Physics Department "E. Fermi"
University of Pisa

EM-shower-simulator-with-NN

An EM shower simulation toolkit based on Generative Adversarial Network

Daniele Passaro
d.passaro1@studenti.unipi.it

Dario Cafasso
d.cafasso@studenti.unipi.it

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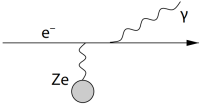
Contents

Introduction

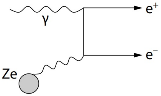
Physics and reasons for our work

EM showers develops through bremsstrahlung and pair production processes. Main physical paramaters:

- X_0 = radiation lenght;
- λ_γ = photon absorption lenght;
- $R_M = \frac{E_S}{E_c} X_0$;

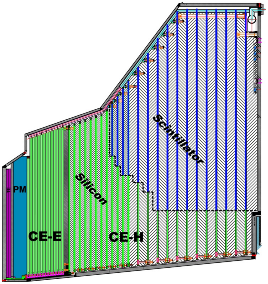


(a) Bremsstrahlung.



(b) Pair production.

Calorimeters : homogeneous vs sampling design. Recently, many experiments are redesigning their calorimeters in order to achieve high energy resolutions (high segmentation).



Package structure

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- the setup.cfg file contains the package metadata and access-points (CLI), while the setup.py file finds dependencies and modules to install.

This package can be installed through pip as showed in the documentation:
`https://em-shower-simulator-with-nn.readthedocs.io/en/latest/?badge=latest`.

Geant4 simulations

Code and data pre-processing

Geant4 simulations are performed with the precompiled executable GEARS (released for Windows, macOs and Linux):

```
gears.exe simulazione.mac
```

Parameters of the simulation:

- Detector: CsI material, $12 \times 25 \times 25$ cells, $1 \times 1 \times 5\,\mathrm{cm}^3$ wide;
- Particle source: $50\%\ \gamma$, $50\%\ e^{\pm}$; energy range $[1\,\mathrm{GeV}, 30\,\mathrm{GeV}]$;
- Analysis manager: tree filled with track ID, xyz position, physical processes involved at each step, ...

```
*****************************************************************************************************
* G4Track Information:   Particle = gamma,   Track ID = 1,   Parent ID = 0
*****************************************************************************************************

Step#    X(mm)    Y(mm)    Z(mm) KinE(MeV)  dE(MeV) StepLeng TrackLeng  NextVolume ProcName
    0     -200      120      120  2.29e+03        0        0         0       world initStep
    1     -191      120      120  2.29e+03        0     8.98      8.98    step0(S) CoupledTransportation
    2     -189      120      120  2.29e+03        0        2        11       world CoupledTransportation
    3      -25      120      120  2.29e+03        0      164       175 cella1313(S) CoupledTransportation
    4    0.879      120      120         0        0     25.9       201 cella1313(S) conv
    :----- List of 2ndaries - #SpawnInStep=  2(Rest= 0,Along= 0,Post= 2), #SpawnTotal=  2 ---------------
    :     0.879      120      120       474                 e-
    :     0.879      120      120  1.82e+03                 e+
    :---------------------------------------------------------------- EndOf2ndaries Info ---------------

*****************************************************************************************************
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Parameters of the simulation:

- Detector: CsI material, $12 \times 25 \times 25$ cells, $1 \times 1 \times 5\,\mathrm{cm}^3$ wide;
- Particle source: 50% γ, 50% $e^{\pm}$; energy range $[1\,\mathrm{GeV}, 30\,\mathrm{GeV}]$;
- Analysis manager: tree filled with track ID, xyz position, physical processes involved at each step, ...

Data pre-processing :

- overall normalization:

$$E^{\mathrm{norm}}_{l,i,j} = \log E_{l,i,j} \cdot \left(\max_{l,i,j} \{ \log E_{l,i,j} \} \right)^{-1} \quad , \quad -1 \text{ if } E_{l,i,j} = 0$$

- new tree containing a $12 \times 25 \times 25 \times 1$ vector, $\mathrm{E_{in}}$, $\mathrm{E_{mis}}$, $\mathrm{P_{ID}}$.

GAN structure

Generator

Generator specifications

- Inputs:

latent_space : R^{1024} noise vector
energy_label : float energy value, from 1 to 30 GeV
particle_label : integer particle class, 0, 2 for $e^{\pm}$ and 1 for γ

- Combination of the noise and the particle ID
- Concatenation with the energy information
- Dense and Conv3DTranspose layers
- Output:

fake_image : tanh, tensor with shape $(12, 25, 25, 1)$

GAN structure
Discriminator

Discriminator specifications

- Input:

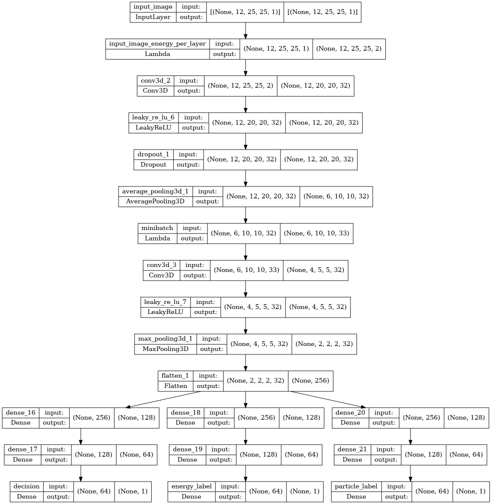
images : shape $(12, 25, 25, 1)$ and pixels $\in [-1, 1]$

- Concatenation of layer energies with features
- Pooling Layers
- Minibatch Std Deviation discrimination
- Outputs:

decision : sigmoid, decides whether the shower is true or fake

energy_label : relu, decides energy of the shower

particle_label : sigmoid, decides primary particle ID



GAN structure
GAN class

The class GAN inherits keras.Model properties and functions. The **constructor, compile, fit and summary** methods have been wrapped using the super function, while new important methods have been implemented, like:

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  Use the current status of the NN to generate images from the noise, plot, evaluate and save them.

