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Convolutional Neural Networks for Low Energy Gamma-Ray Air Shower Identification with HAWC

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A major task in ground-based gamma-ray astrophysics analyses is to separate events caused by gamma rays from the overwhelming hadronic cosmic-ray background. In this talk we are interested in improving the gamma ray regime below 1 TeV, where the gamma and cosmic-ray separation becomes more difficult. Traditionally, the separation has been done in particle sampling arrays by selections on summary variables which distinguish features between the gamma and cosmic-ray air showers, though the distributions become more similar with lower energies. The structure of the HAWC observatory, however, makes it natural to interpret the charge deposition collected by the detectors as pixels in an image, which makes it an ideal case for the use of modern deep learning techniques, allowing for good performance classifers produced directly from low-level detector information.

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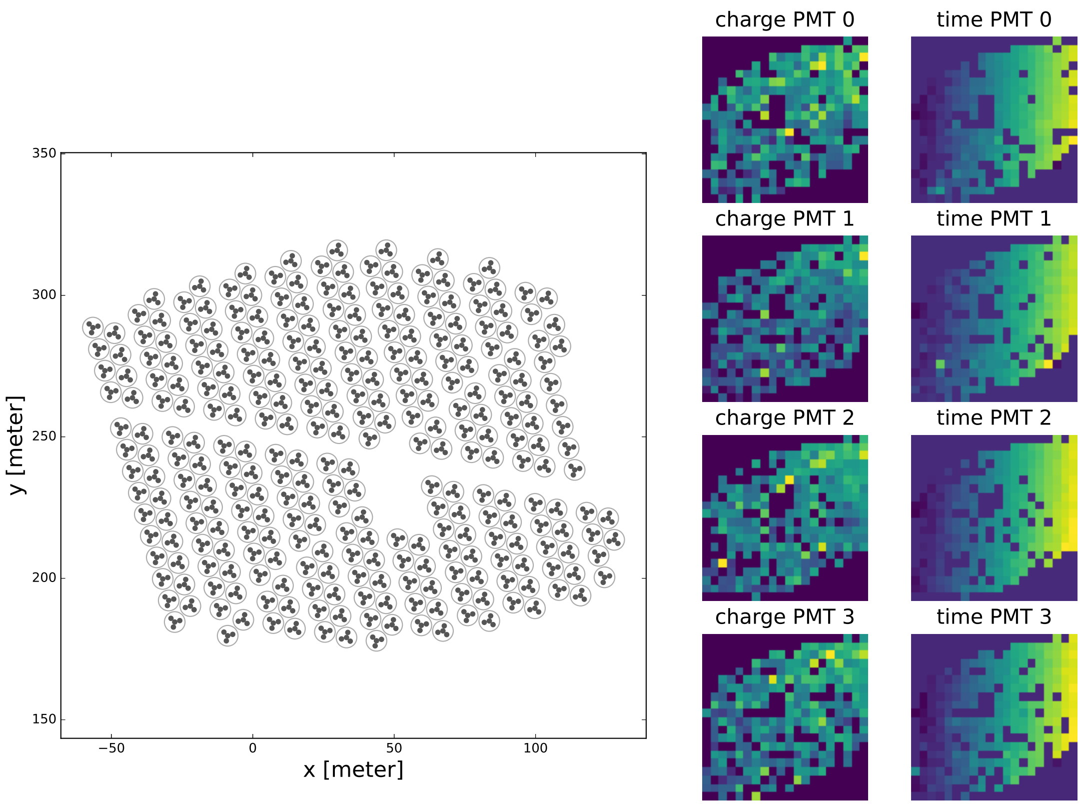

Figure 1: Layout of the HAWC PMTs (left) and example image used in the training of the Convolutional Neural Network (right). Each pixel in the image represents one tank in the HAWC observatory. The image is separated into 8 channels, corresponding to the log-charge and timing information from each of the 4 PMTs in a tank.

1. Introduction

Gamma ray identification is of primary importance for extensive air shower gamma-ray observatories. For HAWC, the low energy regime is particularly difficult to classify gamma-ray events from the overwhelming cosmic ray background. Thus, we are interested in testing new ideas for gamma-ray event classification particularly in order to improve the low-energy separation. Convolutional Neural Networks (CNN) have revolutionized the strength of image classification in recent years. In this paper, we build a CNN which can take in images constructed from HAWC events, and use it to train a gamma-cosmic ray classifier. As the CNN depends on the details of both the showers and the exact PMT response, we use a novel classification scheme based on the weakly supervised learning setup called Classification without Labels [1] in order to train the classifier in a purely data-driven manner.

