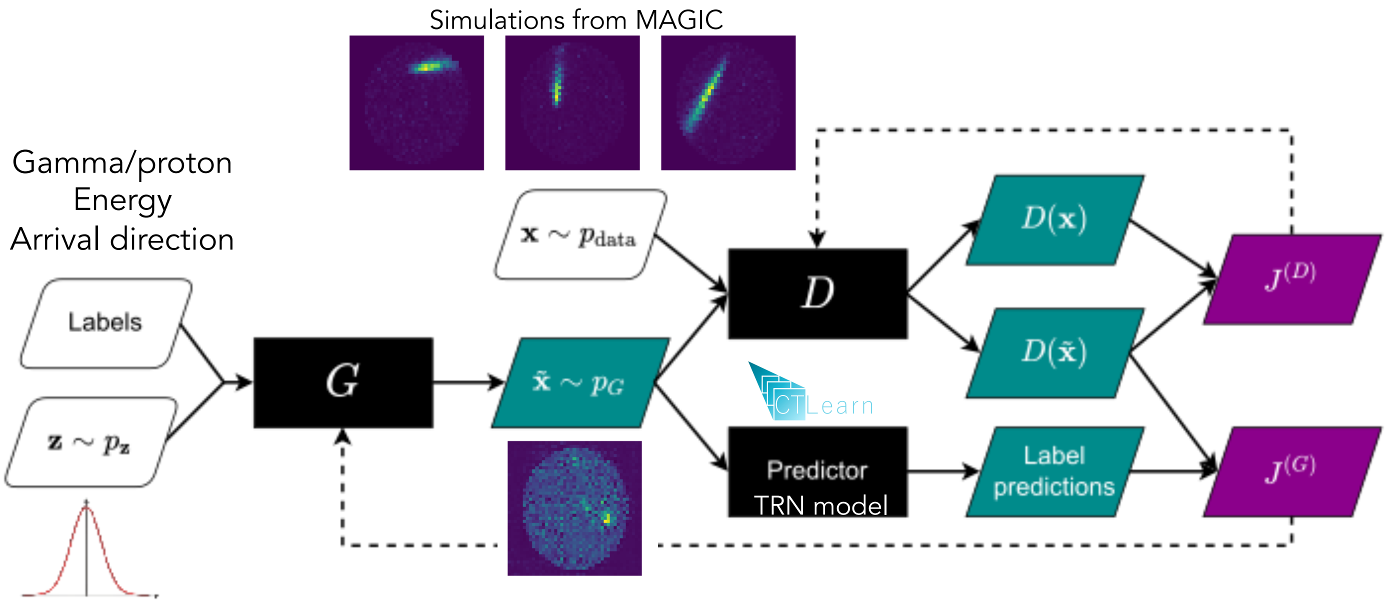
https://apod.nasa.gov/apod/ap200724.html

Dreaming of IACTs



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

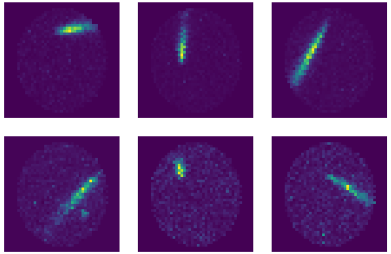
- Auxiliary conditional generative adversarial networks (AC-GANs)



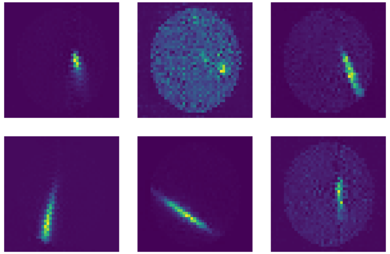
S. García-Heredia et al.

GAMMA RAYS

Simulated

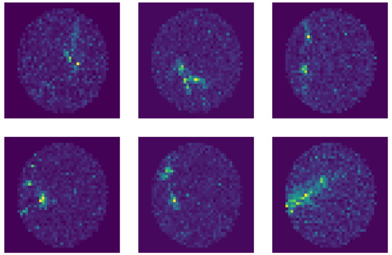


Generated



PROTONS

Simulated



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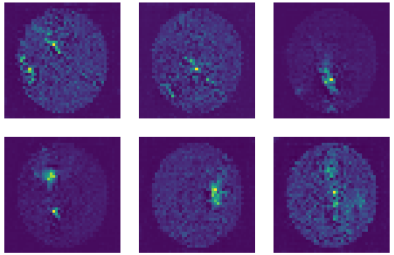
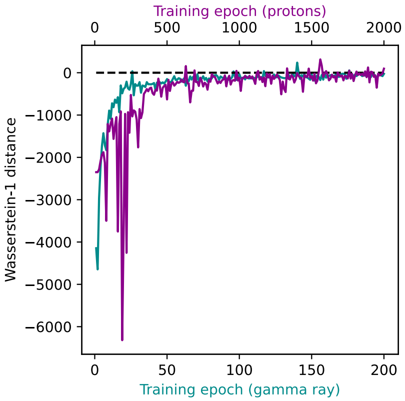
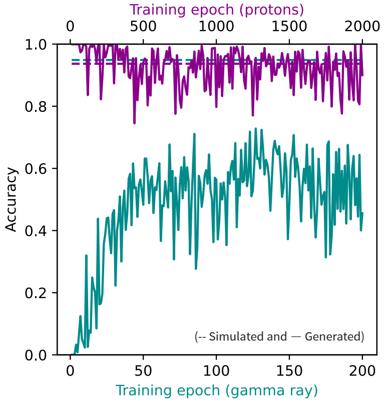
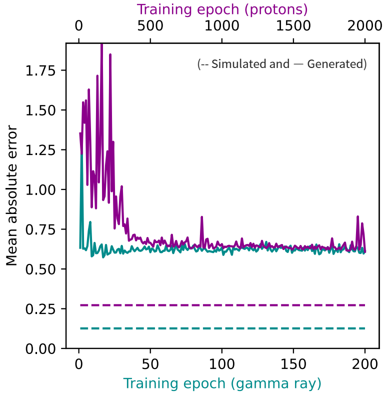
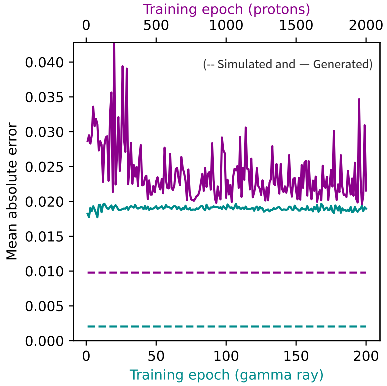


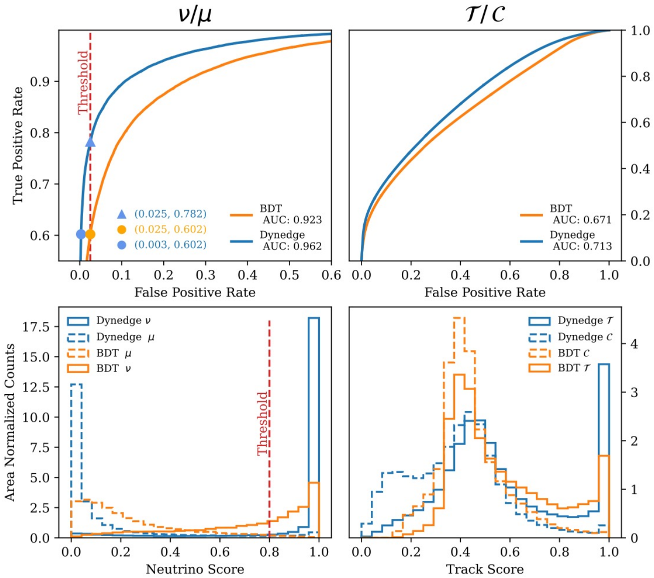






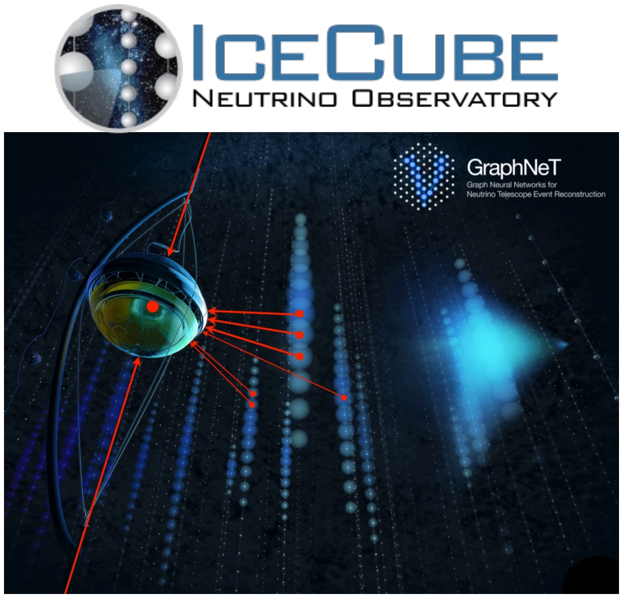


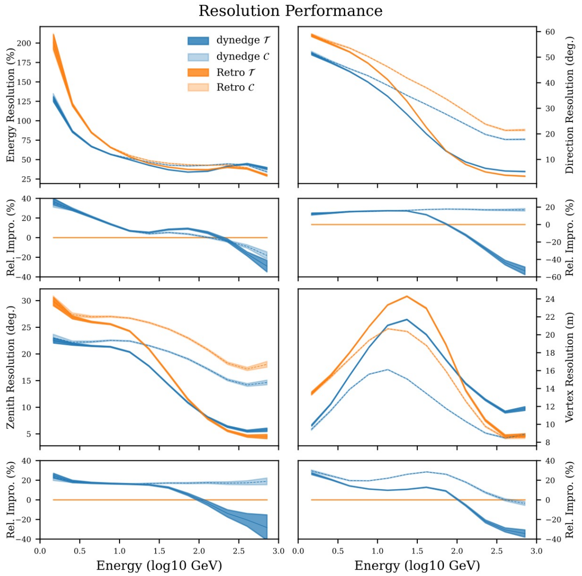
S. García-Heredia et al.



Neutrino vs muon

Track vs cascade

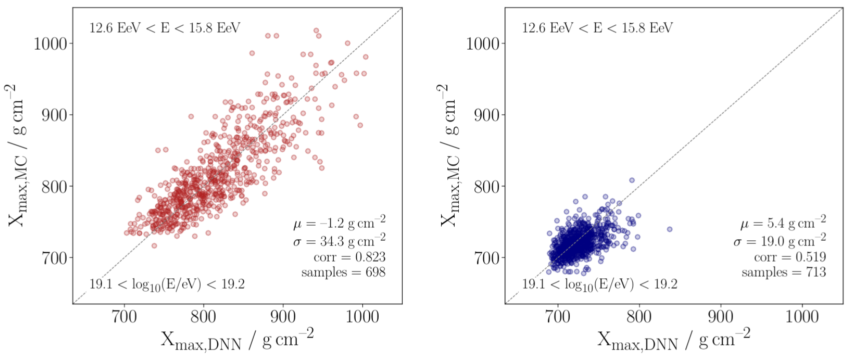




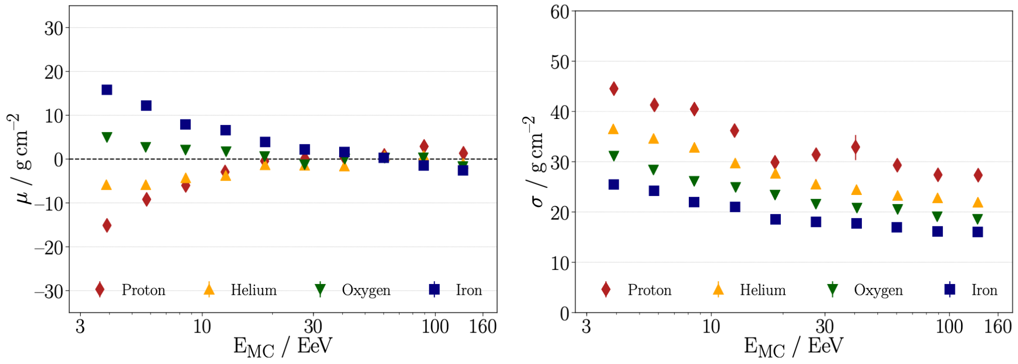
- Graph Neural Networks for low-energy events
- Classification: signal/bkg, neutrino types
- Signal eff. +18%, bkg suppression /8
- Energy, arrival direction ~20% improv
- Processing rate 2x IceCube trigger rate (GPU)

[*JINST* 17 P11003 (2022)]

