MINISTERIO DE CIENCIA, INNOVACIÓN Y UNIVERSIDADES
AGENCIA ESTATAL DE INVESTIGACIÓN
Plan de Recuperación, Transformación y Resiliencia
Comunidad de Madrid
Astrofísica y física de altas energías
GAE
IPARCOS

Deep-learning techniques in ground-based imaging gamma-ray observatories and the CTLearn package

High Energies Group

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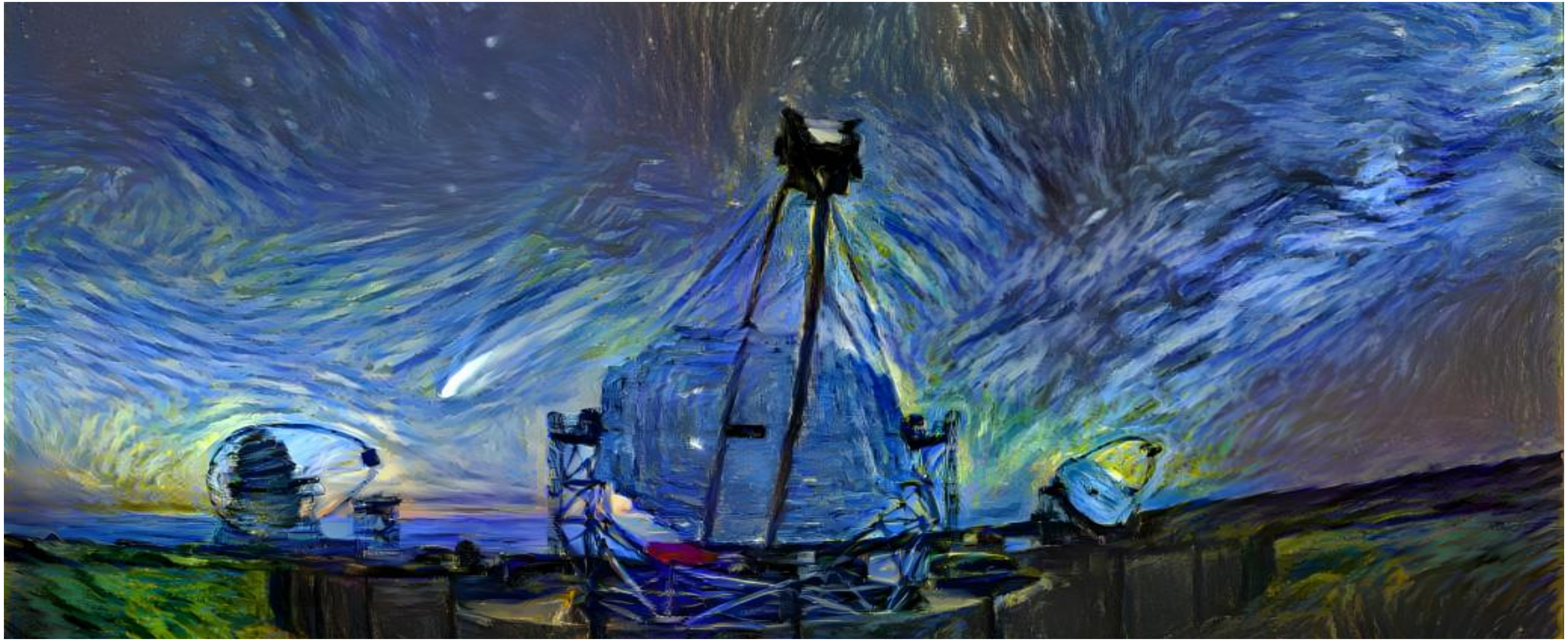
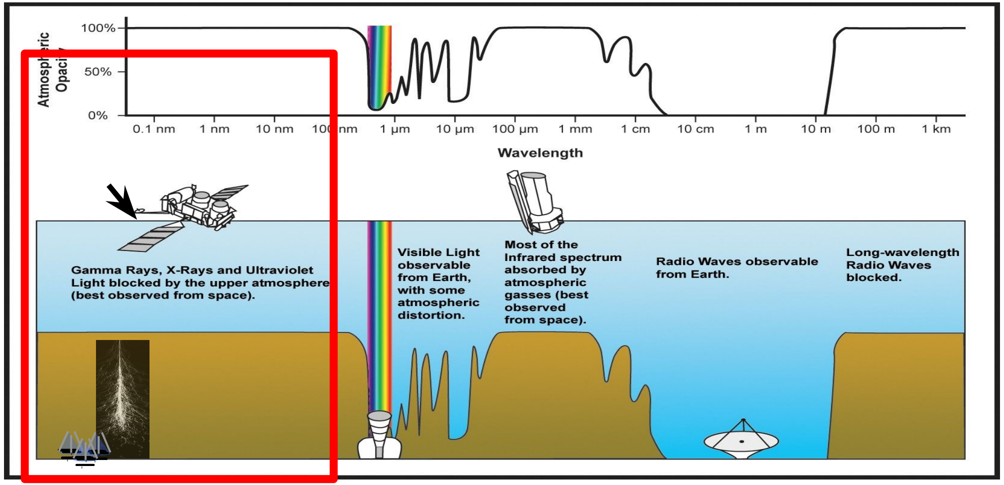
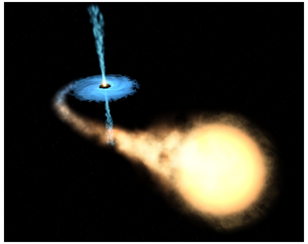


