Fast simulation for scattering muography applications using GAN

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Introduction

Cosmic muons are a product of the interaction of cosmic rays with the nuclei of the atmosphere

- 10000 μ/min · m² at Earth's surface
- Flux proportional to cos²(θ)

Two main interactions with matter:

Ionization

$$-\left\langle \frac{dE}{dx} \right\rangle = \frac{4\pi}{m_e c^2} \cdot \frac{\boxed{n} z^2}{\beta^2} \cdot \left(\frac{e^2}{4\pi\varepsilon_0}\right)^2 \cdot \left[\ln\left(\frac{2 m_e c^2 \beta^2}{\boxed{I} \cdot (1-\beta^2)}\right) - \beta^2\right]$$

$$\boxed{n = \frac{N_A \cdot Z \cdot \rho}{A \cdot M_u}}$$

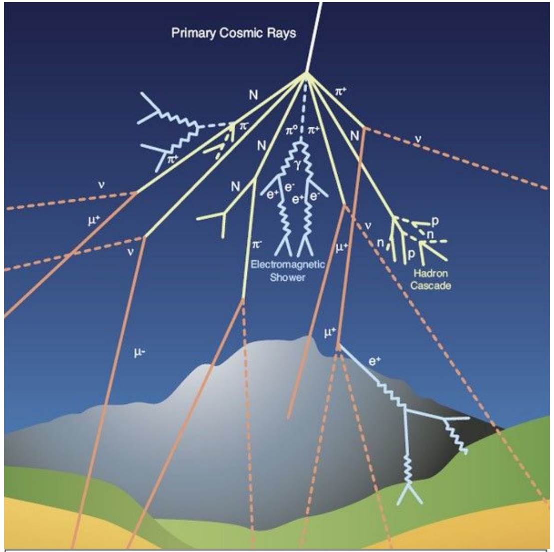
Mean excitation potential

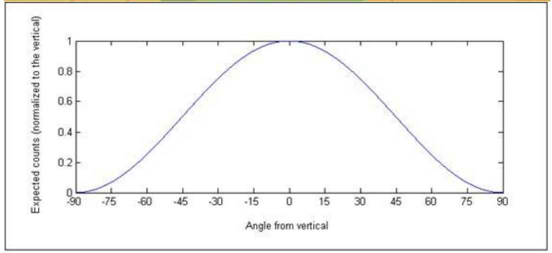
Multiple Coulomb Scattering

Momentum dependence

$$\theta_0 = \frac{13.6}{\boxed{\beta c p}} z \sqrt{x/\boxed{X_0}}\left[1 + 0.038 \ln(x/\boxed{X_0})\right]$$

$$\boxed{X_0 = 716.4\ \mathrm{g\,cm^{-2}} \frac{A}{Z(Z+1)\ln\frac{287}{\sqrt{Z}}}}$$





Statistical processes driven by nature

Energy loss depends on **density, composition and size** of objects

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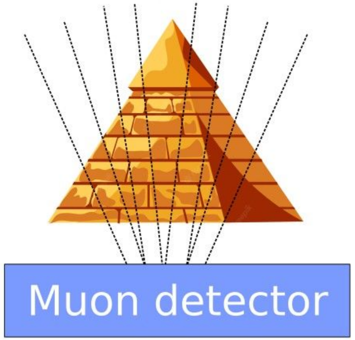
Muon tomography

Muon tomograohy (or muography) is a Non-Destructive Testing (NDT) technique that employs cosmic muons to obtain images of inaccessible places

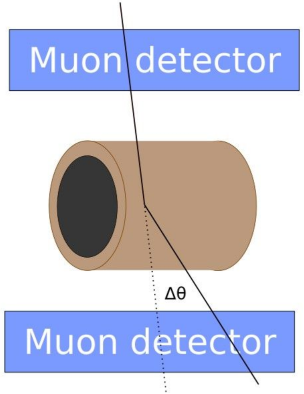
Absorption muography

- Incident flux vs direction → Transmittance
- One detector
- Large scale objects (pyramids, civil structures...)
- Long exposure times



