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Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA
ICSC Centro Nazionale di Ricerca in HPC, Big Data and Quantum Computing

Extending Cosmic Ray Background using Generative Adversarial Networks

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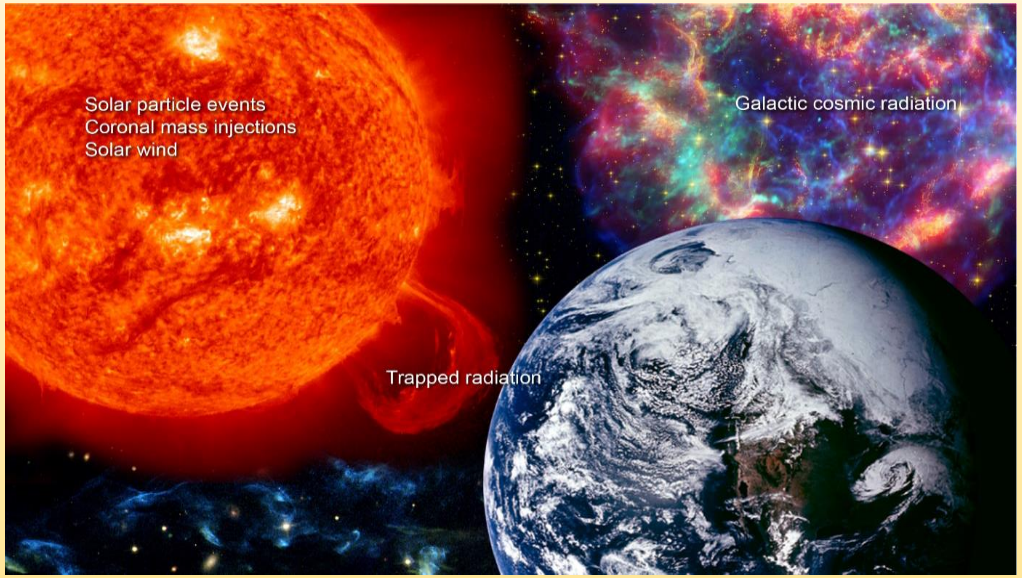
ML4ASTRO2, Catania 8-12 / 07, 2024

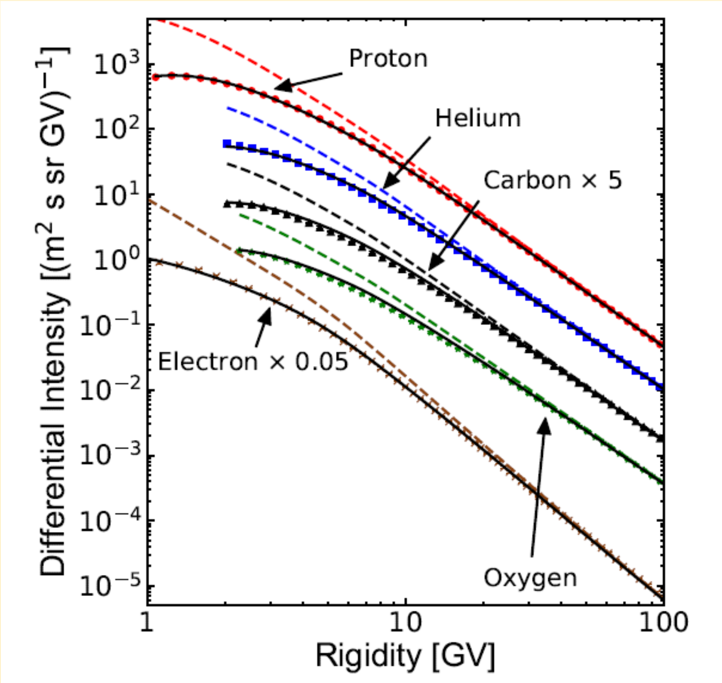
Cosmic Rays & space experiment overview

Galactic Cosmic Rays from astrophysical sources



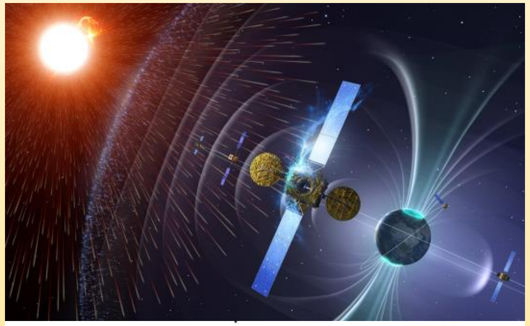
John D. Wrbanek and Susan Y. Wrbanek Glenn Research Center, Cleveland, Ohio, NASA/TP—2020-220002, "Space Radiation and Impact on Instrumentation Technologies"

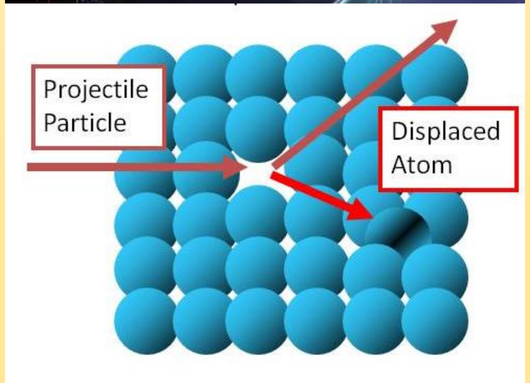
Heliospheric modulation by solar wind



Boschini et al. (2019)

