Addressing Domain Adaptation Issues with CRNNs and VERITAS Data

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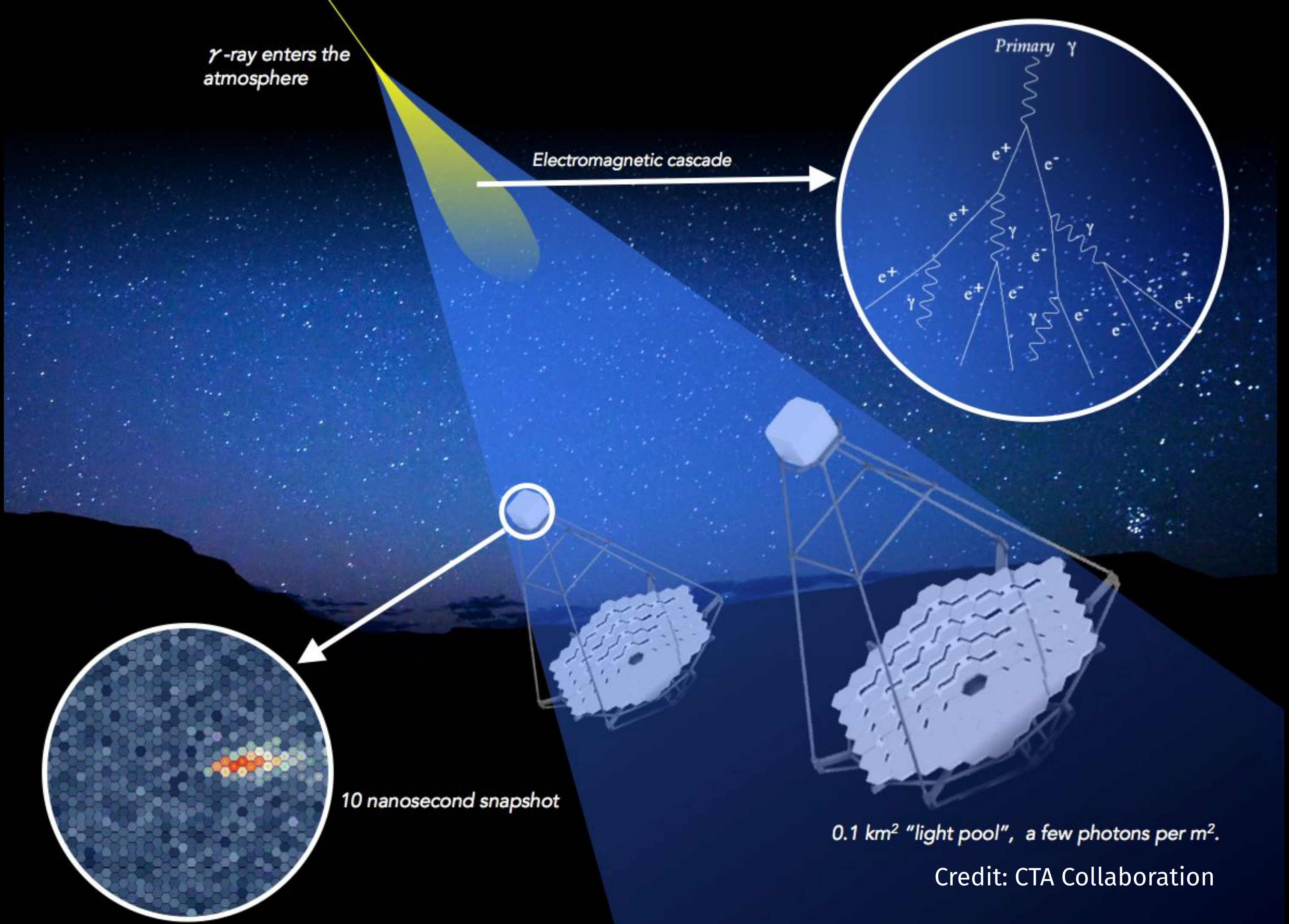
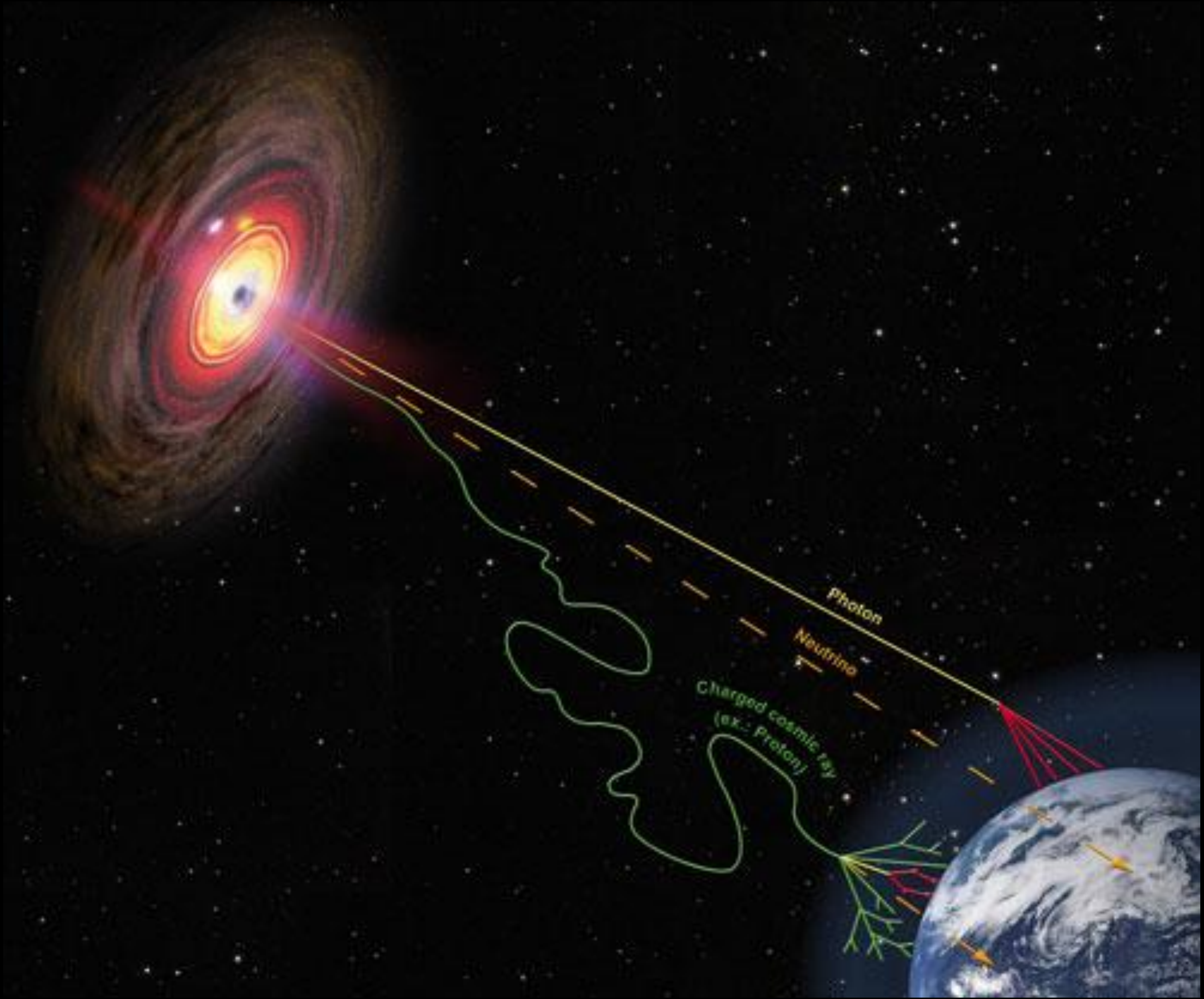
Image Credit: ESO