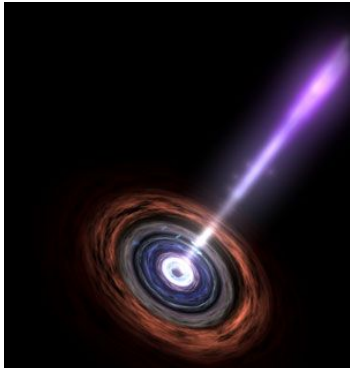
INTRODUCTION



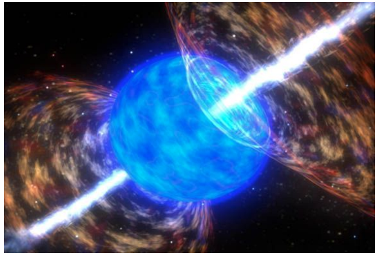


Gamma-ray Binaries

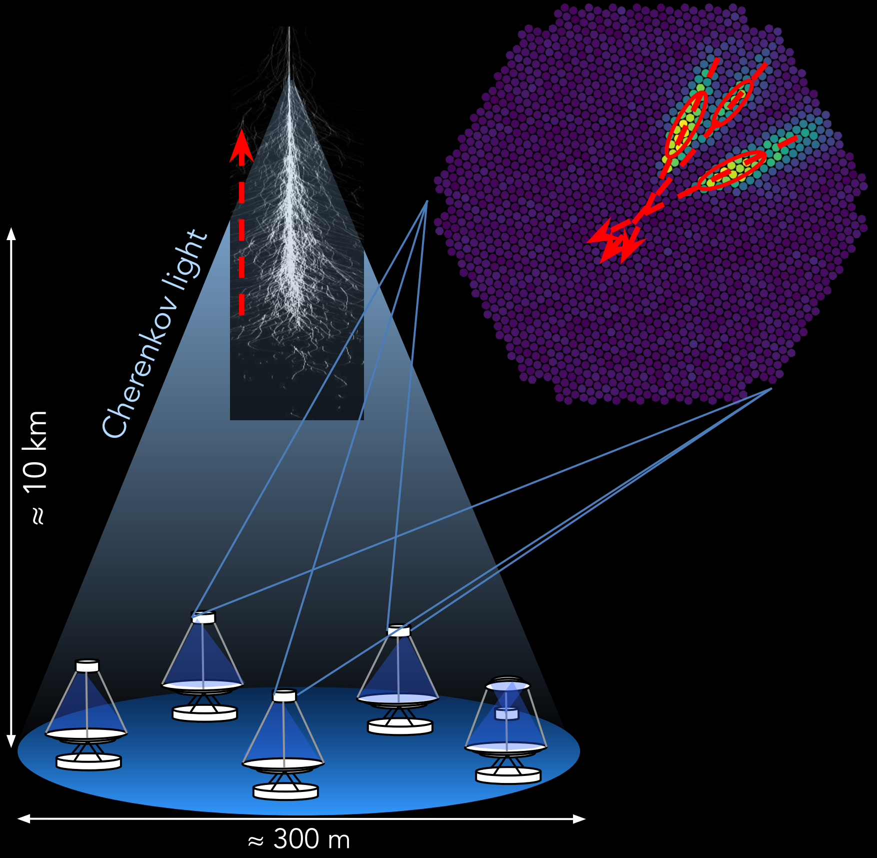
Supernova



Active Galactic Nuclei



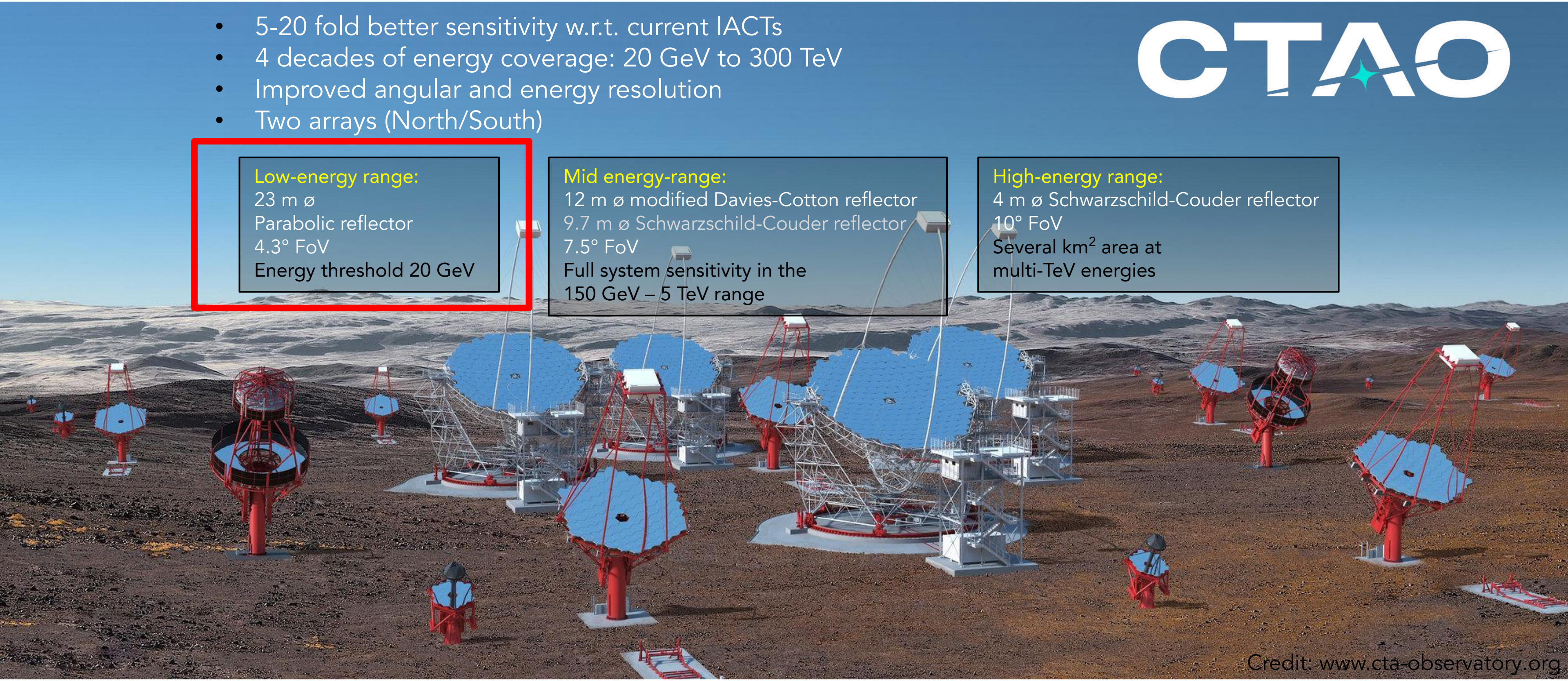
Gamma-ray Bursts



- Imaging Atmospheric Cherenkov Telescope (IACT)
- 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

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)



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

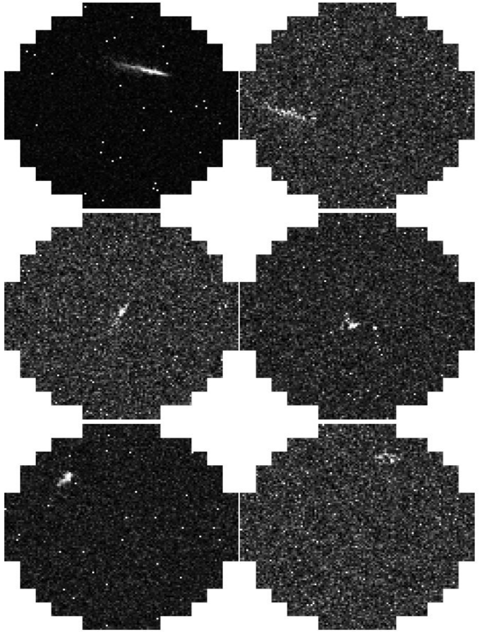
Mid energy-range:
12 m ø modified Davies-Cotton reflector
9.7 m ø Schwarzschild-Couder reflector
7.5° FoV
Full system sensitivity in the 150 GeV – 5 TeV range