- ❖ Single event effect
- ❖ CR background





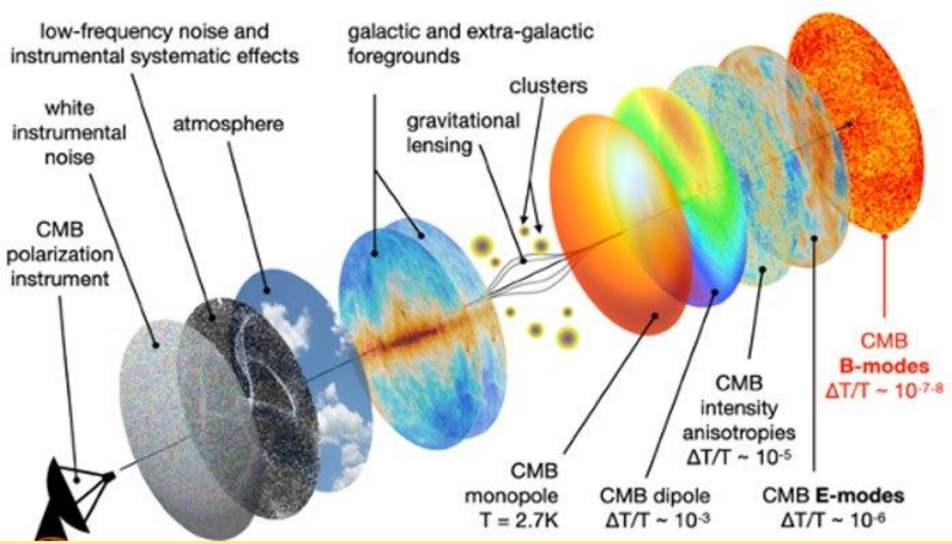
[5] SR-NIEL-7

Scientific case of study

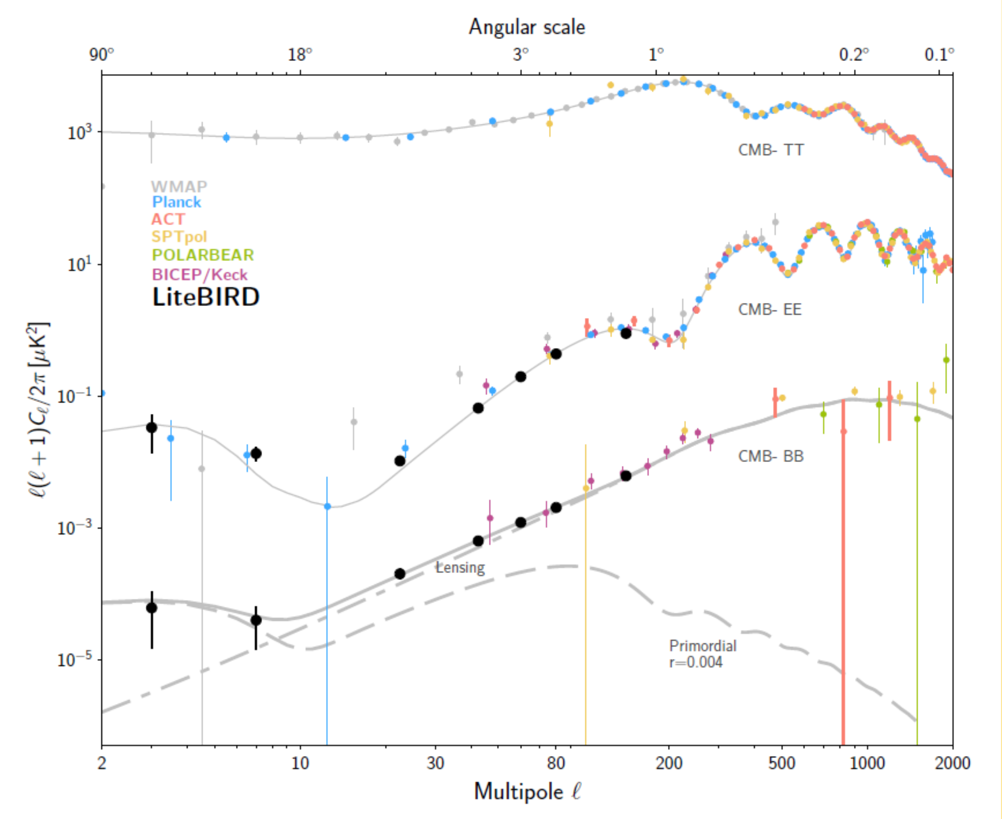
LiteBIRD study *B*-mode polarization and Inflation from Cosmic Background Radiation:

- ❖ Making a discovery or ruling out well-motivated inflationary models
- ❖ Insight into the quantum nature of gravity

CMB noise superimposition



Expected LiteBIRD sensitivity



[6] E. Allys et al. (2022)

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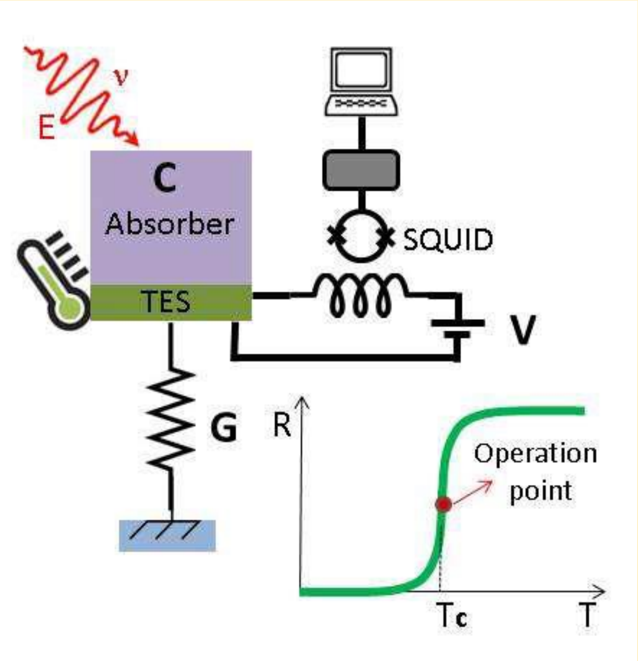
Scientific case of study

- ❖ Experiment with Cryogenic Transition Edge Sensors (TES)
- ❖ In space environment
- ❖ Long exposure (faint signal along the visible universe)

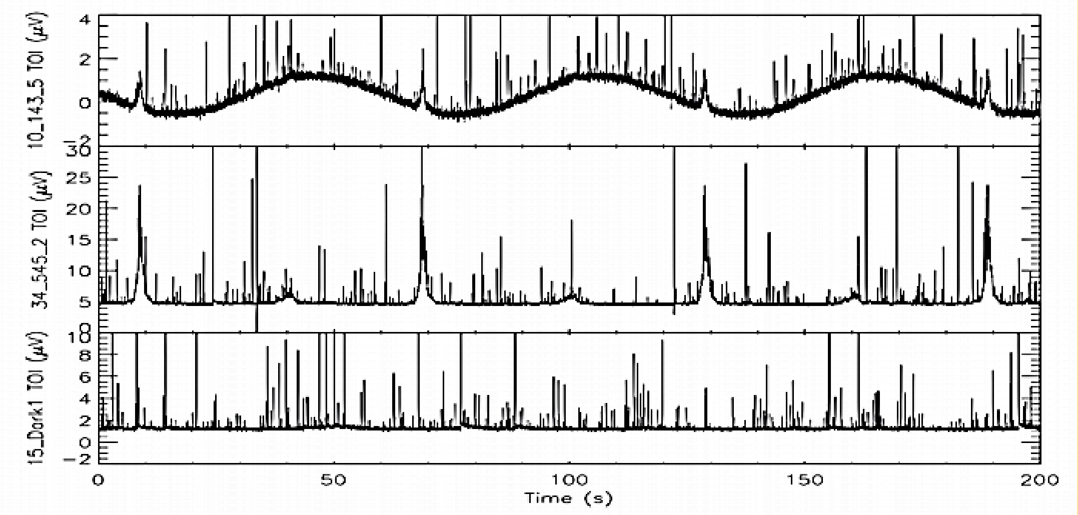
Planck (predecessor) → LiteBIRD (~2032)

- 90% of Plank data affected by CR background
- $\mathrm{B-modes} \approx 10^{-3}$ CMB signal & sensitivity $\approx$ 30x of Plank



Lourdes Fàbrega, Transition Edge Sensors, ALBA, July 10th 2019

Plank CR glitches



[2] A. Catalano et al. (2014)

Monte Carlo simulation VS Machine Learning

- Computational expensive
- Time consuming

Resample & hit injection:

- Insertion artificial harmonics
- Poor statistics
- Sample not independence

Expand a small MC sample to cover the 3 years mission

Data Augmentation

Modulated CR at L2

Detector structure

Energy deposit in wafer

- Bolometer (thermal)
- TES (current) response

Semi analytical

Analytical

CR TOD Background

Data post analysis

Our project: CRAB

Cosmic Rays Artificial Background (CRAB)

ICSC
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Big Data and Quantum Computing

SPOKE 3

ASTROPHYSICS & COSMOS OBSERVATIONS

WP3

Big Data Analysis, Machine Learning and Visualization

- **Main page:** ttps://www.supercomputing-icsc.it/en/spoke-3-astrophysics-cosmos-observations-en/
- **Open access repository:** https://www.openaccessrepository.it/communities/spoke3/?page=1&size=20
- **GitHub:** https://github.com/ICSC-Spoke3

Technical Objectives

- **Synthetically** generate the time series covering the **whole mission**
- Achieve a reasonable generation **computational time (no ML ≈ 2 - 30x TOD length)**

  $\sim 10^{-2}$ **Training** $\sim 10^{-4}$ **Production**

- Genuine **statistically independent** AI generation
- Mimic MC data sample **peculiar features**
- Study different mission space environment & periods **(CR flux evolution)**

Methodologies

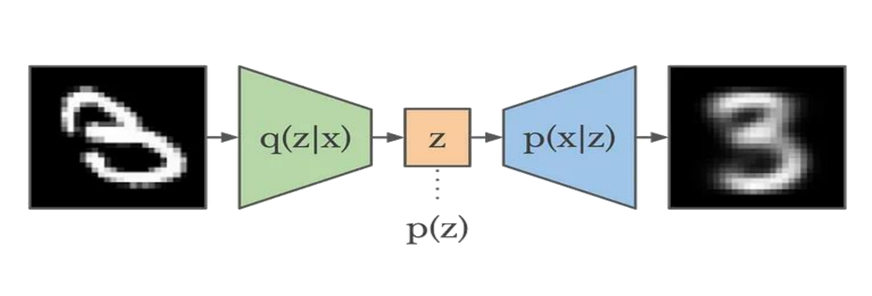
Why Neural Networks?

- Optimal for image reconstruction
- Generative

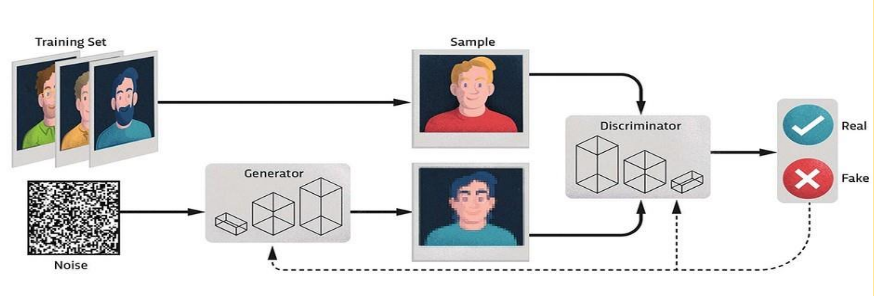
Two convolutional neural network approaches:

- Variational Auto Encoder (VAE)
- Generative Adversarial Networks (GAN)

VAE



GAN



Methodologies

Literature comparison

VAE				
	Training & validation	**Power spectrum**	**Frequency spectrum**	**Bolometer correlation**
Gaussian	minimized	inconsistent	inconsistent	absent
Bernoulli 1	minimized	consistent	inconsistent	absent
Bernoulli 2	~minimized	~consistent	~consistent	~consistent

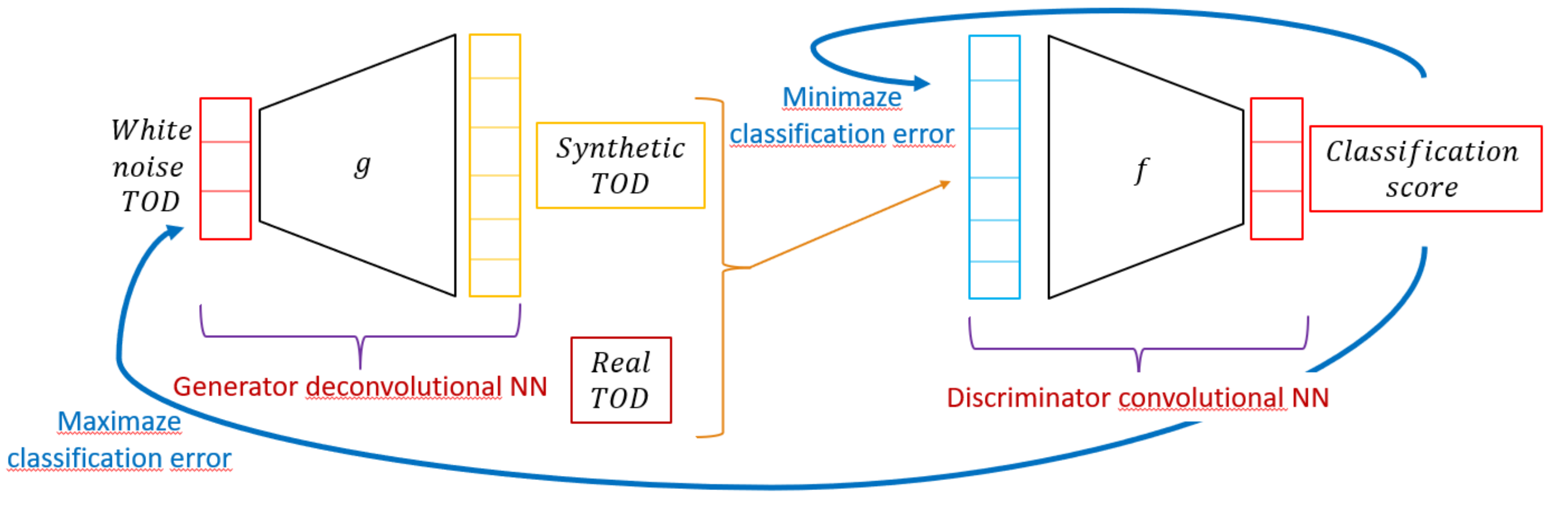
GAN			
Training & validation	**Power spectrum**	**Frequency spectrum**	**Bolometer correlation**
minimized (Discriminator) ~minimized (Generator)	consistent	consistent	consistent

Methodologies

Python & TensorFlow library

- Sequential Convolutional & Deconvolutional NN
- Custom combined training (discriminator & generator)