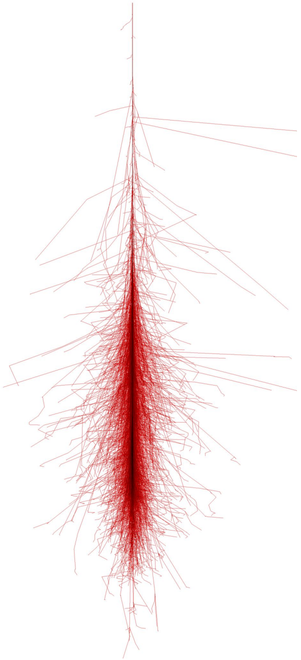


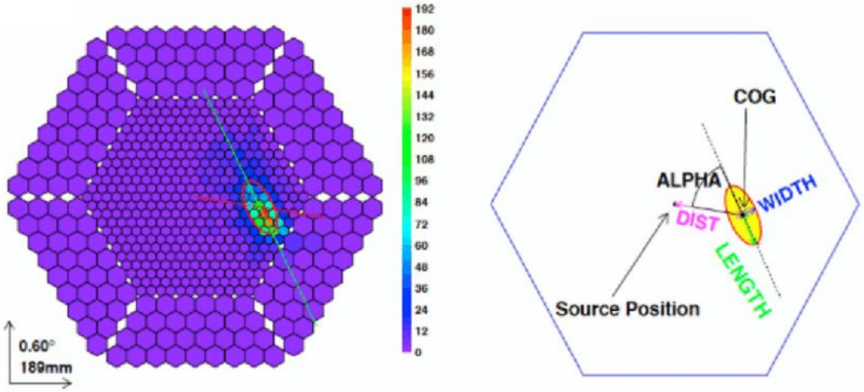
Credit: CTA Collaboration

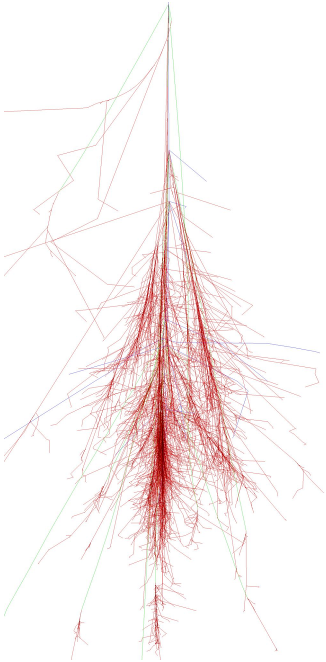


Credit: HAP

Hillas Parameterization







A 100 GeV CORSIKA air shower simulation originating from a photon (left) and a proton (right). Electrons, positrons and gamma rays are shown in red, whilst muons are green and hadrons are blue. Credit: F. Schnapp and J. Knapp.
Center: Illustration of the Hillas Parameter technique. Image Credit: A. Lopez-Aramas / MAGIC

Issues with Hillas Parameters

- Current generation instruments primarily use BDTs/random forests trained on Hillas Parameters to perform event discrimination and energy / directional reconstruction.
- These are known to have to have a ~95% gamma-hadron separation efficiency in their optimal energy range, however even a small increase to this could translate into a significant increase in sensitivity.
- It is increasingly apparent that they don’t use all of the information available to them.
- Fails at particularly low or high energies, a problem for the next generation of instruments.
- Some alternatives do already exist, H.E.S.S. have investigated the use of pixel-wise fits to semi-analytic models of gamma-ray air showers (See astro-ph: 0907.2610), and using the quality of the fit as a gamma-hadron separator.

