Deep Learning Methods for IACT Data Analysis in Gamma-Ray Astronomy

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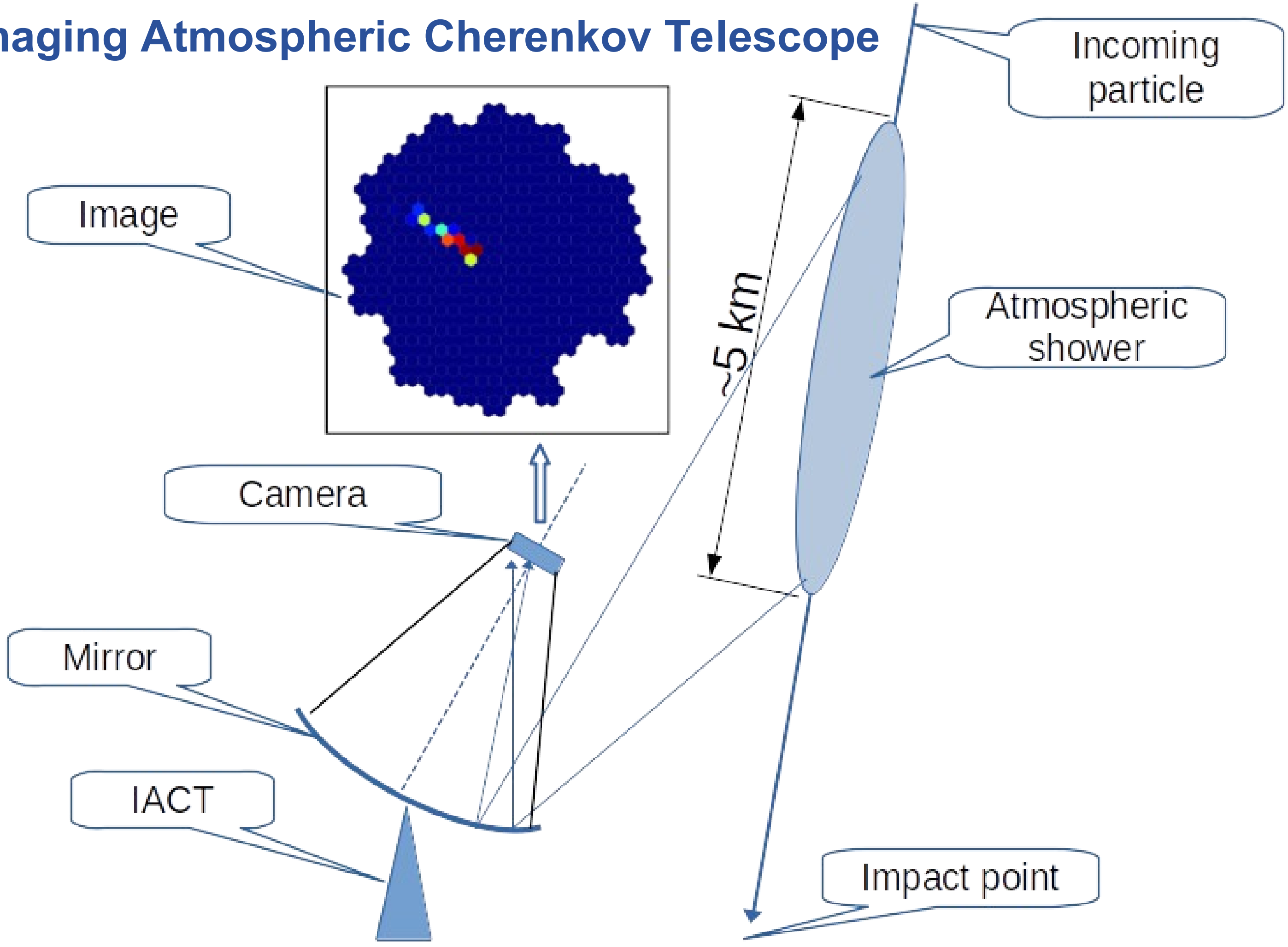
Simplified IACT operation scheme

IACT = Imaging Atmospheric Cherenkov Telescope

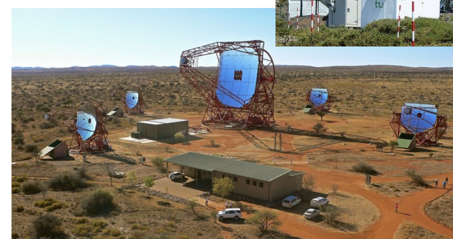


Some gamma-ray observatories with IACTs

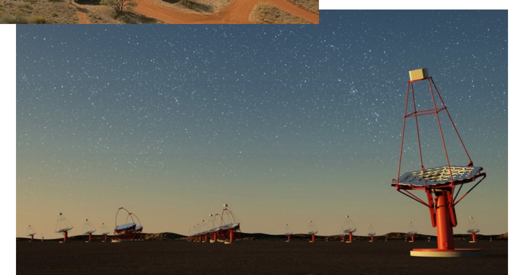
- VERITAS (Very Energetic Radiation Imaging Telescope Array System), Arizona, US