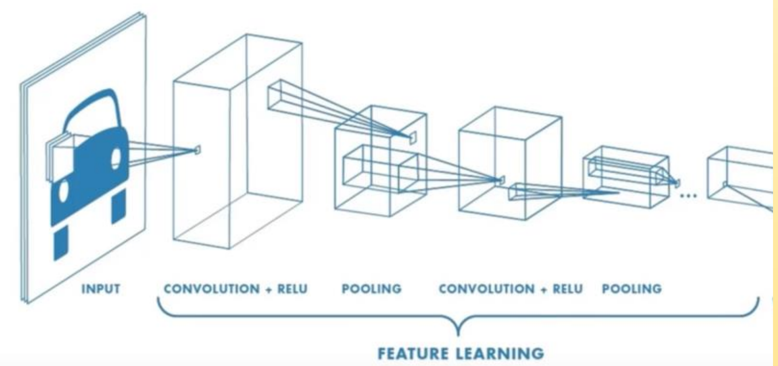
GAN algorithm (NN couple)



$Loss_G = Wess[f(g(x_i))]$

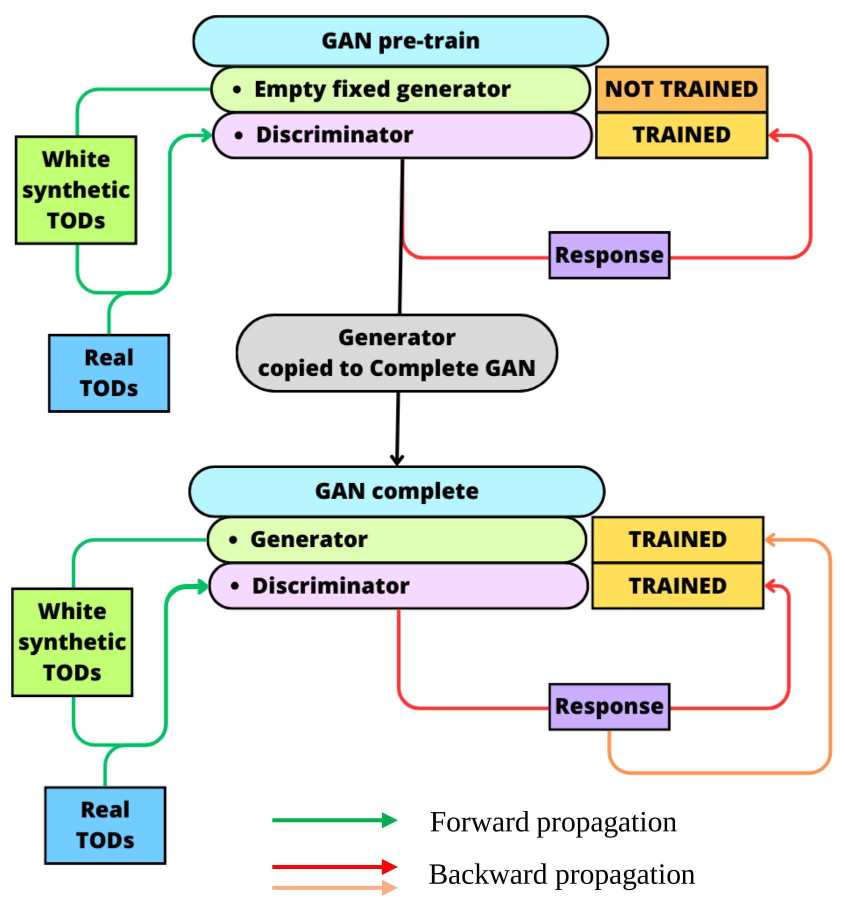
$Loss_D = Wess[f(x_i), f(g(x_i))]$

Convolutional Neural Networks



Solutions: Cosmic Ray Artificial Background (CRAB)

Training scheme



1) Pre-training of the discriminator only for limited epochs
2) GAN building with pre-trained discriminator
3) Complete GAN training
4) (Eventually extra discriminator training steps)
5) Synthetic generation (generator predict)

→ **Learn the real TODs classification (starting from a stable point)**

→ **Avoid generator dominated**

→ **Final TOD outputs**

Implementation

Different loss function and training algorithm

Wasserstein GAN

- Wasserstein loss metric
- Easily stuck in local minima
- Not trivial minimization of the loss (not bounded and negative for the generator)
- Accuracy not normalized
- General distribution separation

Cross entropy GAN

- Binary cross entropy loss metric
- Limited and always positive
- Included in the TensorFlow frame
- Trivial implementation of validation metrics
- Not completely stable

Implementation

NN architecture

Model: "Generator"

Layer (type)	Output Shape	Param
Dense (LeakyReLU)	(None, 265)	26765
Conv1D Transpose (LeakyReLU)	(None, 265, 8)	88
Batch Normalization	(None, 265, 8)	32
Conv1D Transpose (LeakyReLU)	(None, 530, 16)	1296
Batch Normalization	(None, 530, 16)	64
Conv1D Transpose (LeakyReLU)	(None, 1060, 32)	5152
Batch Normalization	(None, 1060, 32)	128
Separable Conv1D (LeakyReLU)	(None, 1060, 1)	353
lambda_1 (Normalization)	(None, 1060, 1)	0

Trainable params: 33766

Model: "Discriminator"

Layer (type)	Output Shape	Param #
Conv1D (LeakyReLU)	(None, 1060, 8)	168
LayerNormalization	(None, 1060, 8)	16
Conv1D (LeakyReLU)	(None, 1060, 8)	648
LayerNormalization	(None, 1060, 8)	16
Conv1D (LeakyReLU)	(None, 530, 16)	1296
LayerNormalization	(None, 530, 16)	32
Conv1D (LeakyReLU)	(None, 106, 32)	5152
LayerNormalization	(None, 106, 32)	64
Dense	(None, 1)	3393