Convolutional LSTM Networks

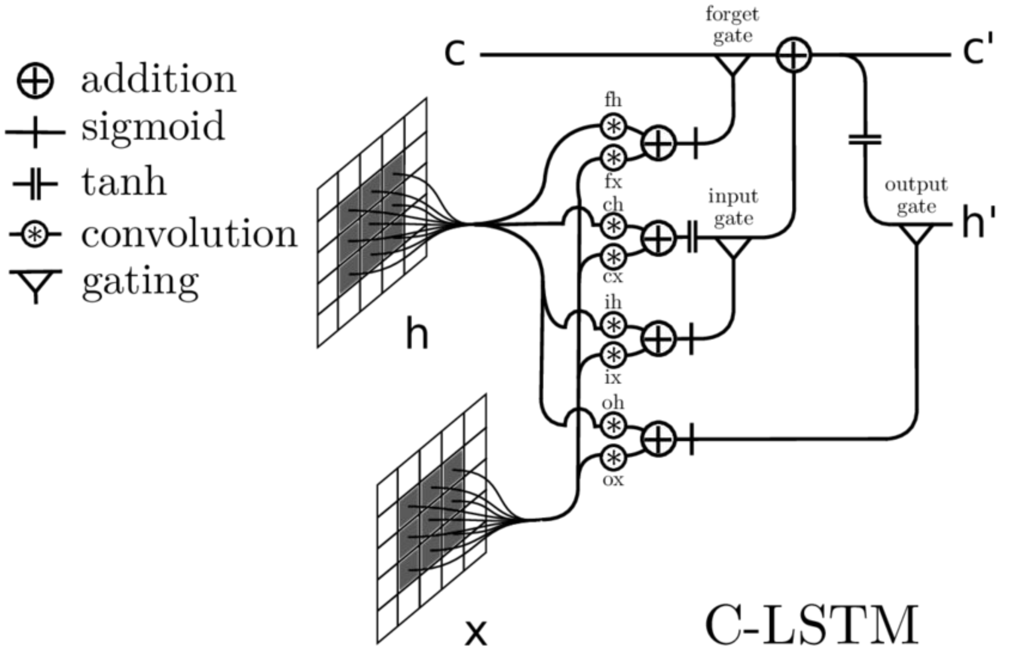


Illustration of a convolutional LSTM. Shilon et.al. propose using a blend of convolution and recurrence (CRNN) techniques as an event classification method in https://arxiv.org/abs/1803.10698. One potential advantage of this is the speed at which classifications can be performed on a GPU.
Image Credit: Marijn Stollenga

The Shilon et.al. Method

- The Shilon et.al. method treats four air shower images from the H.E.S.S. CT1-4 telescopes as a time series, ordered by total intensity of the images (size parameters) with the images with the largest size parameters first.
- Using this they were able to achieve a significant detection of a 2006 flare in the Blazar PKS2155+304, but this event was 7x brighter than the Crab Nebula and was so bright it could be seen in the camera trigger rates.
- However, these neural networks require training on simulated datasets, and minute differences between real data and simulations can potentially create issues in observing dimmer sources.

Source Domain

- Labelled.
- Major features similar to target domain.
- Used to train classifier.
- In our case, Corsika/CARE IACT simulations.

Domain Adaptation

Trained Classifier

Target Domain

- Unlabelled.
- Generally unknown deviations from source domain.
- In our case real IACT images.

Domain Adaptation

Unsupervised DA

Adversarial Methods

Arxiv

- Learning Domain Adaptive Features with Unlabeled Domain Bridges [10 Dec 2019]
- Reducing Domain Gap via Style-Agnostic Networks [25 Oct 2019]
- Generalized Domain Adaptation with Covariate and Label Shift CO-ALignment [23 Oct 2019]
- Adversarial Variational Domain Adaptation [25 Sep 2019]
- Contrastively Smoothed Class Alignment for Unsupervised Domain Adaptation [arXiv 13 Sep 2019]
- SALT: Subspace Alignment as an Auxiliary Learning Task for Domain Adaptation [arXiv 11 Jun 2019]
- Joint Semantic Domain Alignment and Target Classifier Learning for Unsupervised Domain Adaptation [arXiv 10 Jun 2019]
- Adversarial Domain Adaptation Being Aware of Class Relationships [arXiv 28 May 2019]
- Domain-Invariant Adversarial Learning for Unsupervised Domain Adaption [arXiv 30 Nov 2018]
- Unsupervised Domain Adaptation using Deep Networks with Cross-Grafted Stacks [arXiv 17 Feb 2019]
- DART: Domain-Adversarial Residual-Transfer Networks for Unsupervised Cross-Domain Image Classification [arXiv 30 Dec 2018]
- Unsupervised Domain Adaptation using Generative Models and Self-ensembling [arXiv 2 Dec 2018]
- Domain Confusion with Self Ensembling for Unsupervised Adaptation [arXiv 10 Oct 2018]
- Improving Adversarial Discriminative Domain Adaptation [arXiv 10 Sep 2018]
- M-ADDA: Unsupervised Domain Adaptation with Deep Metric Learning [arXiv 6 Jul 2018] [Pytorch(official)]
- Factorized Adversarial Networks for Unsupervised Domain Adaptation [arXiv 4 Jun 2018]
- DiDA: Disentangled Synthesis for Domain Adaptation [arXiv 21 May 2018]
- Unsupervised Domain Adaptation with Adversarial Residual Transform Networks [arXiv 25 Apr 2018]
- Causal Generative Domain Adaptation Networks [arXiv 28 Jun 2018]

6.1.2 SEMANTIC SEGMENTATION

(a) GTA5 (b) GTA5 → Cityscapes (c) CityScapes (d) CityScapes → GTA5

Figure 8: **GTA5 to CityScapes Image Translation.** Example images from the GTA5 (a) and Cityscapes (c) datasets, alongside their image-space conversions to the opposite domain, (b) and (d), respectively. Our model achieves highly realistic domain conversions.