- MAGIC Florian Goebel Telescopes, La Palma, Canary Islands

- H.E.S.S. (High Energy Stereoscopic System), Khomas highlands, Namibia

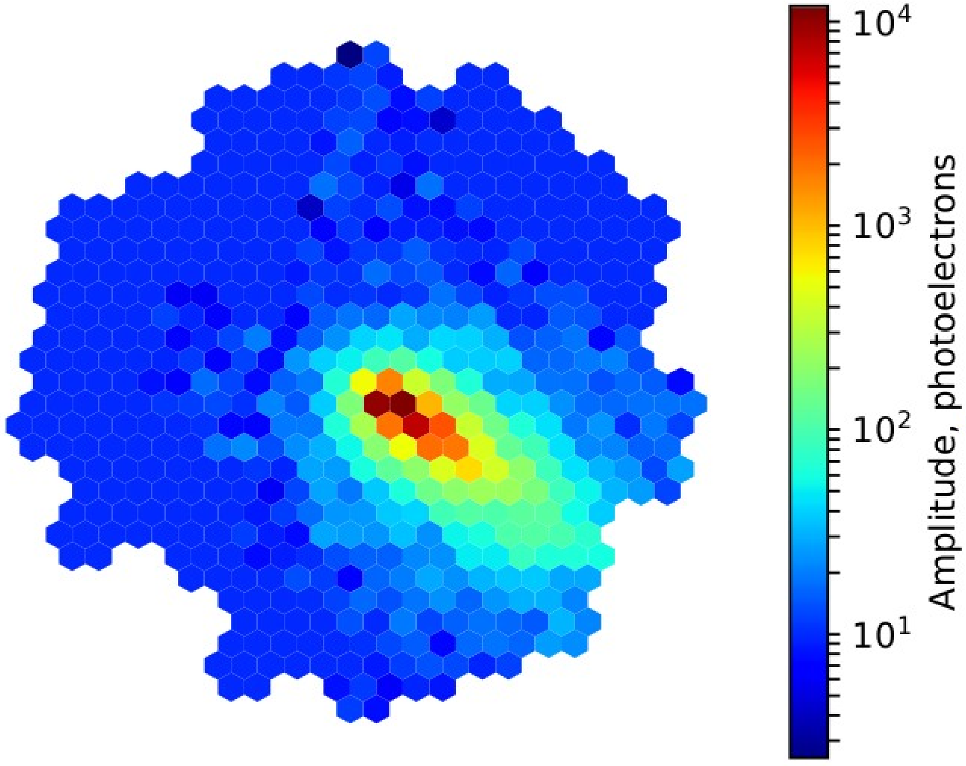


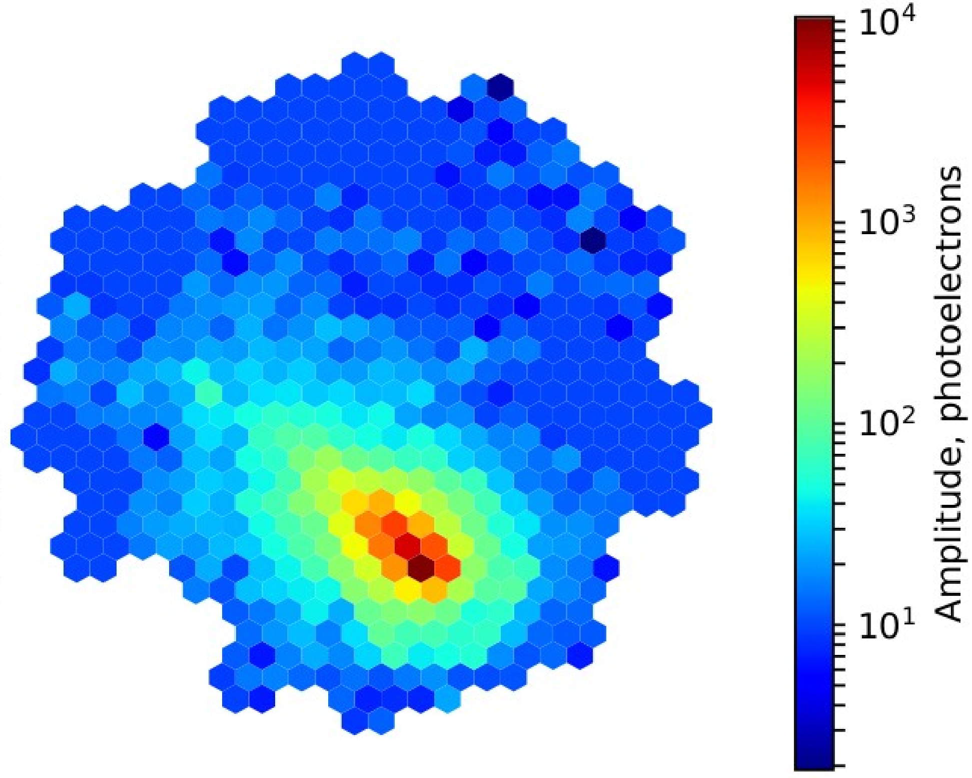
- CTA (Cherenkov Telescope Array), Paranal, Chile + La Palma, Spain



- TAIGA-IACT (Tunka Advanced Instrument for cosmic ray physics and Gamma Astronomy), Tunka valley, Russia

Examples of EAS images in an IACT camera





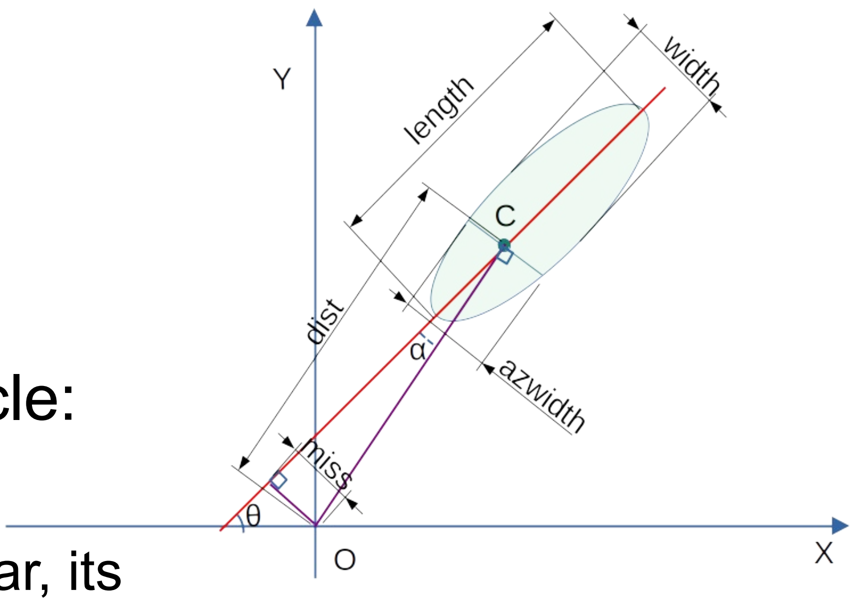
On the left: EAS initiated by gamma. On the right: EAS from proton.