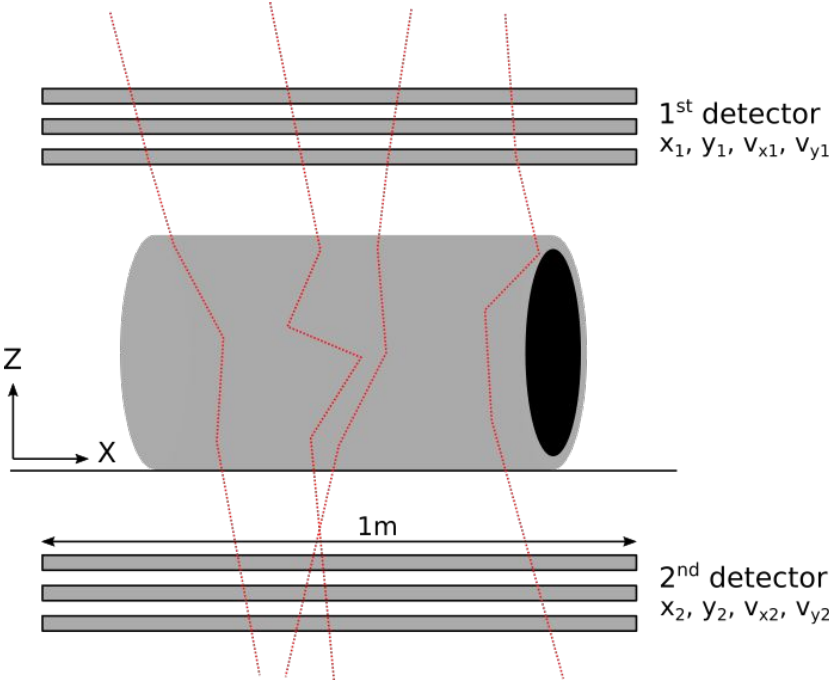
Scattering muography

- Position and angle shift → Change in muon trajectories
- Two detectors
- Small - medium scale objects (industrial applications)
- Shorter exposure times



Scattering muography

Industrial aplications: preventive maintenance, quality control



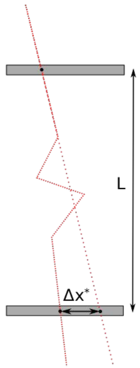
Measure position and direction (at each detector)

x ; y ; $v_x = \tan(\theta_x)$; $v_y = \tan(\theta_y)$

↓

Compute derived variables (**position and direction shift**)

$$\Delta x^* = x_2 - x_1 + Lv_{x_1}$$
$$\Delta y^* = y_2 - y_1 + Lv_{y_1}$$
$$\Delta v_x = v_{x_2} - v_{x_1}$$
$$\Delta v_y = v_{y_2} - v_{y_1}$$



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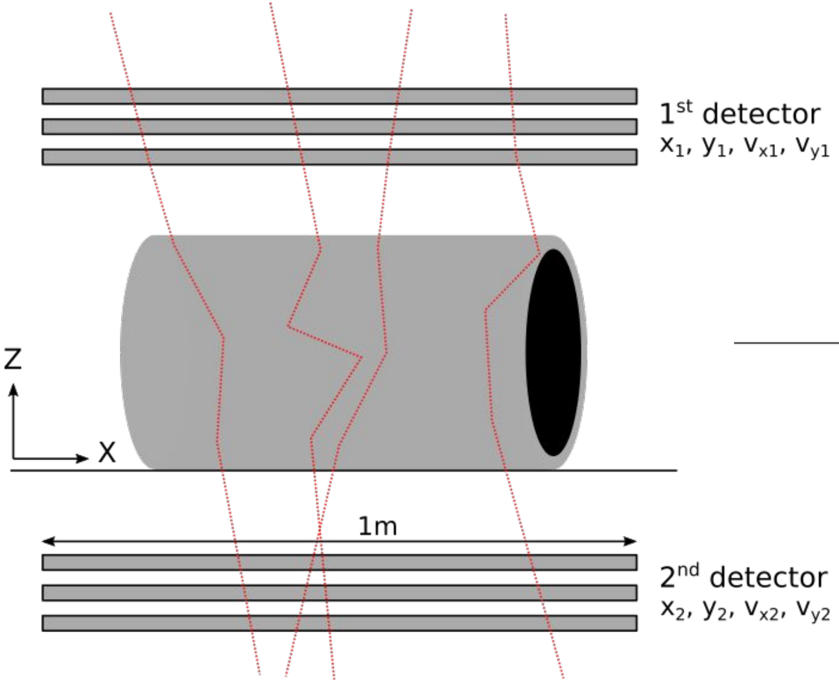
Information about intermediate objects

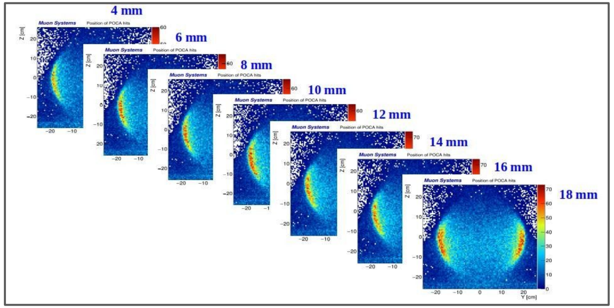
Composition, defects...

