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Single Imaging Atmospheric Cherenkov Telescope Full-Event Reconstruction with a Deep Multi-Task Learning Architecture

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Abstract. The Cherenkov Telescope Array (CTA) is the next generation ground-based observatory for γ-ray astronomy. It will be used to study γ-ray sources, allowing to better understand the Universe. One order of magnitude more sensitive than the current generation of experiments, CTA will propose unseen challenges to standard reconstruction methods. The GammaLearn project offers to apply deep learning as a part of the analysis of CTA data. Its goal is to separate the γ photons from cosmic particles, and reconstruct the γ photon parameters (energy and arrival direction) from noisy unconventional images, with expected better performance and faster reconstruction than standard methods. Here we present a complete reconstruction of IACT events using state-of-the-art deep learning techniques. The network is then applied in the single telescope context of the LST1, the first CTA telescope prototype built on the Northern hemisphere site (La Palma, Canary Island). We show that the full event reconstruction is possible with a single multi-task network, reducing the computing needs.

1. Introduction

Imaging Atmospheric Cherenkov Telescopes (IACT) detect the Cherenkov light induced by particle showers generated by cosmic rays and gamma rays entering the atmosphere. A complex data analysis is then required to reconstruct the direction, energy and type of the incoming particle from the telescope images. Since the 2012 ImageNet breakthrough, deep learning advances have shown dramatic improvements in data analysis across a variety of fields. Convolutional neural networks look particularly suited to the task of analyzing IACT camera images for event reconstruction as they provide a way to reconstruct the interesting physical parameters directly from calibrated images, skipping the preprocessing steps of standard methods, such as image cleaning and image parametrization. Moreover, despite demanding substantial computing resources to be trained and optimized, neural networks show very good performance during inference in a production setup. Some effort has been made to explore deep learning techniques for IACT data analysis, especially to perform gamma event reconstruction of CTA data (Nieto Castaño et al. 2017; Mangano et al. 2018) or other IACTs (Shilon et al. 2019). Although these papers present promising results, especially for gamma/proton classification, they all handle the different reconstruction problems as single tasks, without considering their strong interdependence.

2. γ-PhysNet for Full Event Reconstruction

γ-PhysNet is a multi-task learning (Caruana 1997) architecture that performs full-event reconstruction with a single neural network, exploiting the interdependence of the parameters to reconstruct. It is composed of two parts. The first one is a very deep backbone (the convolutional part of the ResNet 56 (He et al. 2016)) augmented with Dual Attention (Sun et al. 2020). The attention blocks help the model focus on the relevant part of the feature maps to extract a meaningful latent representation of the input data. This representation is then fed to a -task block inspired by the physics knowledge. This block is divided into two paths, a global path to reconstruct the energy and a local path to perform gamma/proton separation, direction reconstruction and virtual impact point reconstruction as an auxiliary task. Multi-task learning helps improve the generalization ability of the model, and so the reconstruction performance by reducing the degeneracy introduced by the monoscopic detection by a single IACT. To automatically balance the tasks during the learning process, we use an adaptive method relying on the modeling of the homoscedastic uncertainty of each task (Kendall et al. 2018). In addition, in order to prevent protons from disturbing the learning of the energy and direction reconstruction of gamma events, we use a masked loss strategy. γ-PhysNet is implemented with indexed convolution (Jacquemont et al. 2019) to apply deep learning directly to the hexagonal pixel images of the LST1, thus reducing the number of preprocessing steps. Besides, γ-PhysNet inference rate on an NVIDIA V100 is compatible with data acquisition rates, making it a potential solution for real-time analysis.

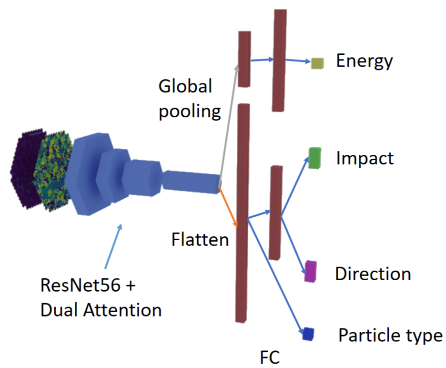

Figure 1. γ-PhysNet, a physically inspired multi-task architecture for single telescope full-event reconstruction.