IACT data processing

- Several stages, including:
  - calibration of individual photomultipliers in the IACT camera
  - image cleaning
  - **aggregating information from individual detectors (pixels)**
    - **on its basis the main parameters of an individual event are determined** ⇦ ***scope of this report***
      - event type (gamma/cosmic rays), its energy, and direction of arrival
  - obtaining of high-level information about the source
    - energy spectrum, structure of the radiation, temporal variability

IACT data processing: non-DL methods

- Simulation of EAS using Monte Carlo methods (CORSICA)
- Hillas parameter technique
  - mainly by the cuts method
  - it is possible to reconstruct the properties of the primary particle:
    - determine its type
    - other characteristics, in particular, its energy *E*, the impact distance *R*



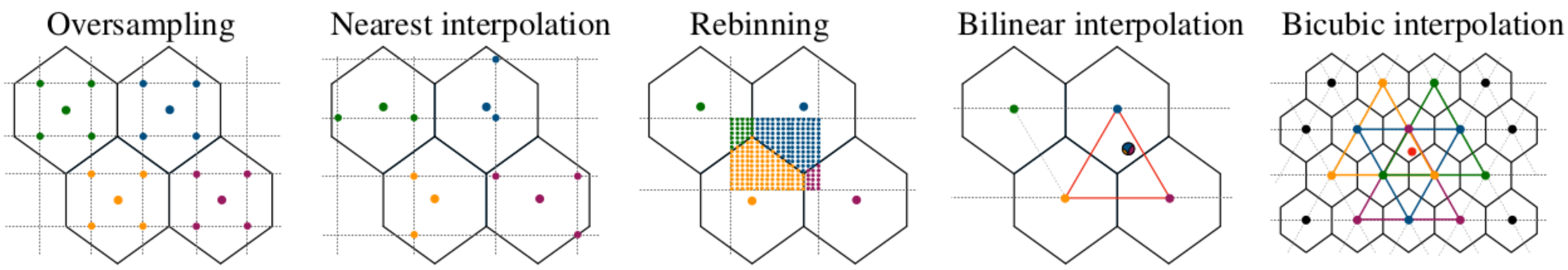
- reduces the information to the small set of parameters
  - **a lot of information is discarded**, which can potentially be important for the reconstruction and classification of events.

DL for particle type classification (background rejection): highly incomplete list

- Nieto Castaño D., et al., 2017. PoS ICRC2017, 809.
- Shilon I., et al., 2019. Astropart. Phys. 105, 44–53.
- Parsons R. & Ohm S., 2020. Eur.Phys.J. C80, 1–11.
- Spencer S., et al., 2021. Astropar.Phys. 129, 102579.
- Riquelme, D., et al., 2023. ICPRAM 2023, 725–732.
- De, S., et al. 2022. arXiv:2206.05296.
- Parsons, R., et al. 2022. arXiv:2203.05315.
- Nieto, D., et al., 2019. arXiv:1912.09898.

Technicality: hexagonal ⇔ square grids

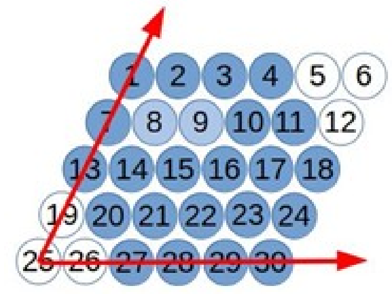
- pixels of most IACTs are arranged in a hexagonal array, while usual NN inputs assume a square grid
- Nieto et al., 2019 considered different image transformations



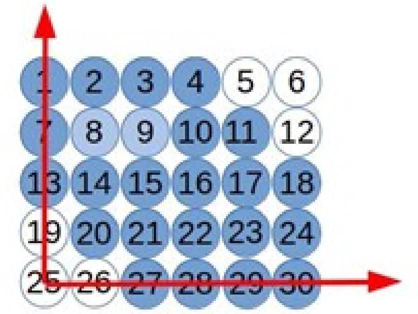
- the main conclusion: accuracy and ROC/AUC, coincide within errors for all the methods studied
- general reason: CNNs percept only topological (neighborhood), not metrical pixel interrelations

Technicality: hexagonal ⇔ square grids (2)

- One more method is based on approximation of the regular square grid by using oblique coordinates with angle 60°
  - changing number of neighbors
  - not compared with other methods
- Another approach: special convolution operations taking into account only neighborhood
  - implementation: IndexedConv package (Jacquemont et al., 2019)



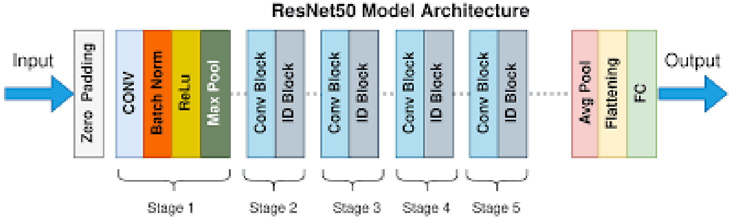
before

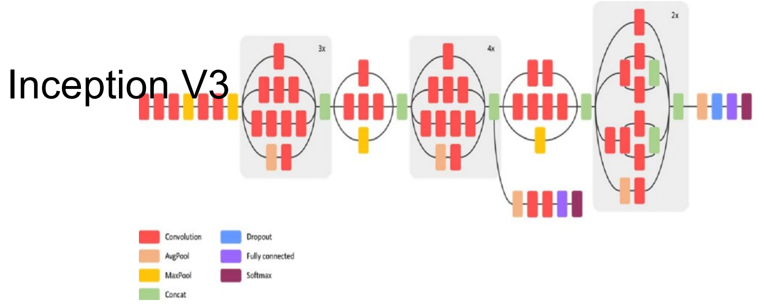


after

1. Convolutional neural network

- Nieto Castaño et al., 2017: using ResNet50 & Inception V3 (a bit **better** performance for this task)
- DL methods can be used to classify IACT images (gamma/proton)
  - **without any prior parameterization or any assumptions** about the nature of the images themselves
  - accuracy of Inception V3 is dependent on the primary particle energy from 81.4% for the low energy; 91.6% for high energy