Industrial applications

Industrial aplications: preventive maintenance, quality control → Monitor wear of metal pipes



1. **Take muon data** and reconstruct pipe images (PoCA)
2. Feed data to a CNN that **returns the pipe thickness**



CNNs require lots of simulation to be trained

→ Currently obtained with CRY* + Geant4 (slow and computationally expensive)

→ *Alternative: generative AI models: GAN*

*CRY: Cosmic-ray shower generator

Generative Adversarial Networks

Generative Adversarial Networks (GAN) are a class of machine learning models based on deep neural networks that are capable (after proper training) of generating new synthetic data with the same characteristics as the training data

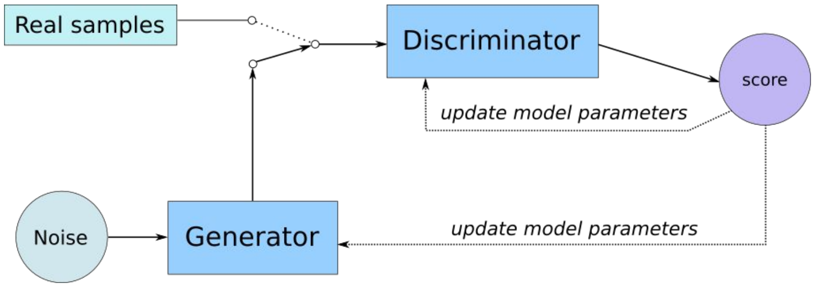
Ian J. Goodfellow (2014)

Frame **generative modeling as a supervised learning task** → Two submodels (NN)

- **Discriminator (D)**: receives a sample → real/fake
- **Generator (G)**: receives noise → generates sample

Adversarial training: shared loss function → "zero sum" game

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$



Equilibrium: G fools D about half of the times

Fast simulation for muography

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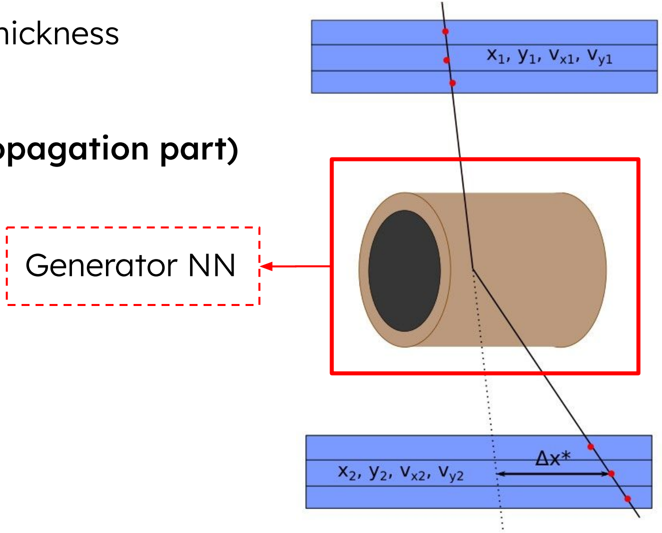
Set up: muon scattering tomography through metal pipes of different thickness

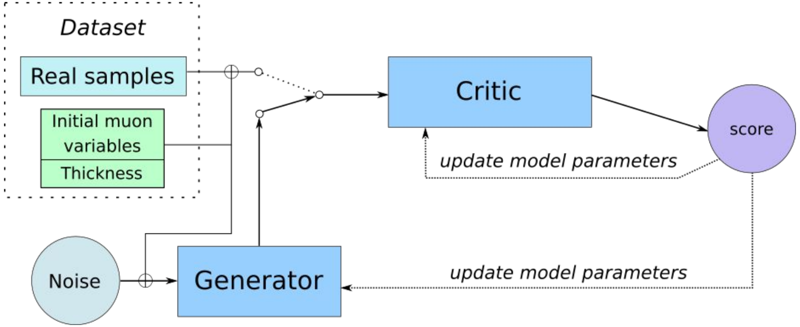
- Top detector measures cosmic flux: cheap (CRY)
- We are interested in simulating bottom detector information **(propagation part)**

We use top detector as additional info



Goal: train a GAN to generate the variables that characterize the muon scattering through metal pipes

→ **Replace muon propagation by a generative ML model**



Conditional WGAN-GP framework:

- Input: latent noise + $(x_1, y_1, v_{x1}, v_{y1})$ + thickness
- Output: shift in position and direction $(\Delta x^*, \Delta y^*, \Delta v_x, \Delta v_y)$

