EM shower simulator with Neural Network

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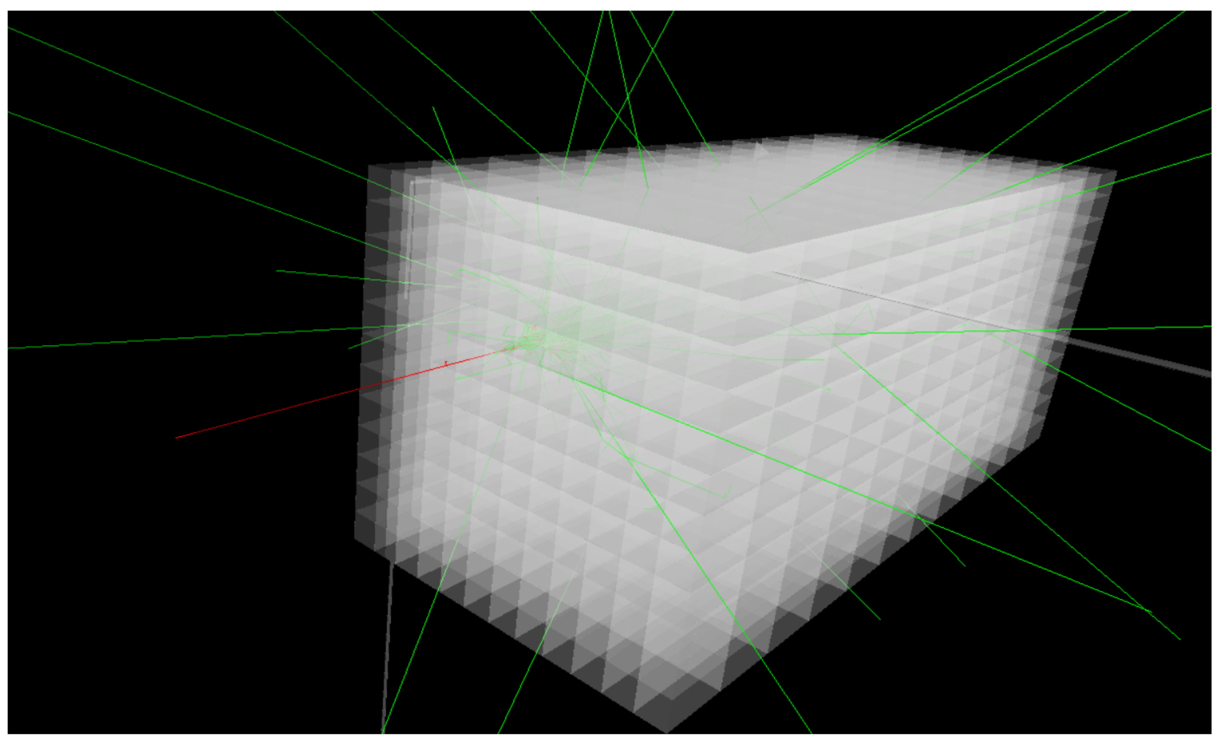
ABSTRACT

Recent developments in calorimeter physics are leading to a new paradigm in calorimeters' design. The aim is to reconstruct the whole spatial distribution of the shower instead of extracting information only about the energy deposition inside calorimeter cells. Many collaborations are designing highly-segmented calorimeters (for instance, CMS High-Granularity CAL and ALICE FoCAL) to reach this goal. In this project, our goal is to build a neural network to simulate electromagnetic shower energy deposition inside a toy segmented calorimeter. Taking inspiration from recent works in this field, like the CaloGAN network, we have built a GAN with auxiliary conditions based on total energy deposition and particle IDs. The neural network was trained with a dataset created on purpose with the Geant4 simulation toolkit. Simulations involve electrons, positrons and photons with energies from 1 to 30 GeV that strike on a CsI calorimeter with 12 layers and 25×25 cells per layer. The results are further analyzed with ROOT to evaluate GAN's performances. Due to time, dataset and hardware constraints, this project must be considered an exploratory work whose results can even be improved with more resources.

Geant4 simulations

Train dataset ($\mathcal{I}$) is produced in Monte Carlo simulations made with Geant4. The used physics list is EM; cells componing the calorimeter are $1 \times 1 \times 5\,\text{cm}^3$ cesium iodide blocks, with no inactive absorbers between them. In figure a 3D visualization of a 2 GeV electron stricking on the calorimeter is shown. Files from Geant4 are then preprocessed to a suitable shape for the multivariate analysis.



GAN structure

After some time involved in studying the best configuration of the network, the final topology contains the following characteristics:

Generator

- Input: noise $\in \mathbb{R}^{1024}$, primary energy (E_{in}) and primary particle identity (P_{in});
- Conv3DTranspose layers;
- Batch Normalization;
- Leaky Relu activation;
- Output: 3D-image ($\mathcal{G}$).

Discriminator

- Input: 3D-image;
- Embedding layers;
- Conv3D layers;
- Pooling3D layers;
- Leaky Relu activation;
- Minibatch discrimination;
- Outputs: Decision ($\mathcal{D}$) on image shape, label asserting initial energy ($E^{label}_{GAN/GEANT}$), label asserting primary particle ID ($P^{label}_{GAN/GEANT}$).

GitHub Repository

`https://github.com/Dario-Caf/EM-shower-simulator-with-NN.git`

Losses implementation

In order to make the generator to learn to reproduce the Geant samples and the discriminator to distinguish real from fake samples, their losses are mutually depending. The losses we use are composed by several terms added together (λ_E is a "normalization" hyperparameter).