Trainable params: 10785

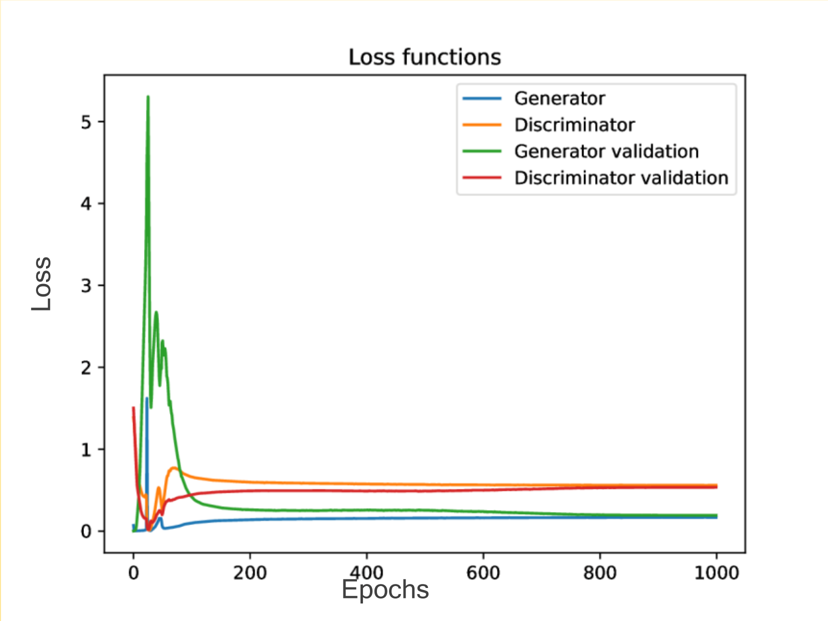
Solutions

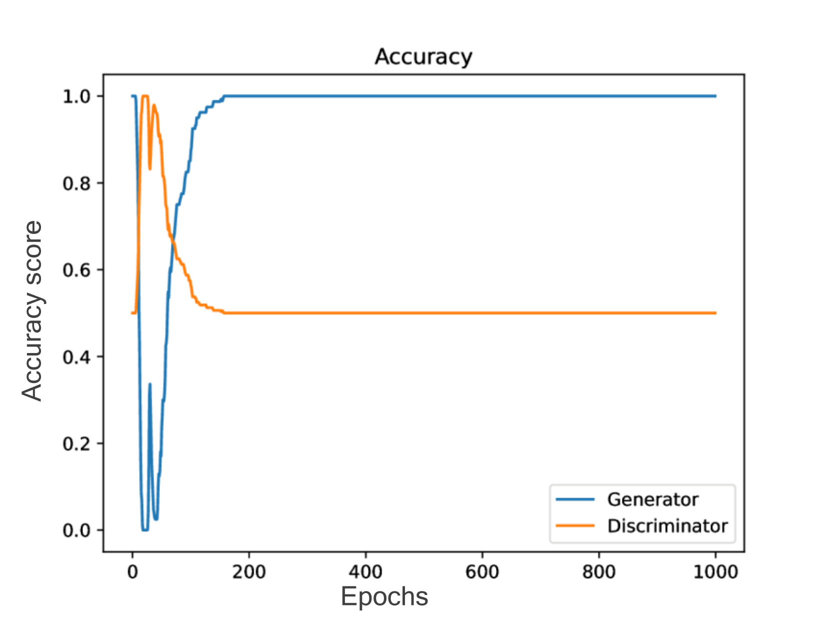
Parameter tuning

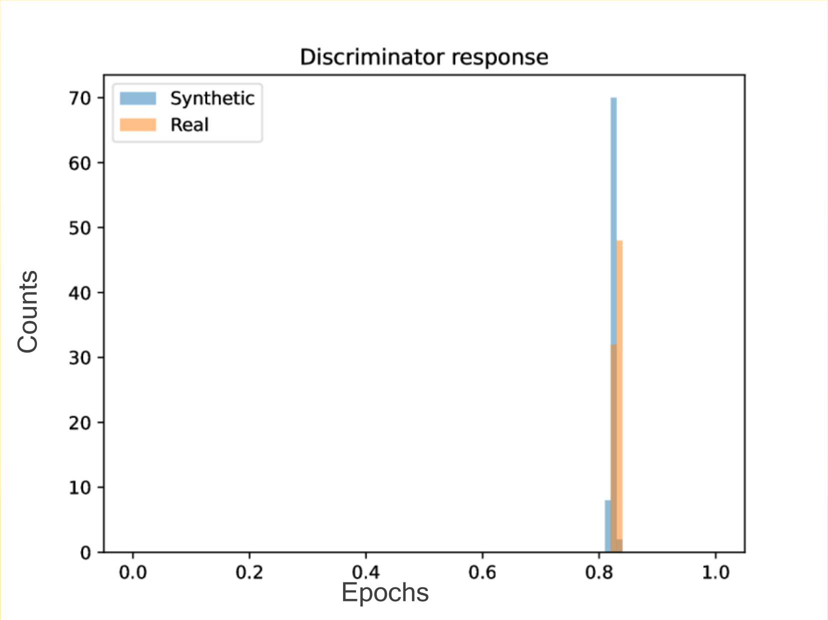
- Filter kernel (Length of deposit energy relaxation * n)
- Activation (LeakyReLU, ReLU, Tanh)
- Optimizers (Adam, Nadam, SGD) Adam for Generator, SGD for Discriminator
  - Discriminator Adam (too aggressive ➡ Discriminator dominated)
  - Generator SGD (too slow learing ➡ Discriminator dominated)
- Synthetic weighting 0.5 (to keep the discriminator focused on real TODs)
- Labem smoothing for generator loss