2. Convolutional Neural Network Setup

We use the PyTorch framework [2] to build the neural network. We create images in a similar manner to the jet images which have been developed from particle physics [3, 4]. We start from images constructed from the charge and timing information collected by the PMTs. The data from the 300 tanks are arranged in a 20x20 grid to form the input images. Each tank therefore is represented by a single pixel in the input image. The 4 PMTs of each tank are represented with 2 channels, one for charge, which is input as the log of the reconstructed charge, and one for timing, which is input as a nanosecond offset from the event trigger, scaled to be between -1 and 1. There are therefore 8 channels in the input image. An example image is shown in figure 1. We use a typical convolutional network setup with seven successive convolutional layers, which reduce the image size to 1x1, followed by a fully connected layer to a single output. The first convolutional layer uses a 1x1 convolutional to conceptually construct a per tank PMT embedding. This is followed by a 2x2 convolution, a 3x3 convolution, then four 5x5 convolutional layers. Each layer has twice the number of channels as the previous layer, and no padding is used, which results in the initial 20x20 image being reduced to a 1024 channel 1x1 image at the final convolution layer, which gets fully connected to the output layer. ReLU [5] is used after each layer as the activation function, except for the final layer, which has a sigmoid activation. The output is therefore a floating point number between 0 and 1, where we interpret 0 as representing a cosmic ray event, and 1 as representing a gamma ray event. After each layer, except the first and last, a Dropout layer is added to help regularize the network and prevent overfitting [6].

We use the Adam optimizer [7] with binary cross-entropy loss during training. We initially tested the network using simulated data produced by CORSIKA [8] connected to the HAWCSim software, based on GEANT4 [9–11]. However, an issue with using the low-level PMT information is that the simulation of the shower and detector response both need to be equivalent to the data at all levels of detail. In order to avoid such issues, after satisfying ourselves with the simulation that a good classifier may be produced with the CNN setup, we investigated using a data-driven regime to train the classifier, thus avoiding potential differences between data and simulation.

3. Training with Weakly Supervised Learning on the Crab Nebula

Following ideas such as learning with labelled proportions [12], weakly supervised classifications scheme have been investigated for use in training binary classifiers in particle physics experiments [13, 14]. In particular, the Classification without Labels scheme [1] simply identifies two regions where different proportions of the two classes are expected. Under the assumption that the *o*nly difference between the events in these regions are the class proportions, it was shown that training a classifier to distinguish the two regions is equivalent to training a classifier to distinguish the two classes. Thus, a binary classifier can be trained using only real data, if two selection regions can be established in the data where the selections have the two classes in different proportions.

In the case of the HAWC Observatory, we developed a CWoLA inspired scheme using the Crab Nebula. The Crab Nebula is typically used as a calibration source, being the brightest source of very high energy gamma rays in the Northern Sky and has been well-measured by HAWC [15]. Additionally, the diffuse gamma-ray emission is for our purposes negligible compared to the overwhelming cosmic-ray background, so outside gamma-ray sources we assume that only cosmic rays contribute to the data events. So, we can develop a gamma-ray enriched sample of events by taking events reconstructed to have arrived from the direction of the Crab Nebula, and a cosmic ray-only sample of events which are reconstructed at slightly higher or lower Right