Generator:

- gener_loss $= \mathcal{L}_{BCE}\left(\mathbb{1}, \mathcal{D}(\mathcal{G})\right)$
- comp_en $= \lambda_E \cdot \mathcal{L}_{MSE}\left(E_{in}, E^{meas}_{GAN}\right)$
- fake_label_en $= \lambda_E \cdot \mathcal{L}_{MSE}\left(E_{in}, E^{label}_{GAN}\right)$
- fake_part_id $= \mathcal{L}_{BCE}\left(P_{in}, P^{label}_{GAN}\right)$

Discriminator:

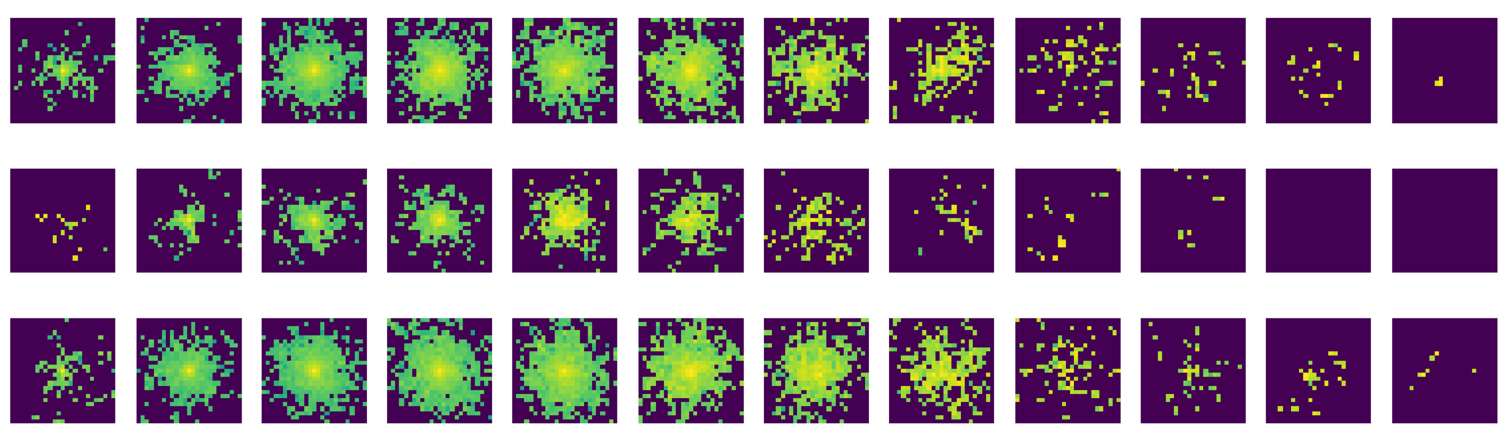
- discr_loss $= \mathcal{L}_{BCE}\left(0, \mathcal{D}(\mathcal{G})\right) + \mathcal{L}_{BCE}\left(\mathbb{1}, \mathcal{D}(\mathcal{I})\right)$
- real_label_en $= \lambda_E \cdot \mathcal{L}_{MSE}\left(E_{in}, E^{label}_{GEANT}\right)$
- real_part_id $= \mathcal{L}_{BCE}\left(P_{in}, P^{label}_{GEANT}\right)$

Analysis of performances

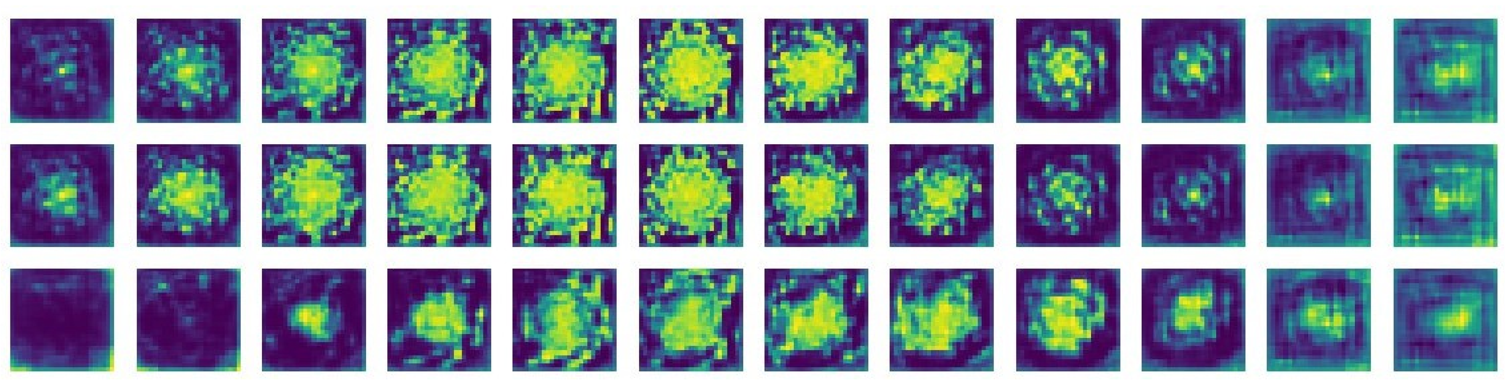
Geant4 and GAN simulations are analyzed to infere about the performances of the neural network. The physical parameters that we confront are : energy deposition inside the calorimeter, shower depth and shape, dependence on primary particle energy and type.

Some examples

Geant4 simulation:



GAN simulation:



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