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



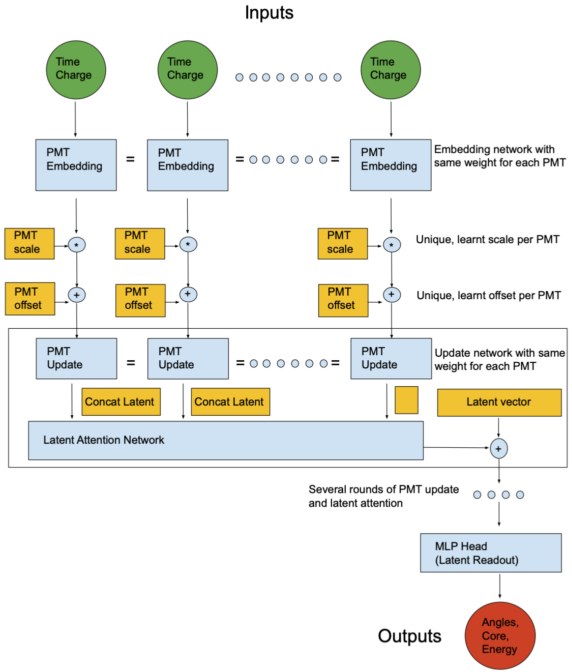
(a) Proton (b) Iron

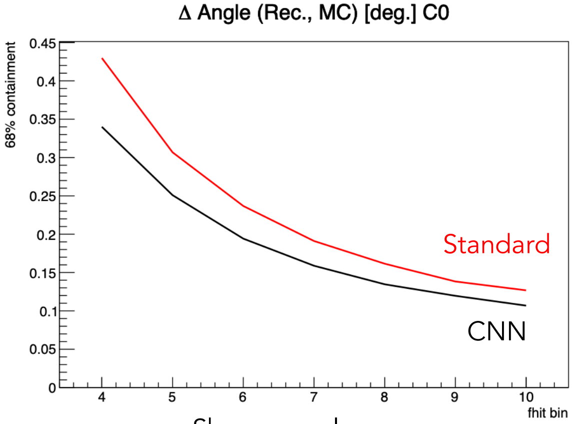


(a) X_{max} reconstruction bias (b) X_{max} resolution

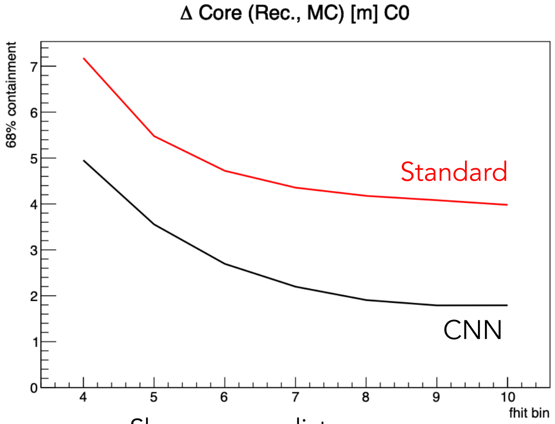
[JINST 16 P07019 (2021)]

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





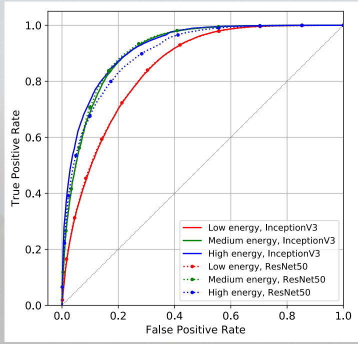
Shower angle reco.

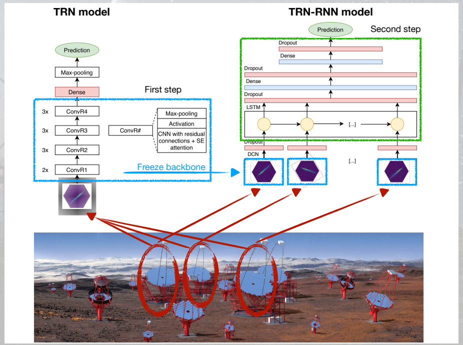


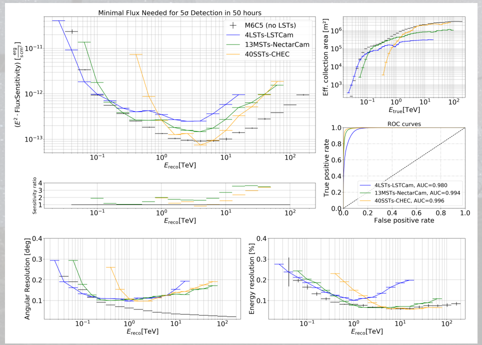
Shower core distance reco.

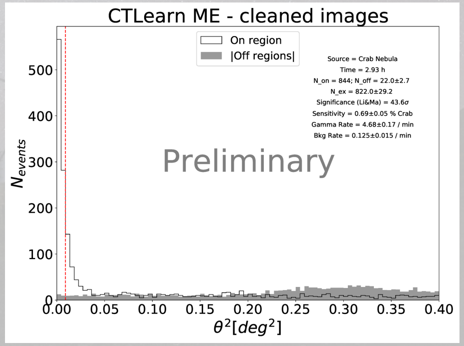
[PoS ICRC (2023) 297]

- 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









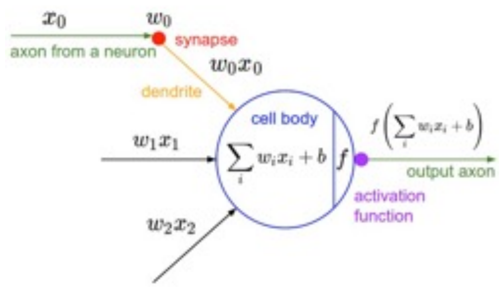
Acknowledgment

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.

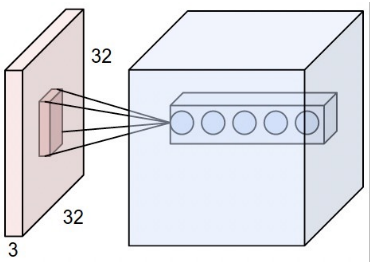
Backup


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

Deep Convolutional Neural Networks

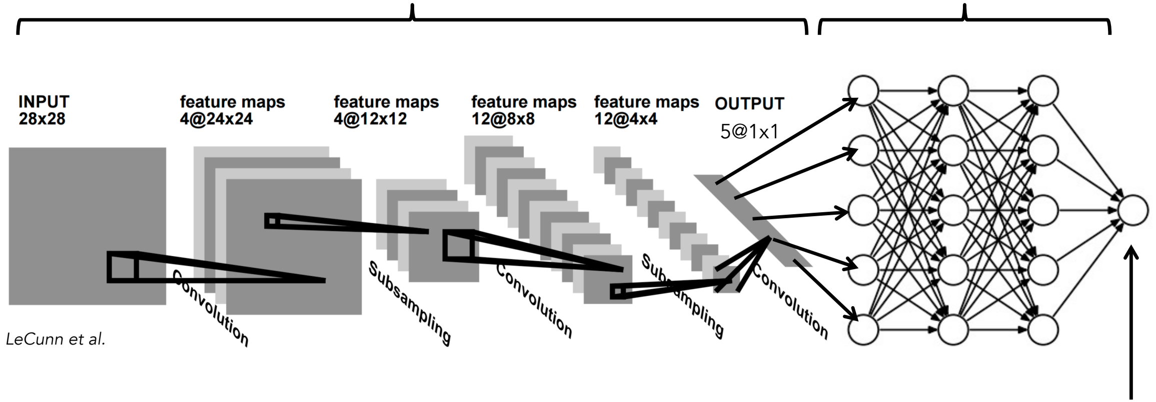


Convolution



Convolution+Activation+Pooling

Fully connected (dense) network

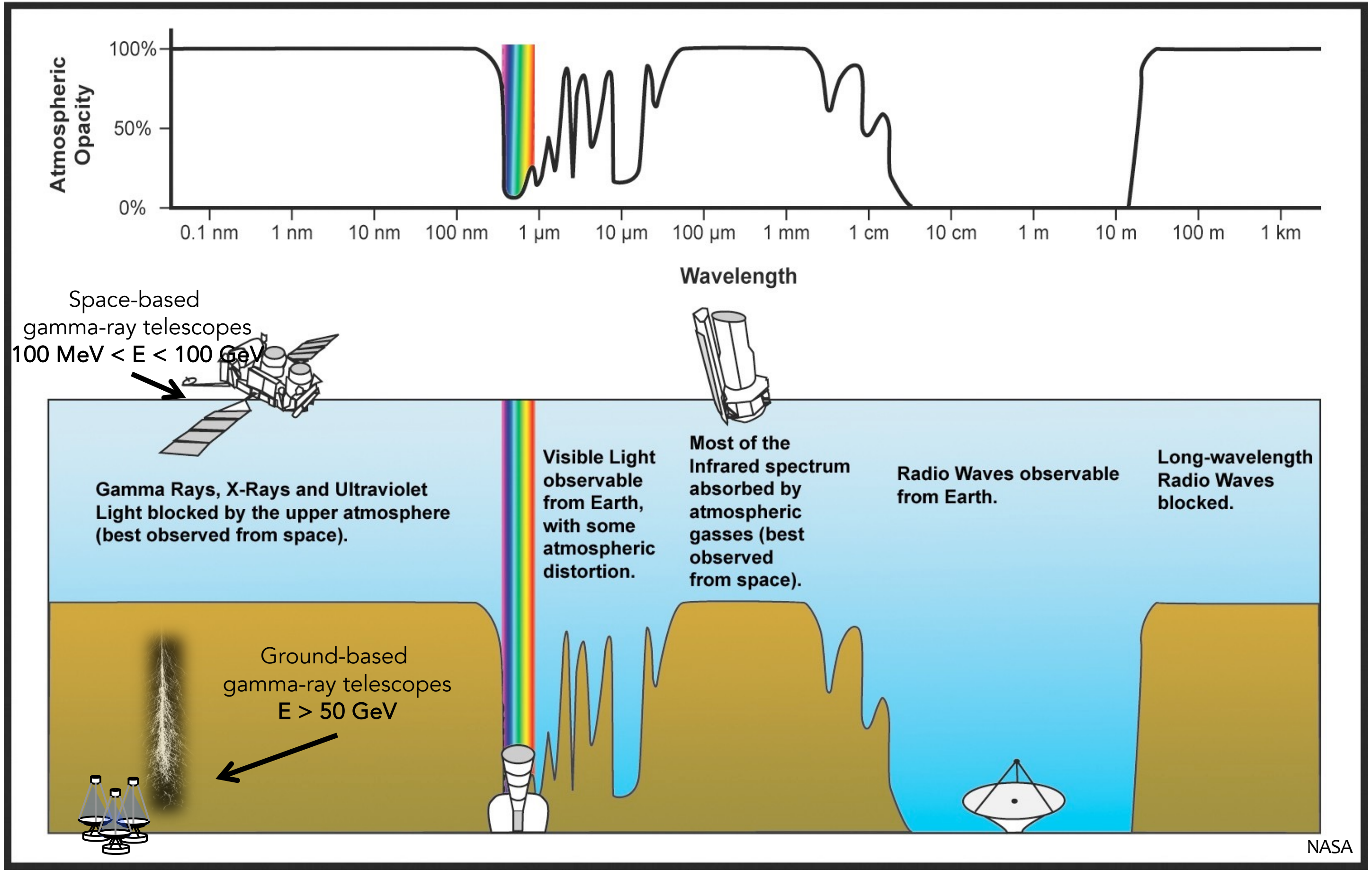


Final output

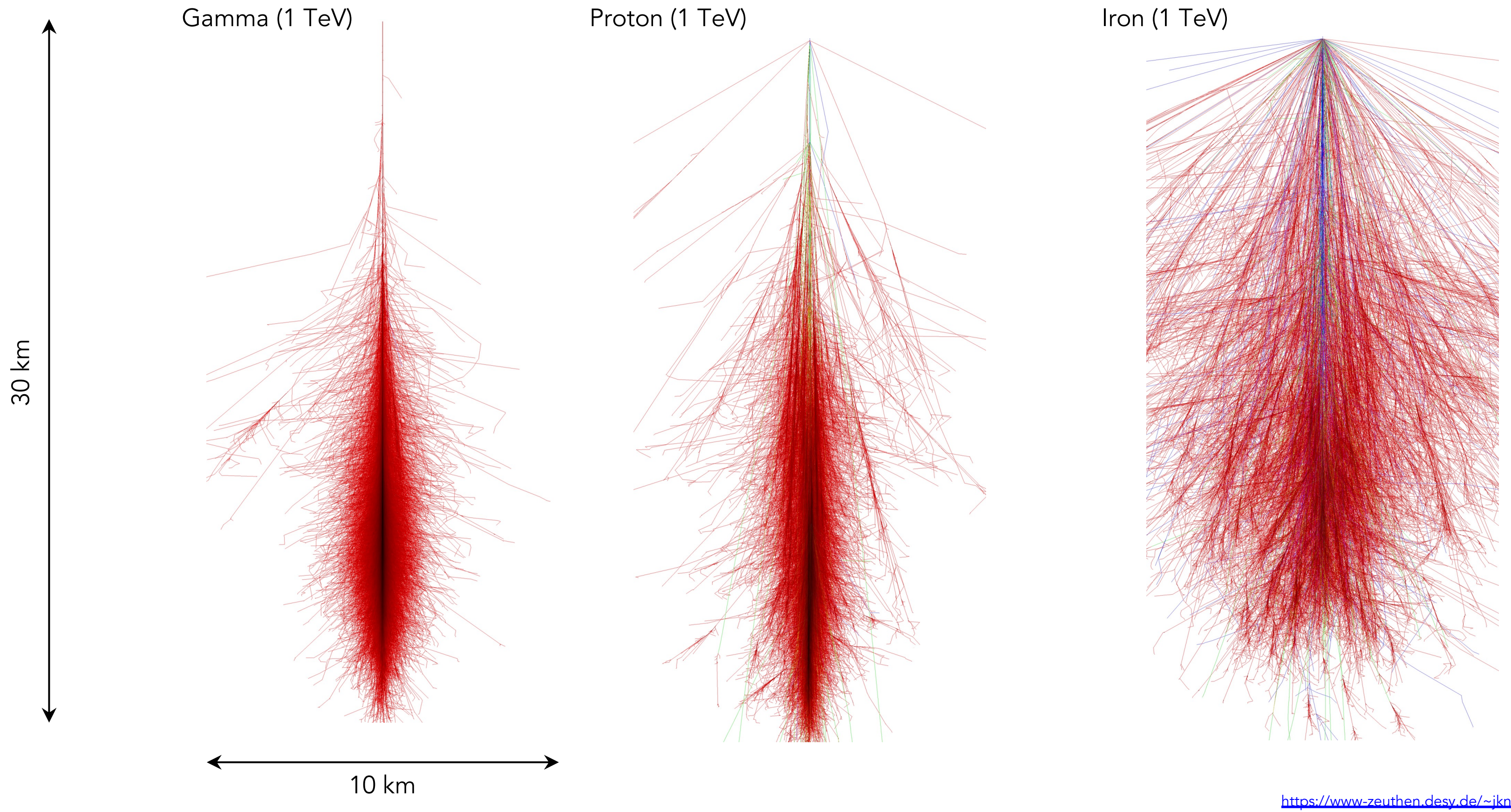
(Classification / regression)

