AI for applied science: tomographic imaging

COMCHA School

8th-15th April, 2026, Zaragoza

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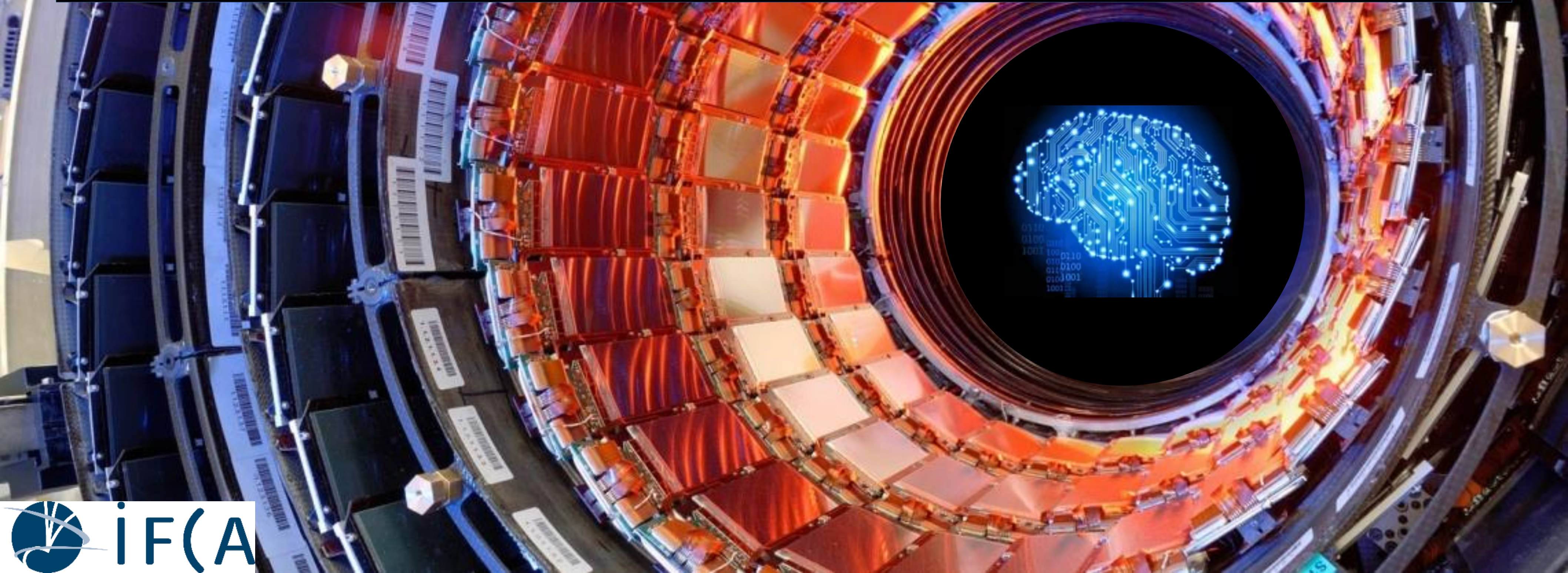


IFCA

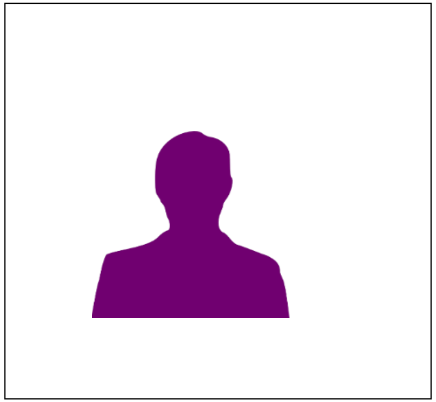
Outline

- What is tomography?
- Muon tomography: using the cosmos as a radiography source
- Some applications of muon tomography
- Proton tomography: the “glasses” for proton therapy
- Particle detectors and imaging: how does it work?
- Artificial intelligence: boosting tomography
- Hands-on exercise

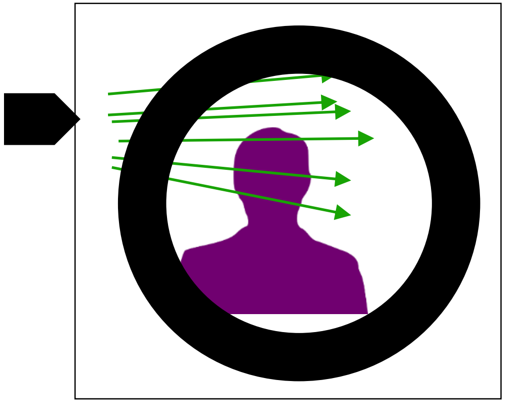
What is tomography?

- Definition: It is a procedure that uses **a physical process** acting on a **target** under study to obtain an **image** of the target through a **reconstruction process**

Target



Physical process



- Radiation on target
- Particle detectors

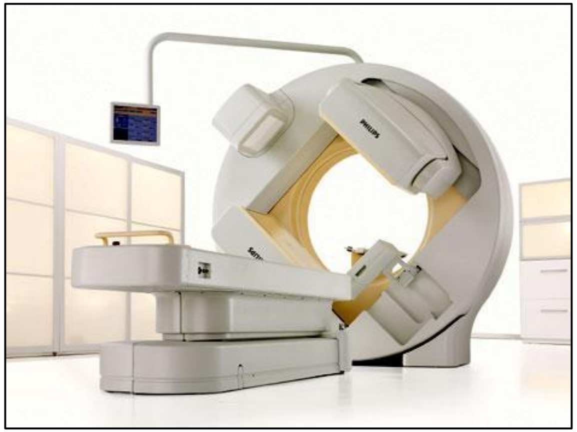
Reconstruction

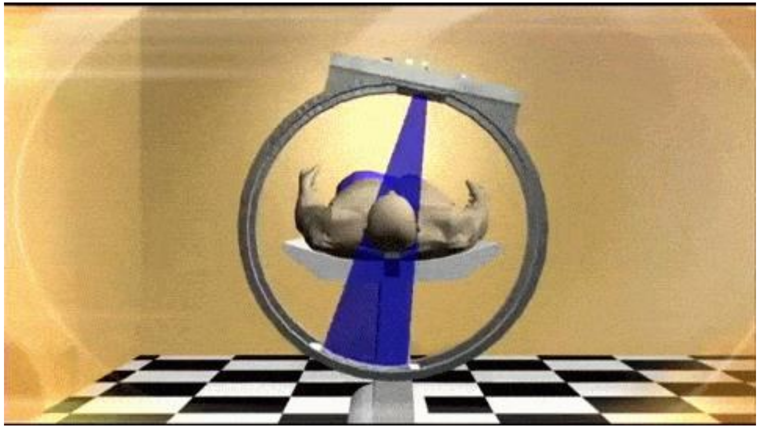
- Reconstruction algorithms
- Inverse problem

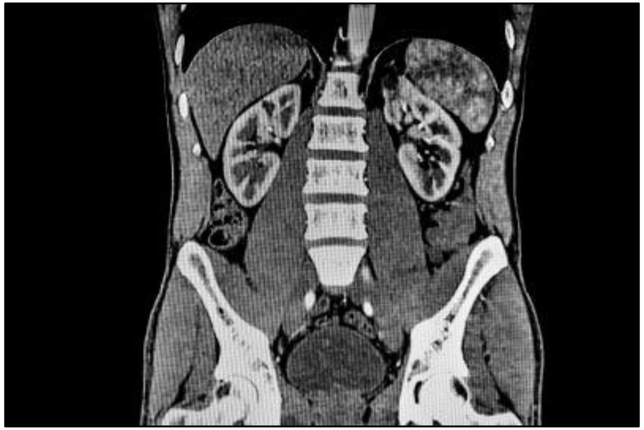
Image

A (classic) example: X-Ray computing tomography

- The radiation used is **light (photons)** in the energy range of X-rays (and thus its name XCT)
- This technique requiers a **source of X-rays** and also **photon detectors**
- Physical process: **attenuation** of the photons when crossing the target: the denser the more attenuation
- Attenuation is measured from **different angles** so a 3D reconstruction is posible
- Classical applications: **healthcare, border security**, industrial maintenance operations, etc