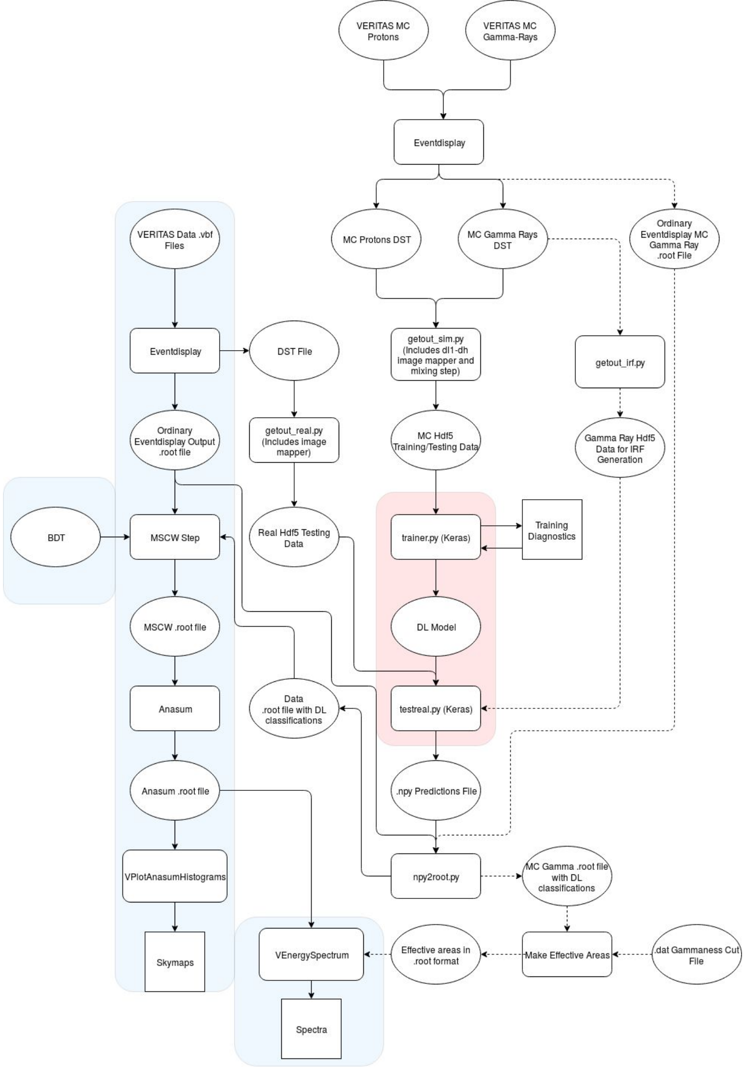
https://github.com/zhaoxin94/awesome-domain-adaptation Right Image Credit: Hoffman et.al.

VERITAS

VERITAS in Arizona is one of the three current IACT arrays in operation, the others being H.E.S.S. in Namibia and MAGIC on La Palma. By using real data from VERITAS, we can check the efficacy of methods needed for the next generation of IACTs.
Image Credit: VERITAS

Analysis Framework

We've been working with colleagues in VERITAS to use CRNN methods with real data as opposed to just simulations. This shows our VERITAS analysis framework using Keras, based around bootstrapping the existing VERITAS analysis chain.



Analysis Framework

- Key point is to extract VERITAS images from the Eventdisplay chain, perform ConvLSTM classification using a pre-trained network and then add these event classifications back into a normal eventdisplay .root file.
- Neural network analysis performed in Keras.
- Also wanted to create a method for generating Effective Areas (to quantify classification accuracy as a function of energy), separate part of the chain for this.
- Used image transformation classes from dl1-data-handler (under development for CTA, https://github.com/cta-observatory/dl1-data-handler) in order to handle camera geometry.

Simulation framework

- The closer the simulations are to the real data, this lessens the challenge of domain adaptation.
- So we ran dedicated simulations to match real data as closely as possible with VERITAS tools (i.e. noise levels matched to observation run, alt/az angle of showers matched).
- This isn't the standard mode of operation for IACTs but was inspired by recent work by H.E.S.S. (https://arxiv.org/abs/1711.01118).
- In particular it meant we ultimately couldn't generate spectra (as the effective areas generated from these simulations only covered a restricted azimuth range).
- Some other complexity in using real data, such as needing to exactly match sample sizes.