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

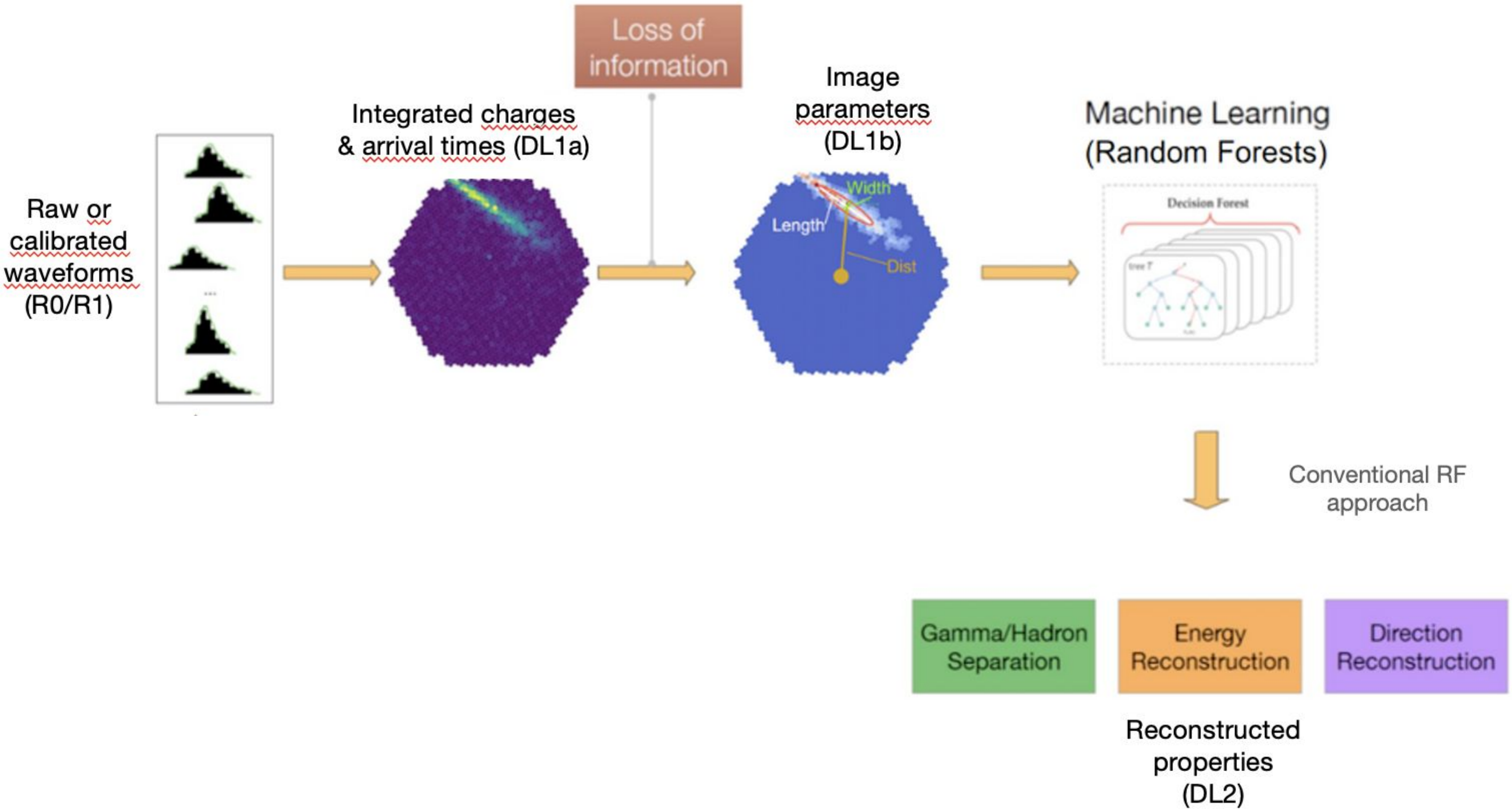
www.ctao.org

Science with CTA, arXiv:1709.07997

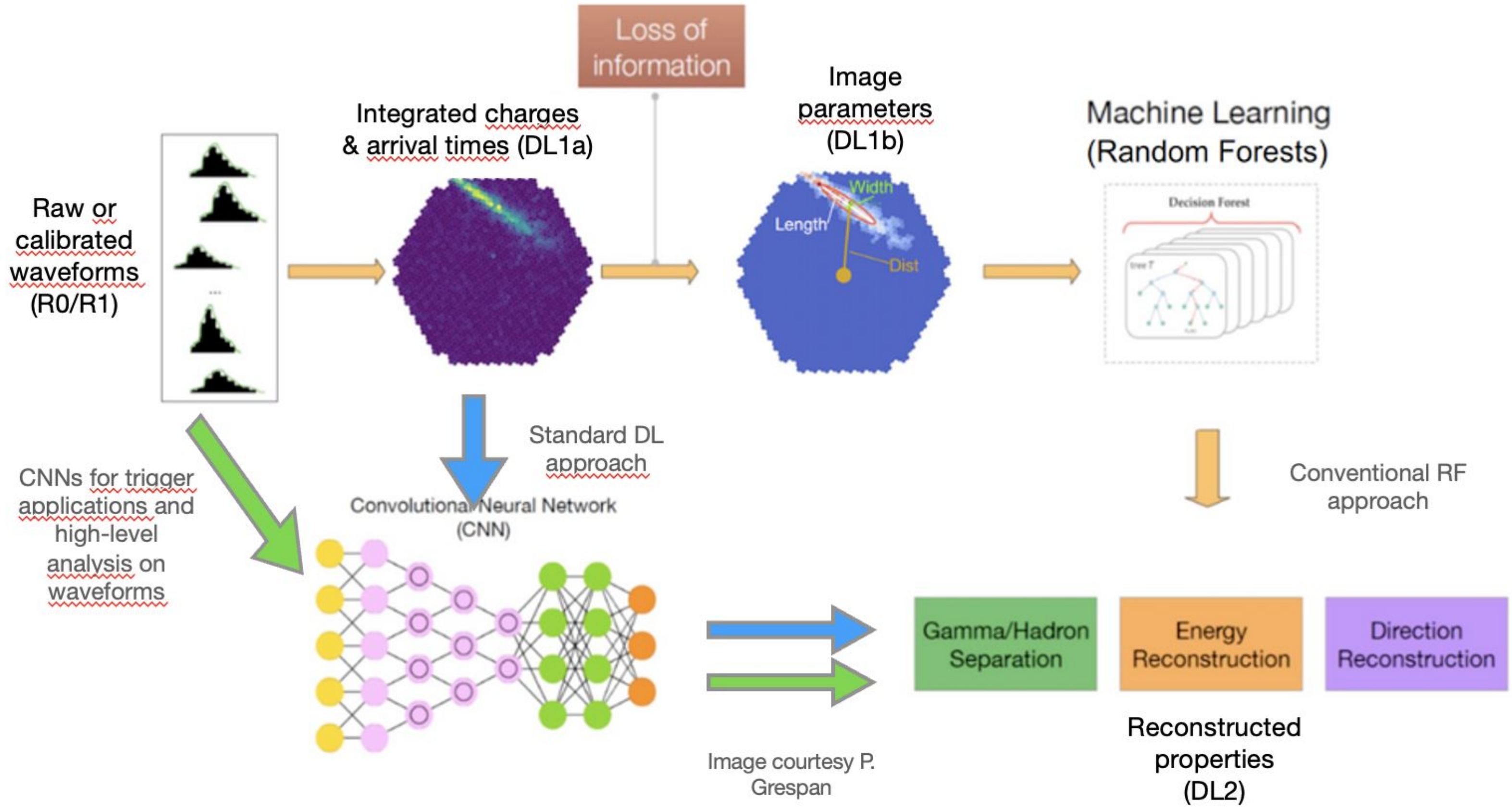
DEEP LEARNING APPLIED TO IACTs



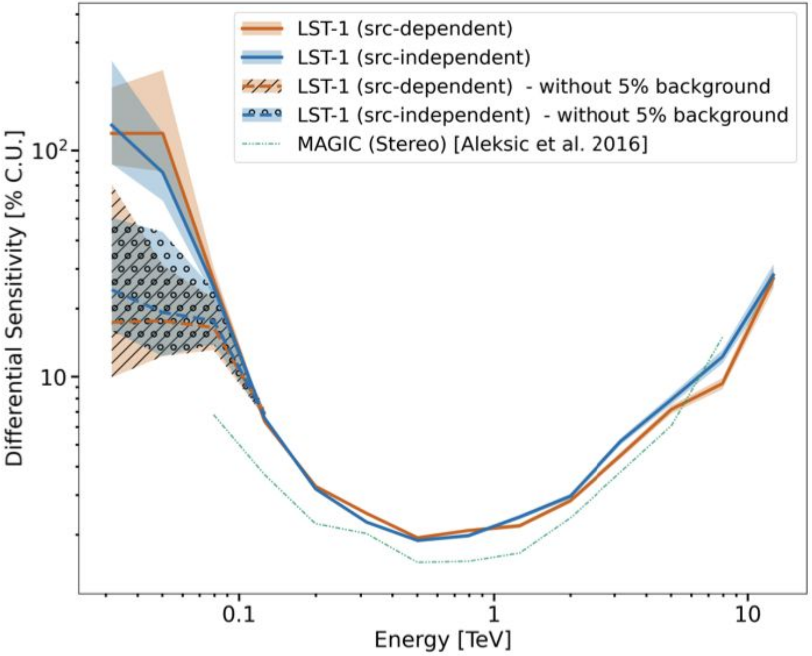
Event reconstruction in IACTs – Current state