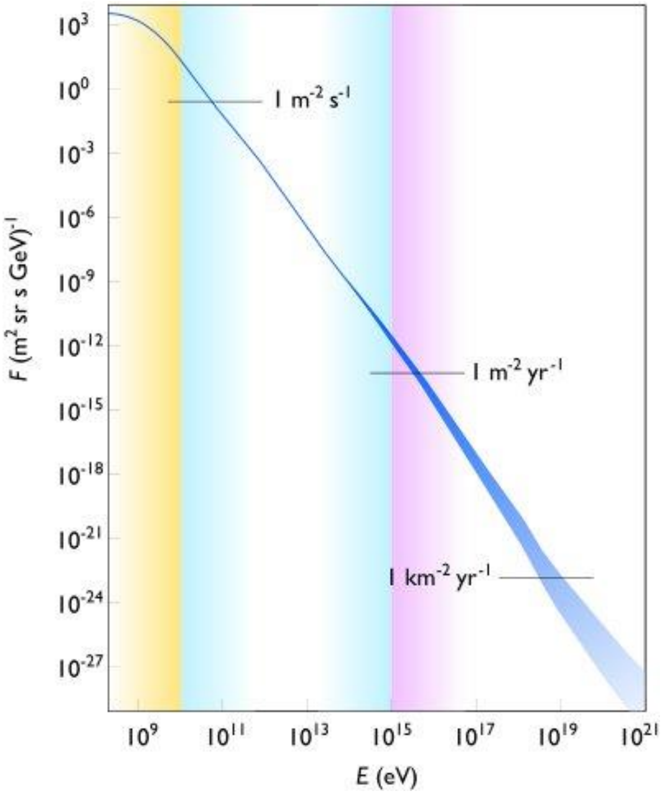




Muon tomography: cosmic rays

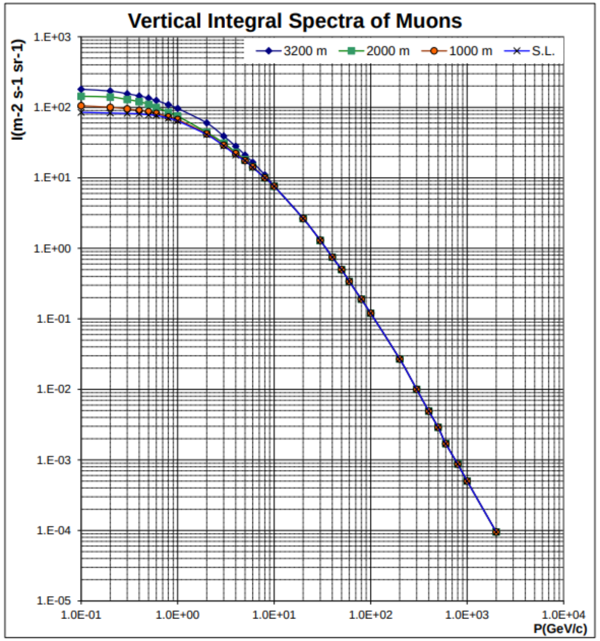
- A constant flux of **high energy particles** is bombarding the Earth from outer space (different sources)
- It is composed mainly by **protons** (98%), alpha particles (~2%), and others like positrons (< 0.1%)

The Oh-My-God Particle 3x10^8 TeV (1991, several since then)



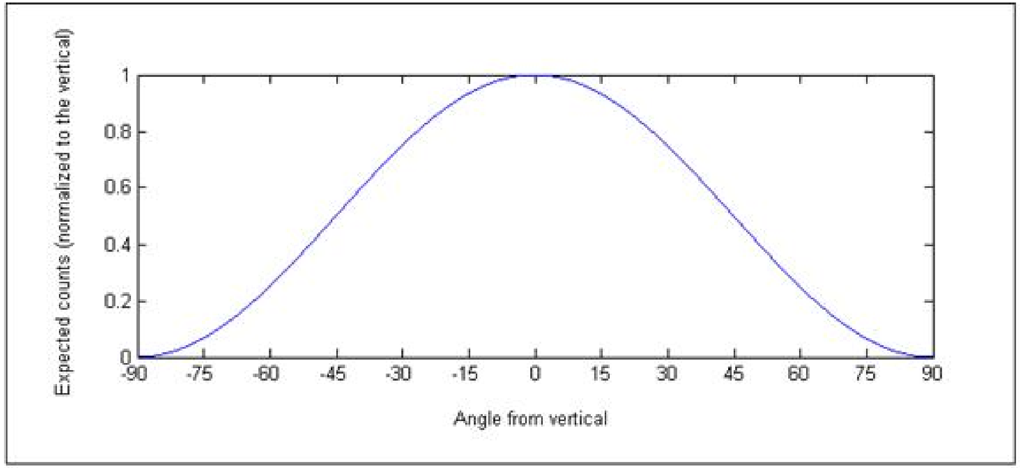
Cosmic muons: flux, energy, spectrum

- Cosmic rays **collide** with the atoms of the upper atmosphere producing **muons** (brothers of electrons)
- These **muons reach the surface of the Earth** with a flux proportional to $\cos^2$(theta) (with the vertical)
- Their spectrum peaks at about **2-3 GeV** and it is **quickly falling**



Rule of thumb at sea level:

10000 muons per squared meter and minute



Muons interacting with matter: ionization

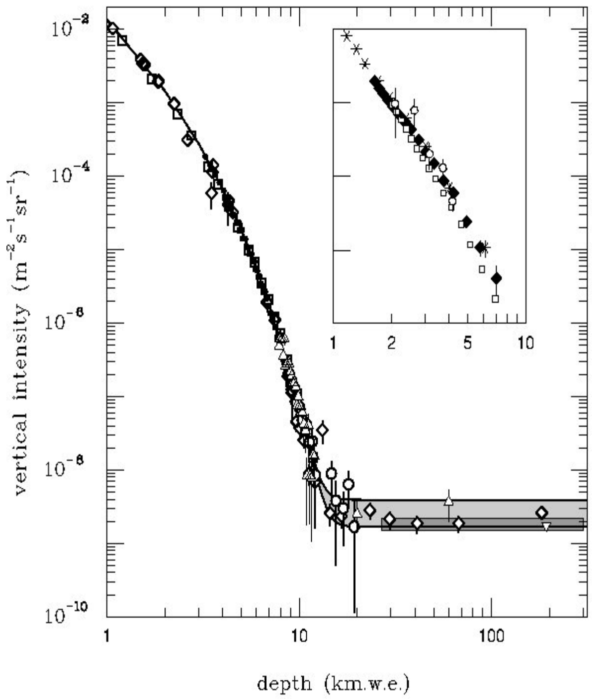
- Charged particles crossing matter loose energy **ionizing the atoms** (remove electrons from the atom)
- The energy loss depends on the energy, the Z of the material, the ionization potential and the size
- The **range** is the average distance in which a charged particle loses all its energy (and dissappears)

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

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

Mean excitation potential

Muon Energy/GeV	Material	Range/m
1	Water	471
10	Water	4260
1	Concrete	228
10	Concrete	2025
1	Standard Rock	209
10	Standard Rock	1857



Muons interacting with matter: multiple scattering

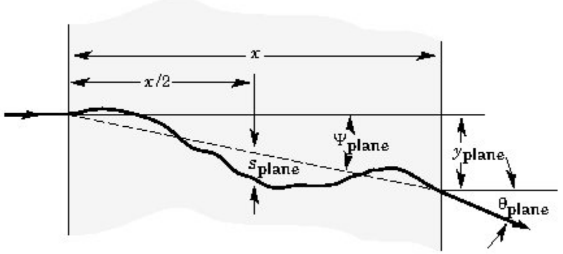
- Charged particles crossing matter **deviate their trajectory** throught the so called **multiple scattering**
- The deviation angular follows a more or less **gaussian distribution**
- The **spread of the distribution depends** on the Z of the **material**, the density and the size

Muon momentum dependence

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

Radiation length

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



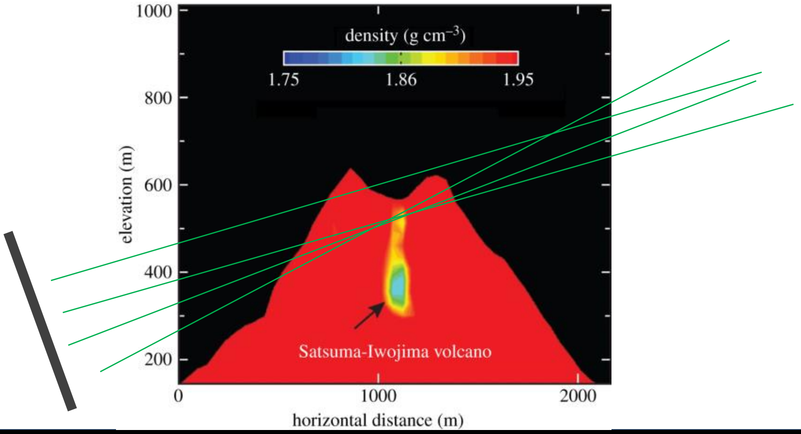
Muon Energy/GeV	Material	Width/cm	Angle/mrad
1	Iron	1	10
10	Iron	1	1
1	Iron	10	34
10	Iron	10	3
1	Lead	1	19
10	Lead	1	2
1	Lead	10	64
10	Lead	10	6
1	Uranium	1	26
10	Uranium	1	3
1	Uranium	10	88
10	Uranium	10	9

Muon tomography

- **Muon attenuation and muon deviation depend on the properties of the material**
- Both can be used as **a Non-Destructive Testing (NDT)** technique to infer the geometry of a target

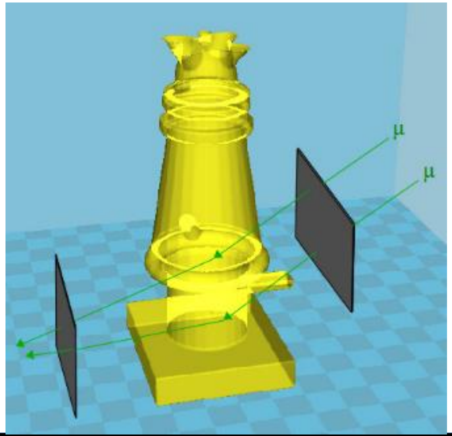
Absorption muon tomography

- Muon flux measured vs direction (attenuation)
- One single detector needed
- Need large object + long exposure times
- Typical applications: geology, volcanology, etc