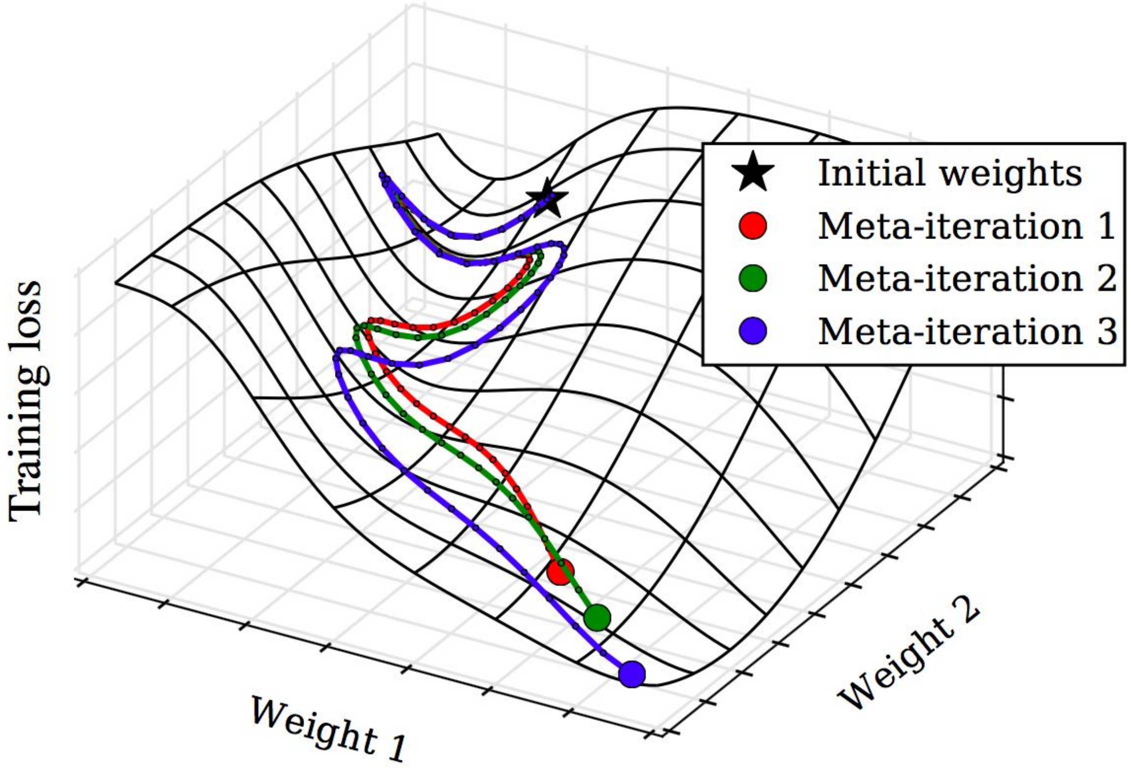
The Crab Nebula

- Obvious galactic target to try first is the Crab Nebula.
- Classic gamma-ray source; first detected on the ground by Whipple in 1989 (ApJ v.342, p.379).
- Shown last year (Phys. Rev. Lett. 123, 051101) to emit photons >100TeV by Tibet AS-γ experiment (highest energy photons ever detected).
- Also recently shown to be extended at TeV energies (https://arxiv.org/abs/1909.09494), though our analysis can't be used to observe this.

Initial Results

- Initial results were poor. Despite getting a reasonable test accuracy on simulations, we only detected the Crab Nebula with a ~7σ significance with one run. This was roughly the same as using a random number generator as a background rejection method (as some light Hillas parameter cuts are applied during the analysis).
- Spent some time looking at possible causes of failure, such as VERITAS always reading out all four telescopes and these empty frames being included in the analysis.
- Also looked at noise levels as a possible culprit; real data used wasn’t especially clean.