cs231n.github.io

Gamma-ray detectors

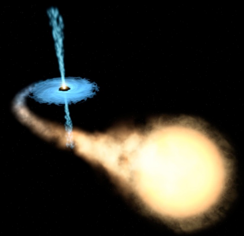


Extended atmospheric showers

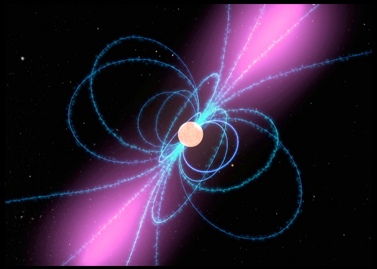


https://www-zeuthen.desy.de/~jknapp/fs/showerimages.html

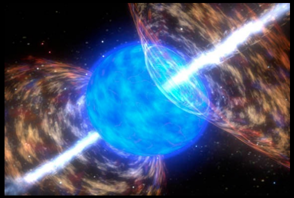
Conventional non-thermal emitters & CR accelerators



Gamma-ray Binaries

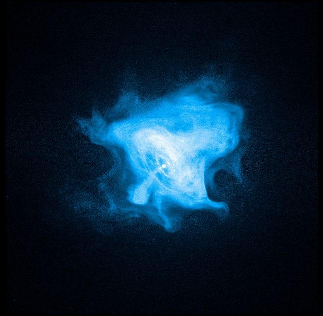


Pulsars

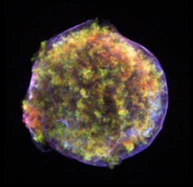


Gamma-ray Bursts

Compact-object mergers



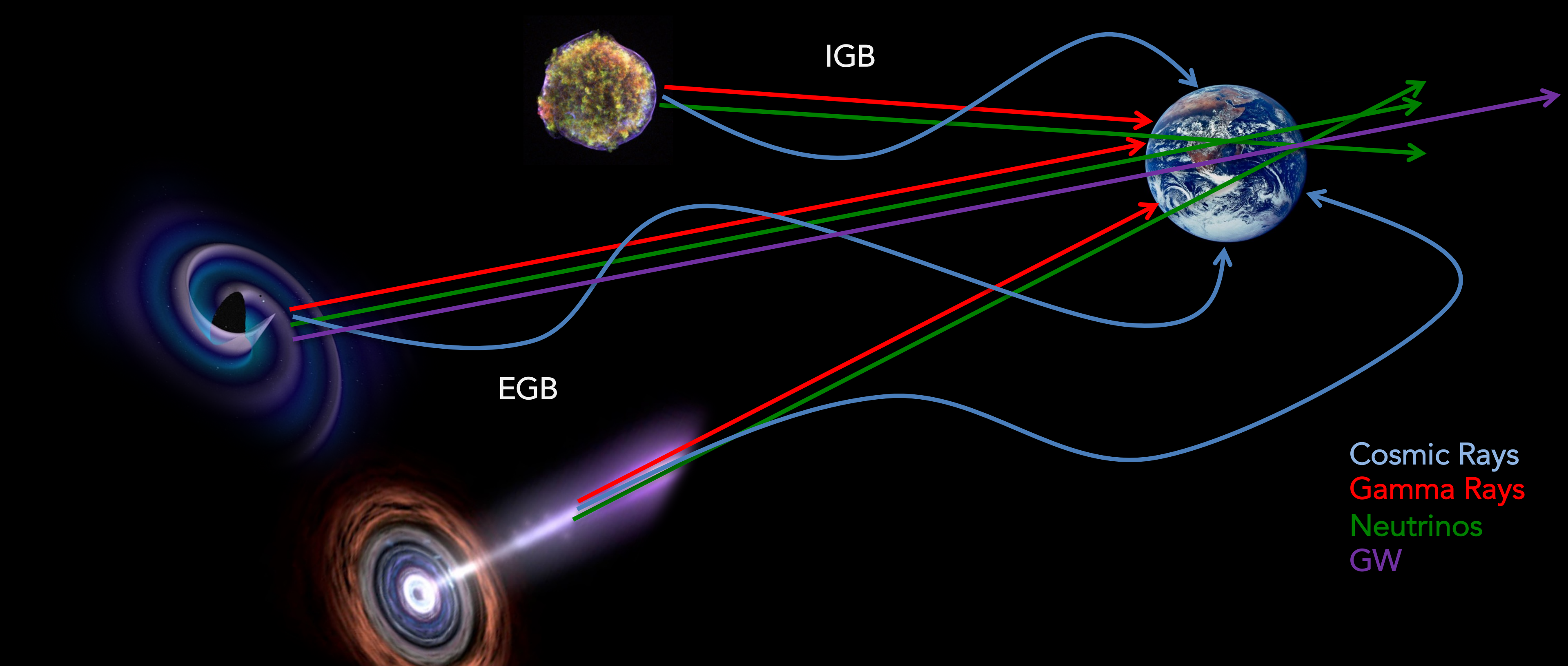
Pulsar Wind Nebulae



Supernova
Remnants

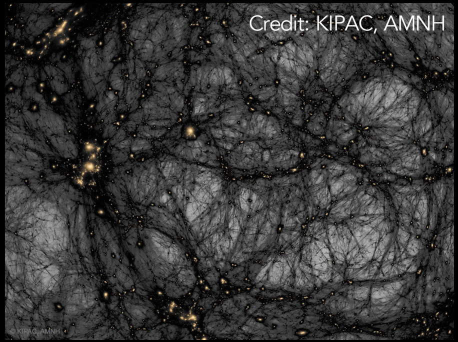
Starburst Galaxies

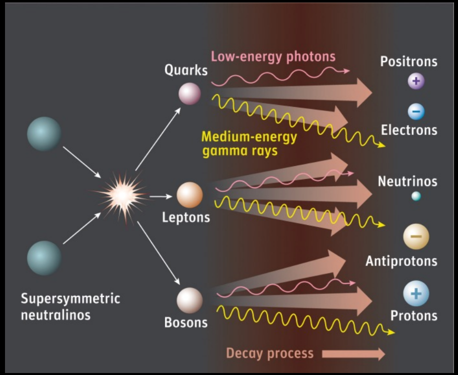
Active
Galactic
Nuclei



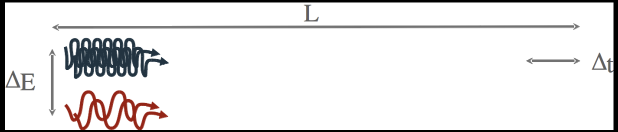
Gamma-ray emission entangled to CR emission
Could carry signatures of hadronic/leptonic production