Scattering muon tomography

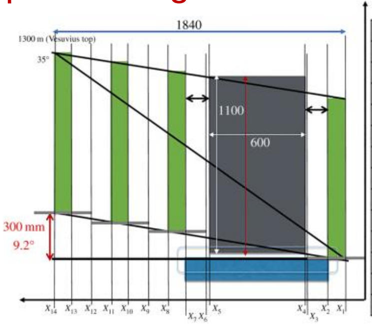
- Muon angular deviation (scattering)
- Two detectors needed
- Small-medium size objects + short exposure times
- Typical applications: border security, nuclear, etc



Some applications: volcanology

Monitoring of Vesuvious volcano in Italy

https://doi.org/10.1098/rsta.2018.0050



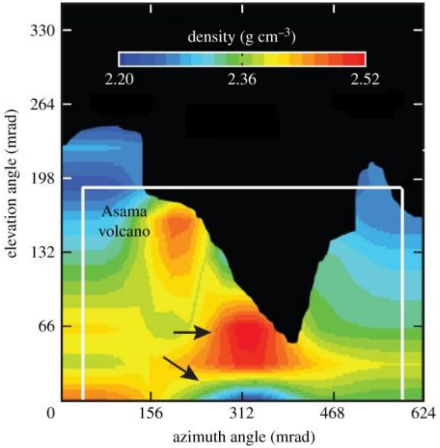
X_1	125	0
X_2	235	+110
X_3	360	+125
X_4	385	+25
X_5	985	+600
X_6	1010	+25
X_7	1135	+125
X_8	1245	+110
X_9	1370	+125
X_{10}	1495	+125
X_{11}	1605	+110
X_{12}	1730	+125
X_{13}	1855	+125
X_{14}	1965	+110

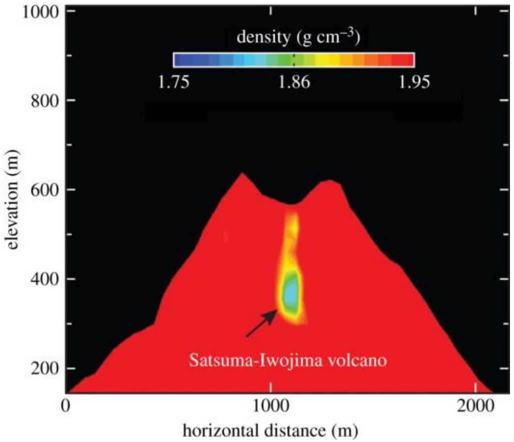
Monitoring of Asama & Iwujima volcanos in Japan

https://doi.org/10.1098/rsta.2018.0142

Exposure time ~ 1 year

Dinamic studies on magma convection





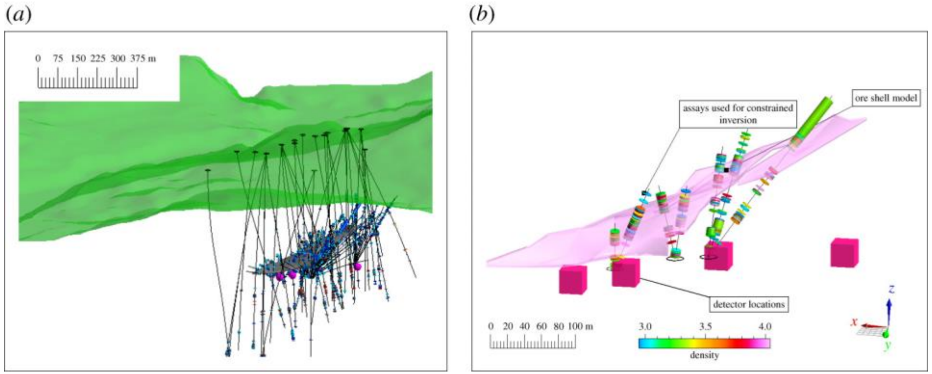
Some applications: mining

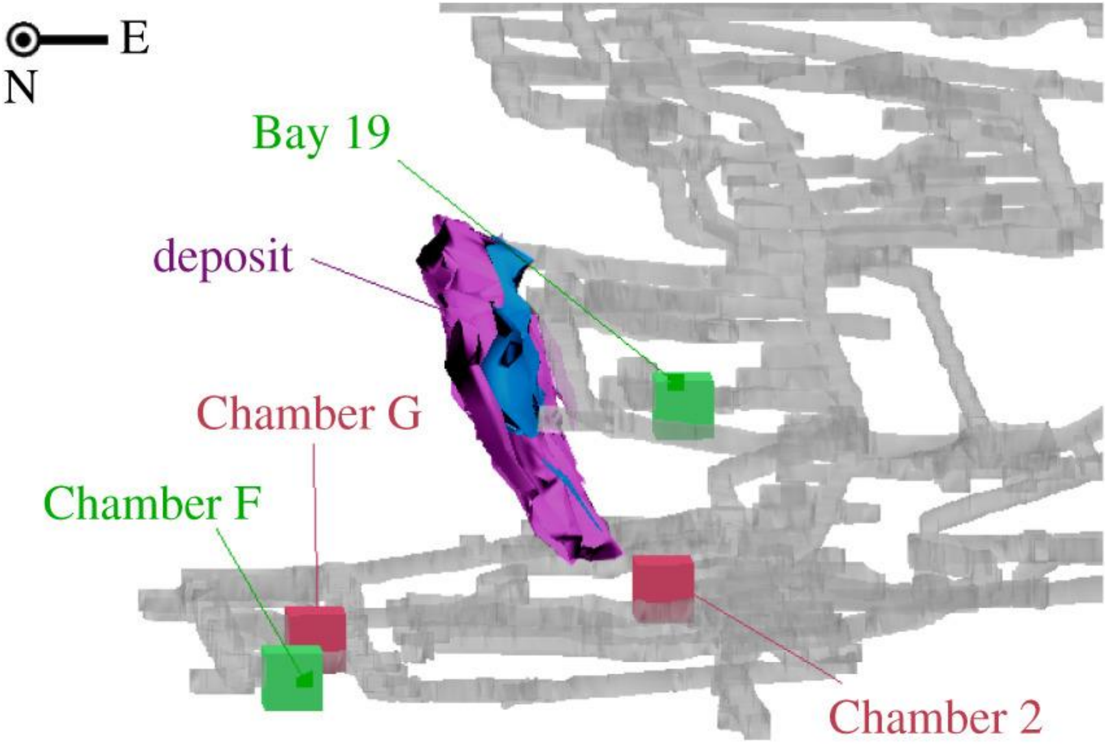
Search for uraunium/lead clusters in McArthur River (Canada) and Pend Oreille (USA)

https://doi.org/10.1098/rsta.2018.0061

Ideon Technologies

Grid of scintillator detectors underground





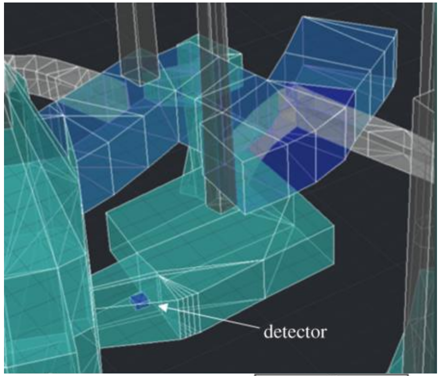
Some applications: archeology/cultural heritage

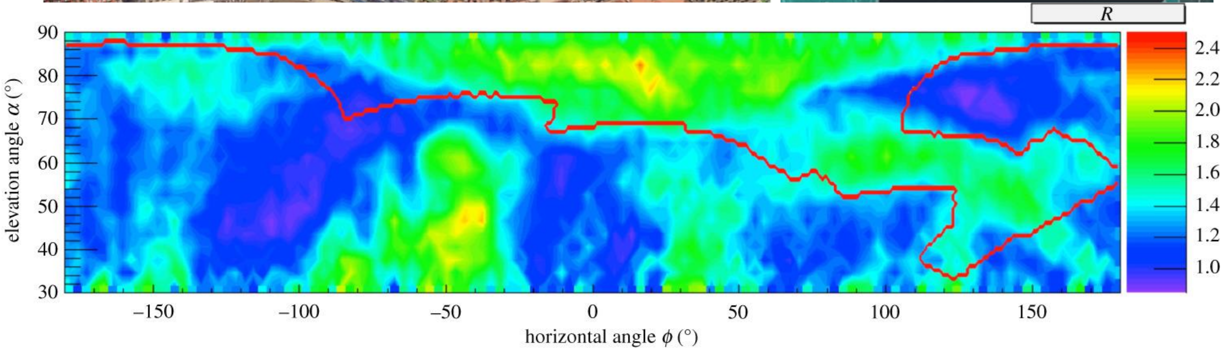
Search for secret galleries at Mount Echia (Borbon tunnel)