Preliminary Results

Output metrics example

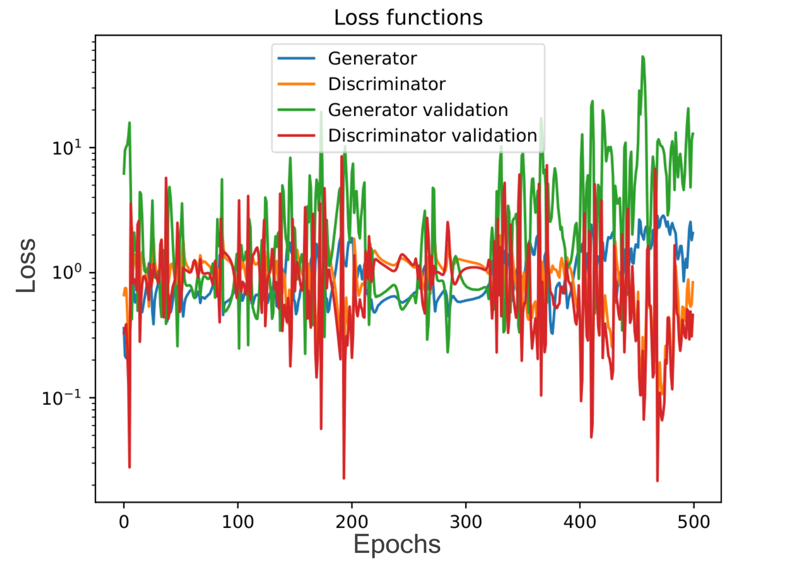


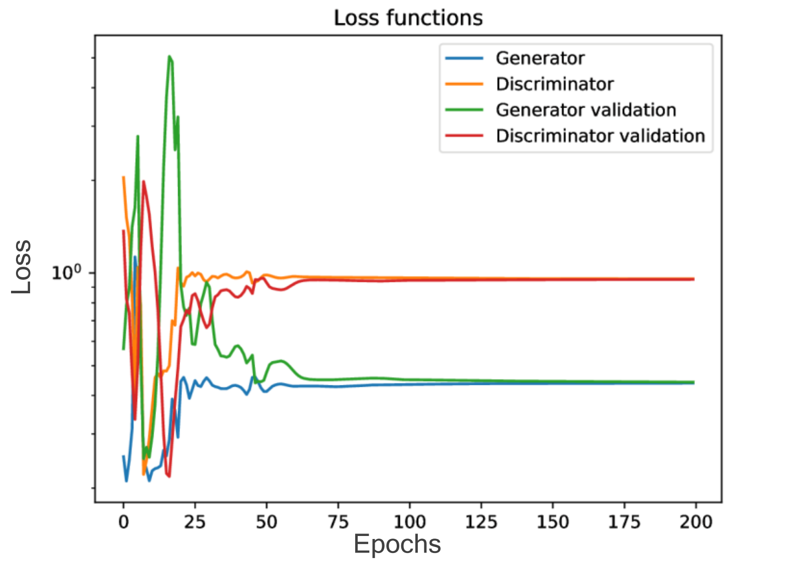


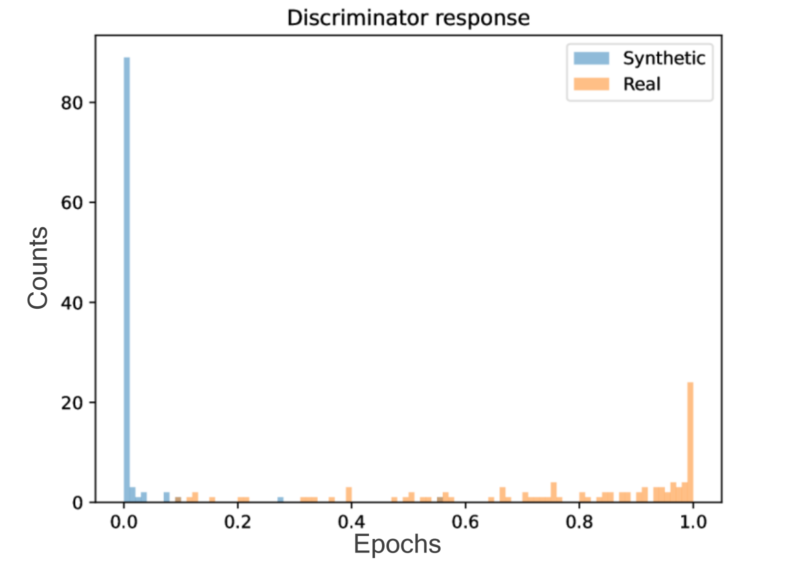


Known issues

Mode collapse	Generator dominated	Real data miss classification
Switching win-lose performances in unstable loop	The discriminator classify all the TODs as real	Loss of discriminator ability to classify real TODs







Next Steps and Expected Results

Conclusions:

- I illustrate the need of modelling CR background in LiteBIRD and similar experiments with TES
- We show the potential of data augmentation for CR background study
- GANs have instable training

Future Steps:

- Overcome the mode collapse issues
- Test the Variational Auto Encoders as alternative
- Conditional generation

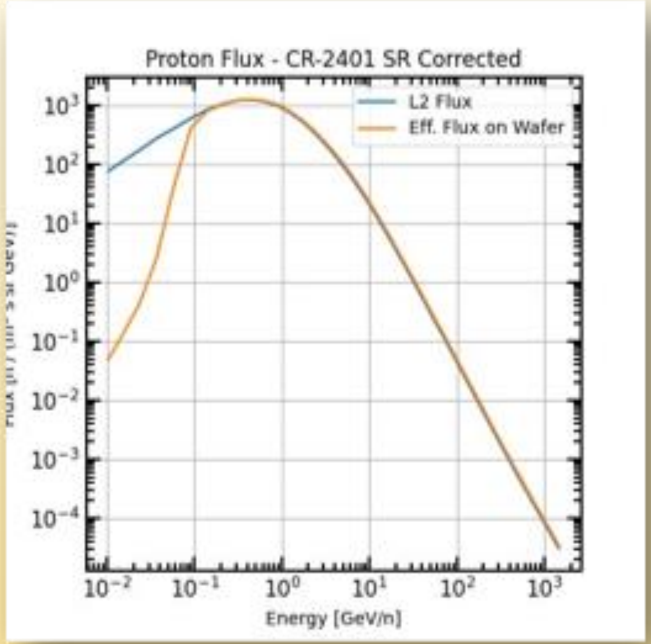
Thanks for your attention

Bibliography

1) S. L. Stever et al., “Simulations of systematic effects arising from cosmic rays in the LiteBIRD space telescope, and effects on the measurements of CMB B-modes”, Journal of Cosmology and Astroparticle Physics, vol. 2021, no. 9, p. 013, Sep. 2021, doi: 10.1088/1475-7516/2021/09/013.
2) A. Catalano et al., “Characterization and Physical Explanation of Energetic Particles on Planck HFI Instrument”, Journal of Low Temperature Physics, vol. 176, no. 5–6, pp. 773–786, Feb. 2014, doi: 10.1007/s10909-014-1116-6.
3) P. A. R. Ade et al., “Planck2013 results. X. HFI energetic particle effects: characterization, removal, and simulation”, Astronomy & Astrophysics, vol. 571, p. A10, Oct. 2014, doi: 10.1051/0004-6361/201321577.
4) M. J. Boschini, S. Della Torre, M. Gervasi, G. La Vacca, and P. G. Rancoita, “The HelMod model in the works for inner and outer heliosphere: From AMS to Voyager probes observations,” Advances in Space Research, vol. 64, no. 12, pp. 2459–2476, 2019, doi: https://doi.org/10.1016/j.asr.2019.04.007.
5) M.J. Boschini, P.G. Rancoita and M. Tacconi (2014), SR-NIEL–7 Calculator: Screened Relativistic (SR) Treatment for NIEL Dose, Nuclear and Electronic Stopping Power Calculator (version 10.16); website https://www.sr-niel.org/
6) E. Allys et al., “Probing cosmic inflation with theLiteBIRDcosmic microwave background polarization survey,” Progress of Theoretical and Experimental Physics, vol. 2023, no. 4, Nov. 2022, doi: 10.1093/ptep/ptac150.

Backup

Monte Carlo simulation VS Machine Learning



Space CR modulated radiation environment at L2 (HelMod)

Energy deposit in wafer

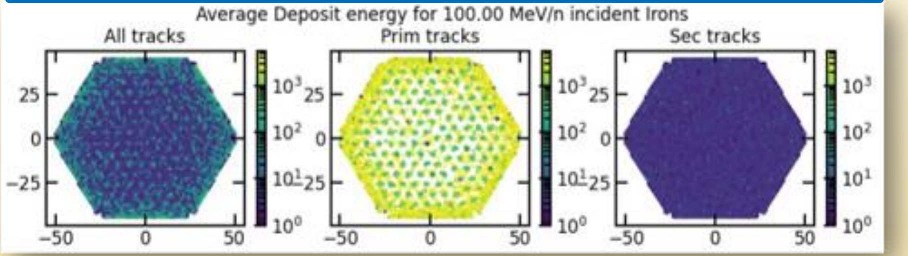
- Bolometer (therma)
- TES (current) response

CR TOD Background

Data post analysis

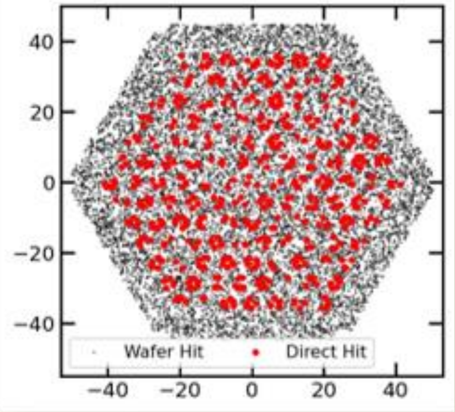
Monte Carlo simulation VS Machine Learning

Synthetically generate CR energy deposit map



- Bolometer correlated white noise
- Delta peaks noise (after decimation)