Results: variable distributions

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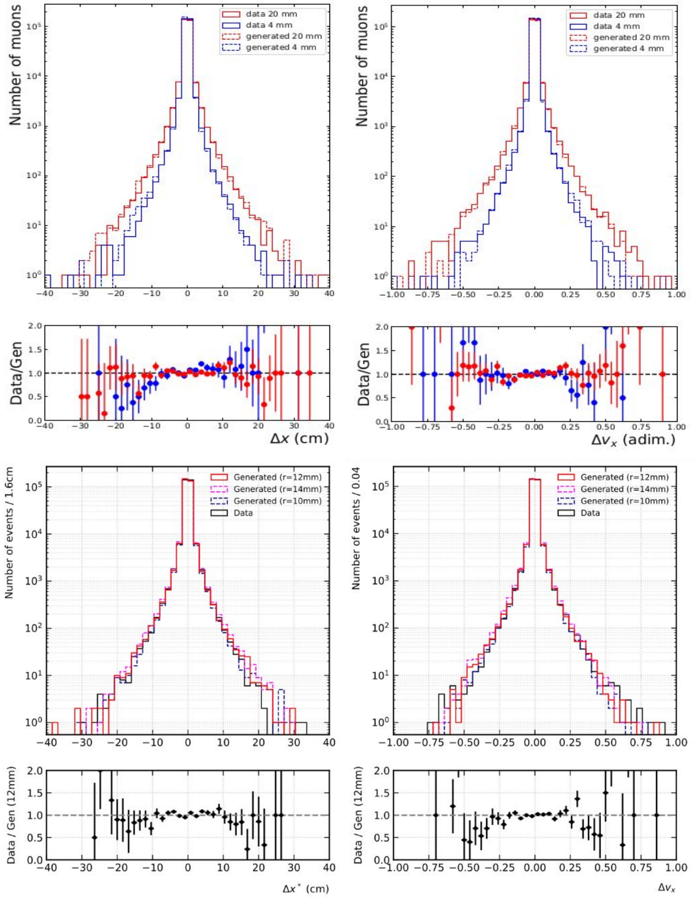
Training data: simulation events of cosmic muons (CRY) and their passage through metal pipes of different thickness (Geant4)

→ Trained on 4, 6, 8, 10, 14, 16, 18, 20 mm

Qualitative results:

- Top: real (—) and generated (--) distributions for 4 mm and 20 mm
- Bottom: generated distribution for 12 mm (never learned) using an interpolated label between 10 and 14 mm

The model is able to generate samples that resemble the original distributions with **modulation and interpolation capabilities**



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Results: density maps and CNN

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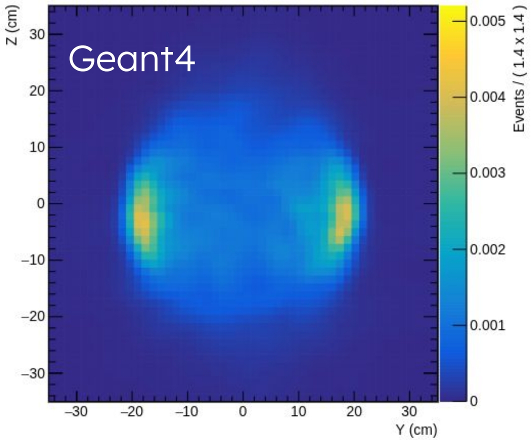
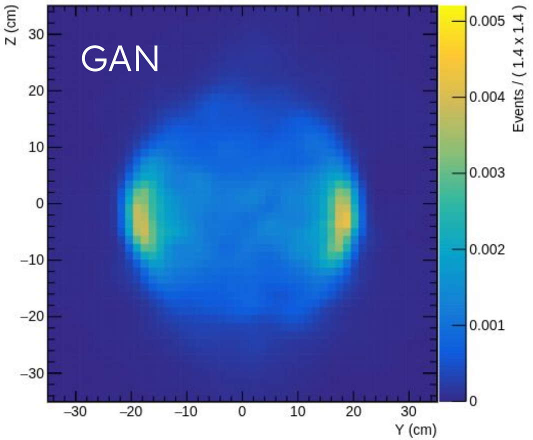
Probe **high level properties** of generated simulation → Test on **real case scenario**:

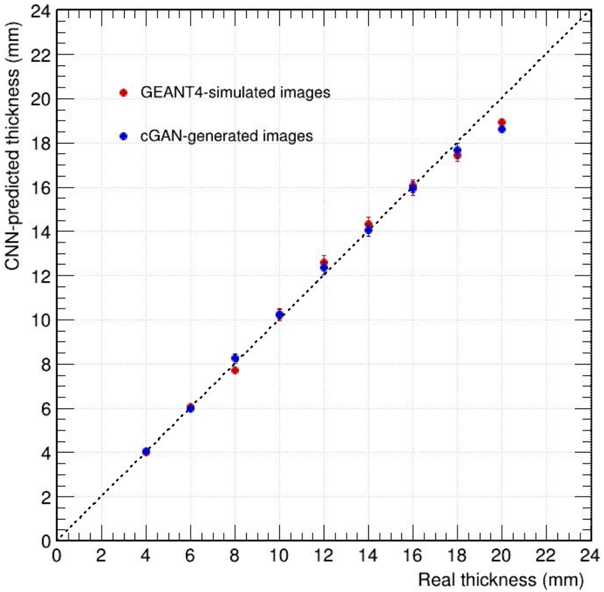
1. Generate simulation events for the different thickness values
2. Compute density maps → PoCA method
3. **Train a CNN** to return the thickness value from a given density map

CNN trained only with Geant4 simulation

Evaluated on GAN simulation → Very good performance







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Results: computational speed

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Compare computational cost of GAN vs Geant4 simulation

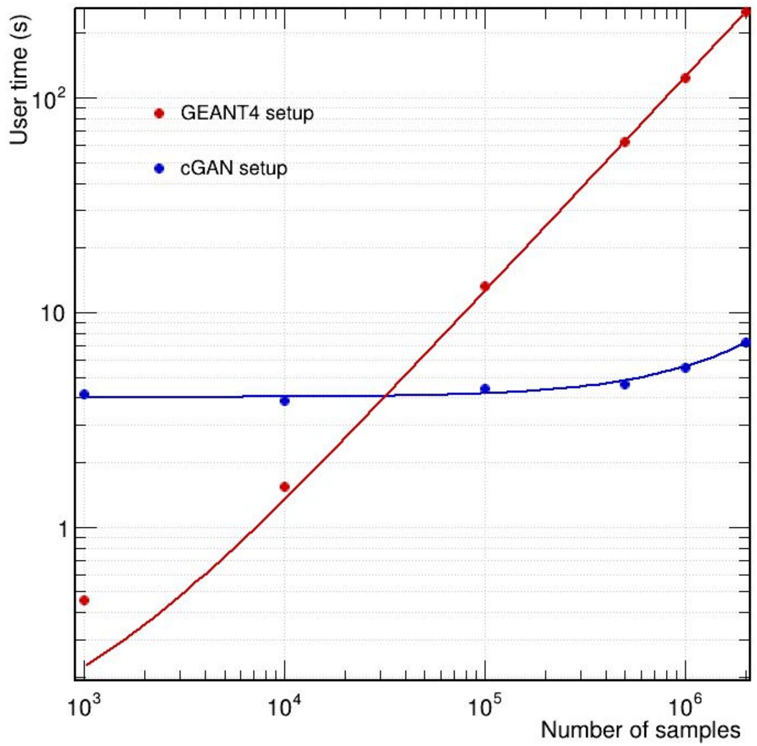
→ Intrinsic differences between both

→ Aim to give a **practical measurement**

User time for different size of generated sample

Linear fit to remove overhead

Result: **speed-up factor of ~80**



Conclusions

- **GAN is an effective tool** for generating muon scattering data for industrial muography applications.
- These model show excellent **modulation and interpolation capabilities** in the task of generating data.
- The generated data **maintains the integrity** of the original Geant4 simulation when tested in real-world scenarios.
- A significant **reduction of computational time** is observed compared to traditional simulation software

References:

[1] López Ruiz, R. , Fernández Madrazo, C., Sánchez Cruz, S., Lloret Iglesias, L., Martínez Ruiz del Árbol, P., (2025) Fast simulation for scattering muography applications using generative adversarial neural networks, *Engineering Applications of Artificial Intelligence*, 162, Article 112357, https://doi.org/10.1016/j.engappai.2025.112357

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Thank you !! :)

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Back up

Training dataset parameters

Conditional GAN		
Pipe thickness (mm)	Number of training samples	Number of evaluation samples
4	619605	300000
6	618798	300000
8	617951	300000
10	616700	300000
14	614944	300000
16	615216	300000
18	614109	300000
20	613692	300000
12*	-	300000

Table 1
cGAN training hyperparameters.

Number of epochs	1000
Optimizer	Adam
Learning rate	0.0001
Batch size	5000
C updates per *G* update	5