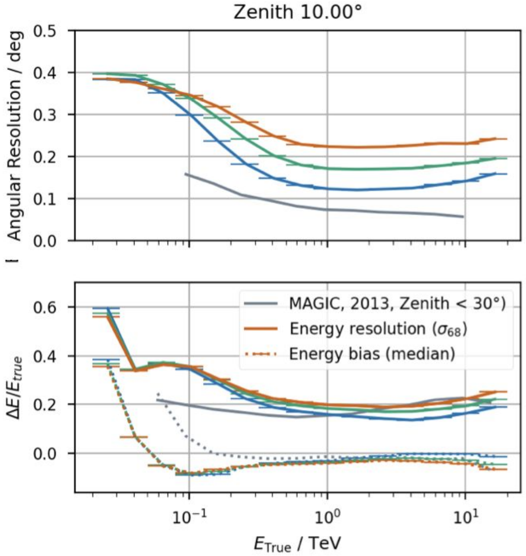


Event reconstruction in IACTs – DL Scenario



- Improvement of current reconstruction and performance metrics with Random Forest





LST Collaboration (2024)

- CTLearn is a high-level Python package for using **Deep Learning models for ground-based gamma-ray data analyses.**
- Core functionality:
  - **Full-event reconstruction** of various imaging atmospheric Cherenkov telescopes in **monoscopic and stereoscopic mode**
  - **CNN-based analysis on waveforms** possible through the efficiently data management package dl1-data-handler
  - Application of an **AI-based Trigger system**, where neural networks are ported on **FPGAs for real time processing.**
- Latest release: v0.10.2 (21/03/2025)

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

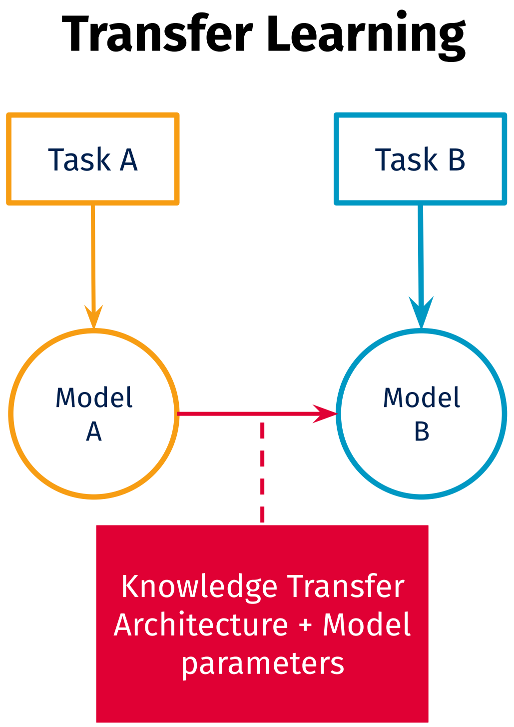
DOI 10.5281/zenodo.3342952

CTLearn

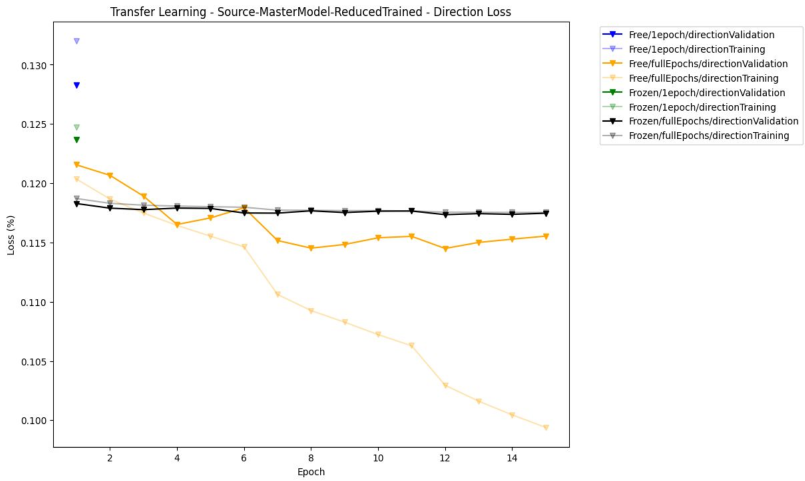
Share knowledge between models

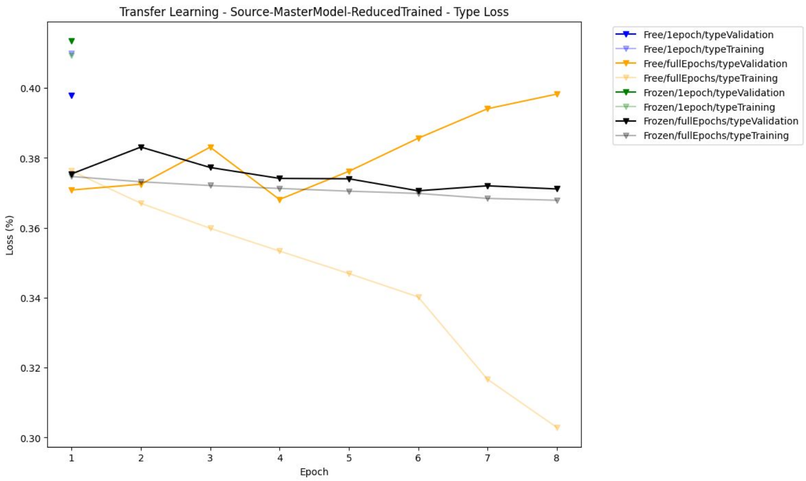
- Variants
  - Differente source models
  - Backbone (Free or Frozen)
  - Train the second model for different number of epochs

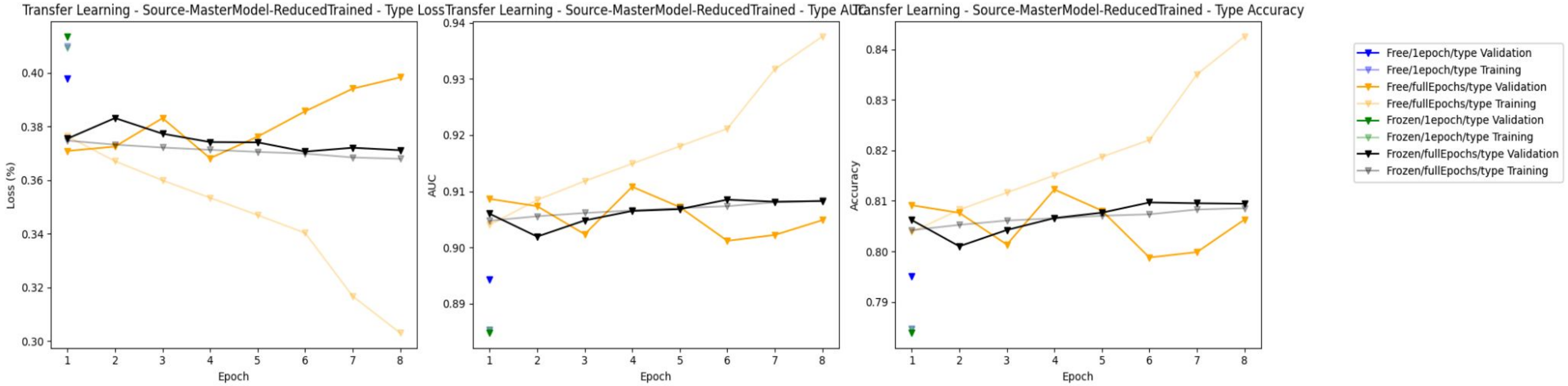
- Goals
  - Save training time
  - Have a main source model