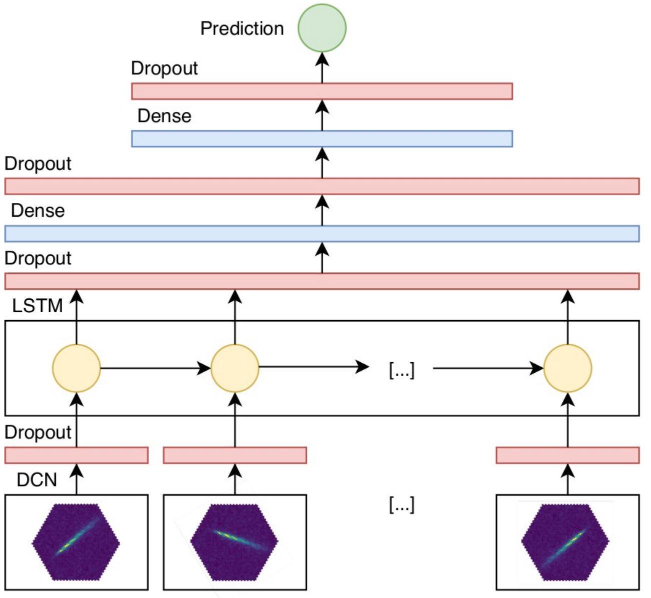


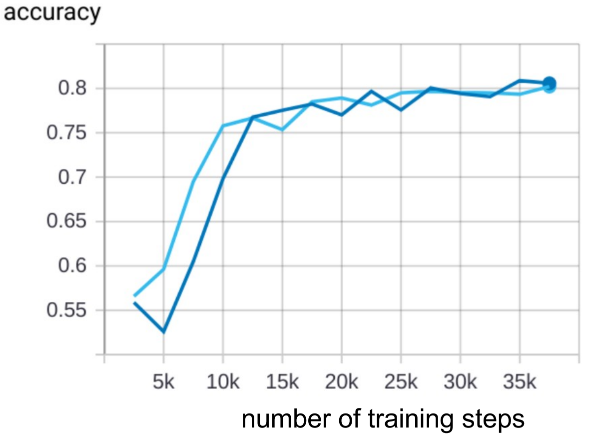
2. Recurrent neural network

- An interesting feature of the work by Shilon et al. (2019) is the *first* attempt to use RNN in combination with CNN to analyze image sequences time-ordered by triggers of each of the four H.E.S.S. IACTs
  - did not find sufficiently convincing arguments for its full-fledged application
- However, later this approach was improved (CRNN=CNN+RNN+LSTM) in a number of works & successfully applied both to background rejection (classification) and parameter reconstruction
  - E.g., Parsons and Ohm, 2020: CRNNs open the possibility of improving the hadronic background rejection of about 20–25% compared to using the Hillas parameters

3. A combination of convolutional neural networks with a recurrent neural network

- Brill et al., 2019:
  - dependence of the CRNN performance on the method of ordering images
  - identification number (arbitrary but rigid order) vs. *Size* parameter (total image intensity ~ proximity to the shower center)
- performance - about the **same**
  - no clear confirmation that sorting by the Size improves





