Extending Cosmic Ray Background in Space Experiments using Generative Adversarial Networks

Giovanni Cavallotto, Stefano Della Torre

Abstract Cosmic rays (CR) reaching telescope detectors in outer space are known to induce glitches and background noise. The presence of CR noise significantly influenced Cosmic Microwave Background (CMB) experiments, like Planck and LiteBIRD, which have a long exposition and hard shelling or filtering. In order to address this challenge, it is imperative to accurately simulate the CR background throughout the duration of LiteBIRD's three-year mission. However, state-of-the-art Monte Carlo (MC) simulations are extremely computational expensive, typically requiring 30 times the simulated period. We present the Cosmic Rays Artificial Background (CRAB) code, extending MC simulations with Generative Adversarial Networks (GAN). By leveraging GANs, we can efficiently generate a sufficient number of genuine, statistically independent images, unlike traditional noise analysis techniques combined with template expansion methods.

1 Introduction

This work aims to show the advantages of generative Machine Learning (ML) methods: Cosmic Rays Artificial Background (CRAB) code, which performs data augmentation applied to the characterization of Galactic Cosmic Rays (GCR) background. In this work, we consider as the use case the thermal background due to GCR interaction with a cryogenic detector. This use case can be applied to several space

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detectors, for the sake of simplicity, in this work, when relevant, we consider the operational condition of the LiteBIRD experiment [1, 2, 3]. The latter was designed to measure the B-mode polarization of Cosmic Microwave Background (CMB) [4] and is designed to operate orbiting at the second Sun-Earth Lagrangian point (L2) for 3 years mission [3]. An experiment on board of space mission, as it is LiteBIRD, is exposed to the incoming GCR [8]. They can, eventually, reach the LiteBIRD detectors, causing not only hardware damage, but also a not negligible background in the signal output [9, 10].

When a CR hits or traverses a layer of material, it releases energy due to Bremsstrahlung [10], which causes, between other effects, a warming of the material [9]. With the current instrument design, the CMB signal will be detected by Transition Edge Sensor (TES) bolometers [12], which are extremely temperature sensible. This kind of noise is not completely avoidable with shielding or veto filters, as shown for Planck experiment [13]. In this case, the best strategy is to simulate the expected background to disentangle the effects on the detector. However, state-of-the-art Monte Carlo (MC) simulations are extremely computational expensive, typically requiring 30 times the simulated period. In this work, we explore the performances of using a Generative Adversarial network (GAN) to extend a small sample of MC simulations maintaining the same statistical properties and signal features.

2 Monte Carlo simulation chain

The Monte Carlo simulation scheme for LiteBIRD were presented in Ref. [9, 10]. According to this, one has to perform a computation of the modulated CR spectra at L2, a propagation of the relevant ions content through the telescope materials, a computation of the energy released in the detector sensible area and a thermal-electric response of the bolometers. Each step of this chain is performed separately and is computationally expensive, especially the second block, executed with Geant4 [16, 17]. This leads to an unaffordable computational effort if one wants to produce the Time Ordered Data (TOD), covering the whole mission duration or even a representative sample of it (see e.g., the 30X factor regarding TOD extension in [9]).

3 Data augmentation

Applying an efficient data augmentation method at the end of the MC simulation chain can be a game changer for future studies. The method presented in this work is a Generative Adversarial Network (GAN) [18], which promises to be efficient in TOD production, genuine generative [19, 20] and statistically independent, unlike traditional noise analysis techniques combined with template expansion methods. The CRAB code is based on the TensorFlow ML python library, due to its code flexibility and integration with GPUs.

3.1 Neural Network architecture

The GAN are composed by two separated Neural Networks (NN): the generator and the discriminator, as shown schematically in Fig. 1. The generator produces synthetic TODs as similar as possible to the real (MC generated) reference ones. The discriminator binary classifies the TODs as real or fake. The two NNs compete one against each other: the generator train itself to produce synthetic TODs classified by the discriminator as real; the latter, instead, trains to distinguish between real and synthetic TODs. For a deeper dissertation on GAN training, see e.g. [21, 22].

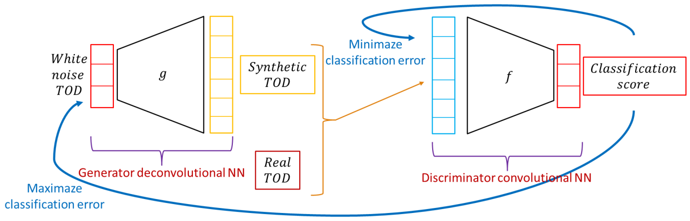

Fig. 1 Scheme of the GAN algorithm and NNs architectures. At the left (right) there is the generator (discriminator). Squares represents inputs or outputs of the respective NNs, while f and g trapezoid stance for the mathematical functional transformation applied by them. Blue lines indicate the backward propagation of the competing training.

We implemented a Convolutional Neural Network (CNN) discriminator and a de-CNN generator. A note here must be done on the fact that all the layers of the GAN are one dimensional. In fact, we are dealing with time series, which are then sliced into a sample of TODs, treated as one dimensional images. The discriminator has four convolutional layers and a dense final one, with the discriminator being its specular version. Between each generator (discriminator) layer, we inserted a batch (layer) normalization [23, 24], to stabilize the training and force the layer activations to stay inside a Gaussian-like distribution [25].