CTLearn - Transfer Learning - Train



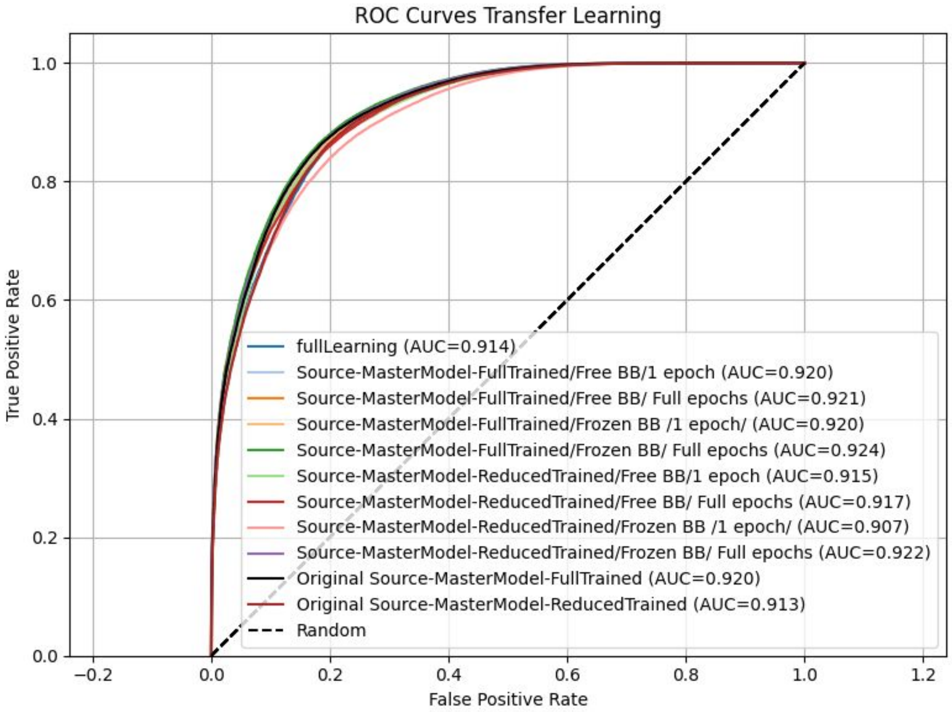




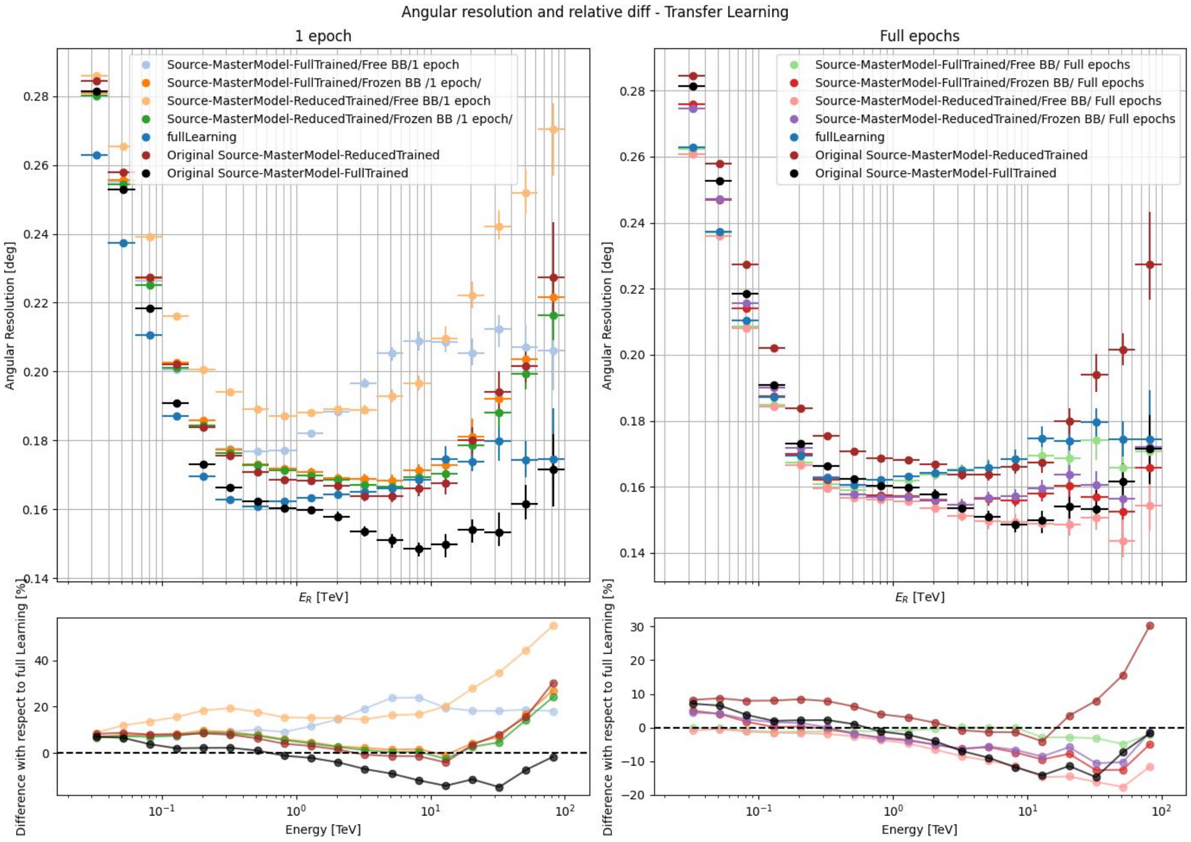
CTLearn - Transfer Learning - Train

Time (relative to full learning)	Energy	Direction	Type
Full Learning	1	1	1
Full Trained - Free - 1epoch	1.46	0.55	1.35
Full Trained - Free - full epochs	1.45	0.54	1.27
Full Trained - Frozen - 1epoch	**0.45**	**0.31**	**0.44**
Full Trained - Frozen - full epochs	**0.49**	**-**	**0.45**
Reduced Trained - Free - 1epoch	1.87	1.72	1.55
Reduced Trained - Free - full epochs	1.85	1.81	1.16
Reduced Trained - Frozen - 1epoch	**0.21**	**0.31**	**0.27**
Reduced Trained - Frozen - full epochs	**0.30**	**0.5**	**0.19**