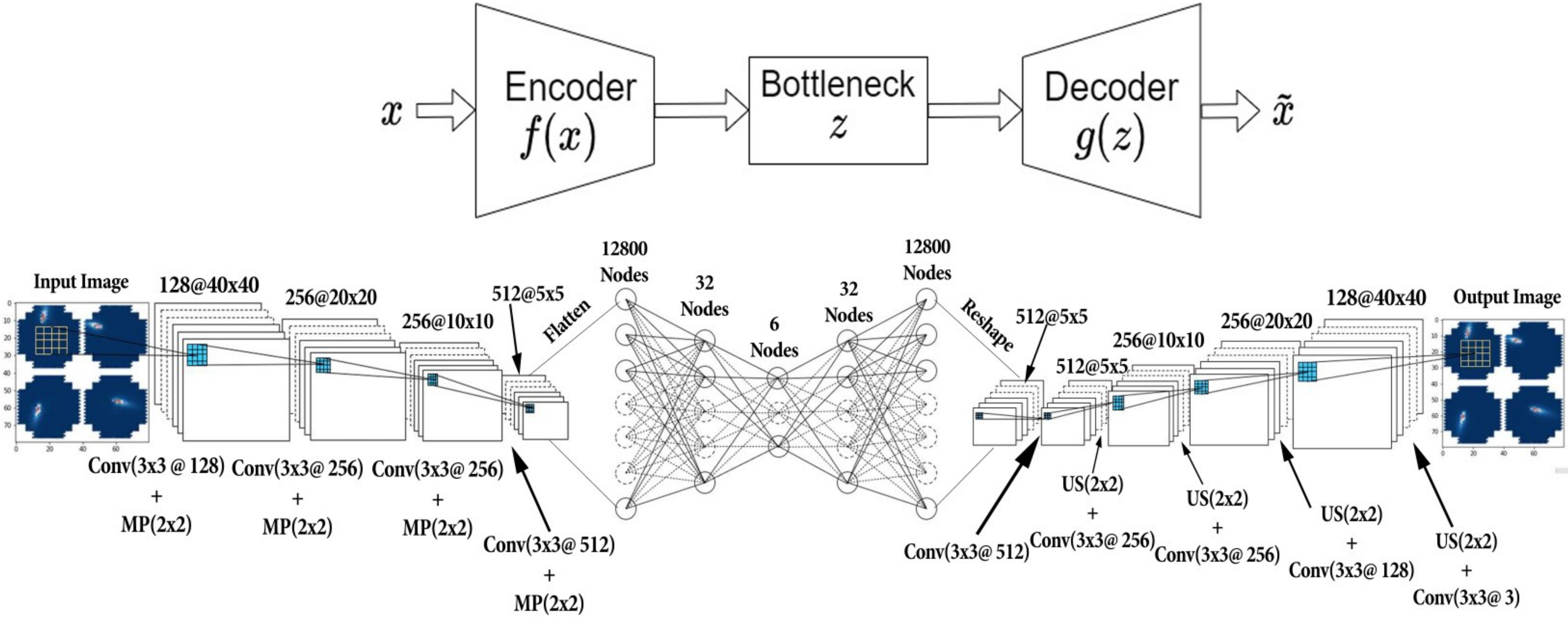
4a. Anomaly detection

- A distinctive feature of (De et al., 2022) is that it not only poses the problem of classifying already known primary particles (Standard Model; SM), but also the search for particles Beyond SM (BSM). Suggestion:
  - CNNs + autoencoders (AE)
  - AE is trained on events (MC-simulated) initiated by SM particles.
  - Then AE restores well IACT images for SM primary particle and distorts it in the case of a BSM particle.
- This may be a signal that there are particles in the cosmic ray flux that are described outside the framework of the Standard Model.

4b. Anomaly detection

De et al., 2022:

- The standard SM induced showers are taken as the training set, and the autoencoder learns relevant features of these images.
- If the resulting image resembles the original input within some tolerance, the image is clas-
- sified as “normal”, otherwise the image is classified as “anomalous”.



The schematic diagram of the implemented autoencoder architecture.

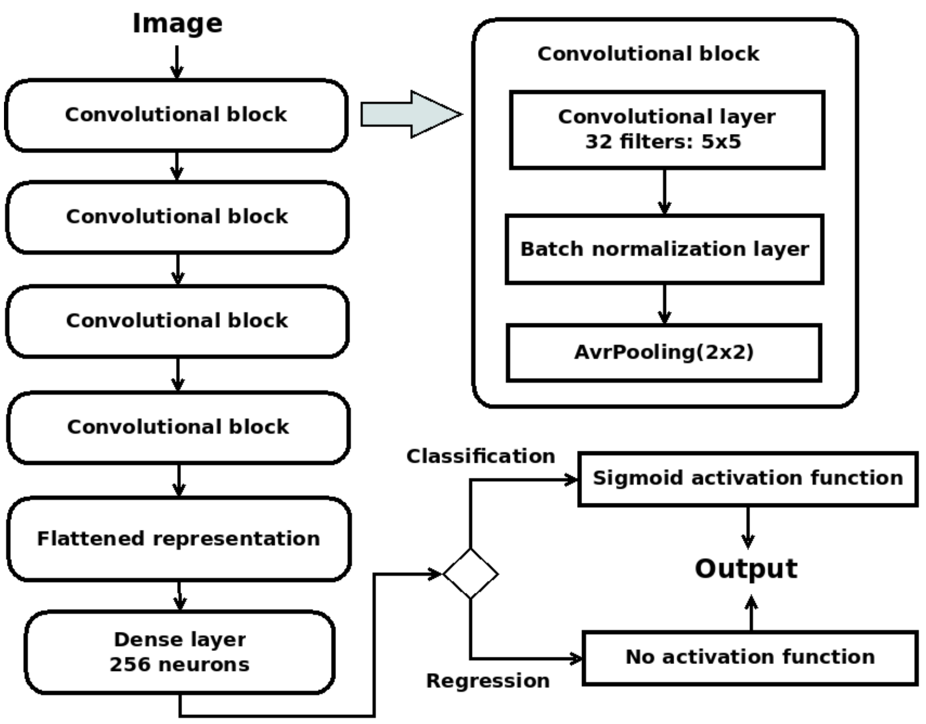
DL for reconstruction of EAS/primary particle parameters: highly incomplete list

- Mangano et al. 2018. IAPR Workshop, pp. 243–254.
- Postnikov et al., 2019. Journ.Phys. p. 012048.
- Polyakov et al. 2021. PoS 395, p.753.
- Gres & Kryukov, 2022. PoS DLCP2022, p.002.
- Jacquemont et al. 2020. ADASS XXX, pp. 1–5.
- Jacquemont et al, 2021.VISAPP 2021, pp. 1–12.
- Abe et al. 2021. PoS ICRC2021, 703.
- Bylund et al. 2021. PoS ICRC2021, 758.

Reconstruction: examples of studies

- Mangano et al., 2018,
- Postnikov et al., 2019,
- Polyakov et al., 2021:
  - rated the results of using CNNs as ***very promising,***
  - although they were still not as good as those of existing algorithms based on Hillas parameters.
  - requires further improvements

Mangano et al., 2018:

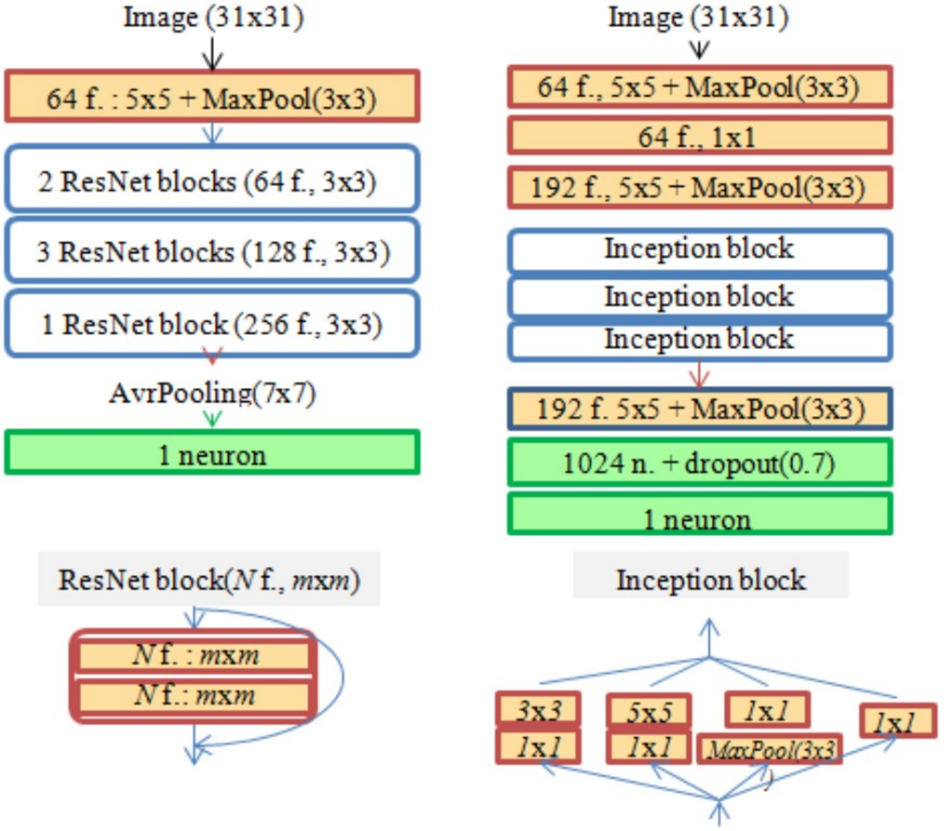


Regression = reconstraction of energy and angle of arrival

Reconstruction: examples of studies (2)

- Polyakov et al., 2021;
  Gres and Kryukov, 2022
  - more complex NN
  - + joint processing of images from ***multiple*** telescopes
- even more promising results, in particular:
  - reconstructed energy spectrum is in good agreement with that of the traditional method and model spectrum.

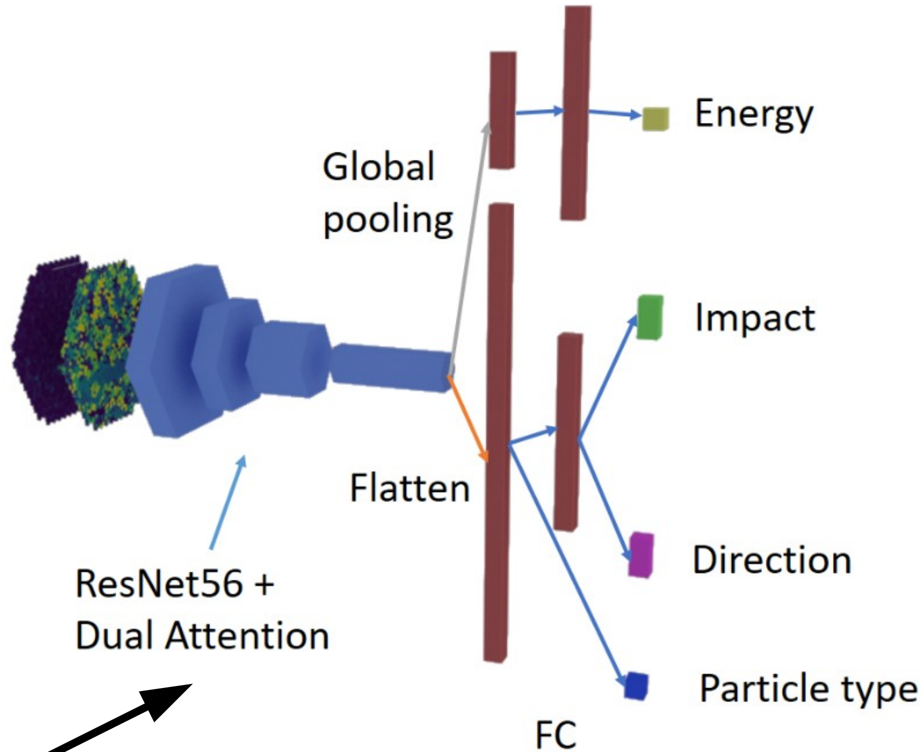
Gres and Kryukov, 2022:



ResNet GoogLeNet

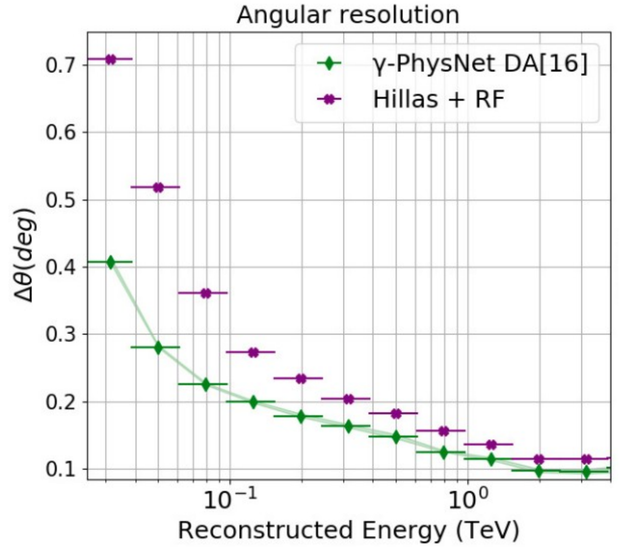
Deep multi-task learning architecture

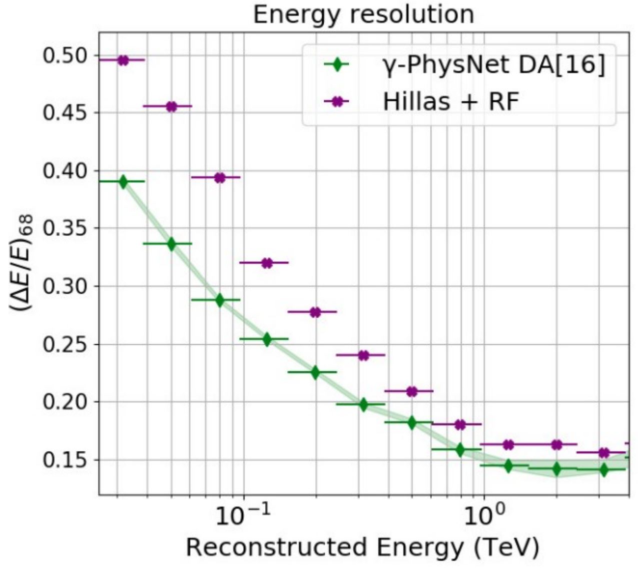
- Jacquemont et al., 2020, 2021a: **γ-PhysNet**
- ***multitasking*** DL architecture that performs full event reconstruction with a single NN using parameter interdependence
- two parts:
  - (ResNet 56 with ***attention***)=encoder
  - **multi-task** block