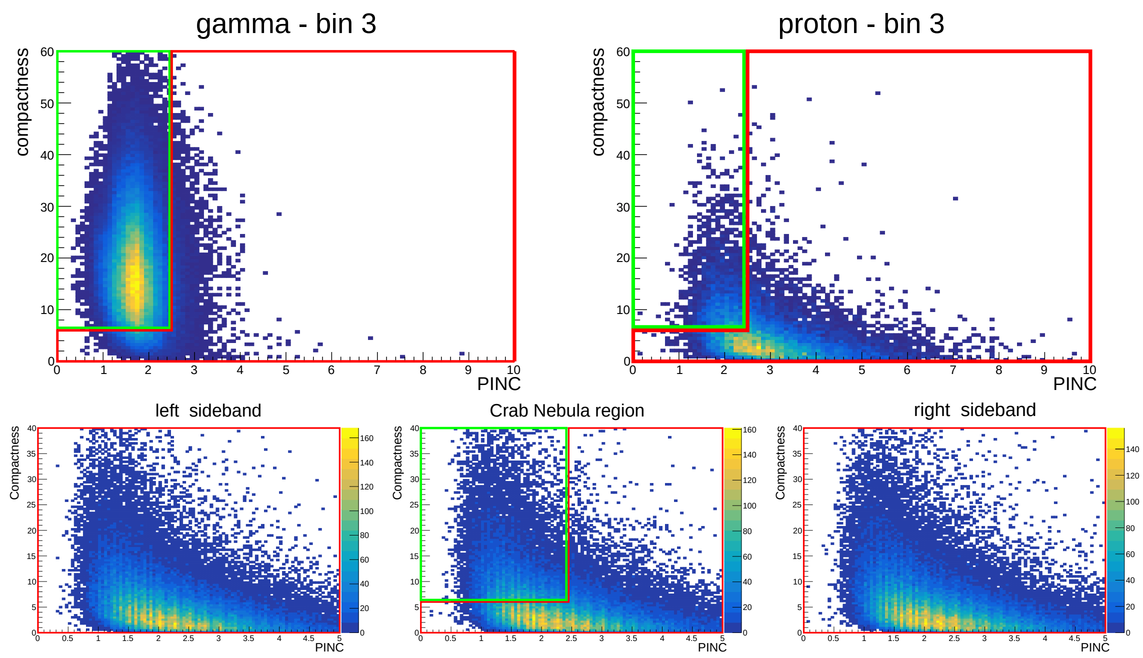

Figure 2: Distribution of PINCness and compactness for various data in fHit bin 3 (described in the text). The top row shows the distribution for simulated gamma-ray initiated events (left) and proton initiated events (right). The bottom row shows data reconstructed in the vicinity of the Crab nebula (center), and in the lower (left) and upper (right) RA sidebands. The labelling scheme is indicated by a green box for events labelled as "signal-enriched" and a red box for "background-only".

Ascension (RA). We use RA because the background is highly variable with changing declination, and we take both upper and lower sidebands in order to cancel out any residual effects which might occur from the change in angle. This gives us our regions for input into CWoLA, a gamma-enriched region of data from the Crab Nebula, and a background-only region of data from RA sidebands. The following table shows the RA and declinations used to define the regions:

Region	RA	Dec.
Center	$\in [83.45, 84.65]$	$\in [21.25, 22.75]$
Left Sideband	$\in [81.05, 82.25]$	$\in [21.25, 22.75]$
Right Sideband	$\in [85.85, 87.05]$	$\in [21.25, 22.75]$

Note that, when processing data, the sidebands are merged together.

In the "gamma-enriched" data region taken from the Crab Nebula, the cosmic ray events still outnumber gamma-rays by a ratio of about 1000 to 1. We found in our tests that with such a small ratio, we were unable to train a network with the CWoLA method. Thus, we looked at using existing summary variables used by HAWC in order to increase the fraction of gamma-ray events in the gamma-enriched region. Two such variables previously used are PINCness and compactness (described in section 2.6 of reference [15]). For this labelling scheme, which we call PC labelling, all the events of the sideband are still background only, while in the Crab region, events are required to pass loose cuts on PINCness and compactness. Data in HAWC is typically binned by the fraction of available PMTs which register light in a given event (fHit), which is correlated with the energy of the shower-initiating particle. In figure 2 we show an example of the distribution of PINCness

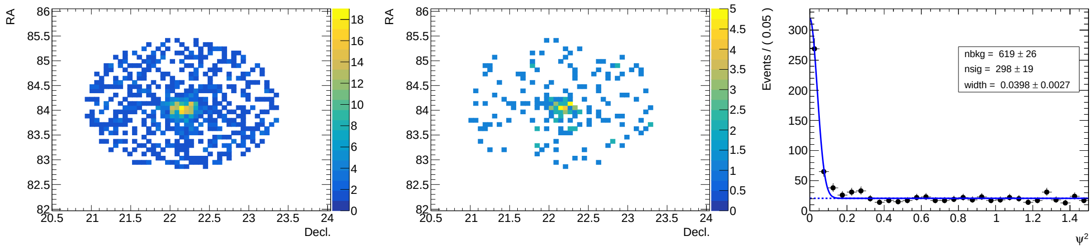

Figure 3: Data collected at the Crab Nebula after gamma-ray selection by the Convolutional Neural Network. The image on the left shows all the data collected in the years 2017 and 2018, including the periods used for training the network with weakly supervised learning. The center image shows only those periods *not* used during the training, thus providing independent confirmation that the training is not over-fitting to the data. The right image shows the data binned in 1d as angle-squared from the Crab Nebula and then fit with a Gaussian signal and flat background.

and compactness in simulated gamma and proton events and the region chosen for the PC labelling for fHit bin 3, which requires the fraction of PMTs hit to be within 16.2% and 24.7%.