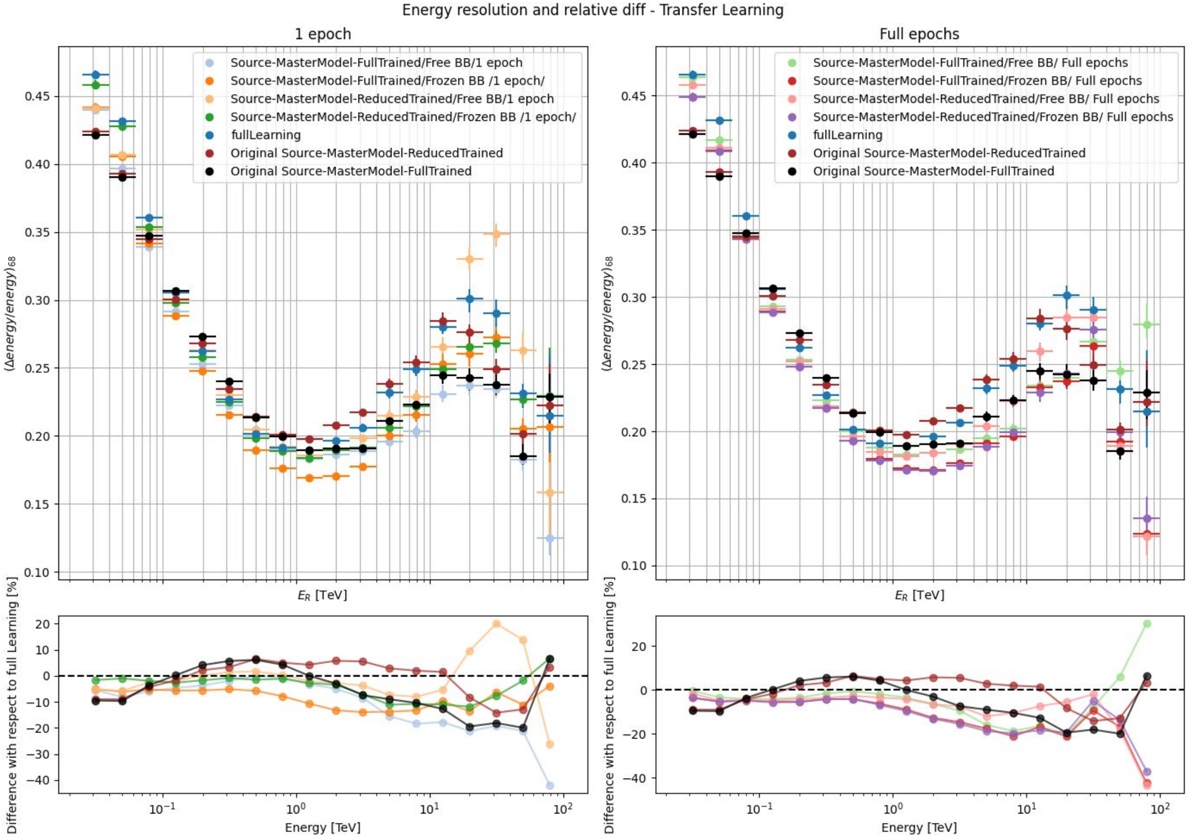
CTLearn - Transfer Learning - Test



CTLearn - Transfer Learning - Test

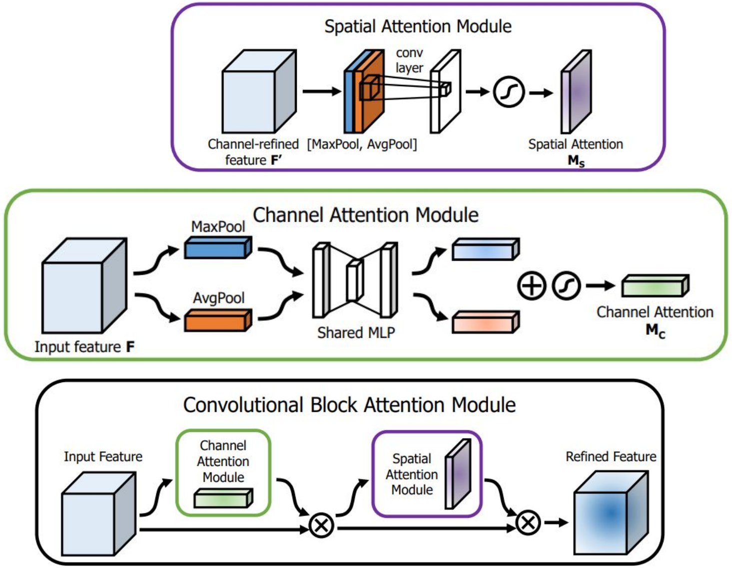


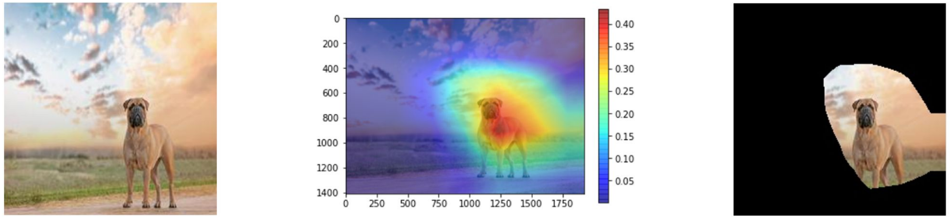
CTLearn - Transfer Learning - Test



Spatial attention (pixels) and channel attention (time, image)

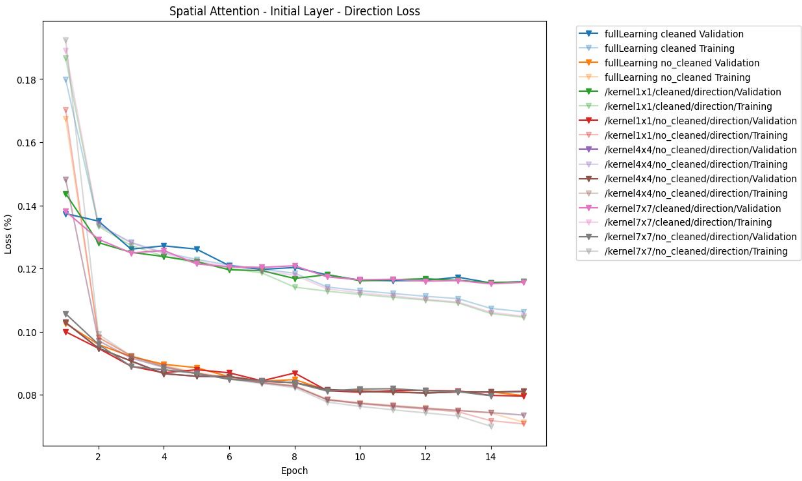
- Variants
  - Structure (Initial layer, between convolutional blocks)
  - Data (Clean; not clean)
  - Kernel (1x1, 4x4, 7x7)
- Goals
  - Understanding CNN’s approaches when predicting
  - Trying to avoid cleaning process