Deep multi-task learning architecture (2)

- LST1 telescope, CTA
- The angular and energy resolution curves, as well as the sensitivity curve, show that **γ-PhysNet** ***outperforms*** the classical method Hillas + RF
- in particular on
    - gamma/proton classification;
    - energy and direction reconstruction;
    - resulting sensitivity





Deep multi-task learning architecture (3)

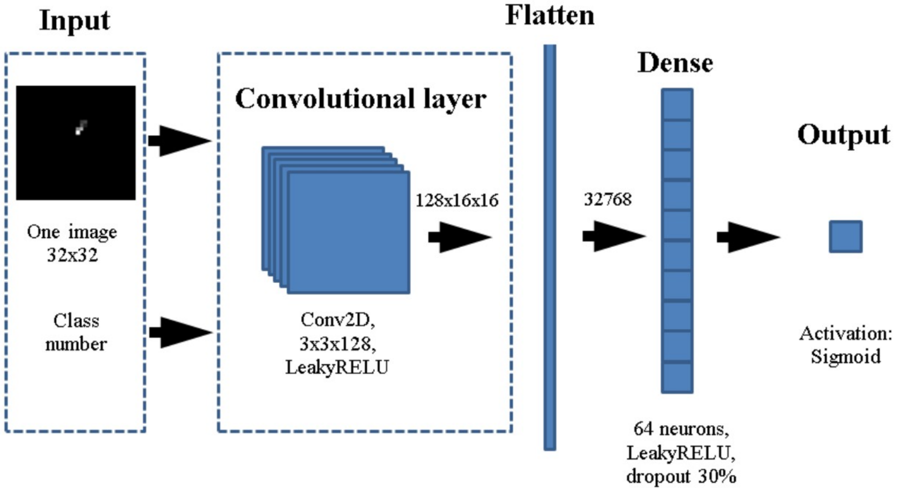
- Jacquemont et al., 2021b; Abe et al., 2021 = continuation and development of the previous work:
  - simulated data ⇒ real experimental data.
  - the systematic learning error due to the difference between them is discussed
    - of particular importance: difference due to night sky background (NSB)
    - solved by **adding noise** to the simulated data used to train the model
  - thanks to the (***DMTL+Attention***) architecture of the γ-PhysNet
    - it was possible to achieve a clear detection of the Crab Nebula with a statistical significance of 14.3 σ,
    - **outperforming** the (Hillas+Random Forest) standard approach

Fast simulation of EAS images in IACTs

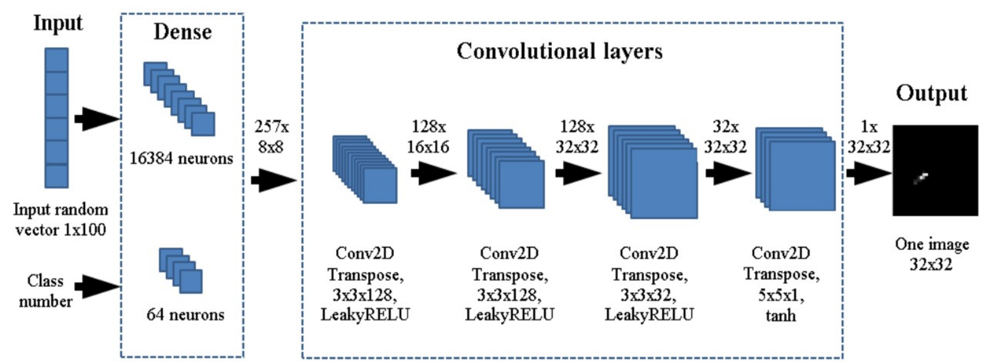
- images of events in IACTs are simulated using the MC-package CORSIKA + specific soft tracing of Cherenkov photons through the IACT optics
  - very ***resource intensive*** and require a lot of computational time
  - for some analysis purposes the complete model information is redundant
- In Dubenskaya et al., 2021:
  - it was proposed to use generative adversarial networks (GAN) for fast imaging of gamma events in IACT
  - although the training can take a long time, the ***generation is very fast***

Fast simulation of EAS images in IACTs (2)

- of particular interest are conditional generative adversarial networks (cGANs)
- produce images with a predetermined spectrum in terms of, e.g., *Size*



Architecture of the discriminator



Architecture of the generator

Fast simulation of EAS images in IACTs (3)

- in (Polyakov et al., 2022), for the same purpose of generating images in an IACT camera with a given spectrum, a conditional variational autoencoder (cVAE) was used.
- thus, in these works, it was shown that GAN, cGAN and cVAE simulate proton and gamma events for the TAIGA-IACT experiment with a high degree of accuracy and reliability.
- see the reports at this conference

Dedicated software for analyzing IACT data using DL methods: CTLearn package

- CTLearn (Nieto Castaño et al., 2019):
- provides a backend for training neural networks for reconstructing IACT events using TensorFlow
  - allows the user to focus on developing and applying new models using functionality specifically designed for IACT event reconstruction
  - uses YAML configuration files to provide reproducible training and prediction.
- also includes a number of helper scripts that provide a convenient way to summarize results and plot relevant graphs