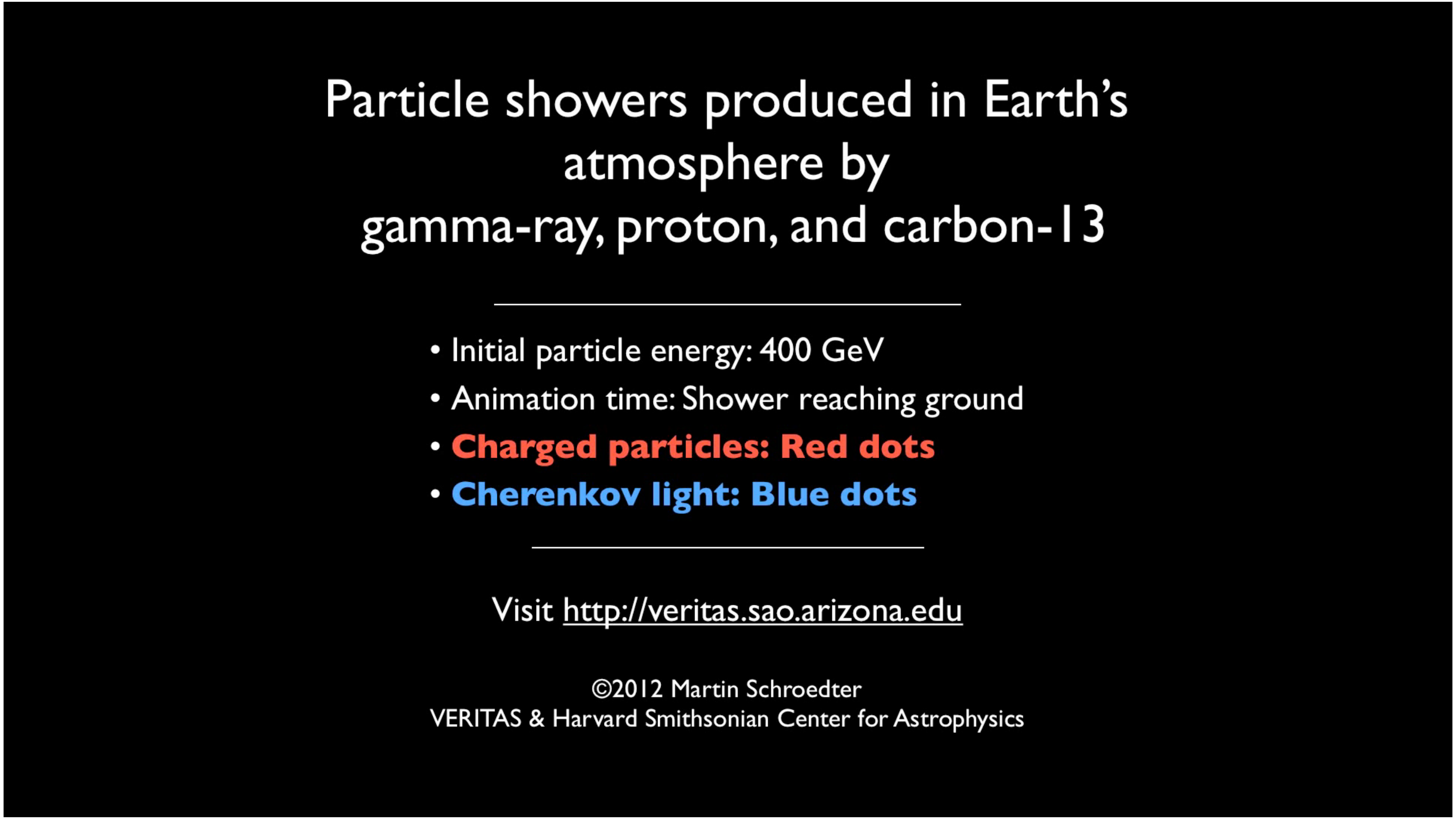
Dark matter searches



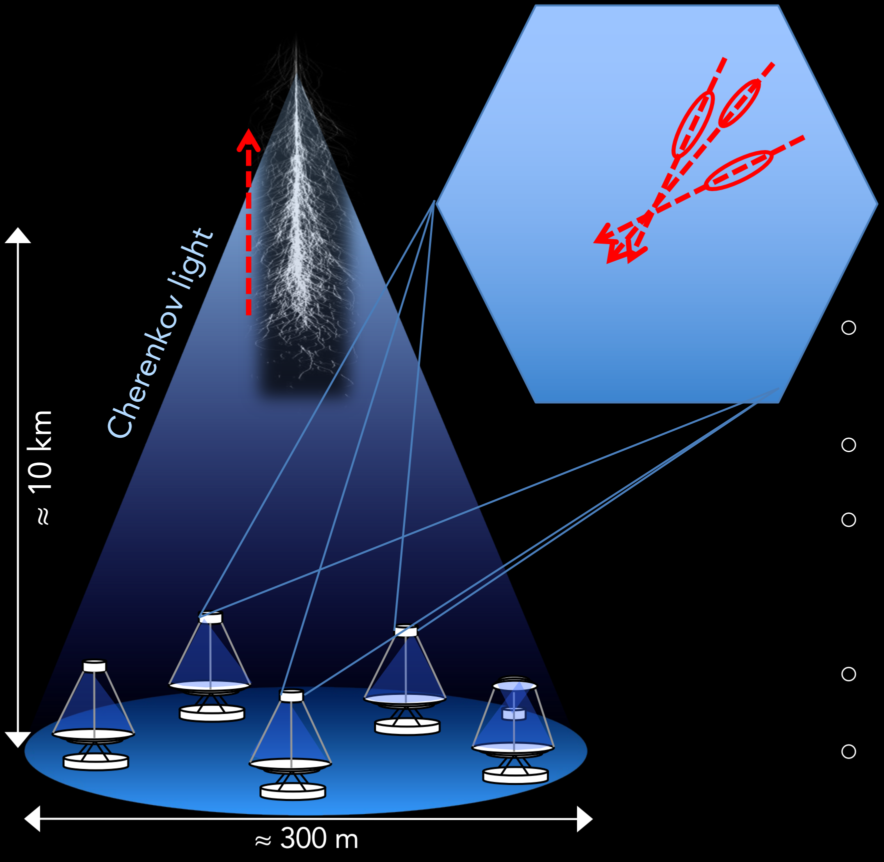


Lorentz invariance

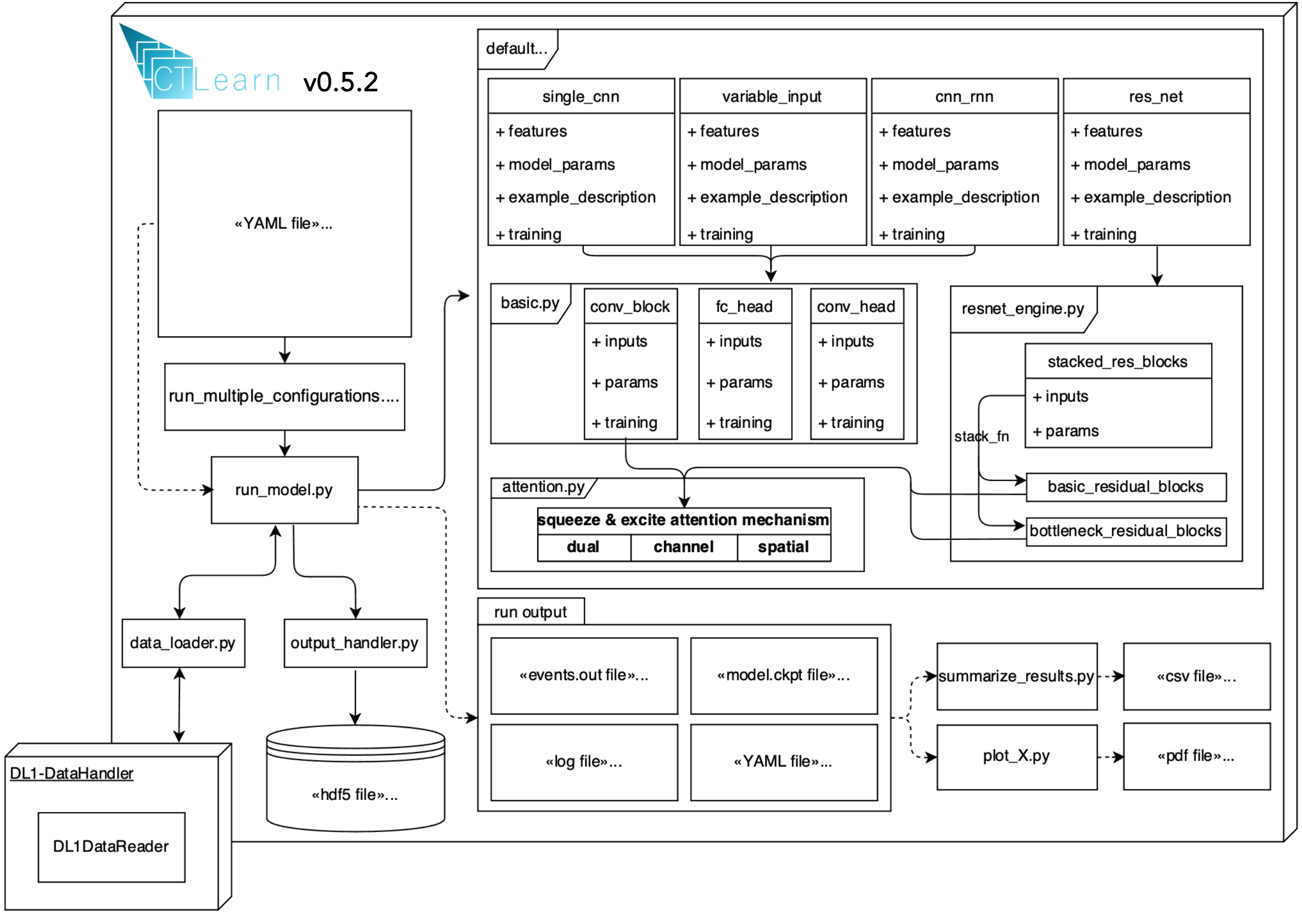




https://www.youtube.com/watch?v=j-BBzWIOai0



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



CTLearn v0.5.2
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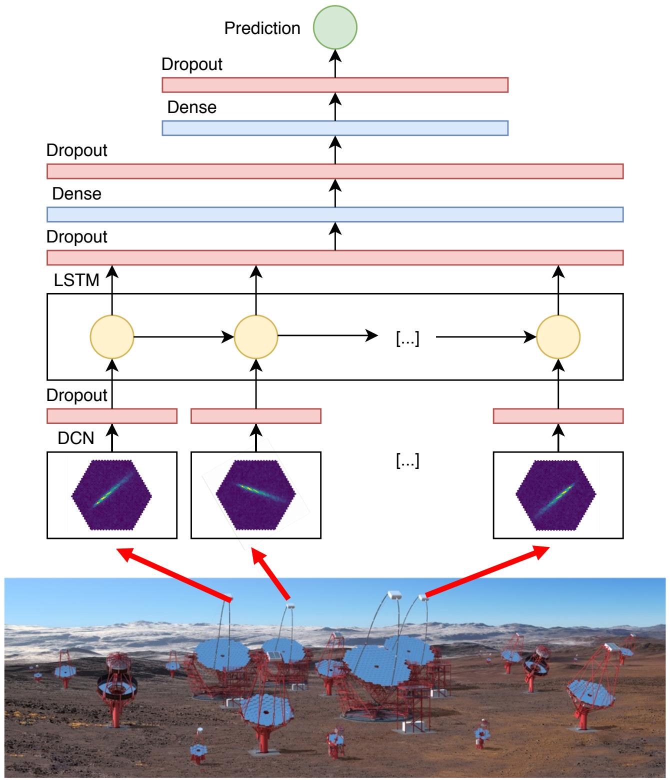
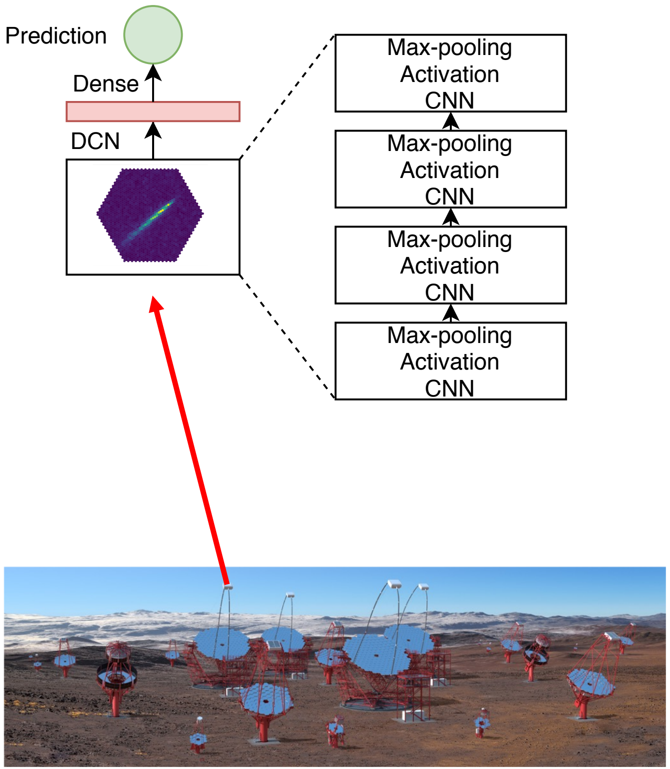
run_model.py
data_loader.py
output_handler.py
DL1-DataHandler
DL1DataReader
«hdf5 file»...
default...
single_cnn
+ features
+ model_params
+ example_description
+ training
variable_input
+ features
+ model_params
+ example_description
+ training
cnn_rnn
+ features
+ model_params
+ example_description
+ training
res_net
+ features
+ model_params
+ example_description
+ training
basic.py
conv_block
+ inputs
+ params
+ training
fc_head
+ inputs
+ params
+ training
conv_head
+ inputs
+ params
+ training
resnet_engine.py
stacked_res_blocks
+ inputs
+ params
stack_fn
basic_residual_blocks
bottleneck_residual_blocks
attention.py
squeeze & excite attention mechanism
dual
channel
spatial
run output
«events.out file»...
«model.ckpt file»...
«log file»...
«YAML file»...
summarize_results.py
«csv file»...
plot_X.py
«pdf file»...

CNN-RNN model

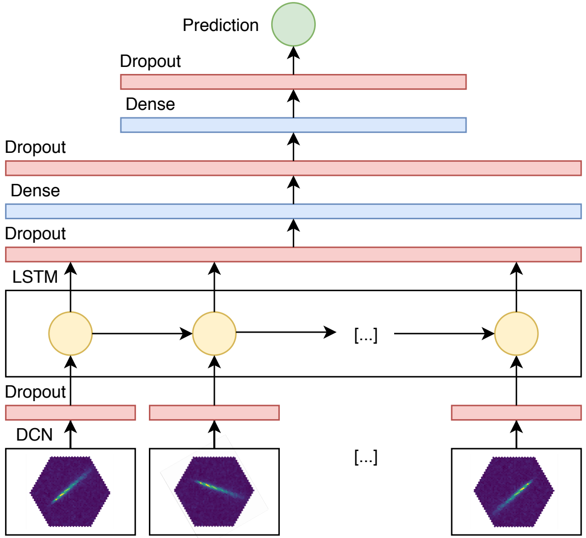


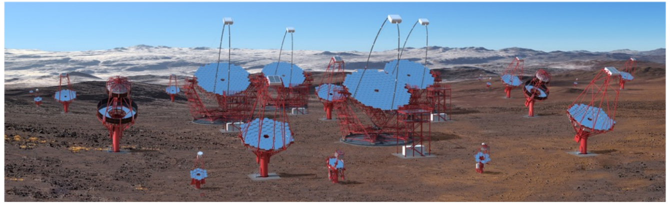
Single-tel model



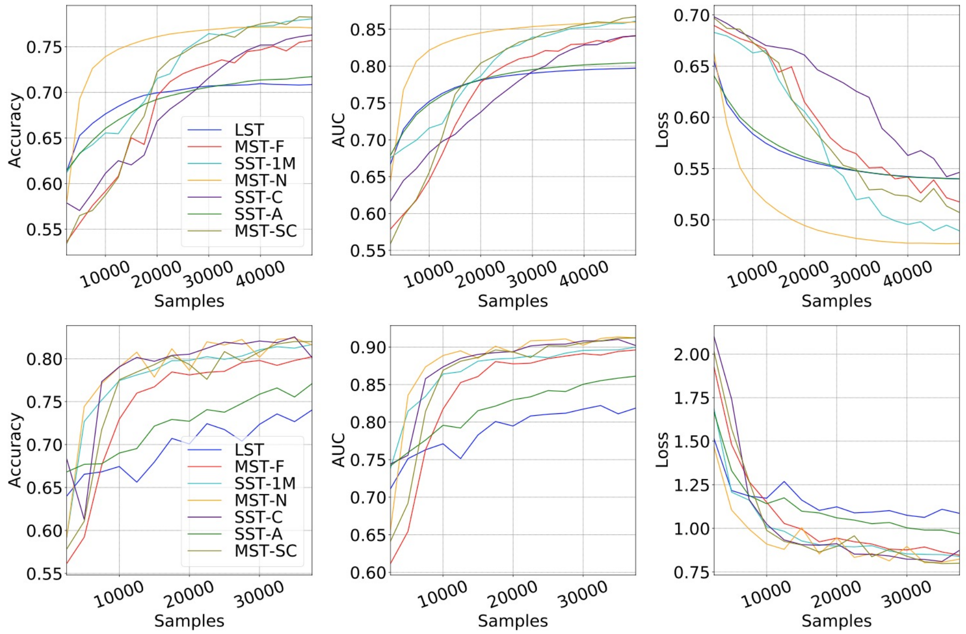
CTLearn: gamma/hadron classification

CNN-RNN model





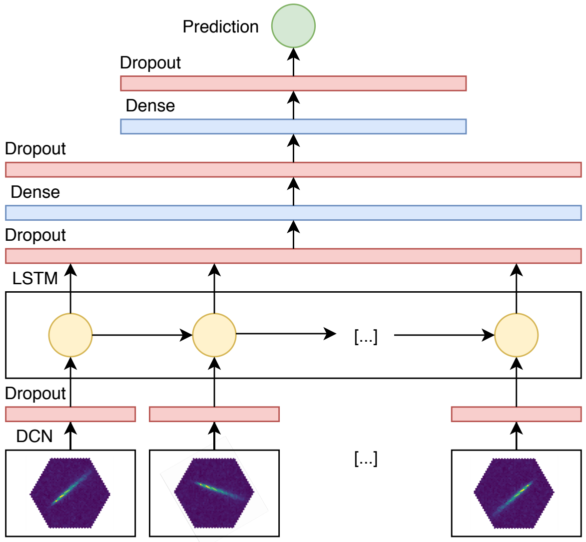
Gamma/hadron classification

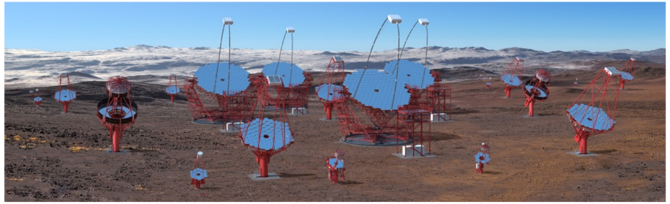


[D. Nieto et al. PoS(ICRC2019)752](#)