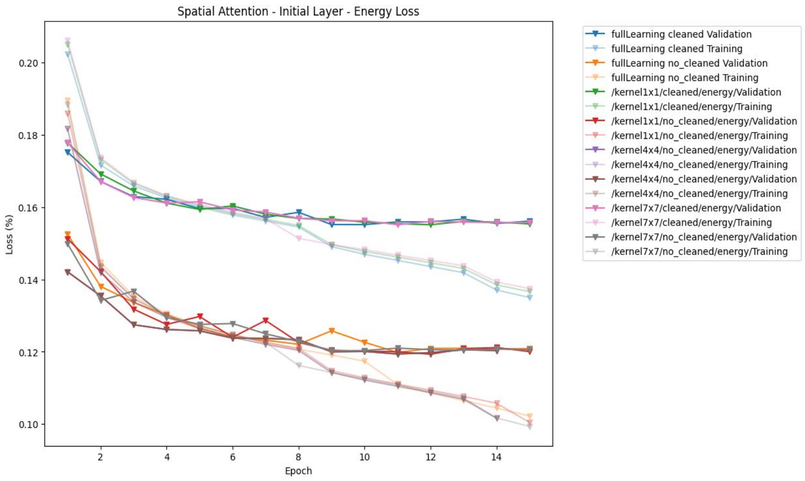


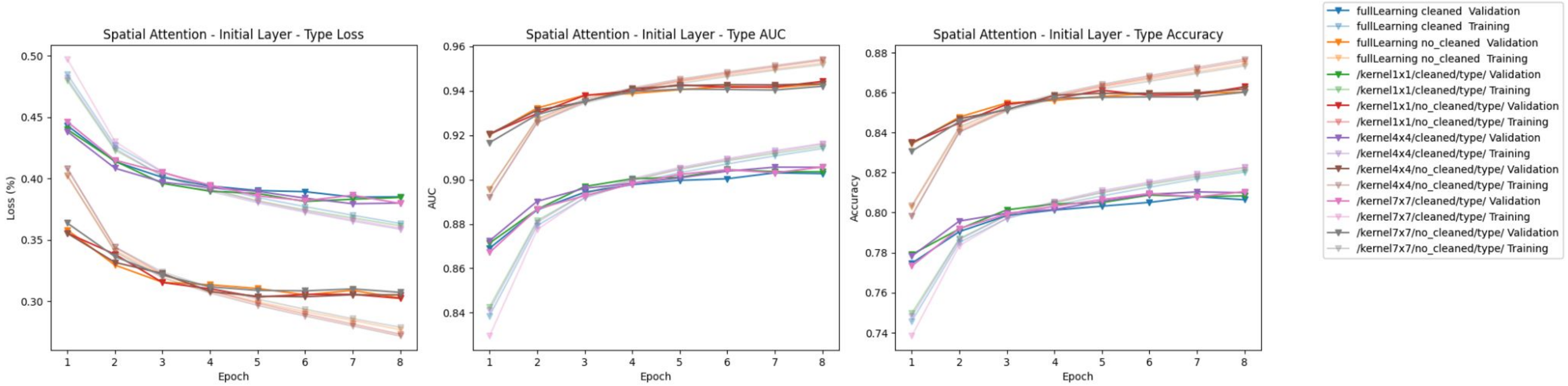


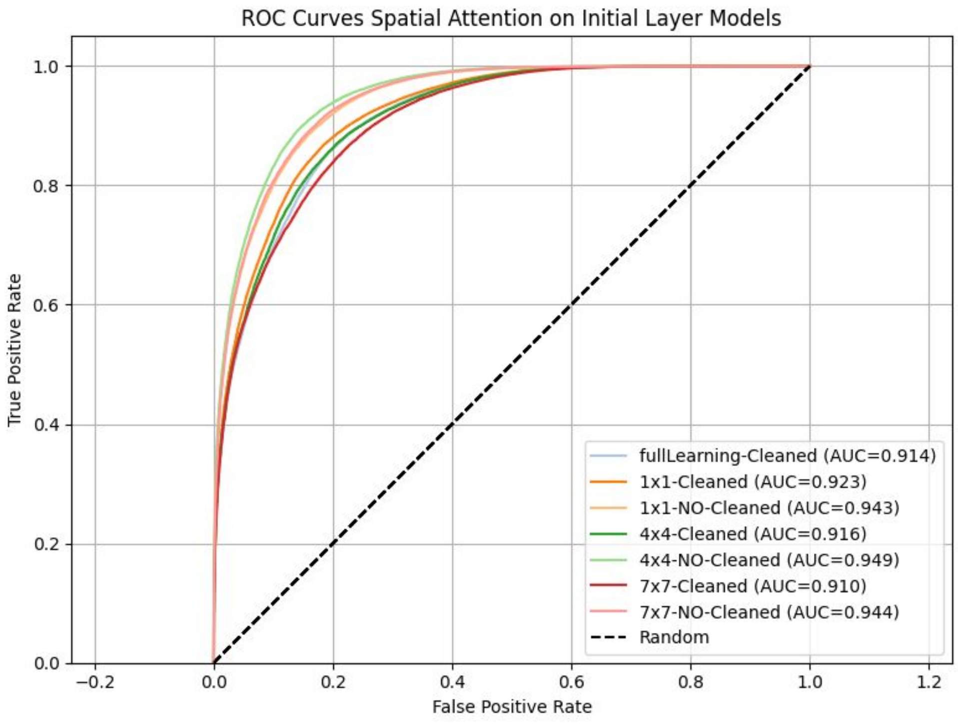
(a) Original image (b) Attention map (c) Visual explanation map

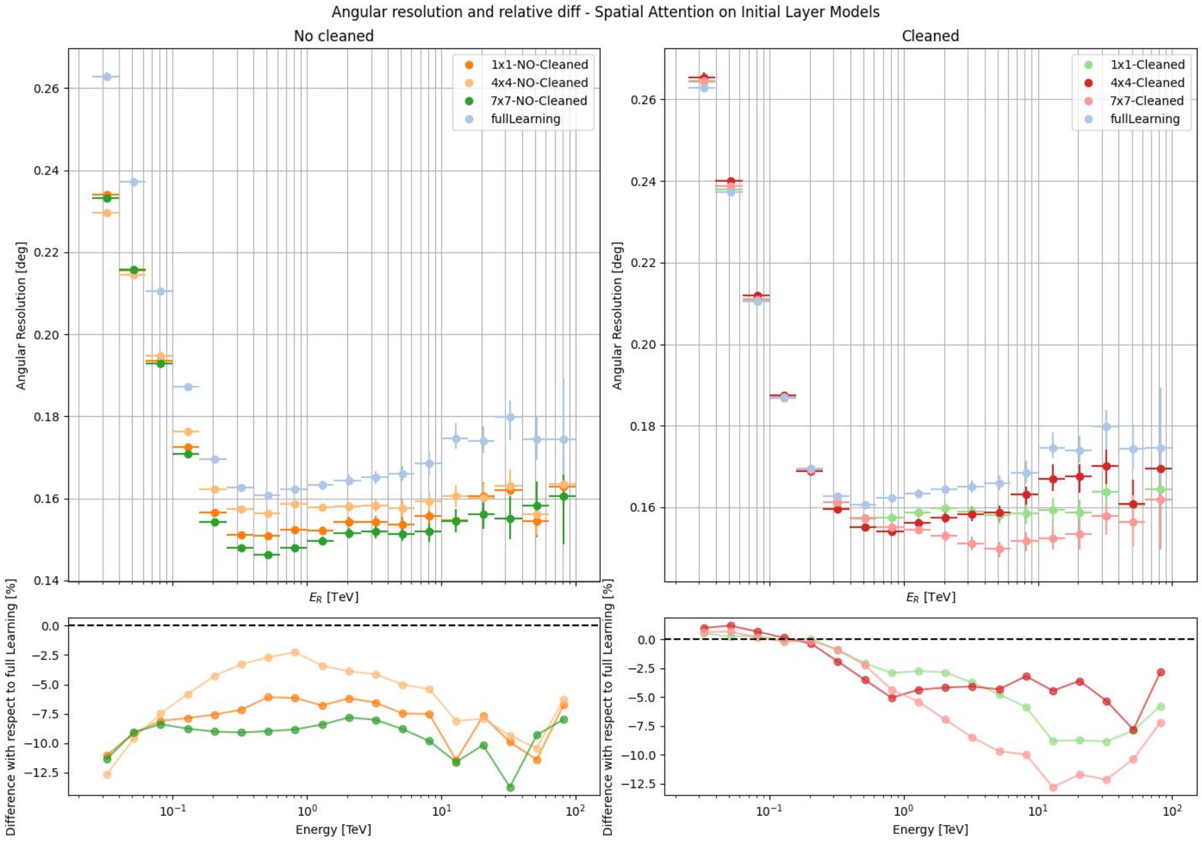
Artemisa
ARTificial Environment for ML and Innovation in Scientific Advanced Computing