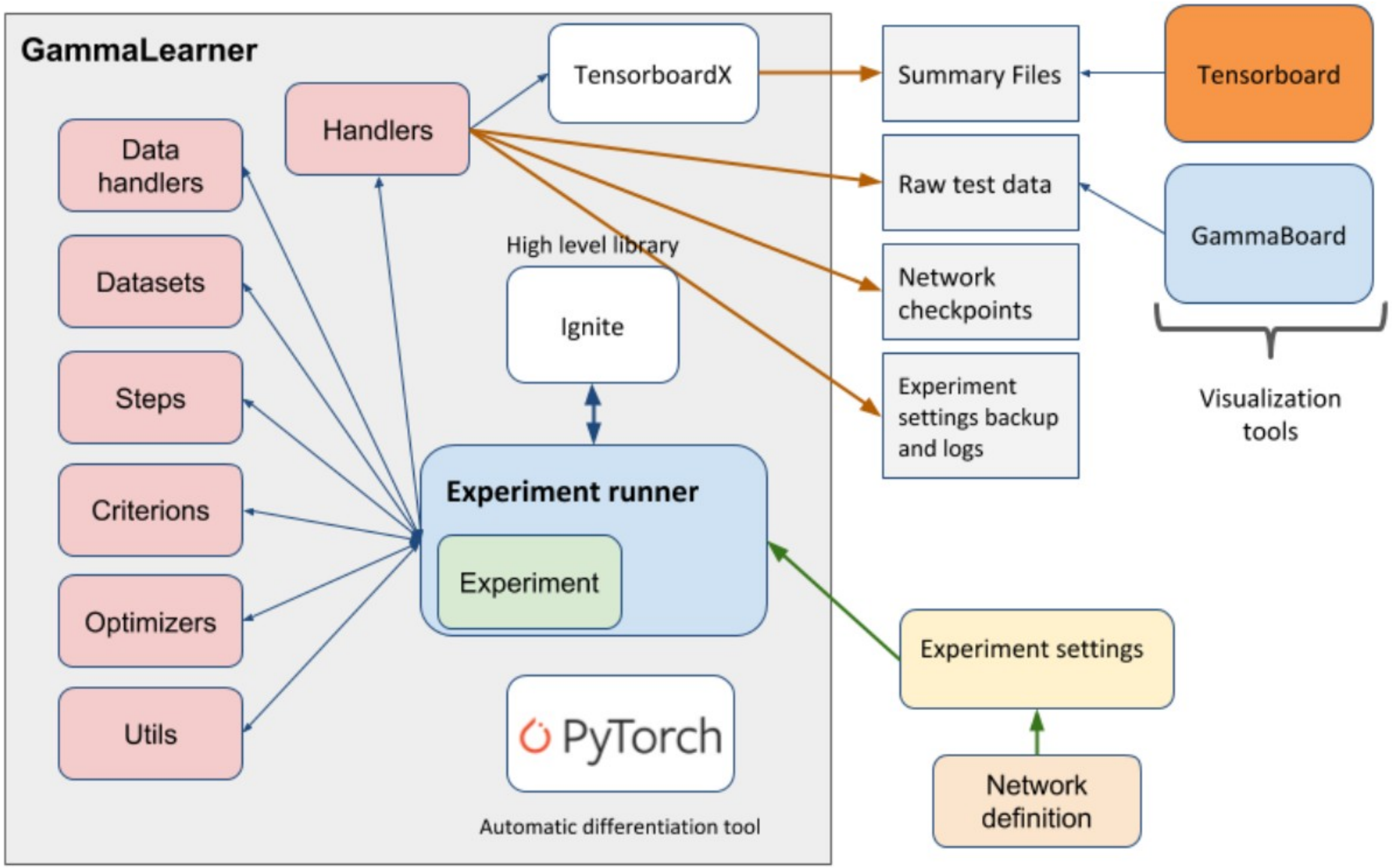
Dedicated software for analyzing IACT data using DL methods: CTLearn package (2)

- Data can be downloaded in three modes:
  - mono (single images from a telescope of a particular type are downloaded);
  - stereo (events recorded by a number of telescopes of the same type are loaded);
  - multi-stereo (events involving several types of telescopes are loaded)
- has three pre-installed models for classifying gamma rays and cosmic rays
- freely available on GitHub: https://github.com/ctlearn-project/ctlearn (license: BSD-3)

Dedicated software for analyzing IACT data using DL methods: GammaLearn platform

- GammaLearn (Jacquemont et al.,2019; Vuillaume et al., 2019)
- modular software written in Python & is based on the PyTorch framework
  - has an advanced set of tools that provide all the functions for:
    - loading datasets;
    - data pre-processing (filtering, augmentation, transformation);
    - network training, validation and testing;
    - tracking the learning process & visualizing it

Dedicated software for analyzing IACT data using DL methods:GammaLearn platform (2)



Dedicated software for analyzing IACT data using DL methods:GammaLearn platform (3)

- IndexedConv package provides convolution and pooling operations for input data (images) on any grid
- The GammaBoard package provides a dashboard that displays metrics for evaluating the performance of IACT event reconstruction
- convenient to use the Tensorboard set of web applications that come with TensorFlow
- freely available on https://gitlab.in2p3.fr/gammalearn/gammalearn (MIT License)

Conclusion (1/2)

- DL methods: achieve an optimal balance between the time/resource intensity of calculations and the requirement to save the maximum possible amount of input experimental information
- very promising for both existing installations and future generation telescopes
- CNNs are the backbone of almost all DL methods
  - even by themselves demonstrate the high quality of IACT data processing
-

Conclusion (2/2)

- considering that future generation installations will consist of several or even many coordinated IACTs (⇒ image sequences), CNNs +RNN+ LSTMs, seems to be very promising
- given that the EAS image usually occupy a relatively small part of the entire camera area, the use of NN with the attention mechanism can be very fruitful
- the emergence of specialized computer platforms also contributes to the widespread use of deep learning methods for analyzing IACT data.