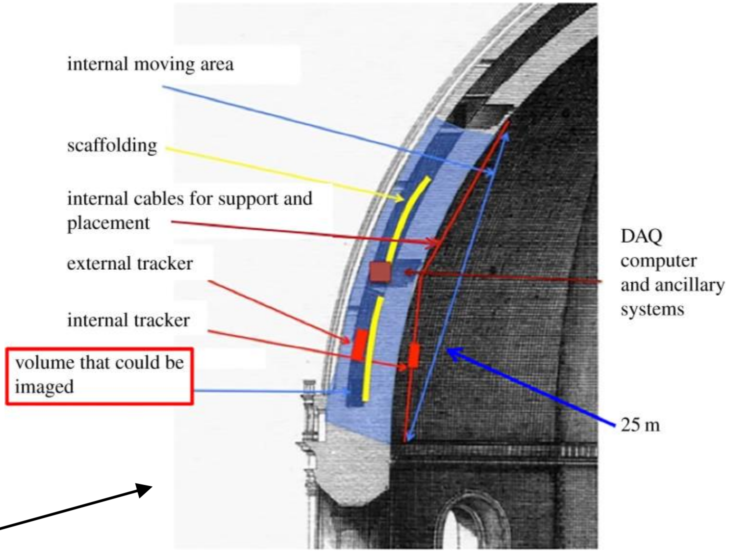
https://doi.org/10.1098/rsta.2018.0057

Just one scintillator detector at different positions

26 days of data taking







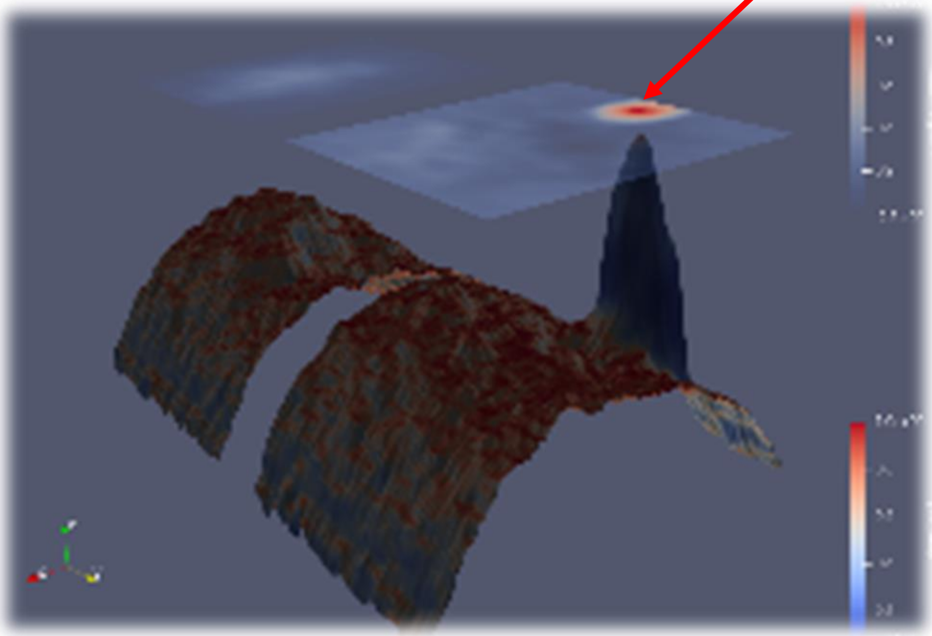
Monitoring of the dome of Santa Maria de Fiore

https://doi.org/10.1098/rsta.2018.0136

Some applications: tunnel inspection

Identification of ventilation tubes at the metro of Madrid

Ventilation tube



Some applications: nuclear industry

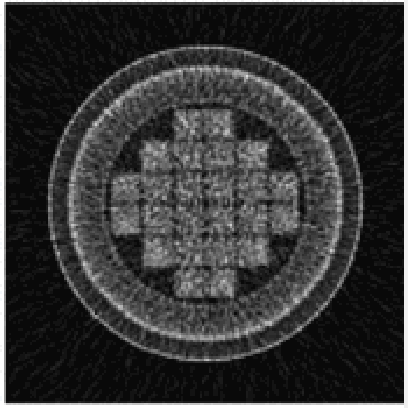
Nuclear waste characterization

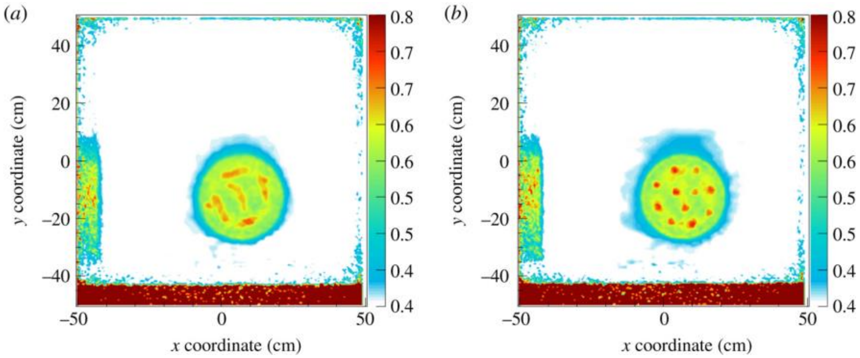
Linkeos Technologies

UK nuclear decommissioning authority

Scintillator detectors

https://doi.org/10.1098/rsta.2018.0048

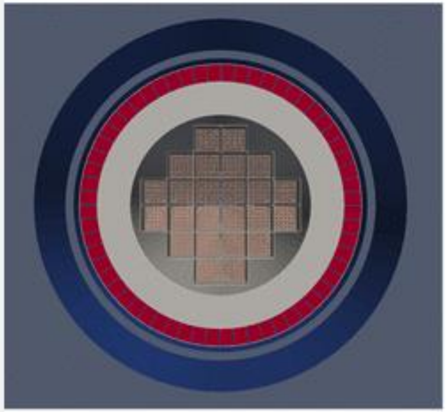




Fuel cask monitoring

Los Alamos NATIONAL LABORATORY EST.1943

https://doi.org/10.1098/rsta.2018.0052



Some applications: furnace integrity

- Inspection of the degradation of the crucible of an **arc voltaic furnace** for melting silicon
- Two competing effects due to chemical reactions: wear but also new solid material attached to the walls
  - Particularly important at the bottom of the furnace