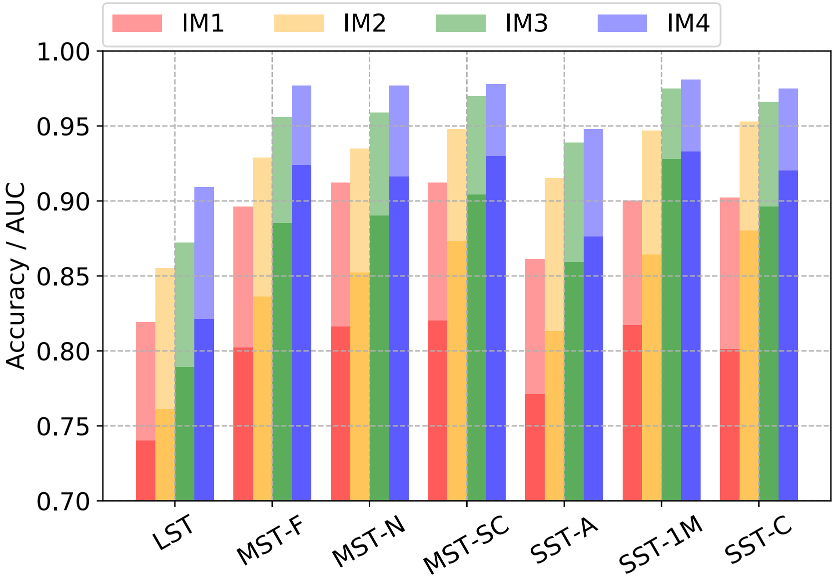
CTLearn: gamma/hadron classification

CNN-RNN model



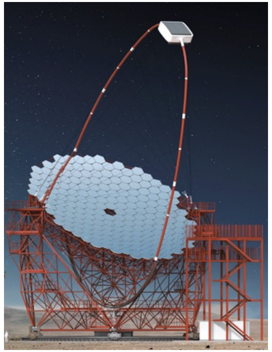


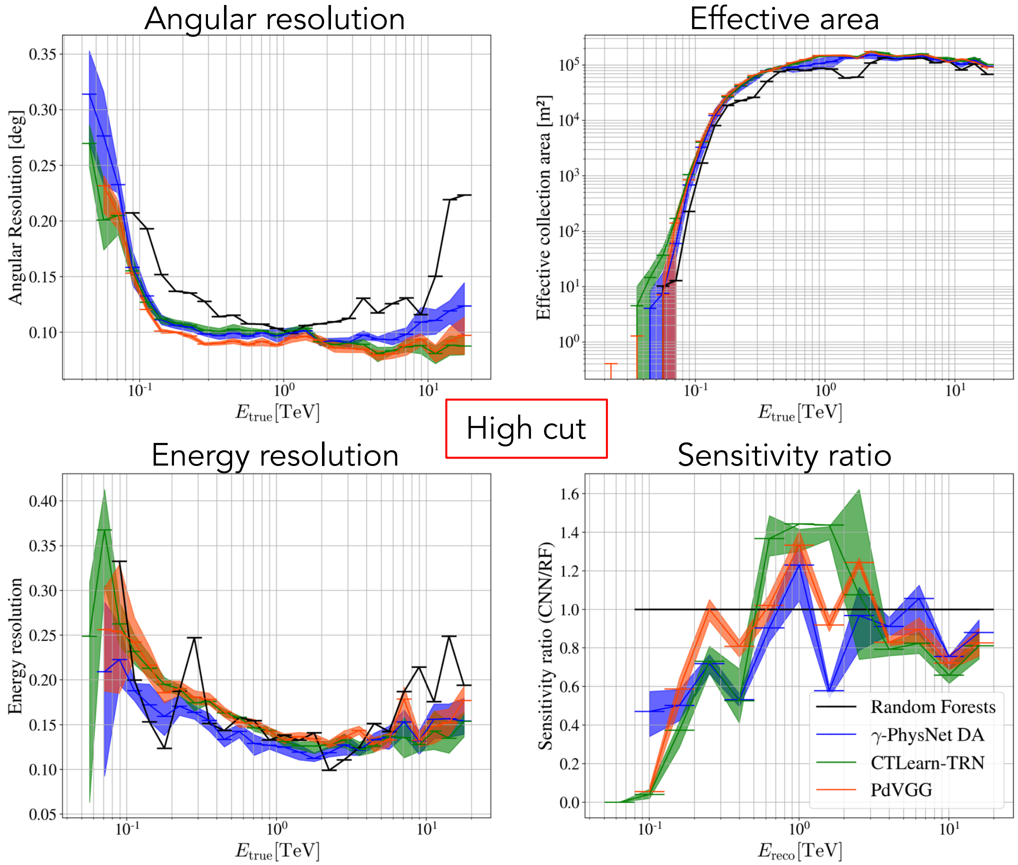
Gamma/hadron classification



D. Nieto et al. PoS(ICRC2019)752

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





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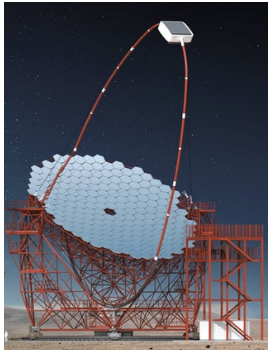
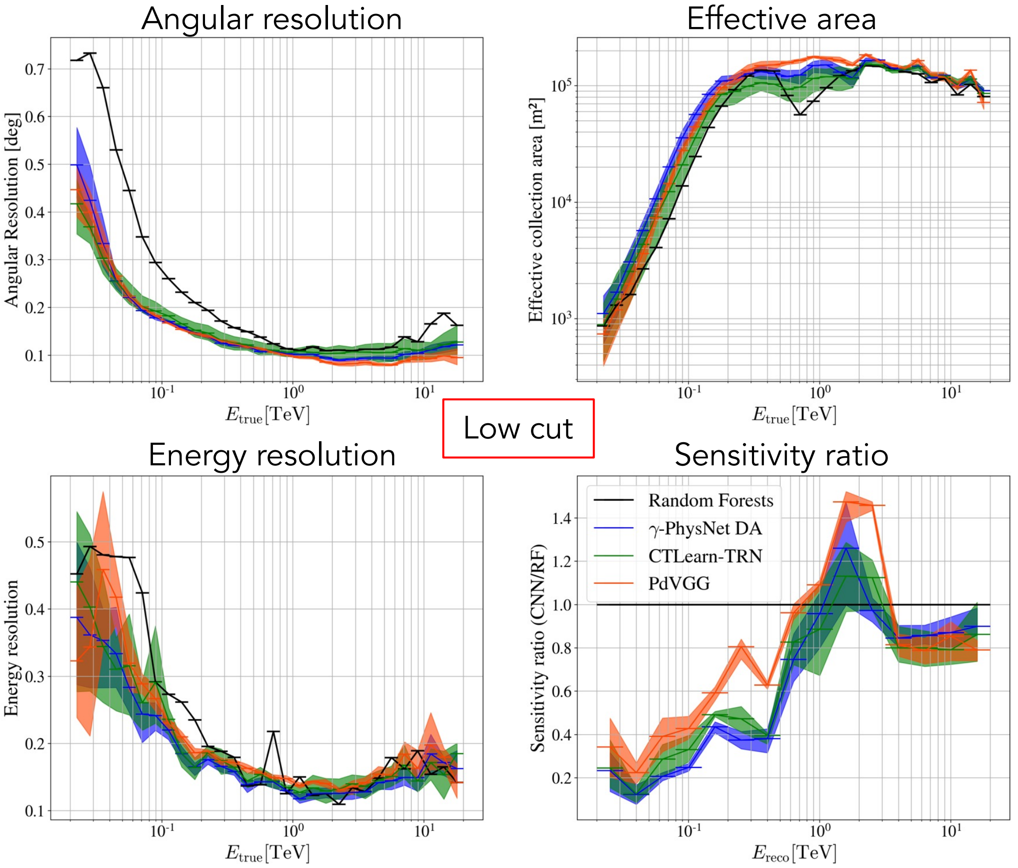
CTLearn: crosschecking results

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





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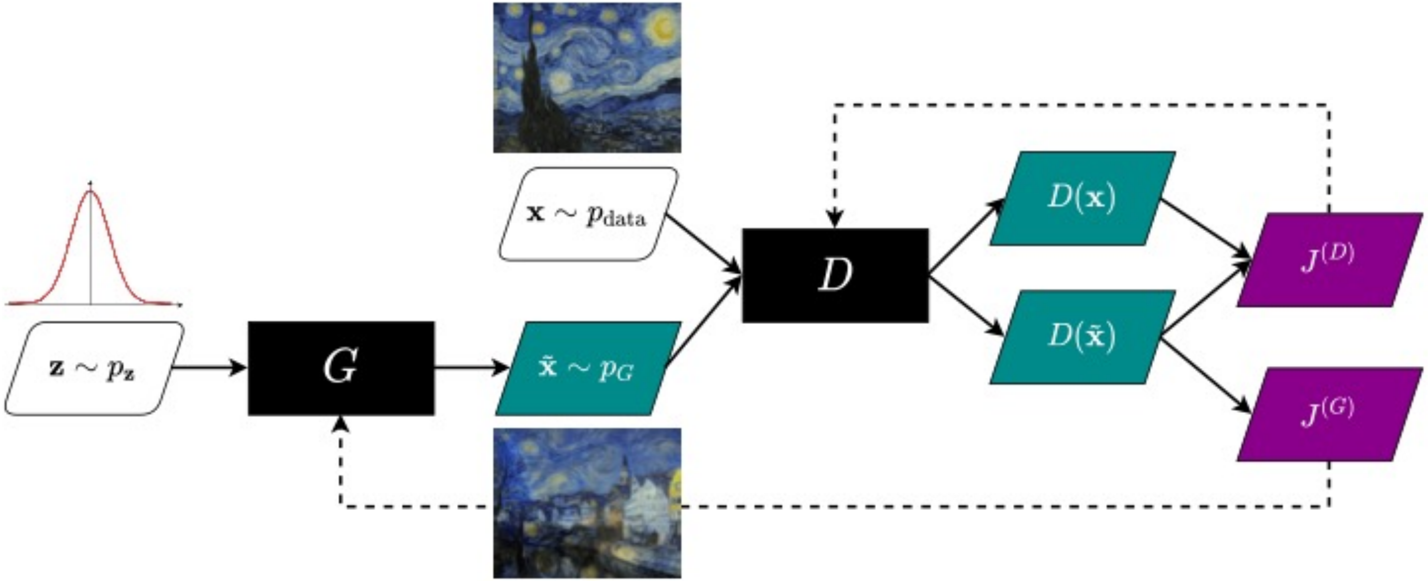
- Generative adversarial networks (GANs)