3. γ-PhysNet Performance

Experiments. We evaluate γ-PhysNet in the single-telescope context of the LST1. We use the large-scale Monte Carlo production generated by the LST collaboration for the LST1 commissioning, referenced as the LST4 mono-trigger Production (from 2019/04/15). This dataset has been calibrated and integrated with DL1Data-Handler (Kim et al. 2019). It is separated into a training set, a validating set and a test set. The images have two channels, one for pixel intensity (unit being the number of photoelectrons) and the other containing per-pixel mean arrival time of the photoelectrons. A series of loose selection cuts on image amplitude and truncated showers is applied to the data, resulting in a training set composed of 874k gammas and 506k protons. With the help of the GammaLearn framework (Jacquemont et al. 2019), we train γ-PhysNet on diffuse gamma and proton events scattered over the full field of view of the 4 telescopes of the dataset to provide a more accurate overview of the data variability. The model is evaluated on point-like gamma and proton events detected by the LST1 only.

Results. We compare the performance of the proposed architecture with the wide-spread Hillas + RF method (Bock et al. 2004) that relies on image Hillas parametrization followed by Random Forest regressions and classifications. We repeat the experiments 10 times for

γ-PhysNet, in order to take into account the variability introduced by the network parameter initialization. The resolution curves and the sensitivity presented in Figure 2 and 2 are then drawn as bands to illustrate this variability. Both angular and energy resolution curves and the sensitivity one show that γ-PhysNet outperforms the Hillas + RF method below 1 TeV. The improvement is remarkable at the lowest energies (below 100 GeV), and is especially relevant for the study of extragalactic sources and transient phenomena. In particular, γ-PhysNet improves the direction reconstruction up to 0.3 degree at very low energy. Moreover, it has a sensitivity twice better on the same energy range. Besides, we observe a very low variability for the three metrics presented, highlighting the robustness of our architecture. Combined with its computing performances, this approach is therefore a good candidate for offline and online analysis for CTA, although moving from simulations to real data will be challenging.

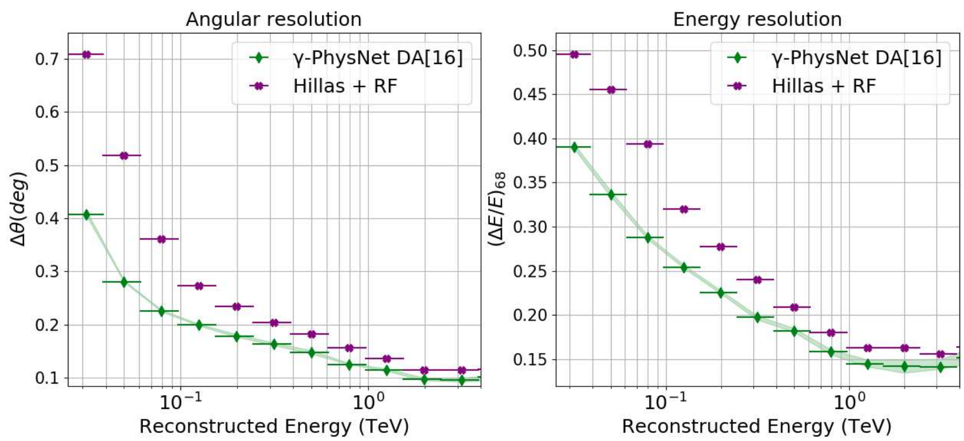

Figure 2. Comparison of γ-PhysNet and Hillas + RF. Angular (*left*) and energy (*right*) resolutions representing the 68% containment of the error per energy bin.

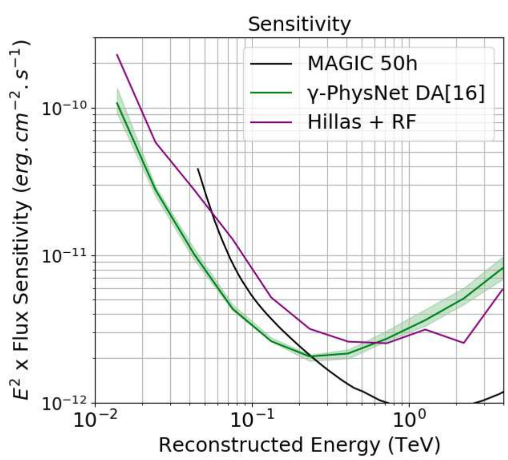

Figure 3. Sensitivity. Comparison of γ-PhysNet and the widespread Hillas + RF method. The performance of MAGIC (Aleksić et al. 2016) is included for reference.

4. Conclusion

The results obtained by γ-PhysNet on Monte Carlo simulations show that full-event reconstruction form a single IACT data is possible with a deep multi-task architecture. In a future work, we will probe how this good results transfer to real data by analyzing the data produced by the LST1. We also plan to lean on this good performance in a single telescope context to build a model for stereoscopic data reconstruction.

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