MUON systems Ferroglobe

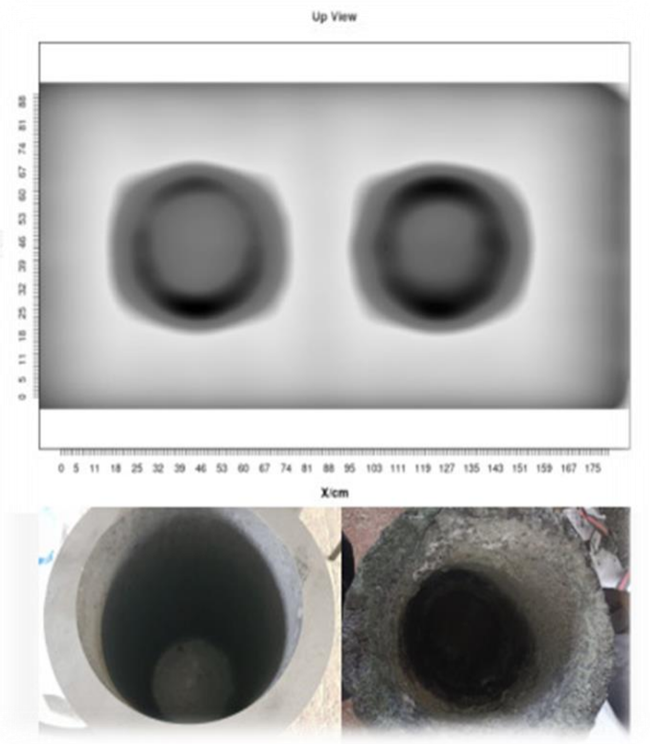
Almost perfect crucible

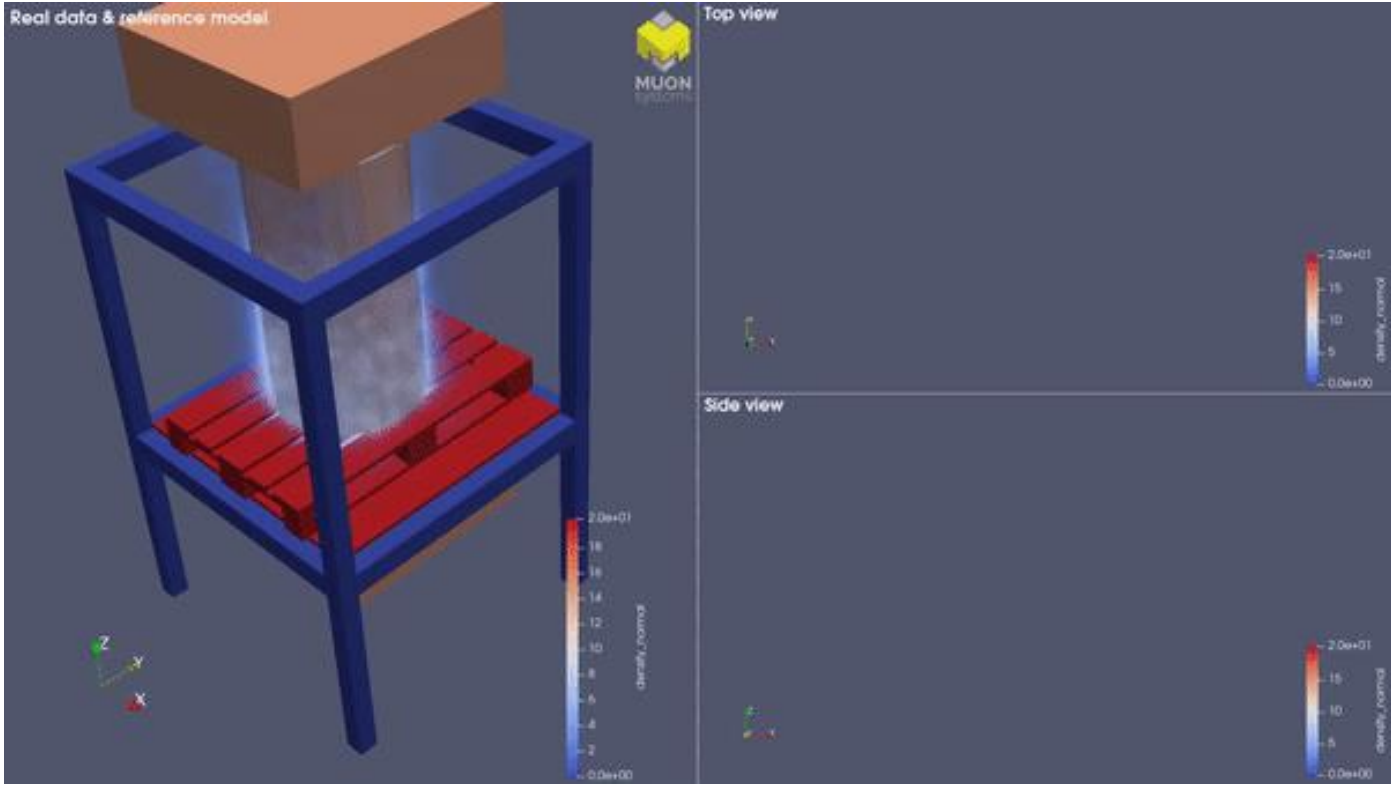
Used crucible

Detail of the bottom

Some applications: furnace integrity

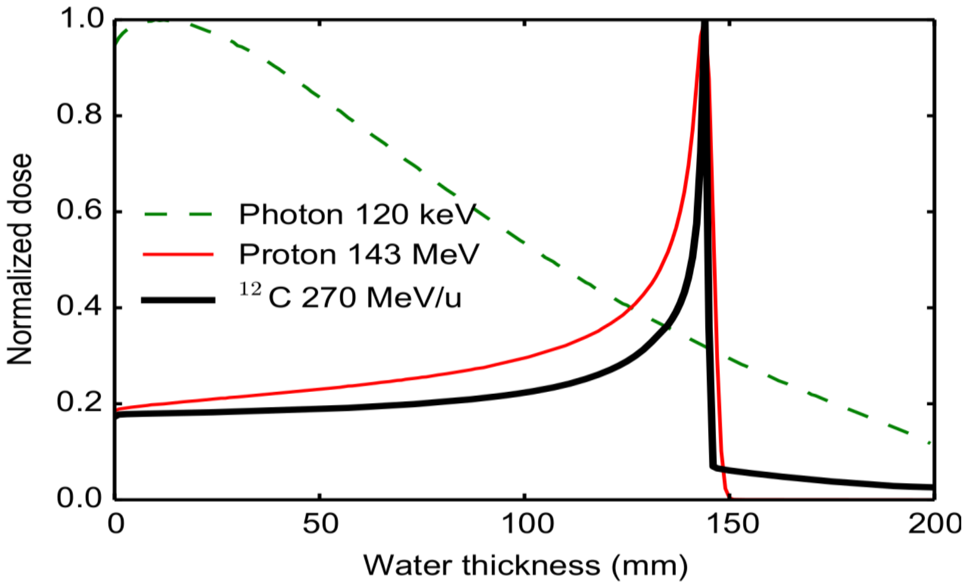
3D reconstruction of damaged furnace





Proton therapy

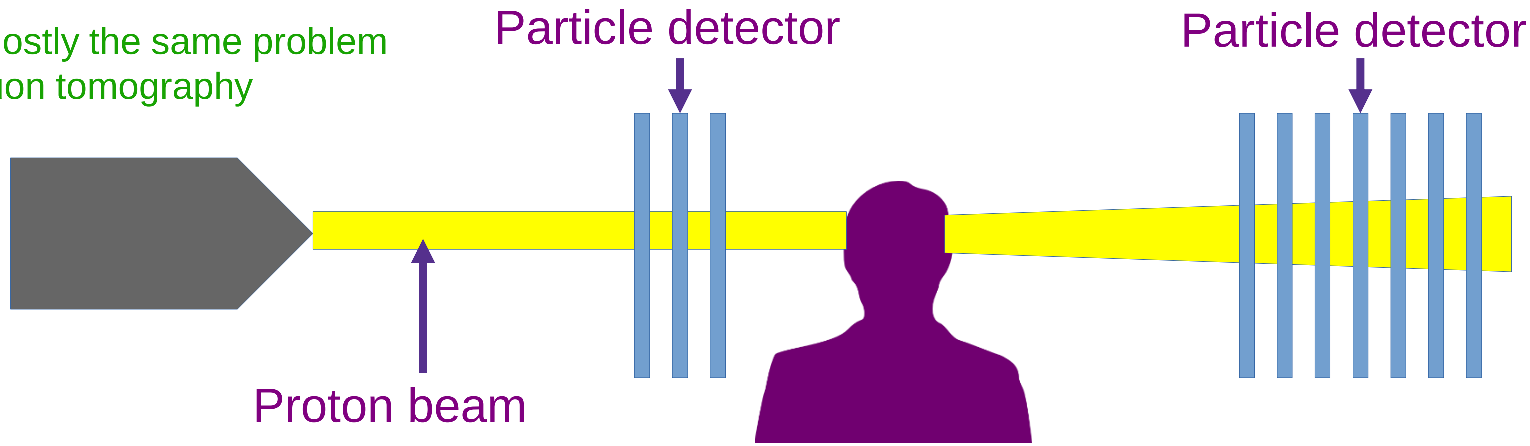
- Proton therapy is a new technique that **uses protons instead of photons** to attack tumors
- Traditional radiation essentially **burns the tissues** before the tumors (negative exponential absorpotion)
- However the energy loss of protons (muons) gives place to a peak where most of the energy is deposited
- **The tumor can be attacked with minimal radiation dose received by the surrounding tissues**



Proton tomography: the glasses of proton therapy

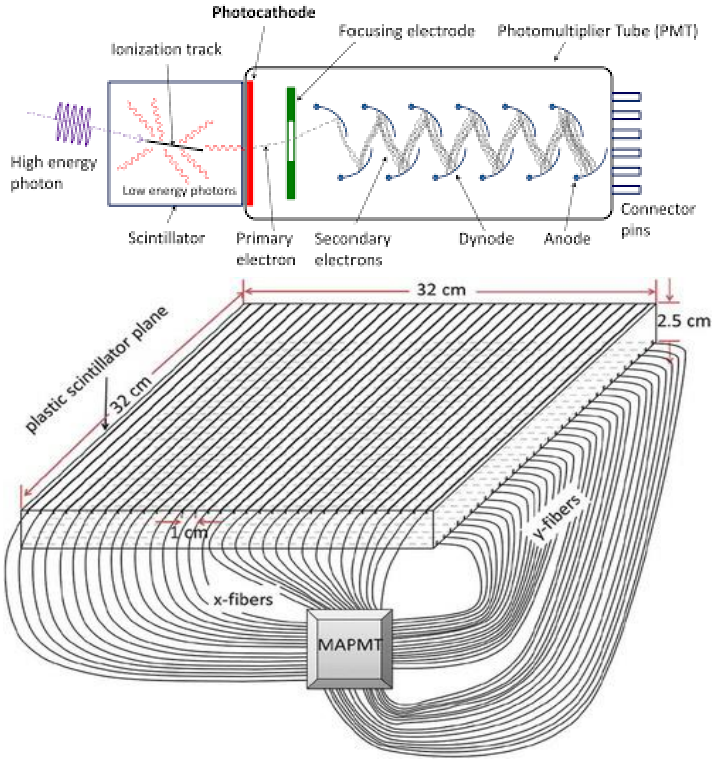
- There is a problem: the **density and position** of the tumor and surrounding tissues must be known
  - In such a way the beam of protons can be calibrated to be absorbed exactly at the tumor
- Nowadays, the mapping of the tumor is done with **traditional X-Ray scans**
  - But this introduces a **big uncertainty** because photons are not absorbed as protons
- Proton tomography uses the very **same protons of the treatment** to do the imaging of the tissues
  - The safety margins applied to avoid damaging healthy tissues can be reduced < 1 mm

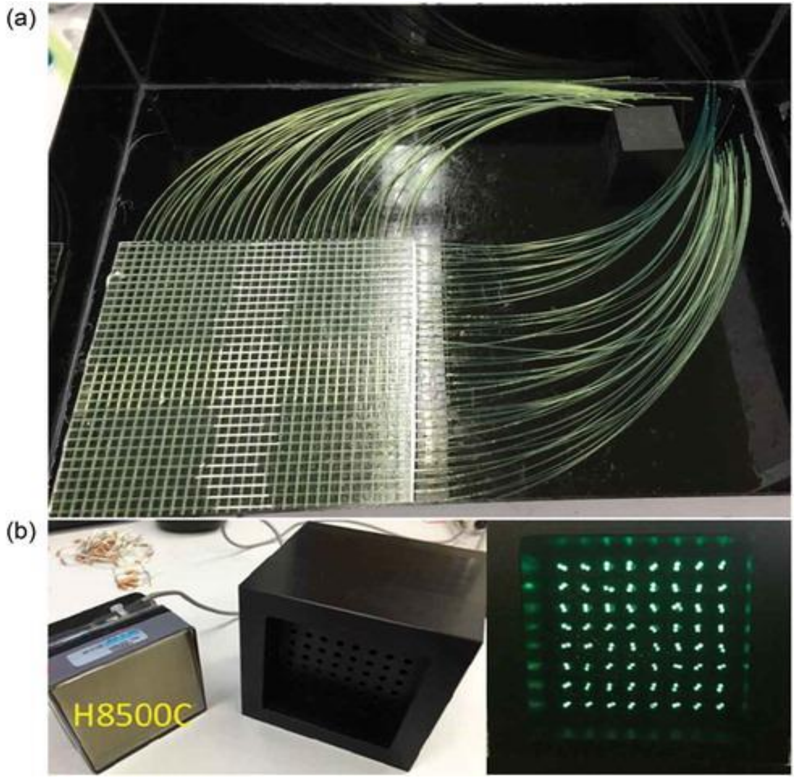
It is mostly the same problem as muon tomography