Spatial Attention - Initial Layer - Direction Loss
Loss (%)
Epoch
fullLearning cleaned Validation
fullLearning cleaned Training
fullLearning no_cleaned Validation
fullLearning no_cleaned Training
/kernel1x1/cleaned/direction/Validation
/kernel1x1/cleaned/direction/Training
/kernel1x1/no_cleaned/direction/Validation
/kernel1x1/no_cleaned/direction/Training
/kernel4x4/no_cleaned/direction/Validation
/kernel4x4/no_cleaned/direction/Training
/kernel4x4/no_cleaned/direction/Validation
/kernel4x4/no_cleaned/direction/Training
/kernel7x7/cleaned/direction/Validation
/kernel7x7/cleaned/direction/Training
/kernel7x7/no_cleaned/direction/Validation
/kernel7x7/no_cleaned/direction/Training

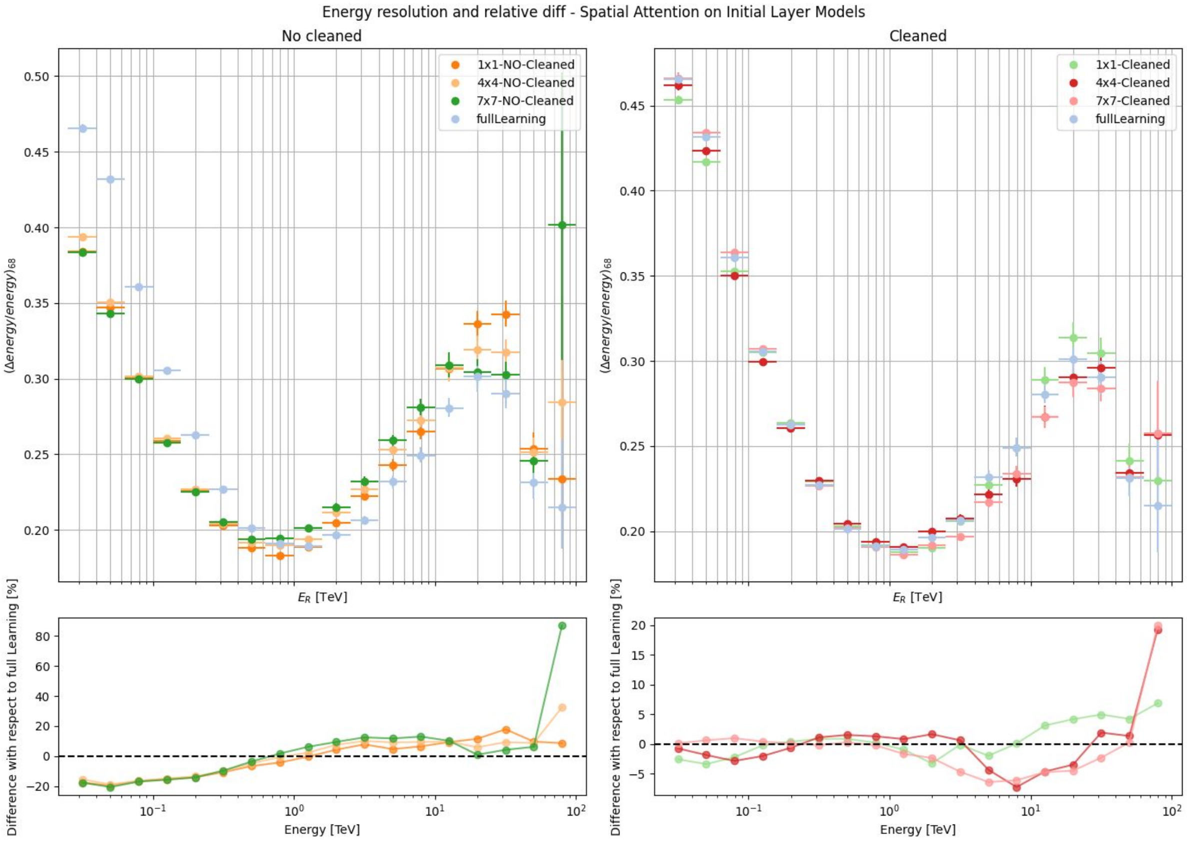

Spatial Attention - Initial Layer - Energy Loss
Loss (%)
Epoch
fullLearning cleaned Validation
fullLearning cleaned Training
fullLearning no_cleaned Validation
fullLearning no_cleaned Training
/kernel1x1/cleaned/energy/Validation
/kernel1x1/cleaned/energy/Training
/kernel1x1/no_cleaned/energy/Validation
/kernel1x1/no_cleaned/energy/Training
/kernel4x4/no_cleaned/energy/Validation
/kernel4x4/no_cleaned/energy/Training
/kernel4x4/no_cleaned/energy/Validation
/kernel4x4/no_cleaned/energy/Training
/kernel7x7/cleaned/energy/Validation
/kernel7x7/cleaned/energy/Training
/kernel7x7/no_cleaned/energy/Validation
/kernel7x7/no_cleaned/energy/Training


Spatial Attention - Initial Layer - Type Loss
Loss (%)
Epoch
Spatial Attention - Initial Layer - Type AUC
AUC
Epoch
Spatial Attention - Initial Layer - Type Accuracy
Accuracy
Epoch
fullLearning cleaned Validation
fullLearning cleaned Training
fullLearning no_cleaned Validation
fullLearning no_cleaned Training
/kernel1x1/cleaned/type/ Validation
/kernel1x1/cleaned/type/ Training
/kernel1x1/no_cleaned/type/ Validation
/kernel1x1/no_cleaned/type/ Training
/kernel4x4/cleaned/type/ Validation
/kernel4x4/cleaned/type/ Training
/kernel4x4/no_cleaned/type/ Validation
/kernel4x4/no_cleaned/type/ Training
/kernel7x7/cleaned/type/ Validation
/kernel7x7/cleaned/type/ Training
/kernel7x7/no_cleaned/type/ Validation
/kernel7x7/no_cleaned/type/ Training


ROC Curves Spatial Attention on Initial Layer Models
True Positive Rate
False Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
fullLearning-Cleaned (AUC=0.914)
1x1-Cleaned (AUC=0.923)
1x1-NO-Cleaned (AUC=0.943)
4x4-Cleaned (AUC=0.916)
4x4-NO-Cleaned (AUC=0.949)
7x7-Cleaned (AUC=0.910)
7x7-NO-Cleaned (AUC=0.944)
Random


Angular resolution and relative diff - Spatial Attention on Initial Layer Models
No cleaned
Cleaned
1x1-NO-Cleaned
4x4-NO-Cleaned
7x7-NO-Cleaned
fullLearning
1x1-Cleaned
4x4-Cleaned
7x7-Cleaned
Angular Resolution [deg]
E_R [TeV]
Difference with respect to full Learning [%]
Energy [TeV]

CTLearn - Attention experiments - Test



THANK YOU

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

Acknowledgment

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