Deep Learning Research for Imaging Atmospheric Cherenkov Telescopes

samuel.spencer@physics.ox.ac.uk

Samuel Spencer, Adi Jacobson, Gernot Maier and Garret Cotter

Oxford Astrophysics, Denys Wilkinson Building, Keble Road, Oxford, OX1 3RH, United Kingdom

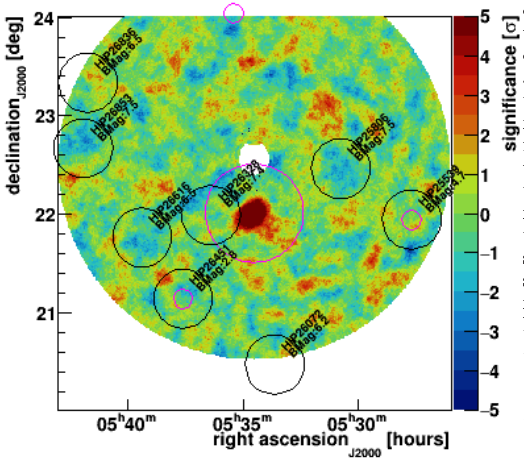
Abstract

New deep learning analyses are a promising new method of background rejection and event reconstruction for Imaging Atmospheric Cherenkov Telescopes (IACTs), particularly in the context of the next generation Cherenkov Telescope Array (CTA). This is because they allow for sensitive analysis of complete camera images at high speed. Unlike other fields of astrophysics, where deep learning is being used to characterise astronomical sources, deep learning use in IACT astronomy is comparatively unusual in that the analysis targets are Extensive Air Showers (EAS) in Earth's atmosphere. As such, we have access to large datasets of highly complex Monte Carlo simulations of both the air shower particle physics and our detectors. However, this in turn leads to a highly non-trivial domain gap problem when attempting to apply deep learning methods trained on simulations to real data. We will present state-of-the-art results displaying the combined effects of custom simulations, optimisation and graph-based network architectures to attack this problem.

Introduction

The sensitivity of Imaging Atmospheric Cherenkov Telescopes depends crucially on the rejection of events caused by proton-induced EAS. New deep learning methods based on Convolutional Neural Networks (CNNs) have the potential to leverage complete image data for this purpose [1][2]. The current standard for handling images from multiple IACTs in an array (such as CTA), is to treat the images from the Cherenkov cameras as a spatiotemporal sequence, and process the data using a blend of convolutional and recurrent network features [1][2]. However it is becoming increasingly clear that these methods suffer from a 'real data problem' whereby discrepancies between Monte-Carlo simulations (generated using CORSIKA and instrument simulation packages) and real IACT data limits their efficacy in practice. Recent work with H.E.S.S. has used image cleaning as a means of reducing these issues [1][3], however this removes the subtle evidence of shower substructure that deep learning methods hope to exploit. We present an attempt with VERITAS to observe the Crab Nebula utilising deep learning with photomultiplier charge data as an event classifier.

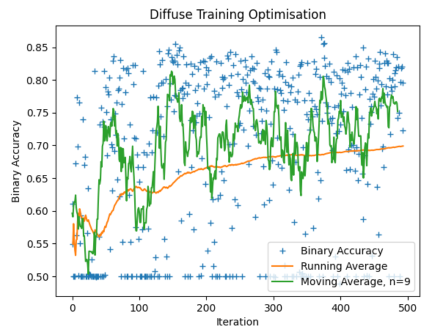
Real Results and the Effect of Bayesian Optimisation



Without resorting to image cleaning on charge data, initial results were poor. This was despite reasonable performance of the classifier on custom simulations (84% test accuracy). A meaningful stereoscopic detection of the Crab Nebula (at 13.8σ, which is around 7σ greater than using a random number generator as a gammaness metric) was only possible after Bayesian optimisation of the deep learning classifier hyperparameters using simulations (which raised the test accuracy to 87%). Small differences in simulated accuracy can therefore amount to significant changes of deep learning performance on real data, however conventional BDT analysis achieves 21σ.

Left: Crab nebula significance map with VERITAS run 64080 using an optimised ConvLSTM2D deep learning event classifier. The positions of bright stars from the Hipparcos catalogue are also shown.

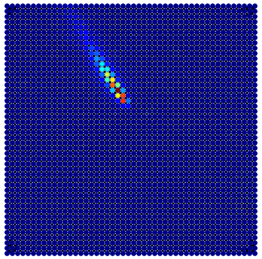
Further Bayesian Optimisation



Further Bayesian optimisation attempts on the VERITAS simulated data. Each blue cross is the final test accuracy from a ConvLSTM2D deep learning classifier

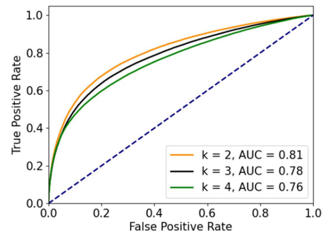
Further, more computationally intensive (240 GPU-days) attempts to increase simulation performance without adding event pre-selection were run, but did not yield superior results to the initial Bayesian optimisation attempt. However, these are noteworthy in that they show convergence of the optimisation process, indicating that the results presented here probably represents the feasibility limit for accuracy on simulations.

Chebyshev Networks



Chebnet γ-ray event input for data from CHEC-S, a silicon photomultiplier based camera prototype for the CTA small size telescopes.

Chebshev networks (Chebnets) are a graph-based alternative to CNN analysis. These may be more robust to night sky background as they share weights differently compared to CNN-type methods. Recent results from [4] show that Chebyshev networks can perform well on simulated IACT data.



Test-of-concept Chebnet performance (without event selection or image cleaning) with varying hyperparameters on CHEC-S simulated data. Credit: A. Jacobson [4]

References

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Conclusions

- Deep learning event classification methods can be used to detect astronomical sources in real IACT data.
- However, their computational cost, sensitivity to hyperparameter selection, and comparatively poor performance limit their viability.
- Initial results based on alternative Chebnet methods are promising.