Particle detectors: scintillators

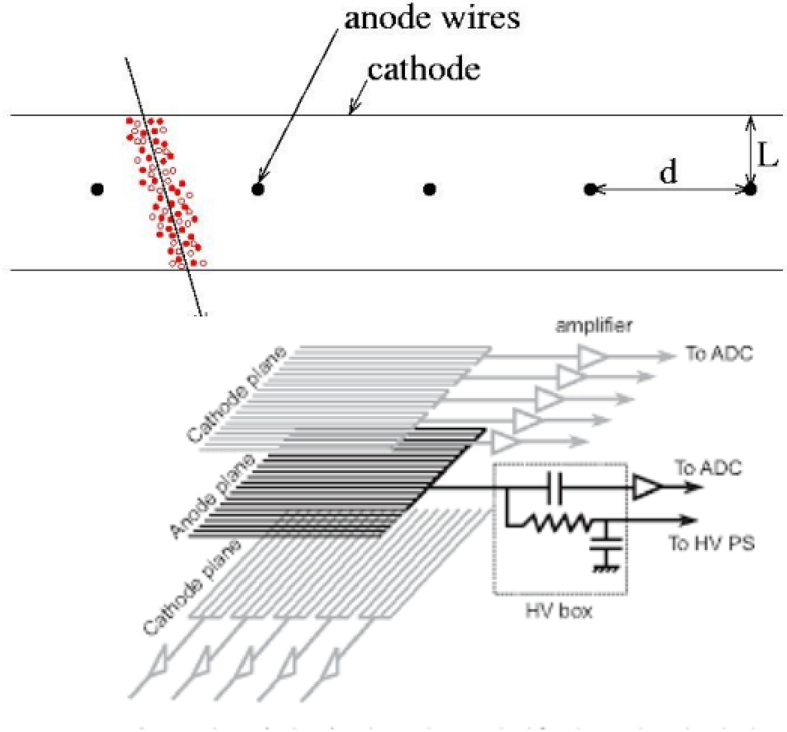
- Charge particles, including muons, produce light when crossing a scintillator material
- The light is collected by a photomultiplier (a classic one or more recently a SiPM)

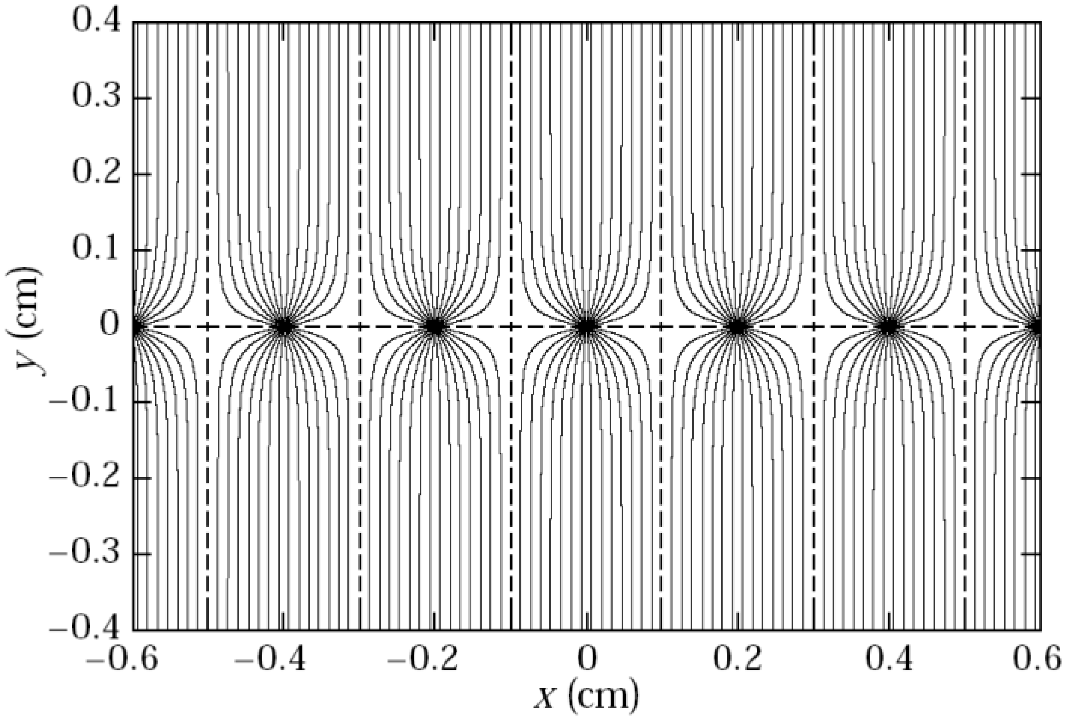




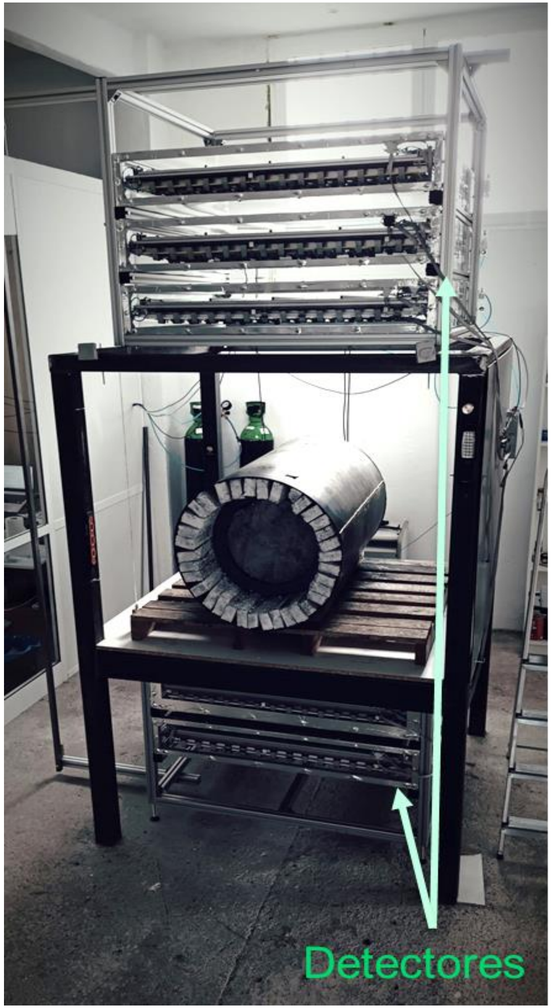
Particle detectors: gas detectors

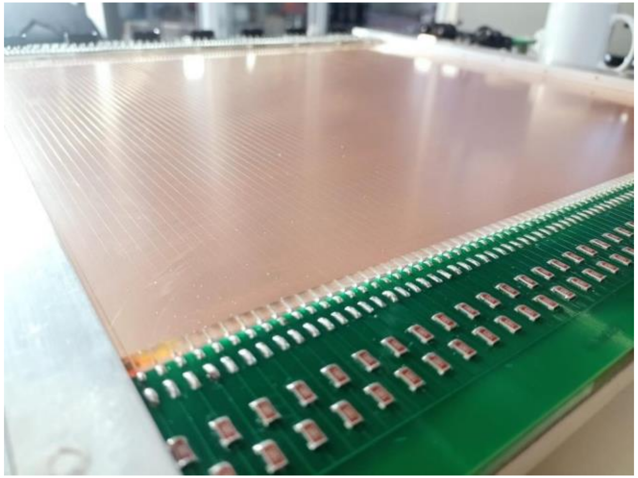
- Ions generated by the muon in the gas drift towards the field lines (electrons to wires, ions to planes)
- These detectors only measure one coordinate so usually planes are stacked with a 90º rotation



