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Generative adversarial neural network for cosmic ray background simulations

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Scientific Rationale

- **The CR background affects each space experiment**
- **LiteBIRD CMB measurements are particularly sensitive to CR energy deposit & direct hits (Bolometers + TES) (arXiv:2107.00473)**
- **90% of Plank data affected by CR background (arXiv:1303.5071)**
- **19Hz final sampling frequency covering 3 years mission**

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- Statistically indipendent data
- Different space environment

Modulated CR at L2

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Energy deposit in HFT

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- Bolometer (thermal)
- TES (current) response

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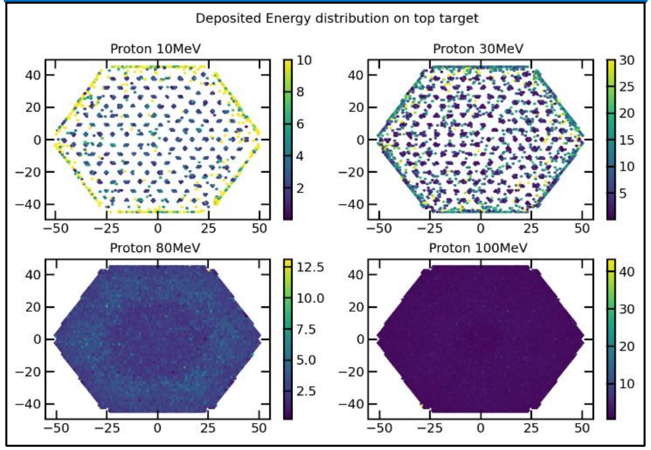
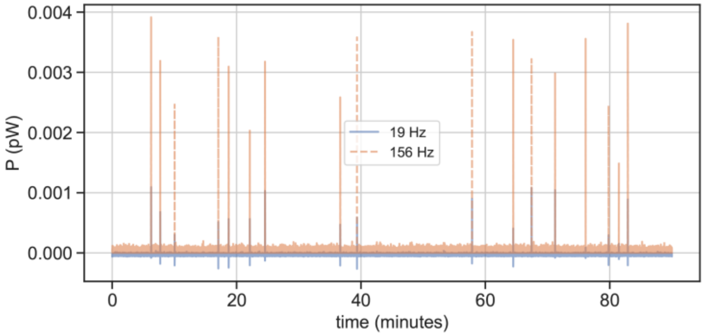
TOD

Technical Objectives, Methodologies and Solutions

Synthetically generate CR energy deposit map



Synthetically generate TOD output



Modulated CR at L2

Detector structure

Energy deposit in HFT

- Bolometer (therma)
- TES (current) response

Semi-analitical

Analitical

CR TOD Background

Data post analysis

Technical Objectives, Methodologies and Solutions

- Synthetically generate the time series covering the whole mission
- Achieve a reasonable computation time (no ML ≈ 30x TOD length)
- Genuine statistically independent generation
- Take in account bolometers correlation

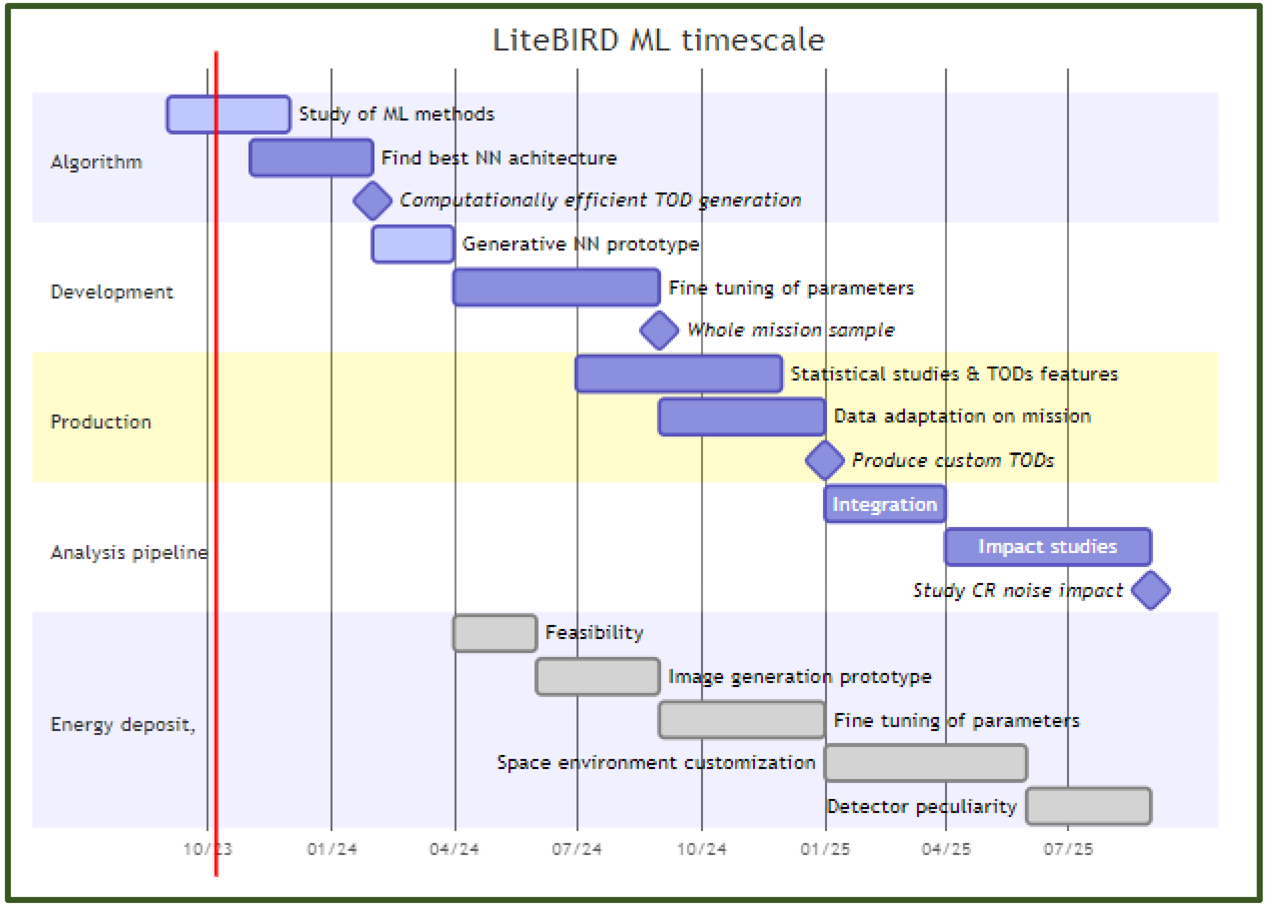
Tools:

- TensorFlow inside Jupyter shell
- Exploit GPUs for larger training

Algorithms:

- Generative adversarial network (convolutional)
- Variational Auto-Encoder

Timescale, Milestones

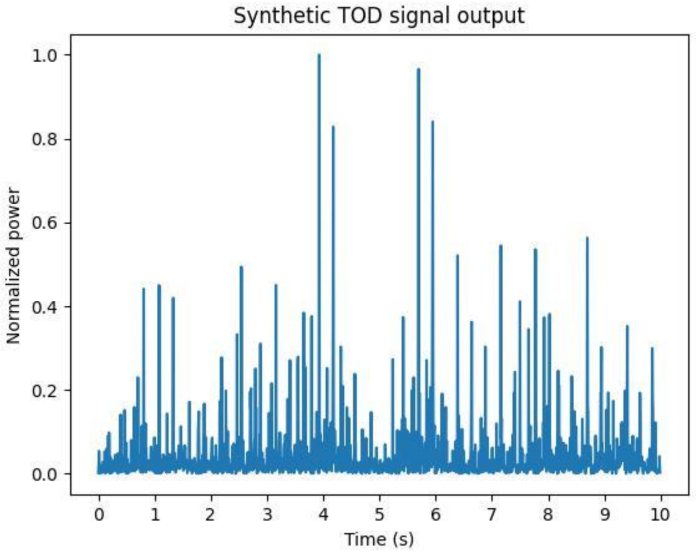


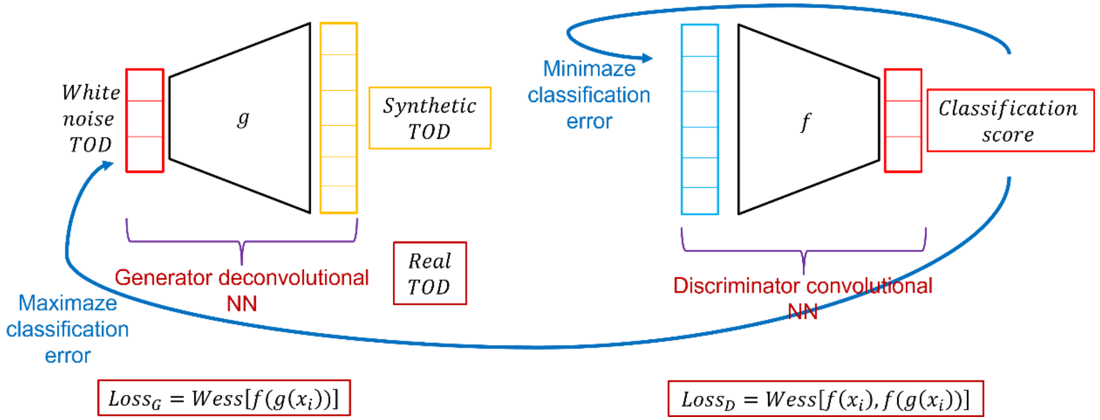
KPIs

- **Test both GAN & VAE**
- **Cover the whole mission period**
- **Generation time ≤1% of TOD length**
- **Sample correlation ≤1%**
- **Publication of CR impact on LiteBIRD measurement**
- **Generate samples for each mission & environment configuration**

Accomplished Work, Results

- **Hiring of Giovanni Cavallotto since 01/09**
- **Comparison of Variational Auto-Encoder and Generative Adversarial Netwok algorithms**
- **Prototype of the GAN trained with homemade data set (just get access to real data)**
- **Test different NN configurations:**
  - training steps of NN couple
  - NN deepth
  - latent space
  - layers hyperparameters
  - loss metrics (Weissenstein, Binary Cross Entropy)





Next Steps and Expected Results (by next checkpoint: April 2024)

Identified optimization points:

- Exploit GPU tensorflow integrated API for deeper training
- Increase generated TODs complexity
- Overcome the discriminator dominated model and mode collapse issues
- Insert noise in the training input
- Test VAE algorithm

Expected results:

- Find the best ML architecture, training strategy and the computationally cheaper generation
- Produce first realistic TODs samples