Reconstruction of IACT events using deep learning techniques with CTLearn

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Abstract. Arrays of imaging atmospheric Cherenkov telescopes (IACT) are superb instruments to probe the very-high-energy gamma-ray sky. This type of telescope focuses the Cherenkov light emitted from air showers, initiated by very-high-energy gamma rays and cosmic rays, onto the camera plane. Then, a fast camera digitizes the longitudinal development of the air shower, recording its spatial, temporal, and calorimetric information. The properties of the primary very-high-energy particle initiating the air shower can then be inferred from those images: the primary particle can be classified as a gamma ray or a cosmic ray and its energy and incoming direction can be estimated. This so-called full-event reconstruction, crucial to the sensitivity of the array to gamma rays, can be assisted by machine learning techniques. We present a deep-learning driven, full-event reconstruction applied to simulated IACT events using CTLearn. CTLearn is a Python package that includes modules for loading and manipulating IACT data and for running deep learning models with TensorFlow, using pixel-wise camera data as input.

1. Introduction

The ability of deep learning to assist in the analysis of data from imaging atmospheric Cherenkov telescopes (IACT) was first demonstrated by the detection of muon rings in real data (Feng & Lin 2016) and by the classification of gamma-ray and cosmic-ray simulated events (Nieto et al. 2017). Subsequent studies proved its capability to reconstruct the energy and arrival direction of simulated gamma-ray events (Mangano et al. 2018; Jacquemont et al. 2020) and to improve IACT sensitivity on real data (Shilon et al. 2019). CTLearn (Nieto et al. 2019a, Brill et al. 2019) is a high-level, open-source Python package providing a backend for training deep learning models for IACT event reconstruction using TensorFlow. CTLearn allows its user to focus on developing
and applying new models while making use of functionality specifically designed for IACT event reconstruction. The user can customize the training and built-in models hyperparameters. Hyperparameter optimization is available through the accompanying CTLearn-optimizer package. Data loading and pre-processing are performed using an associated external package, DL1-Data-Handler (Kim et al. 2020). A diagram summarizing CTLearn architecture is shown in Fig. 1.

![Diagram summarizing CTLearn’s framework design.](image)

**Figure 1.** Diagram summarizing CTLearn’s framework design.

## 2. Full-event reconstruction

### Model architecture. CTLearn works with any TensorFlow model obeying a generic signature. In addition, CTLearn includes two built-in models for gamma/hadron classification of stereoscopic data (Brill et al. 2019) and a third one for full-event reconstruction of monoscopic data, dubbed TRN-single-tel model (see Fig. 2 left panel). This last model is based on a deep convolutional neural network (CNN)-based architecture with residual connections (He et al. 2015) adapted from a thin ResNet (Xie et al. 2019). A squeeze-and-excitation attention mechanism (Hu et al. 2017) was added into the CNN blocks. The architecture ends on a selectable fully-connected head that performs either particle classification or regression (energy or arrival direction reconstruction).

### Experiments. We trained and tested our TRN-single-tel model with a dataset of simulated events for the Cherenkov Telescope Array (Acharya et al. 2018, CTA), the next generation ground-based observatory for gamma-ray astronomy at very-high energies. 2 million images from events having triggered an array of 4 large-sized telescopes (LSTs) in monoscopic mode. We considered diffuse gamma-ray and proton-initiated events, simulated within a cone of 10° radius - covering the whole field of view (FoV) of the instrument - in a balanced way. An 80% of the data were used for training and a 20% for testing. We trained the model on 200k batches of 64 images, validating periodically. The pixel layout in the original images is a hexagonal lattice, mapped to a Cartesian lattice using bilinear interpolation. The model was

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Trained independently for each reconstruction task. Two experiments were conducted: a) training and testing on all triggered events and b) training and testing on events where the images of the showers were mostly contained within the field of view of the telescope (no more than 20% of the total image charge within the two outermost rings of pixels on the camera). Training was repeated 10 times for each experiment, setting a different random seed that varied the weight initialization and training set shuffling.

**Results.** The TRN-single-tel model successfully learned to perform full-event reconstruction across the entire FoV of the telescope. The classification accuracy (0.5 threshold) on the test set of diffuse events was 0.748 ± 0.002 (0.756 ± 0.001), with an area under the ROC curve of 0.848 ± 0.002 (0.856 ± 0.001) for the all-events (contained-events) experiment (average and standard deviation computed from the results of all training runs). An example of ROC curves can be found in Fig. 2, right panel. The energy resolution and bias, and angular resolution provided by the model on the test set of diffuse gamma-ray events can be found in Fig. 3, where the data points represent the median of all training runs and 16%–84% containment bands are shown, illustrating the inference robustness of the model. We remark that these results come from the reconstruction of diffuse events and note that the reconstruction for events showing arrival directions close to the center of the FoV would perform substantially better.

3. **Conclusions and outlook**

CTLearn’s design and main features have been presented, showing its high level of configurability and flexibility, and demonstrating its potential for monoscopic full-event reconstruction using CTA simulated events. Areas where development is planned or already ongoing are: building models for stereoscopic full-event reconstruction; exploiting multitask learning; implementing models that could combine event-level data from a heterogeneous collection of telescope types, enabling IACT-specific metrics and loss functions; and ultimately applying full-event reconstruction to real IACT data.
Figure 3.  

| Figure 3 | Left | Energy resolution; center | Energy bias; right | Angular resolution (all vs. reconstructed energy). Tested on diffuse gamma-ray events. |

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