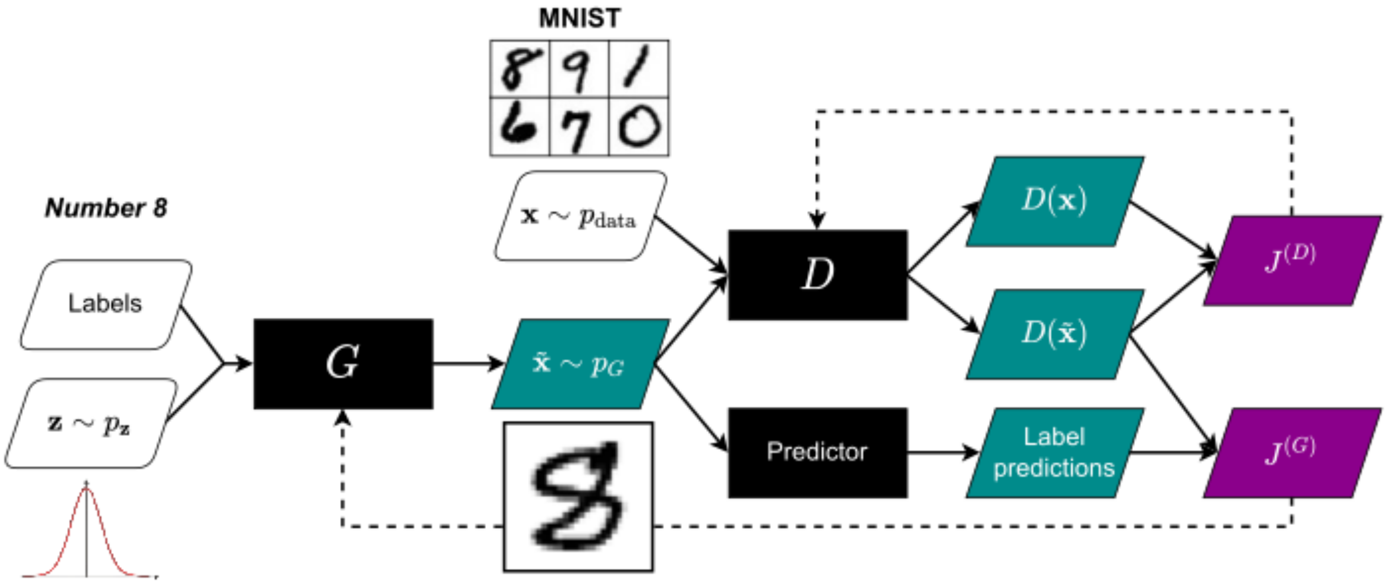


$$J^{(D)} = \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}}[D(G(\mathbf{z}))] - \mathbb{E}_{\mathbf{x}\sim p_{\text{datos}}}[D(\mathbf{x})]$$

$$J^{(G)} = -J^{(D)} = \mathbb{E}_{\mathbf{x}\sim p_{\text{datos}}}[D(\mathbf{x})] - \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}}[D(G(\mathbf{z}))] \rightarrow -\mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}}[D(G(\mathbf{z}))]$$

S. García-Heredia et al.

- Auxiliary conditional generative adversarial networks (AC-GANs)

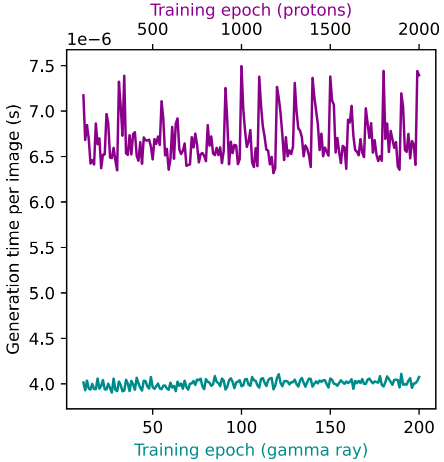


S. García-Heredia et al.

- Generation time

GANS

Using a GPU Nvidia 3090:



SIMULATIONS

- $\sim 1 \text{ s/event}$
- Each event consists of one image for each detector
- Depends on what is being simulated and the computational capacity.

S. García-Heredia et al.

Enhancing IACT's performance with deep learning

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
  - …

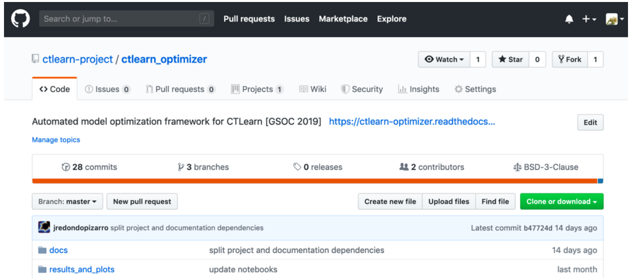
- Optimization strategies
  - Grid searches
  - Random searches
  - Bayesian optimization
  - Evolutionary algorithms
  - Reinforcement learning
  - …

CTLearn Optimizer

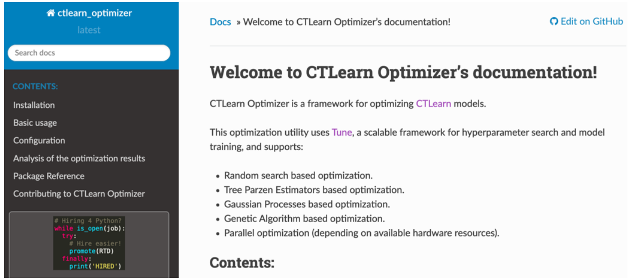
- Framework for hyperparameter optimization of CTLearn models (Although can be adapted to any config-file based DCN framework)
- Based on Tune: a scalable hyperparameter tuning library
- Supported optimization strategies:
  - Random search
  - Tree Parzen Estimators
  - Gaussian Processes
  - Genetic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

Bayesian optimization

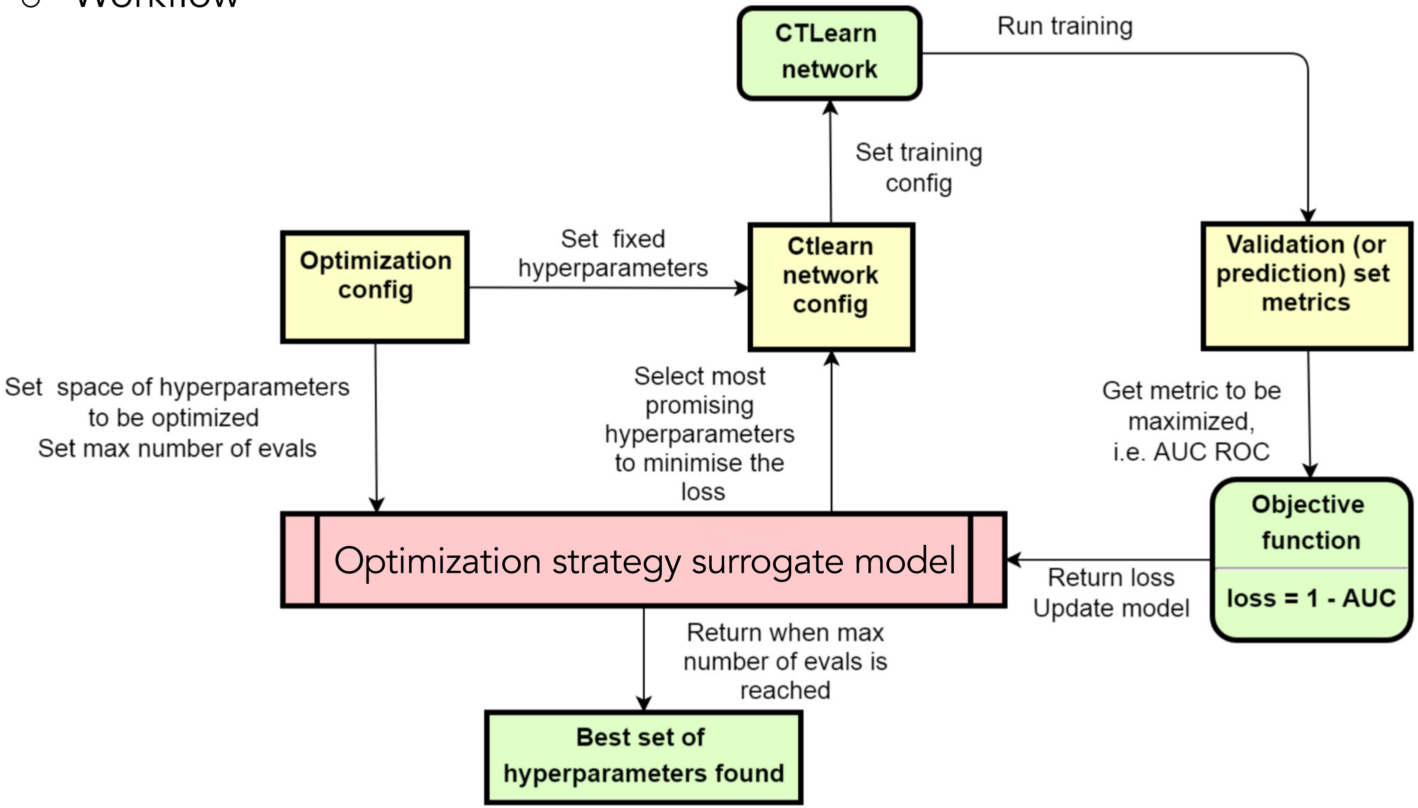
github.com/ctlearn-project/ctlearn_optimizer



ctlearn-optimizer.readthedocs.io

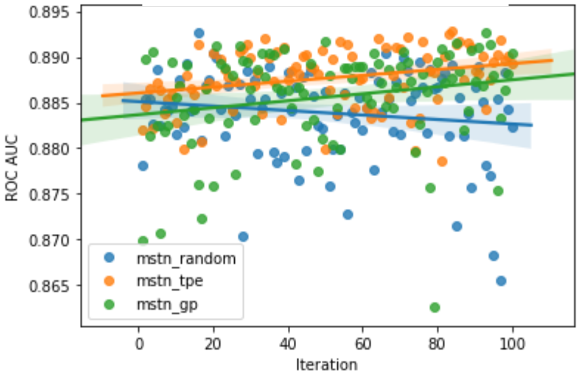


- Workflow

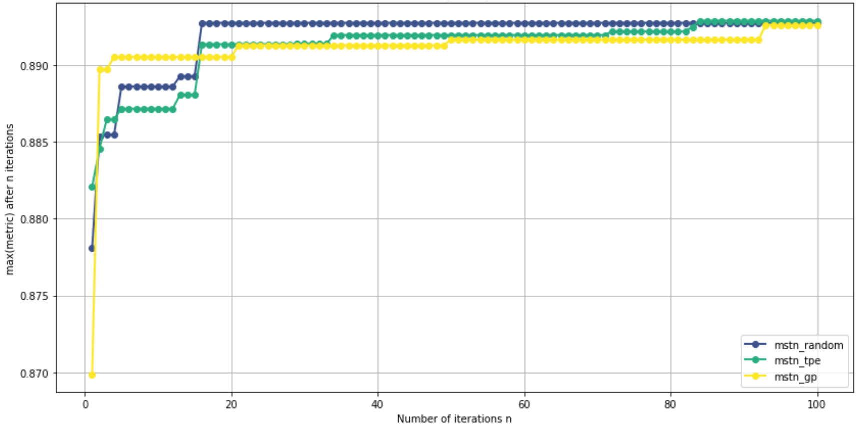

CTLearn network
Run training
Set training config
Optimization config
Set fixed hyperparameters
Ctlearn network config
Validation (or prediction) set metrics
Set space of hyperparameters to be optimized
Set max number of evals
Select most promising hyperparameters to minimise the loss
Get metric to be maximized, i.e. AUC ROC
Objective function
loss = 1 - AUC
Optimization strategy surrogate model
Return loss
Update model
Return when max number of evals is reached
Best set of hyperparameters found