- Wafer warming
- TES direct hits



Propagation of CR inside telescope & Energy deposit in detector materials (Geant4)

Energy deposit in wafer

- Bolometer (therma)
- TES (current) response

CR TOD Background

Data post analysis

Monte Carlo simulation VS Machine Learning

Modulated CR at L2

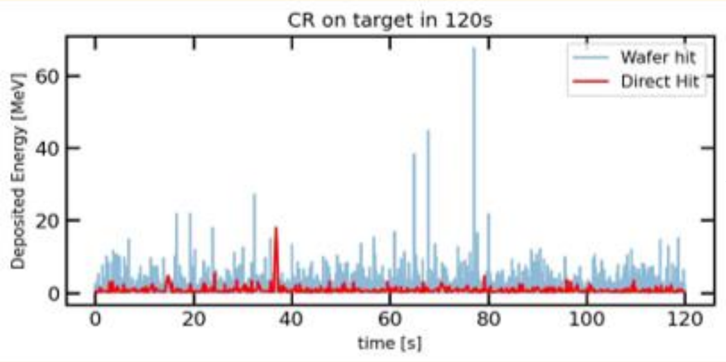
Detector structure

Energy deposit in wafer

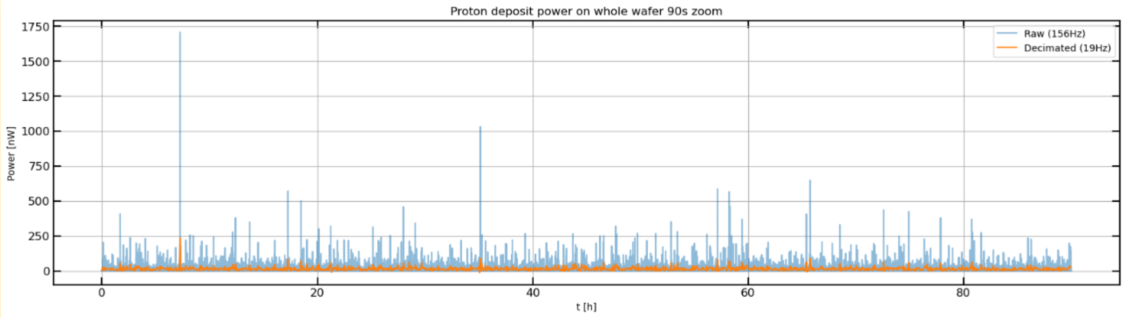
- 3D bolometer heat transfer model and thermal response(COMSOL)
- TES current response calculation

CR Time Ordered Data Background

Data post analysis



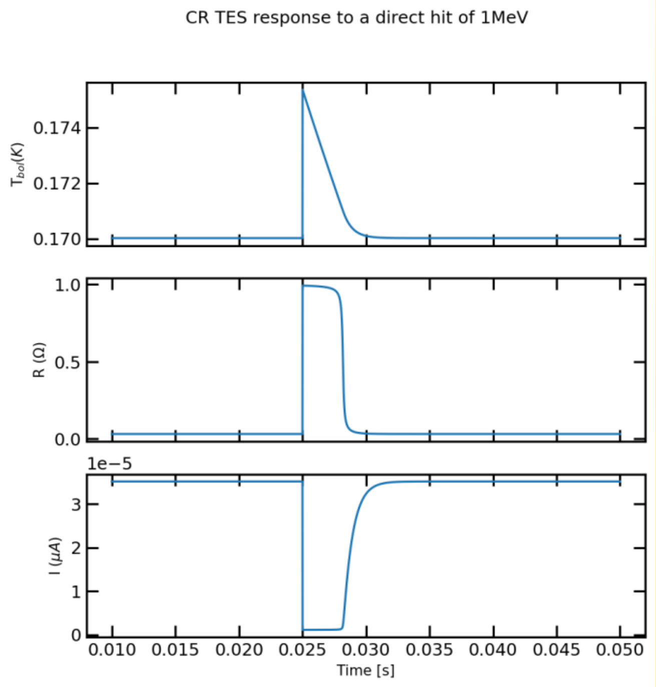
MC generate TOD output



Scientific case of study

Direct hits

$$I(singal) = \frac{V_{TES}}{R(T)} \approx \frac{V_{TES}}{arctan(T - T_{Crit})} = \frac{V_{TES}}{arctan\left(T_{CR}\, e^{-\frac{G}{C}t} - T_{Crit}\right)}$$