We started from a Wasserstein GAN architecture, which uses the homonym metric as loss function [26, 22] and a custom training loop. This metric has the advantages of computing the distance between the predicted and real classification distributions and having a never vanishing gradient. However, in our use case, it leads to poor reproduction of TODs features and a not trivial accuracy evaluation, due to its non-binary and unbounded classification output. As an alternative choice, we use the standard binary cross entropy loss, which has a trivial mathematical interpretation.

As activation function, we chose the LeakyReLU, after testing tanh and ReLU, especially for its non-vanishing gradient.

3.2 Training

The GAN training is commonly unstable due to its adversarial nature [27]. In this work, we pre-train the discriminator, fixing the generator weights, for 10 to 20 epochs, depending on the tuning adopted. Thus, it learns to classify real TODs well and fixes a target point for minimization. Then an ordinary training of the NN couple is performed, with extra discriminator training cycles with respect to generator, eventually. In Fig. 1 we report the complete training scheme.

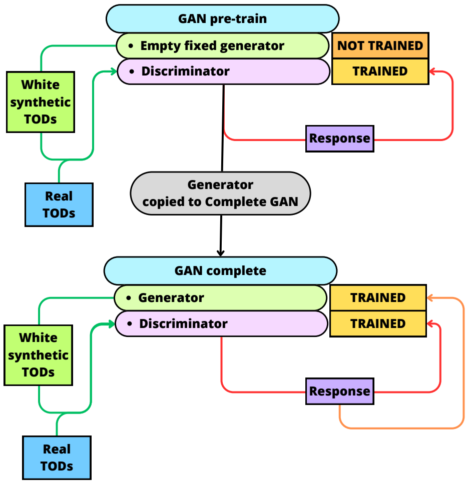

Fig. 2 Flowchart of the CRAB training. In the middle, the NNs composing each GAN step is pictured. At the left and right, there are the discriminator inputs and the backward-propagation schemes relative to each section of the GAN, respectively.

3.3 Tuning

As training optimizers, we tested combinations of the Stochastic Gradient Descendent (SGD) and Adam algorithms. The best results were obtained adopting SGD for the discriminator and Adam for the generator. In fact, when Adam is used to optimize the discriminator it acts too aggressively and leads to stuck training of the generator.

We end up with a discriminator dominated GAN. When, instead, the SGD is used for the generator, it learns slowly, leading again into a discriminator dominated training stagnation.

Other two training hyperparameters investigated in this work are the label smoothing and the synthetic TODs weighting. The first increases the stability and smoothness of the training, keeping the discriminator more generalized and less overtrained. The second modification pushes the discriminator to keep the real TODs classification stable as a target, and guides the generator towards the real TODs output. This also avoid the entering into the so-called mode collapse [28, 29].

4 Results

The preliminary dataset produced to train the GAN consist of 264 TODs corresponding to an acquisition time of 1800 s.

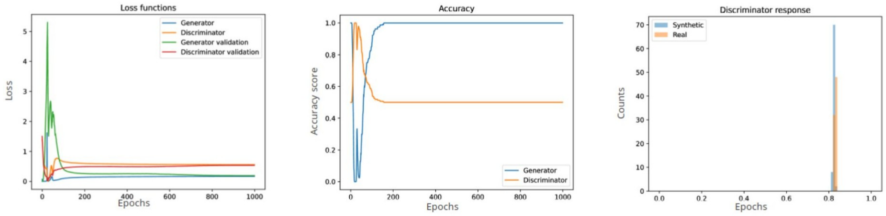

Fig. 3 In the left panel, the loss function of discriminator and generator on training and validation datasets along the epochs. In the middle panel, the accuracy of the discriminator on the real and synthetic TODS. In the right panel, the discriminator score for real and synthetic TODs.

The training history of the CRAB best model, illustrated before, can be seen in the Fig. 3. There is an initial instability period, where the discriminator and generator switch their optimization trends, then the loss functions converge. There, discriminator is confused by good synthetic TODs, with which the generator achieves nearly zero loss. Furthermore, one can note the absence of overtraining, manifested by the validation dataset losses overlapping to the training ones. The accuracy score and discriminator response, in the right panels of Fig. 3, are the proof of GAN convergence to an optimum. In fact, the discriminator classifies as real both the reference and synthetic TODs, as desired.

A remarkable result of CRAB is the fact that only 751.54 seconds are needed for a whole code execution, mostly due to the training. This is less than half of the TOD extension. Furthermore, the computational time to produce a 1h TOD is just 0.16 seconds. The training computational time has to be added to the one of MC chain producing the training dataset. However, it is just a $2-5\%$ overhead, and it is no more necessary to produce an extended MC dataset, but just a representative training one, which could be of the order of days or weeks. Then, it will be extended to 3 years TOD by CRAB, spending only 70.08 minutes.

5 Conclusions

CR signal in cryogenic space experiment will be a major source of background, which need to be characterized for the whole mission period and different CR fluxes conditions. The computational effort to do so with MC methods alone exceeds the mission duration and thus make the issue untreatable. In this work, we illustrated the CRAB code: a generative ML method to extend a limited classical dataset, to the mission requirements. CRAB is a prototype, which need deeper development to be generalized and reproduce all the TOD features. Furthermore, there is room for a complete study considering multiple ions and inserting simulation tuning of forecasted environments and solar activities of the mission period. Nevertheless, we illustrated the workflow and efficiency of CRAB, demonstrating its capabilities of reducing the computational cost and produce synthetic TODs.

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