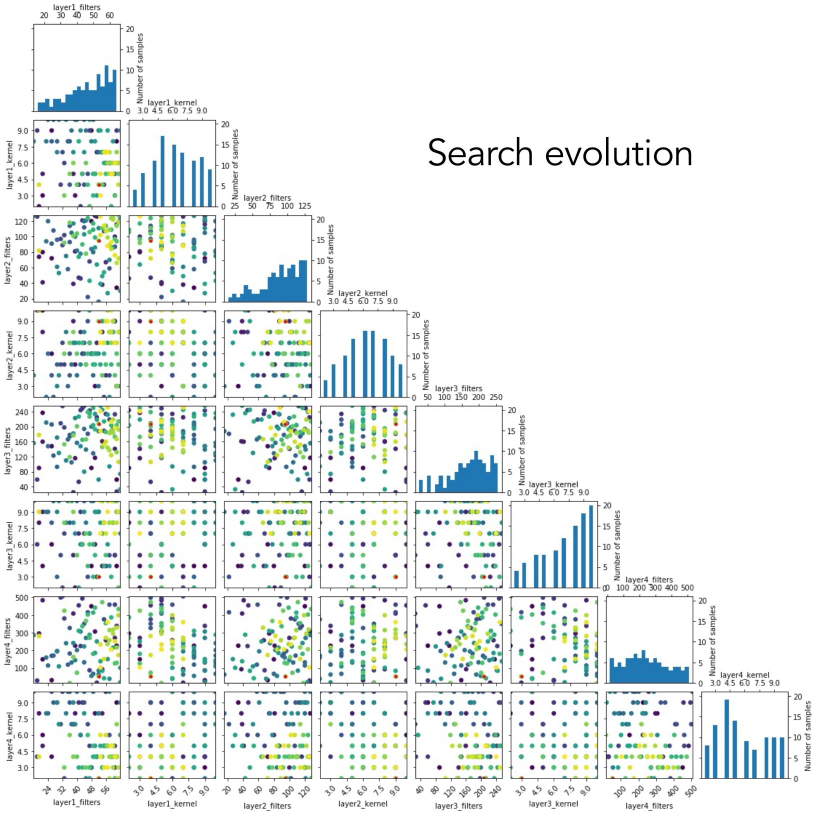
- Visualization

Evolution of the metric



Convergence of the metric

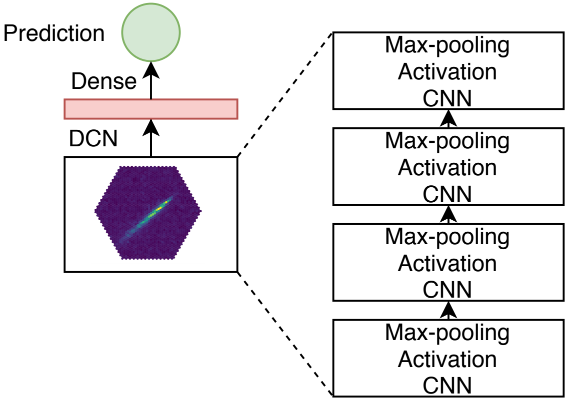




Search evolution

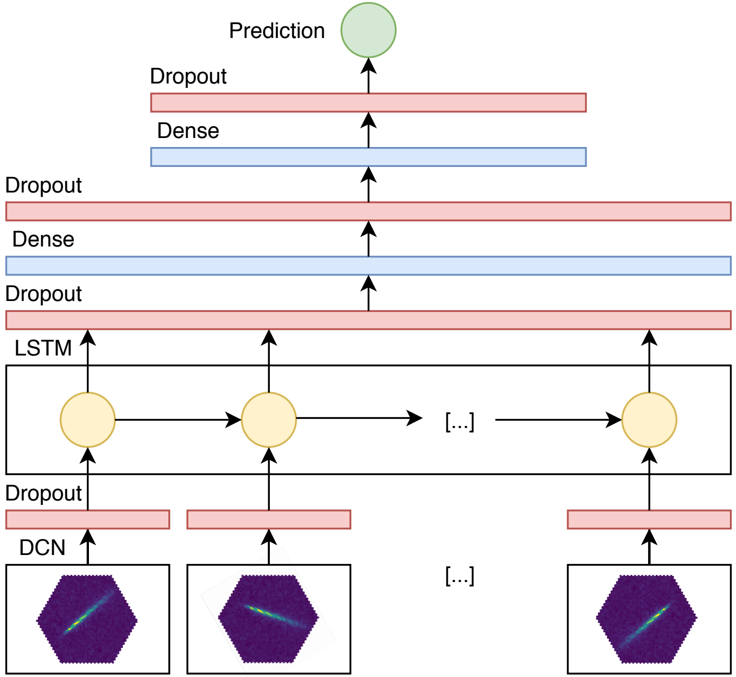
CTLearn Optimizer: some results

Single-tel model

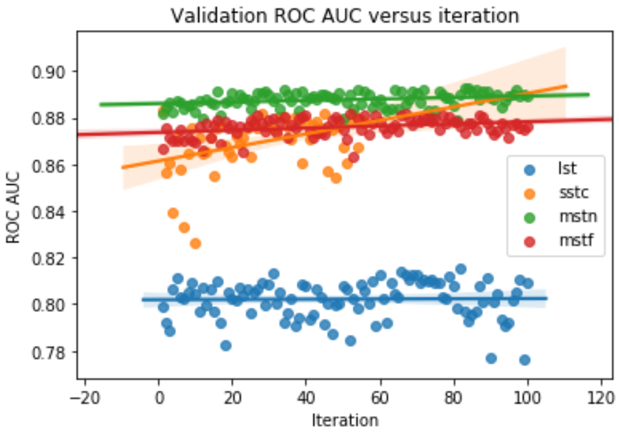


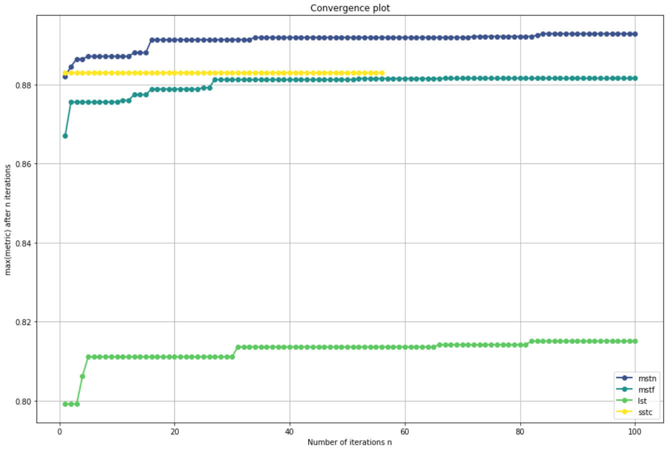
Number of kernels
Size of kernels
Number of CNN layers

CNN-RNN model



CTLearn Optimizer: some results

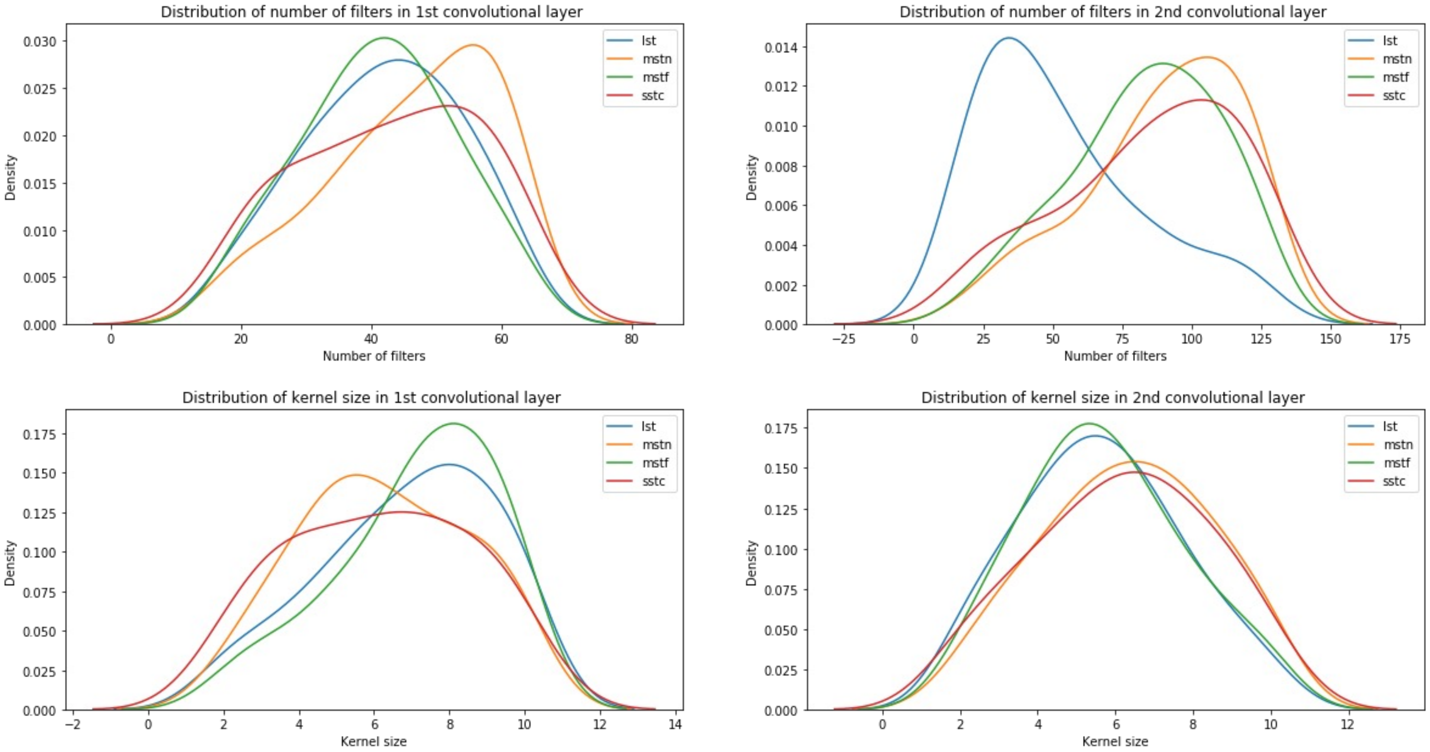




Hyperparameters	Telescope Type	Validation Accuracy	Validation AUC	Training Time
Base	LST	70.38%	0.7887	0h 41m 22s
Optimized	LST	72.45%	0.8150	0h 39m 14s
Base	SSTC	73.90%	0.8118	0h 42m 4s
Optimized	SSTC	79.87%	0.8830	1h 16m 4s
Base	MSTN	78.04%	0.8659	0h 58m 10s
Optimized	MSTN	80.11%	0.8929	0h 52m 48s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

Telescope Type	Metric	Improvement
LST	Validation Accuracy	2.07%
LST	Validation AUC	2.63%
SSTC	Validation Accuracy	5.97%
SSTC	Validation AUC	7.12%
MSTN	Validation Accuracy	2.07%
MSTN	Validation AUC	2.70%
MSTF	Validation Accuracy	4.41%
MSTF	Validation AUC	4.56%

- Single_tel & TPE search



Optimized hyperparameters seem to be telescope-type dependent

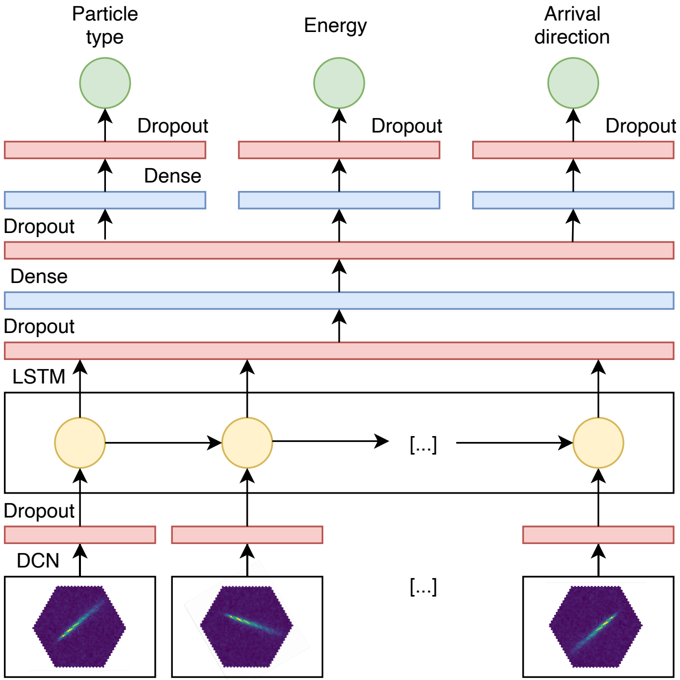
CTLearn Optimizer: some results

- Single_tel & TPE search: transfer to CNN-RNN

Hyperparameters	Telescope Type	Validation Accuracy	Validation AUC	Training Time
Base	LST	73.43%	0.8285	0h 41m 22s
Optimized	LST	74.96%	0.8422	0h 46m 53s
Base	SSTC	80.64%	0.9072	1h 51m 5s
Optimized	SSTC	83.49%	0.9217	3h 31m 43s
Base	MSTN	83.10%	0.9169	2h 15m 52s
Optimized	MSTN	84.20%	0.9313	6h 43m 14s

Telescope Type	Metric	Improvement
LST	Validation Accuracy	1.53%
LST	Validation AUC	1.37%
SSTC	Validation Accuracy	2.85%
SSTC	Validation AUC	1.45%
MSTN	Validation Accuracy	1.10%
MSTN	Validation AUC	1.44%

- Multi-task learning



- Tackling the real-data problem

Using GANs to bridge the gap between performances on simulations and observations

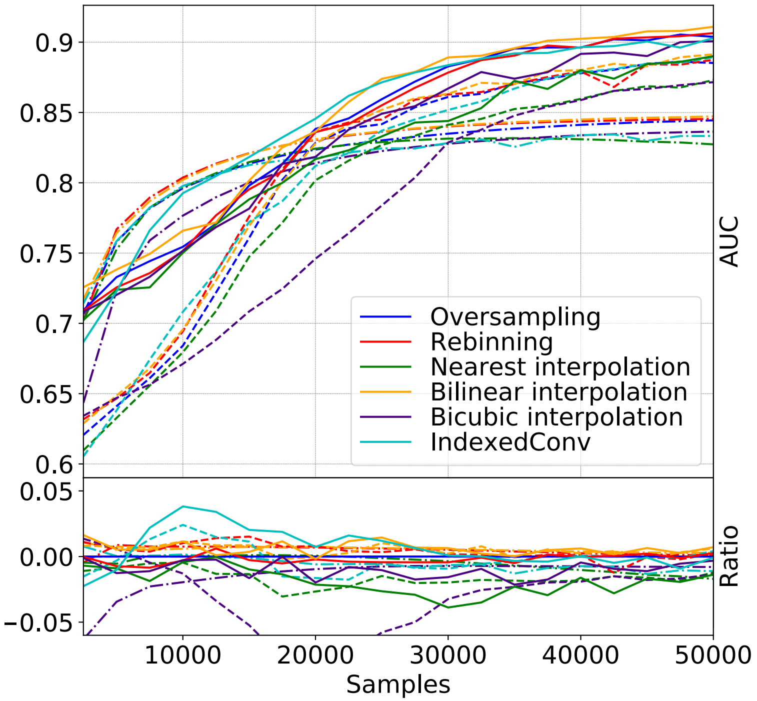
- Model optimization

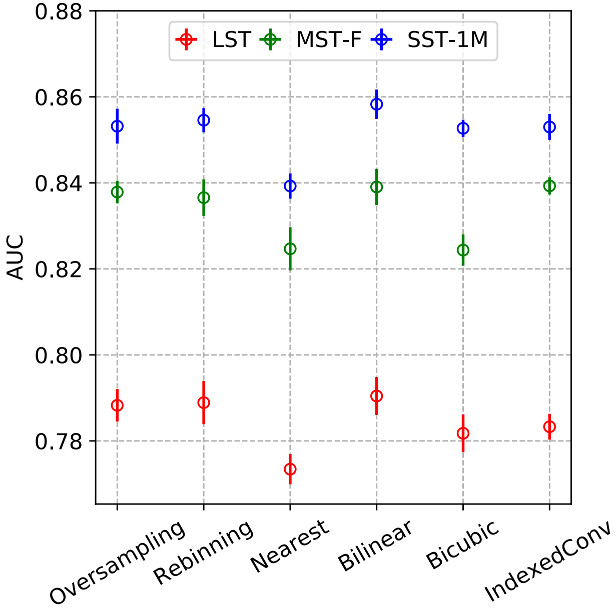
Combine heterogeneous cameras in one model
Implement and test deeper models
Enable optimization on large GPU clusters