HYPEROPT

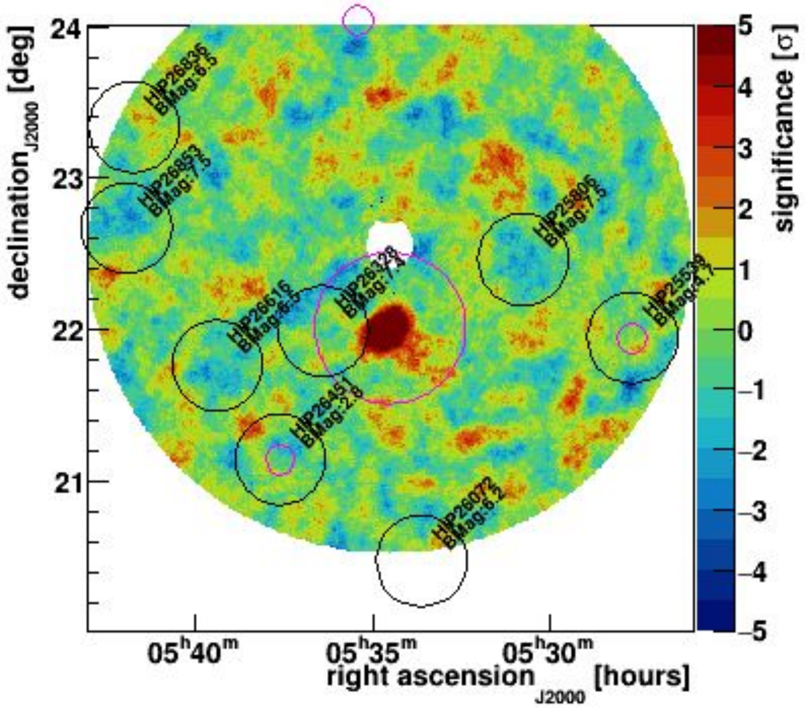


Bayesian Hyperparameter Optimisation. We implemented this using Hyperas, a wrapper around Hyperopt. See also: https://github.com/ctlearn-project/ctlearn_optimizer. Image Credit: Dan Mackinly.

Bayesian Hyperparameter Optimisation (BHO)

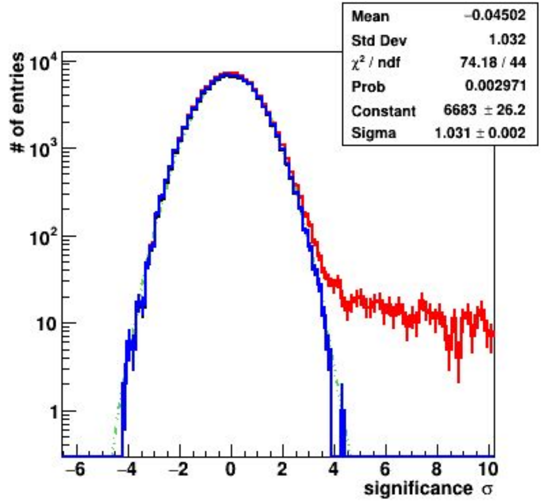
- We wanted to investigate if optimising further on simulations would have an adverse effect on the real data results.
- However, BHO is very (very) computationally expensive. We don't have the resources to perform this with our complete dataset for a typical number of iterations.
- Ran single epoch training for numerous hundred of hyperparameter configurations, tried to find best starting position before performing full training with ~100 epochs.
- Managed to obtain a 3% test accuracy boost on simulations using this method.

Real Data



PRELIMINARY

With this framework, we have managed to detect the Crab Nebula using a CRNN method for the first time in VERITAS data, with a 13.8 σ significance. Whilst we have managed to overcome some hurdles, there are still challenges to be overcome with new simulation frameworks being required.



Ongoing issues

- It’s not currently clear how to handle a number of ongoing issues with using CRNN methods.
- In particular, how to handle the issue of class imbalance in the training dataset: IACTs detect ~10,000 protons for every gamma-ray but these odds are then cut down by trigger selection etc.
- How to perform gammaness cut optimisation for different sources is also not obvious; the event scores from our CRNN aren’t necessarily meaningful. We experimented with ‘Bayesian’ variational dropout layers in our networks but this performed poorly.

Conclusions

- A blend of CNN and RNN techniques is a promising analysis method for IACTs.
- However, these methods are sensitive to differences between simulations and real data.
- Using a novel approach, we have created an analysis framework to perform CRNN analysis with VERITAS.
- Through this we have performed the first CRNN detection of the Crab Nebula, although the results are currently still inferior to a BDT analysis.