4. Results

We applied the PC labelling scheme to HAWC data from 2017 and 2018, and used it to train a CNN on fHit bin 9, which requires above 84% of the PMTs to have registered light. Figure 3 shows data collected from the Crab Nebula after selection by the neural network, clearly showing an excess of events at the location of the Crab Nebula. During the training, only events from January to September of each year were used, while events from October to December were set aside. The figure also separately shows the events after network selection from the October to December dataset. This separate set also shows an excess at the Crab Nebula, indicating that the network has not overfit to the training dataset, and that we have successfully trained a gamma-cosmic ray CNN classifier using only data with our CWoLA-like scheme.

5. Conclusion

We built a Convolutional Neural Network for performing gamma-cosmic ray classification with data from the HAWC Gamma-Ray Observatory. We developed a method for training on data using the Classification without Labels technique with data taken on and off the Crab Nebula. The network was trained using the technique and we showed with an independent dataset that the classifier is able to discriminate gamma rays from Cosmic Rays using a high energy dataset. Further work is ongoing to train networks on the lower energy datasets, which are in general more difficult to classify. There is also ongoing work to further optimize the network and training regimen.

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References

[1] E.M. Metodiev, B. Nachman and J. Thaler, *Classification without labels: learning from mixed samples in high energy physics*, *Journal of High Energy Physics* **2017** (2017) .

[2] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan et al., *Pytorch: An imperative style, high-performance deep learning library*, in *Advances in Neural Information Processing Systems 32*, H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox and R. Garnett, eds., pp. 8024–8035, Curran Associates, Inc. (2019), http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf.

[3] J. Cogan, M. Kagan, E. Strauss and A. Schwartzman, *Jet-images: computer vision inspired techniques for jet tagging*, *Journal of High Energy Physics* **2015** (2015) .

[4] P.T. Komiske, E.M. Metodiev and M.D. Schwartz, *Deep learning in color: towards automated quark/gluon jet discrimination*, *Journal of High Energy Physics* **2017** (2017) .

[5] X. Glorot, A. Bordes and Y. Bengio, *Deep sparse rectifier neural networks*, in *Proceedings of the fourteenth international conference on artificial intelligence and statistics*, pp. 315–323, JMLR Workshop and Conference Proceedings, 2011.

[6] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever and R. Salakhutdinov, *Dropout: A simple way to prevent neural networks from overfitting*, *Journal of Machine Learning Research* **15** (2014) 1929.

[7] D.P. Kingma and J. Ba, *Adam: A method for stochastic optimization*, *arXiv preprint arXiv:1412.6980* (2014) .

[8] D. Heck, J. Knapp, J. Capdevielle, G. Schatz, T. Thouw et al., *Corsika: A monte carlo code to simulate extensive air showers*, *Report fzka* **6019** (1998) .

[9] S. Agostinelli, J. Allison, K. Amako, J. Apostolakis, H. Araujo, P. Arce et al., *Geant4—a simulation toolkit*, *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment* **506** (2003) 250.

[10] J. Allison, K. Amako, J. Apostolakis, H. Araujo, P. Arce Dubois, M. Asai et al., *Geant4 developments and applications*, *IEEE Transactions on Nuclear Science* **53** (2006) 270.

[11] J. Allison, K. Amako, J. Apostolakis, P. Arce, M. Asai, T. Aso et al., *Recent developments in geant4*, *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment* **835** (2016) 186.

[12] G. Patrini, R. Nock, P. Rivera and T. Caetano, *(almost) no label no cry*, in *Advances in Neural Information Processing Systems*, pp. 190–198, 2014.

[13] L.M. Dery, B. Nachman, F. Rubbo and A. Schwartzman, *Weakly supervised classification in high energy physics*, *Journal of High Energy Physics* **2017** (2017) 1.

[14] T. Cohen, M. Freytsis and B. Ostdiek, *(machine) learning to do more with less*, *Journal of High Energy Physics* **2018** (2018) 1.

[15] A.U. Abeysekara et al., *Observation of the crab nebula with the hawc gamma-ray observatory*, *The Astrophysical Journal* **843** (2017) 39.

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