- Invert models to explore pseudo-simulators

- …

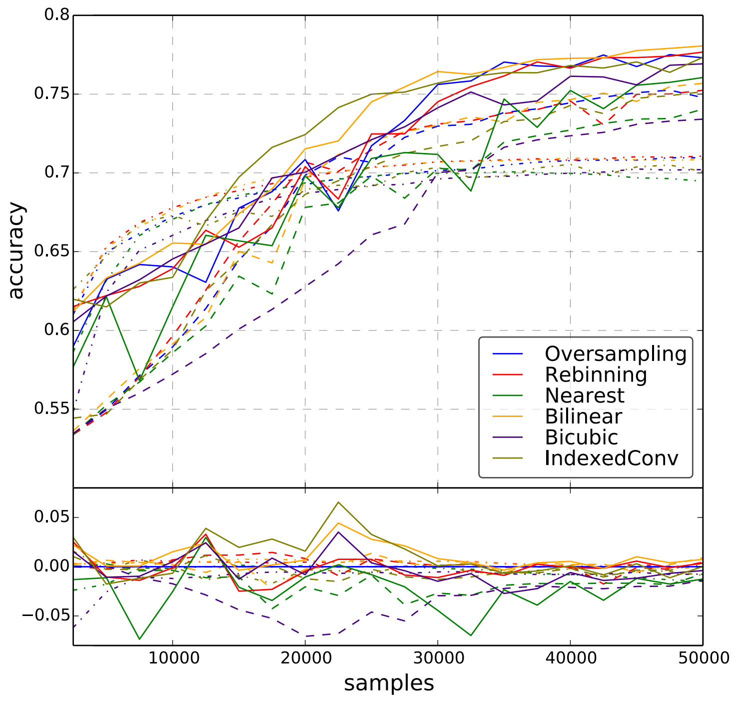
- Event classification task (AUC)

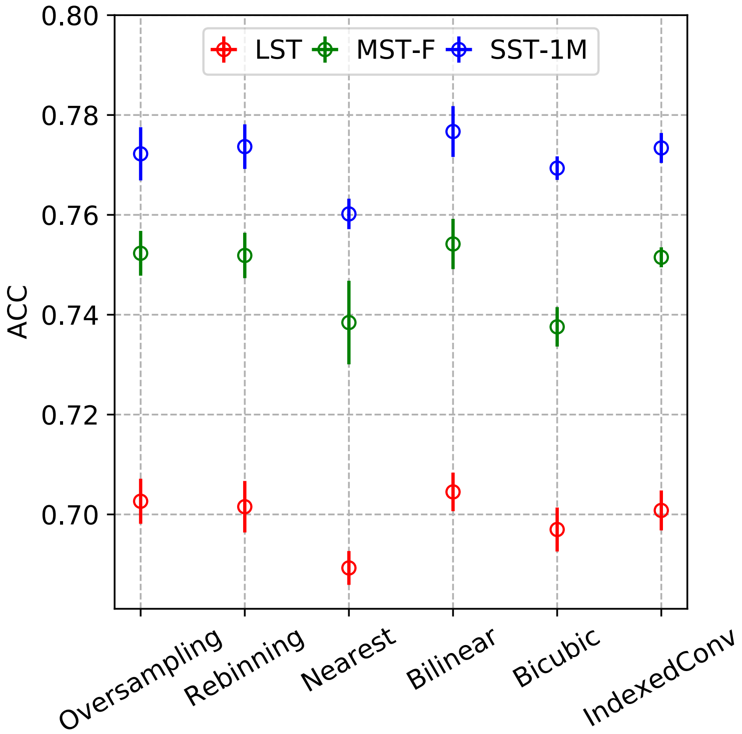




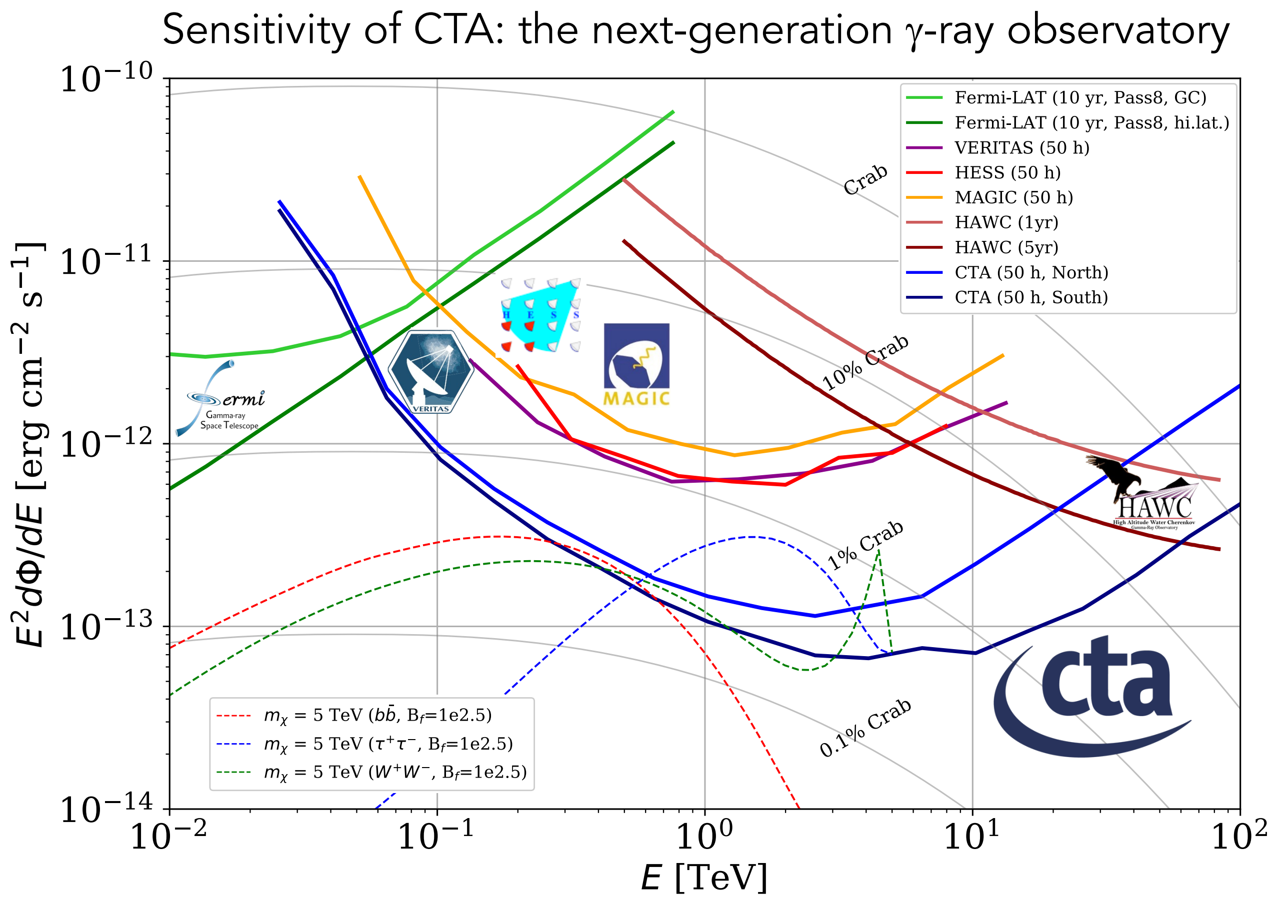
https://arxiv.org/abs/1912.09898

- Event classification task (ACC)



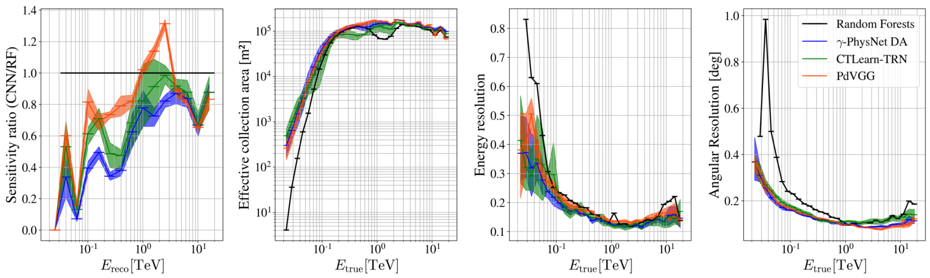


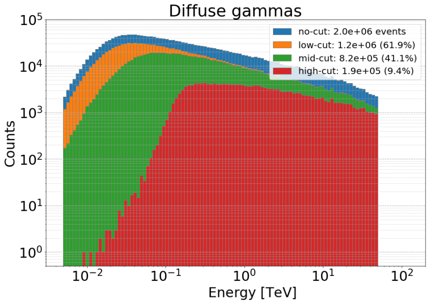
https://arxiv.org/abs/1912.09898


Sensitivity of CTA: the next-generation γ-ray observatory
$E^2 d\Phi/dE$ [erg cm^{-2} s^{-1}]
10^{-10}
10^{-11}
10^{-12}
10^{-13}
10^{-14}
10^{-2}
10^{-1}
10^{0}
10^{1}
10^{2}
E [TeV]
Fermi-LAT (10 yr, Pass8, GC)
Fermi-LAT (10 yr, Pass8, hi.lat.)
VERITAS (50 h)
HESS (50 h)
MAGIC (50 h)
HAWC (1yr)
HAWC (5yr)
CTA (50 h, North)
CTA (50 h, South)
Crab
10% Crab
1% Crab
0.1% Crab
m_χ = 5 TeV ($b\bar{b}$, B$_f$=1e2.5)
m_χ = 5 TeV ($\tau^+\tau^-$, B$_f$=1e2.5)
m_χ = 5 TeV (W^+W^-, B$_f$=1e2.5)
Fermi
Gamma-ray Space Telescope
VERITAS
H E S S
MAGIC
HAWC
High Altitude Water Cherenkov
cta

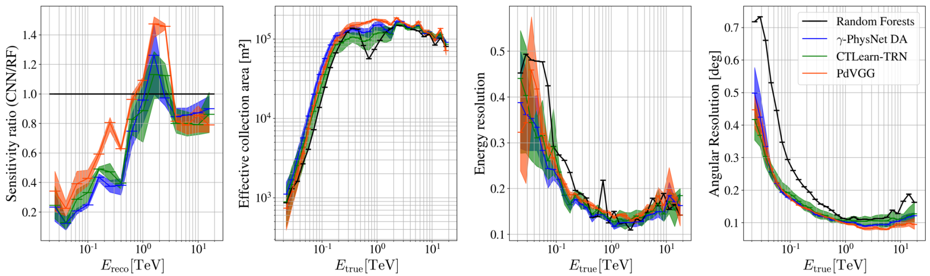
CTLearn: crosschecking results

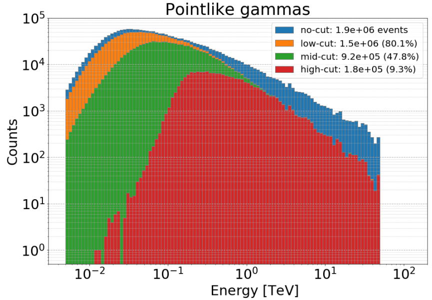
Low cuts



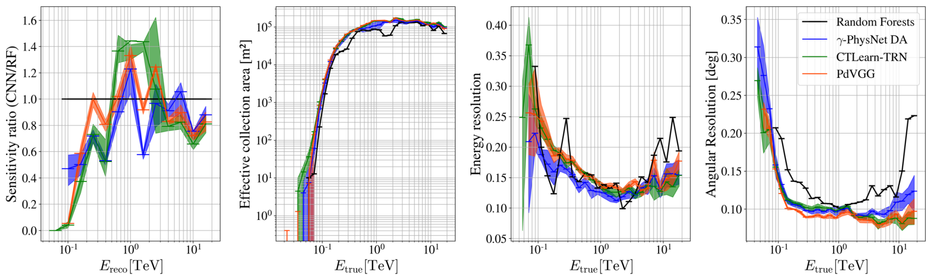


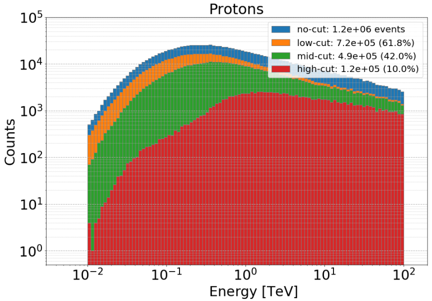
Mid cuts





High cuts





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