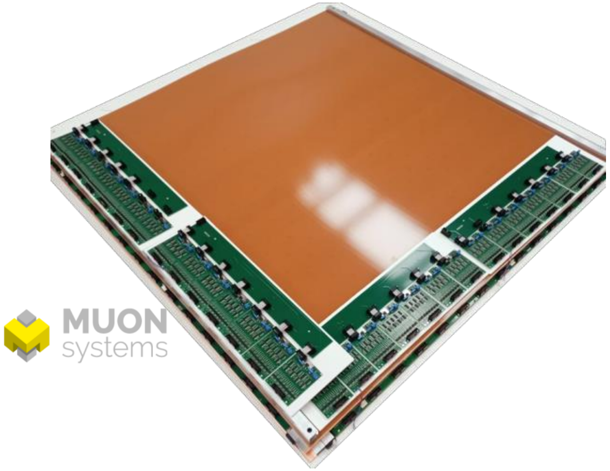


Particle detectors: gas detectors



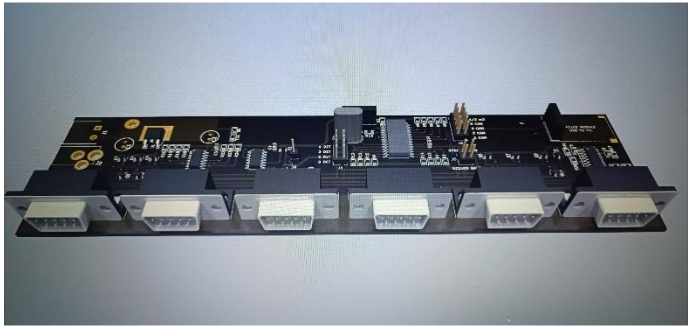


Muon detectors

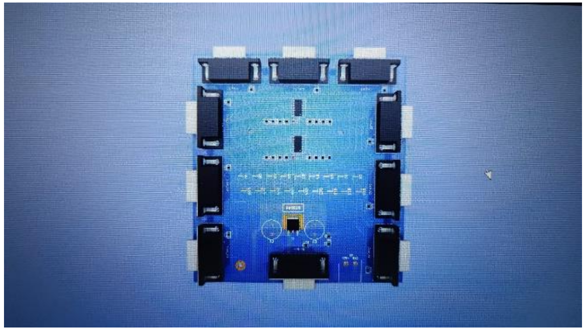


Readout ASICs

Concentration card (per layer)

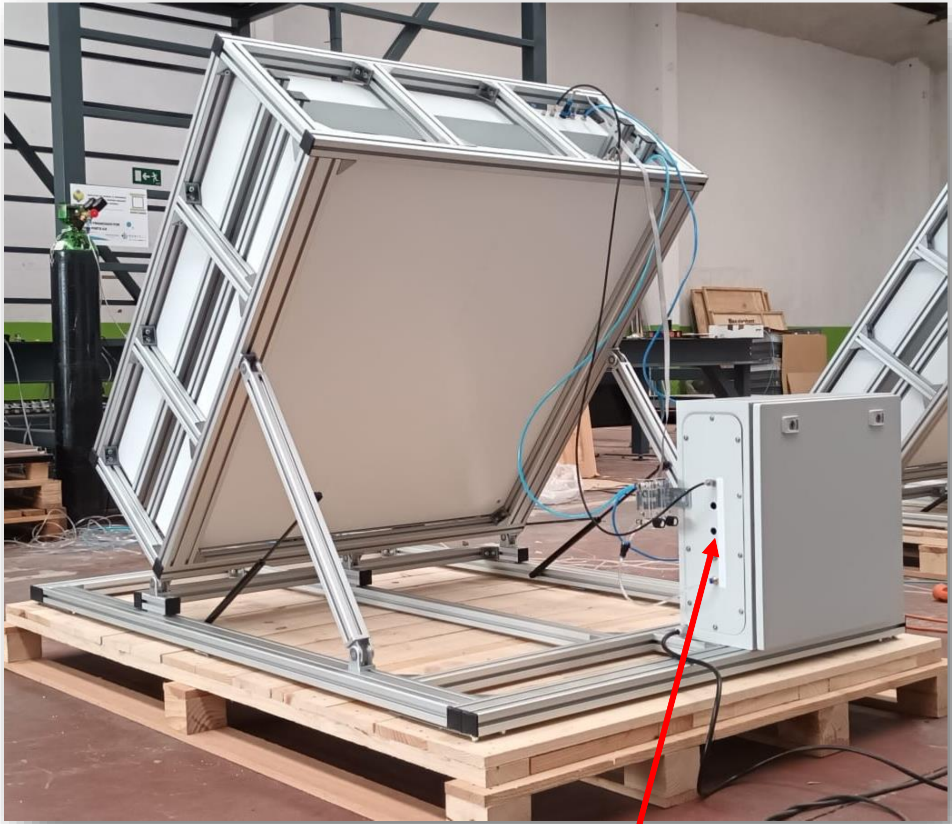


Master (Trigger + DAQ)



Particle detectors: gas detectors

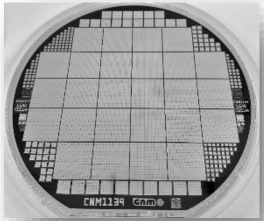
Adjustable inclination

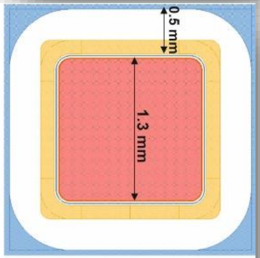


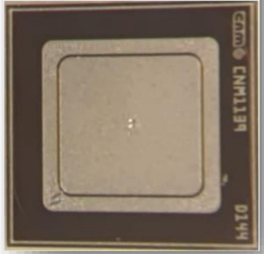
Control system

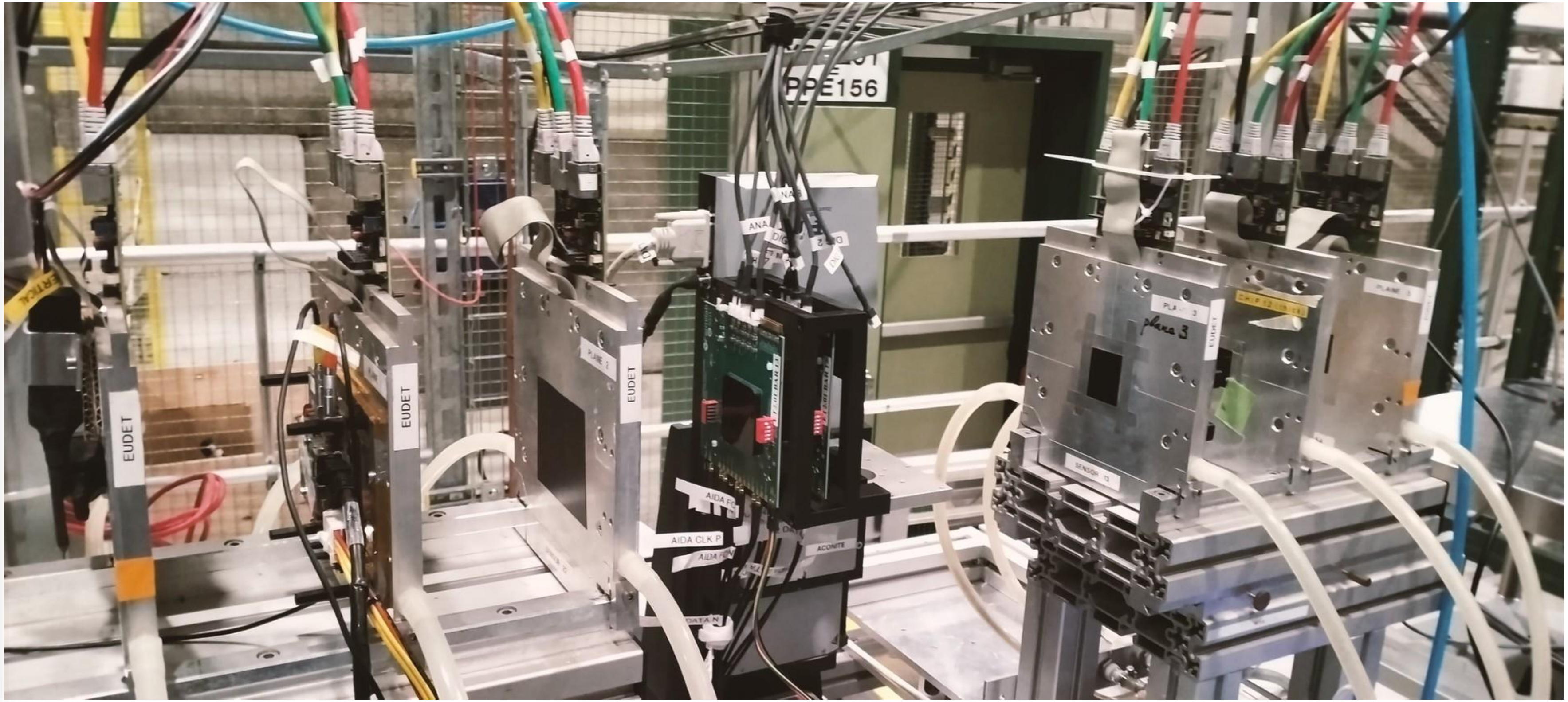
Particle detectors: sillicon detectors

- Charged particles also produce ionization in the **depletion region of a p-n jonction** reversely polarized
- Ions generated by the particles drift to the anodes following the field lines









Particle imaging: the inverse problem

- Tomography reconstruction belongs to a problem category known as **“inverse problem”**

Input Observables

Position and Direction of the tracks in the upper detector

→

Physical process

“$f(x,\lambda_i)$”

The λi represent the Geometry and densities

→

Output observables

“$y = f(x,\lambda_i)$”

Position and Direction of the tracks in the lower detector

- Predicting the output observables from the input and knowing the process is call **“forward problem”**
- Knowing the output and the input and predicting which λi yielded that result is the **“inverse problem”**
  - It is in general a much harder problem to solve
  - In general no unique solutions can be found
- The problem can be further divided into **deterministic or stochastic** physical processes
- Spoiler: in **tomography they are stochastic** (more complicated to deal with)