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- **generate_and_save_images**
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  Train the generator and the discriminator simultaneously, save checkpoints and print examples of fake_images.

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- **train** and **train_step**
  Train the generator and the discriminator simultaneously, save checkpoints and print examples of fake_images.
- **restore**
  Restore the last checkpoint and return generator and discriminator models for further operations.

GAN structure
Losses implementation

Generator:

- $\text{gener\_loss} = \mathcal{L}_{BCE}(1, \mathcal{D}(\mathcal{G}))$

Discriminator:

- $\text{discr\_loss} = \mathcal{L}_{BCE}\,(0, \mathcal{D}(\mathcal{G})) + \mathcal{L}_{BCE}(1, \mathcal{D}(\mathcal{I}))$

Generator:

- $\text{gener\_loss} = \mathcal{L}_{BCE}(1, \mathcal{D}(\mathcal{G}))$
- $\text{comp\_en} = \lambda_E \cdot \mathcal{L}_{MSE}(E_{in}, E_{GAN}^{meas})$
- $\text{fake\_label\_en} = \lambda_E \cdot \mathcal{L}_{MSE}(E_{in}, E_{GAN}^{label})$
- $\text{fake\_part\_id} = \mathcal{L}_{BCE}(P_{in}, P_{GAN}^{label})$

Discriminator:

- $\text{discr\_loss} = \mathcal{L}_{BCE}\,(0, \mathcal{D}(\mathcal{G})) + \mathcal{L}_{BCE}(1, \mathcal{D}(\mathcal{I}))$
- $\text{real\_label\_en} = \lambda_E \cdot \mathcal{L}_{MSE}(E_{in}, E_{GEANT}^{label})$
- $\text{real\_part\_id} = \mathcal{L}_{BCE}(P_{in}, P_{GEANT}^{label})$

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We introduced two *unbiased metrics* to evaluate GAN performances in emulating shower samples during the training. The unbiased metric we use are physical properties of EM showers: **shower longitudinal depth** and **shower lateral width**

Analysis

Performances evaluation

The performance evaluation is based on:

1. Deposited energy vs initial energy
2. Mean energy deposition per layer
3. Mean energy deposition per cell in each layer
4. Shower mean depth per primary particle ID:

$$\hat{d}(E_{in}, P_{ID}) = \frac{1}{N_{P_{ID}}} \sum_{P_{ID}} \left(\sum_{l=0}^{11} \frac{l \cdot E_l}{E_{in}} \right)$$

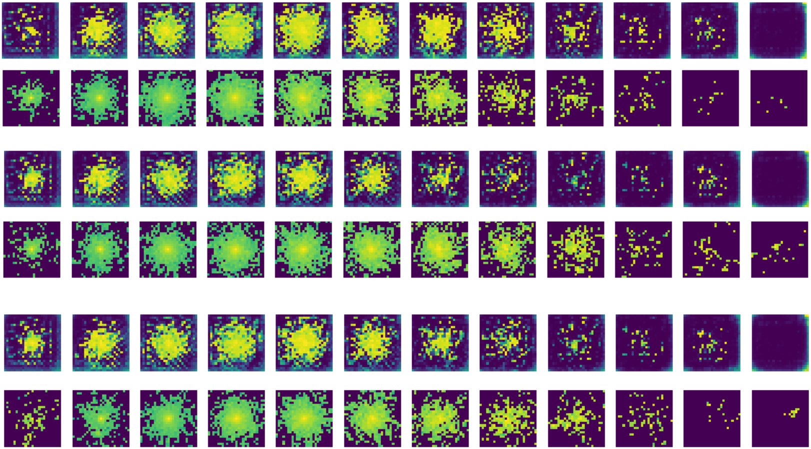
5. Shower depth's mean width per primary particle ID:

$$\hat{w}_{long}(E_{in}, P_{ID}) = \frac{1}{N_{P_{ID}}} \sum_{P_{ID}} \left(\sqrt{\sum_{l=0}^{11} \frac{l^2 \cdot E_l}{E_{in}} - \left(\sum_{l=0}^{11} \frac{l \cdot E_l}{E_{in}} \right)^2} \right)$$

6. Shower mean lateral width per primary particle ID:

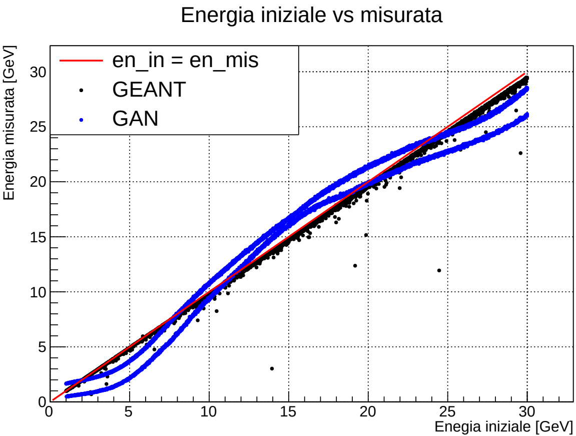
$$\hat{\sigma}(E_{in}, P_{ID}) = \frac{1}{N_{P_{ID}}} \sum_{P_{ID}} \frac{1}{12} \sum_{l=0}^{11} \left(\sqrt{\frac{l^2 \cdot E_l^w}{E_{in}} - \left(\frac{l \cdot E_l^w}{E_{in}} \right)^2} \right) \quad , \quad E_l^w = \sum_{n_x, n_y = 0}^{24} E_{l, n_x, n_y} \cdot (n_x - 12)$$

GAN vs GEANT4



Analysis

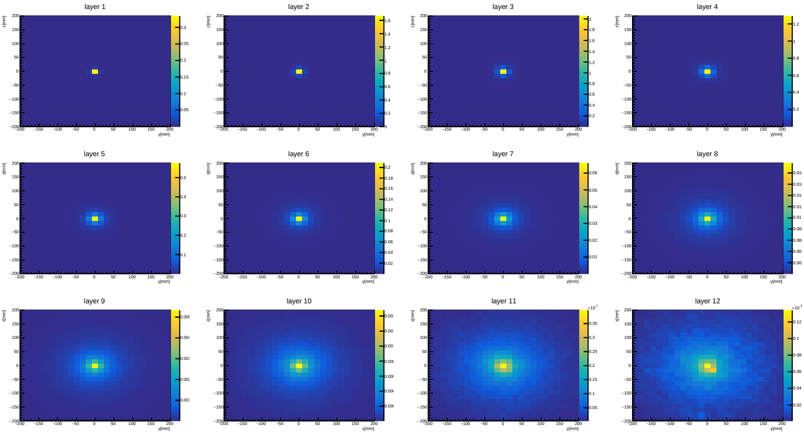
Results : Deposited energy vs initial energy



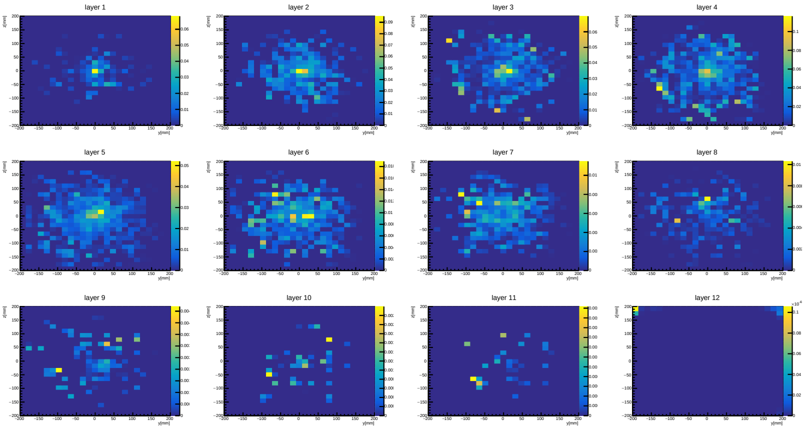
Analysis

Results : Mean energy deposition per cell per layer

Geant4 samples:



GAN samples:

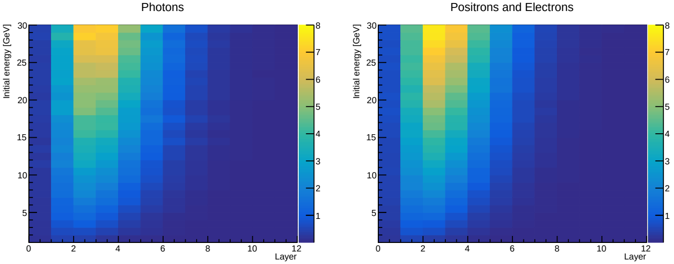


layer 1
layer 2
layer 3
layer 4
layer 5
layer 6
layer 7
layer 8
layer 9
layer 10
layer 11
layer 12
z[mm]
y[mm]

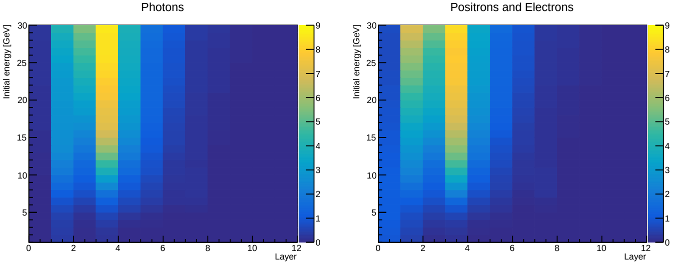
Analysis

Results : Mean energy deposition per layer per primary particle energy

Geant4



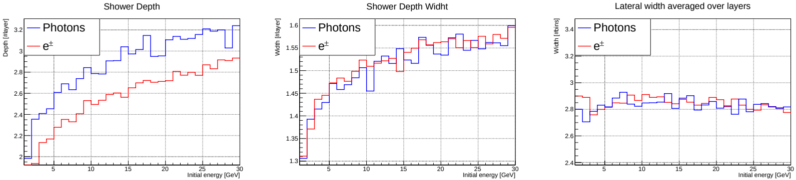
GAN



Analysis

Results : Shower mean depth; Shower depth width; Shower lateral width

Geant4



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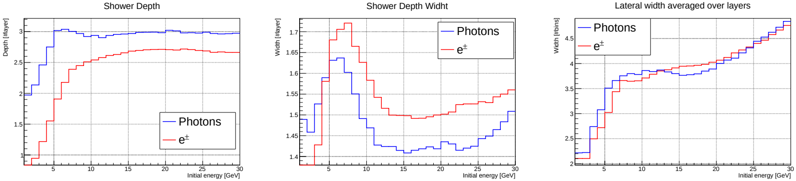


It's possible to clone the repository and install the package typing:

```
$ git clone
https://github.com/Dario-Caf/EM-shower-simulator-with-NN.git
$ cd EM-shower-simulator-with-NN
$ python3 -m pip install -e .
```

Once installed, it can be used typing:

from bash

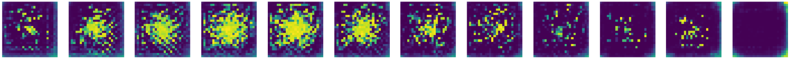
```
$ simulate-EM-shower -f 10. 1
```

from Python

```
>>> import em_shower_simulator as EM
>>> em.simulate([10., 1.], verbose=0)
```

The output is...

```
simulating event with features: [10.0, 1.0]
Restored from ./checkpoints/ckpt-14
Example 1 Primary particle = 0 Predicted particle = 0.1849
Initial energy = 10.0 Generated energy = 9.3354
Predicted energy = 8.5973 Decision = 0.0021
The work is done.
```



Conclusions

What we achieved:

- the synthesis of different ideas and perspectives
- a complete package structure
- a basis for further ML works
- an evidence that ML techniques can be useful in future HEP

What we learned:

- collaborative coding
- how to create a package
- create and train on purpose neural-networks models with personalized train_step
- how to use the ROOT toolkit to evaluate performances
- **simulating physics is very difficult !!**

Thank you for your attention!