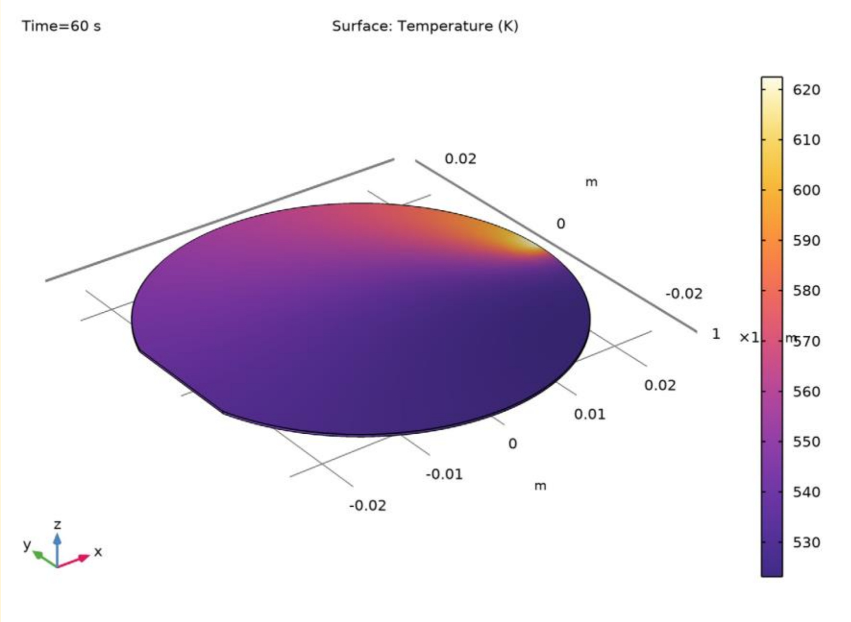


$$\frac{\Delta E_{CR}}{C} = T_{CR}$$

$$\Delta T = [P_{TES} - G(T - T_{bath})]\frac{\Delta t}{C}$$

$$T(t) = T_{CR}\, e^{-\frac{G}{C}t}$$

Wafer warming



Laser Heating of a Silicon Wafer, Guide

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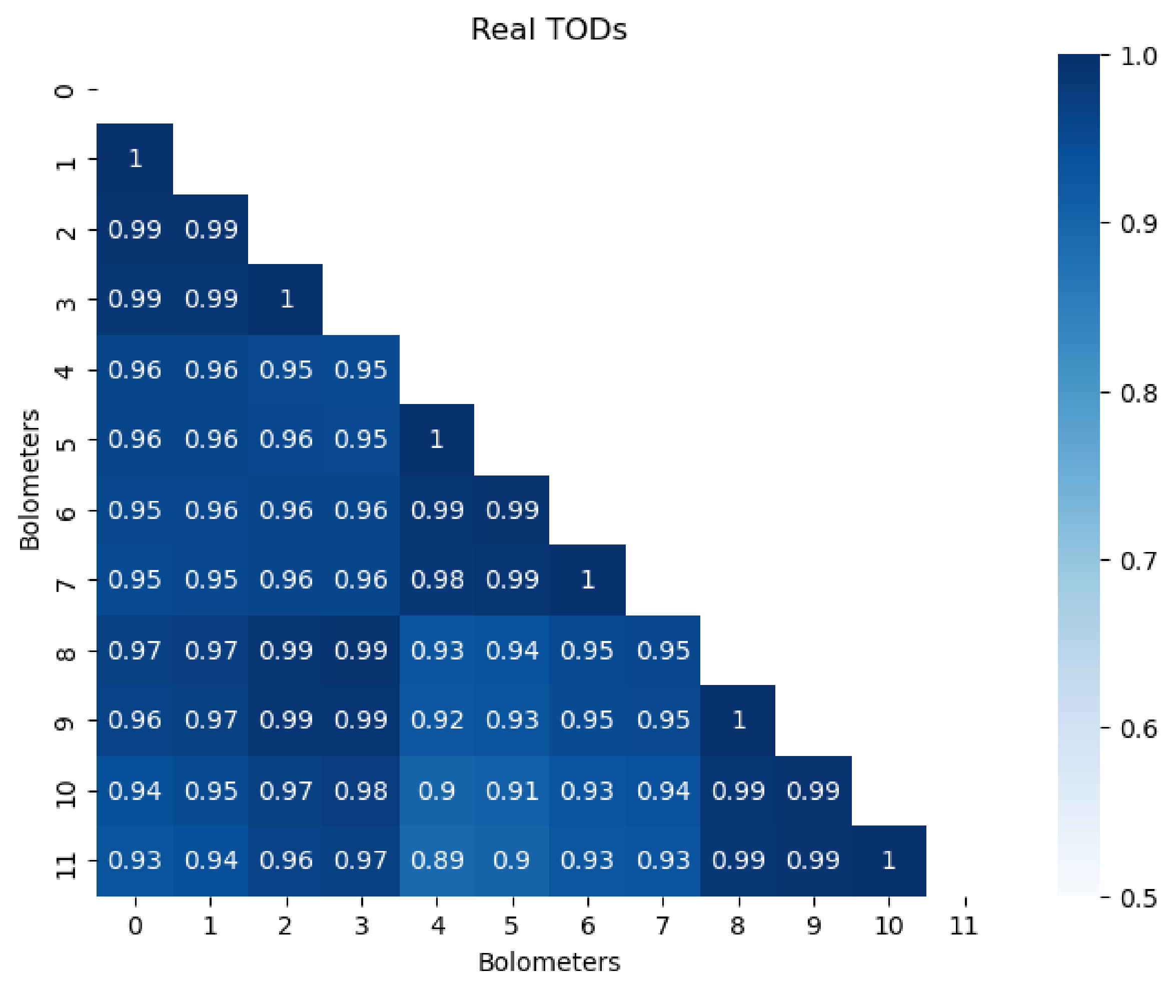
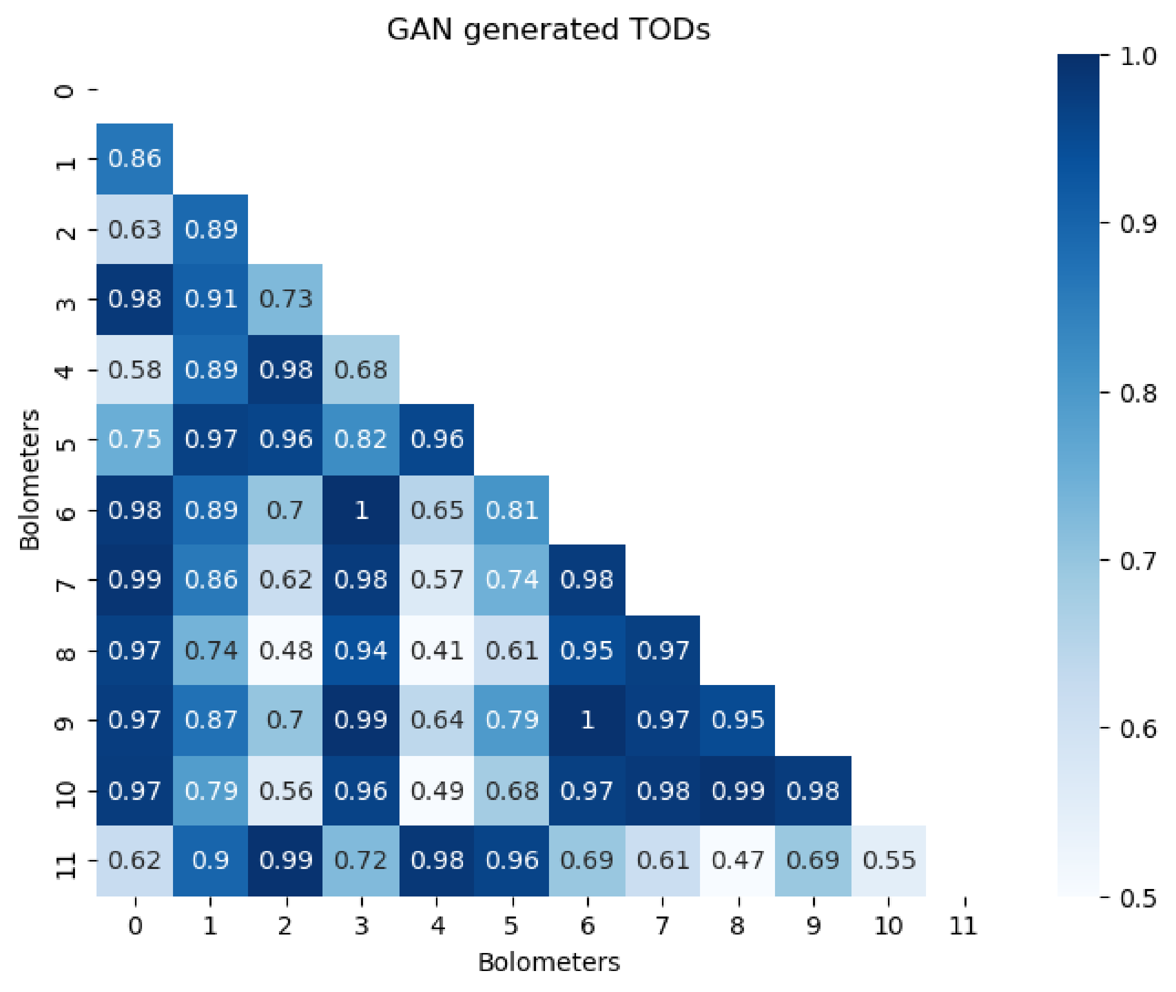
Preliminary Results





Preliminary Results

- **WGAN model 21**