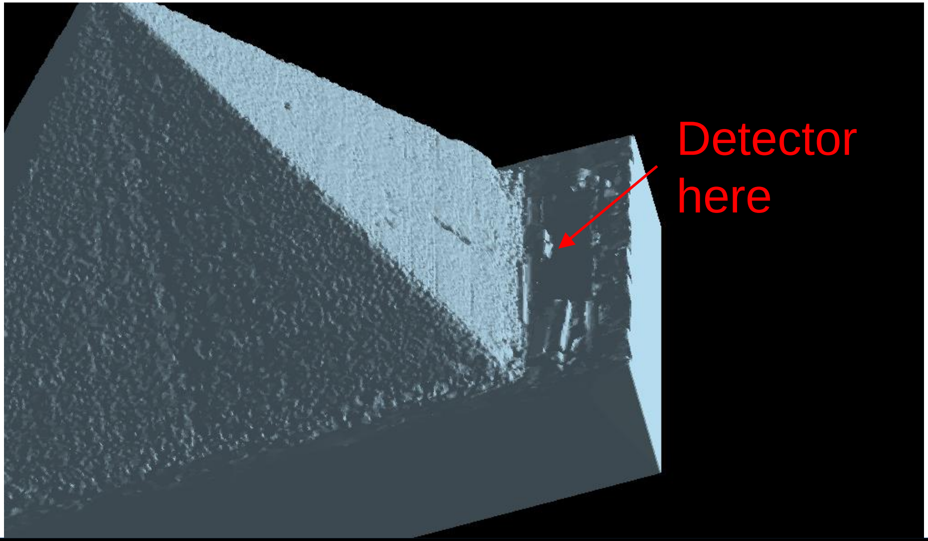
Transmission tomography

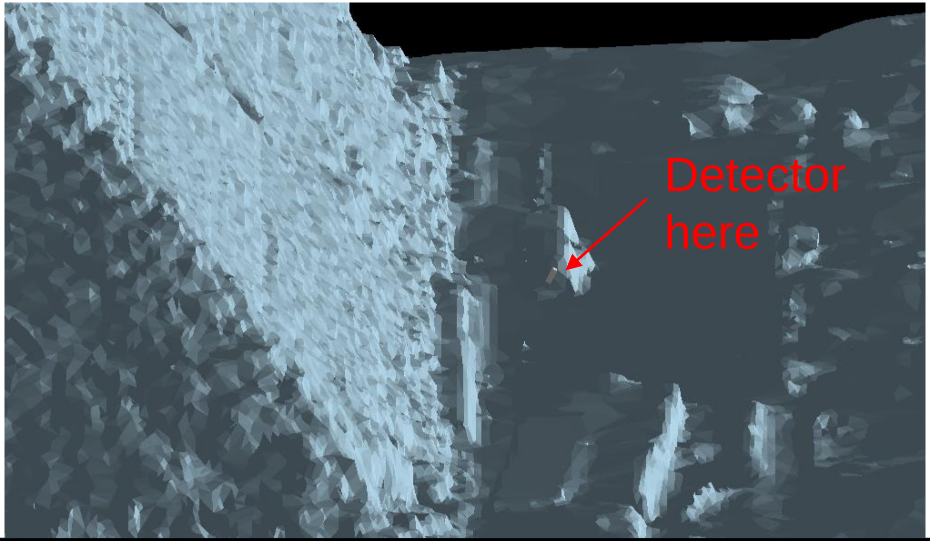
- In transmission muography the directional flux is compared between open sky and with-target data
- The ratio between the two is called the transmission coefficient and it's a function of the direction

$$T(\varphi,\theta)=\frac{\#N\ Muons\ with\ target(\varphi,\theta)}{\#N\ Muons\ open\ sky(\varphi,\theta)}$$

- It is critical for this technique that detector conditions (efficiencies, etc) are exactly the same
  - Otherwise there will be deficits or excesses not related to absorbtion but something else

Khufu Pyramid Model
Courtesy of emmisive S.L.



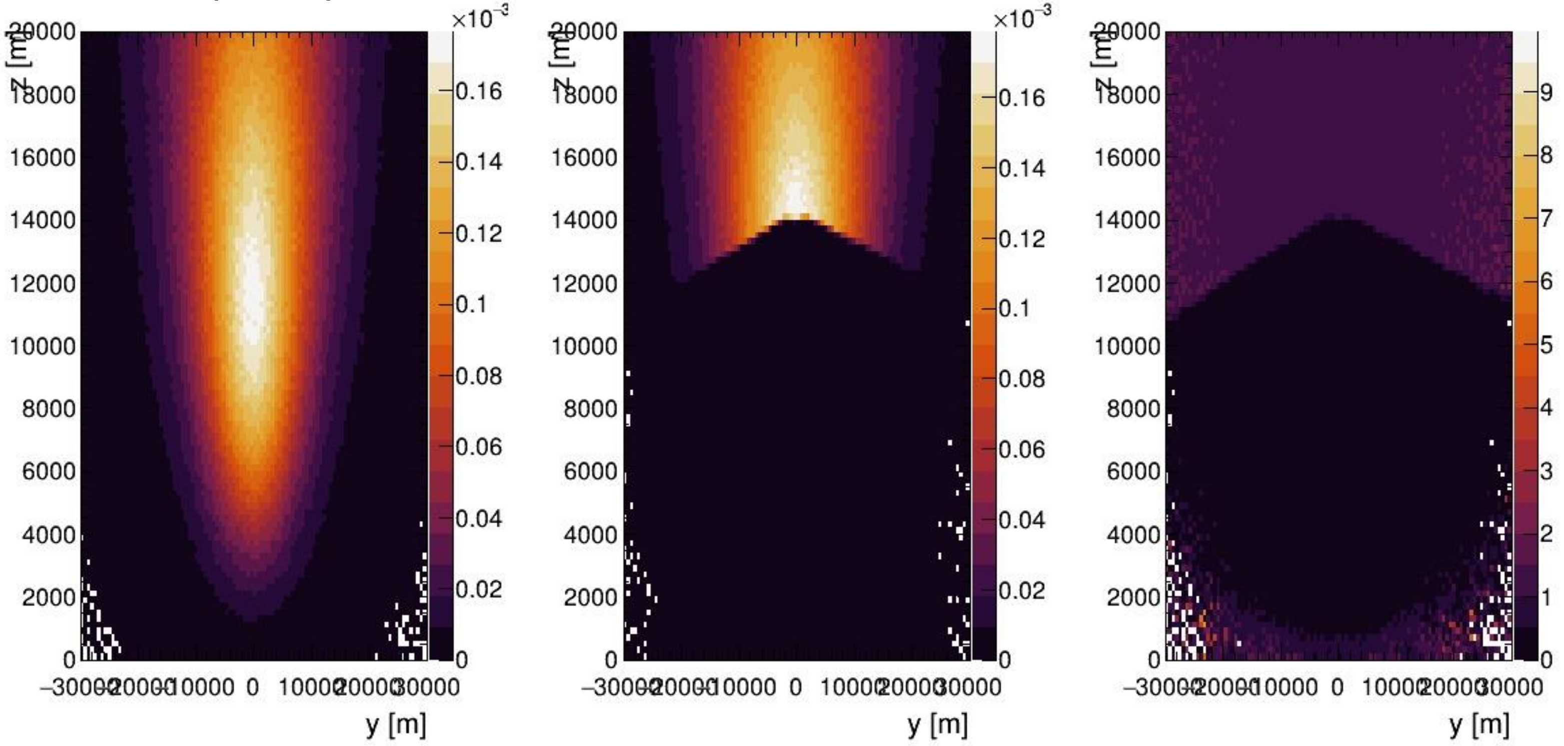


Transmission tomography

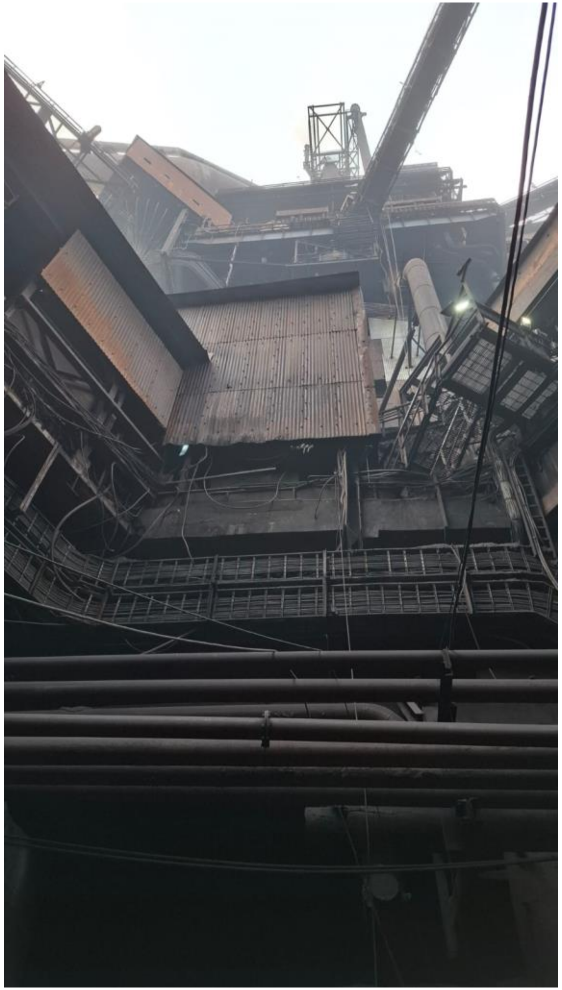
Instituto de Física de Cantabria

- Sometimes muons can be projected into a plane of interest (in this case the middle plane)
- Measurements from many positions can be combined to produce a 3D image

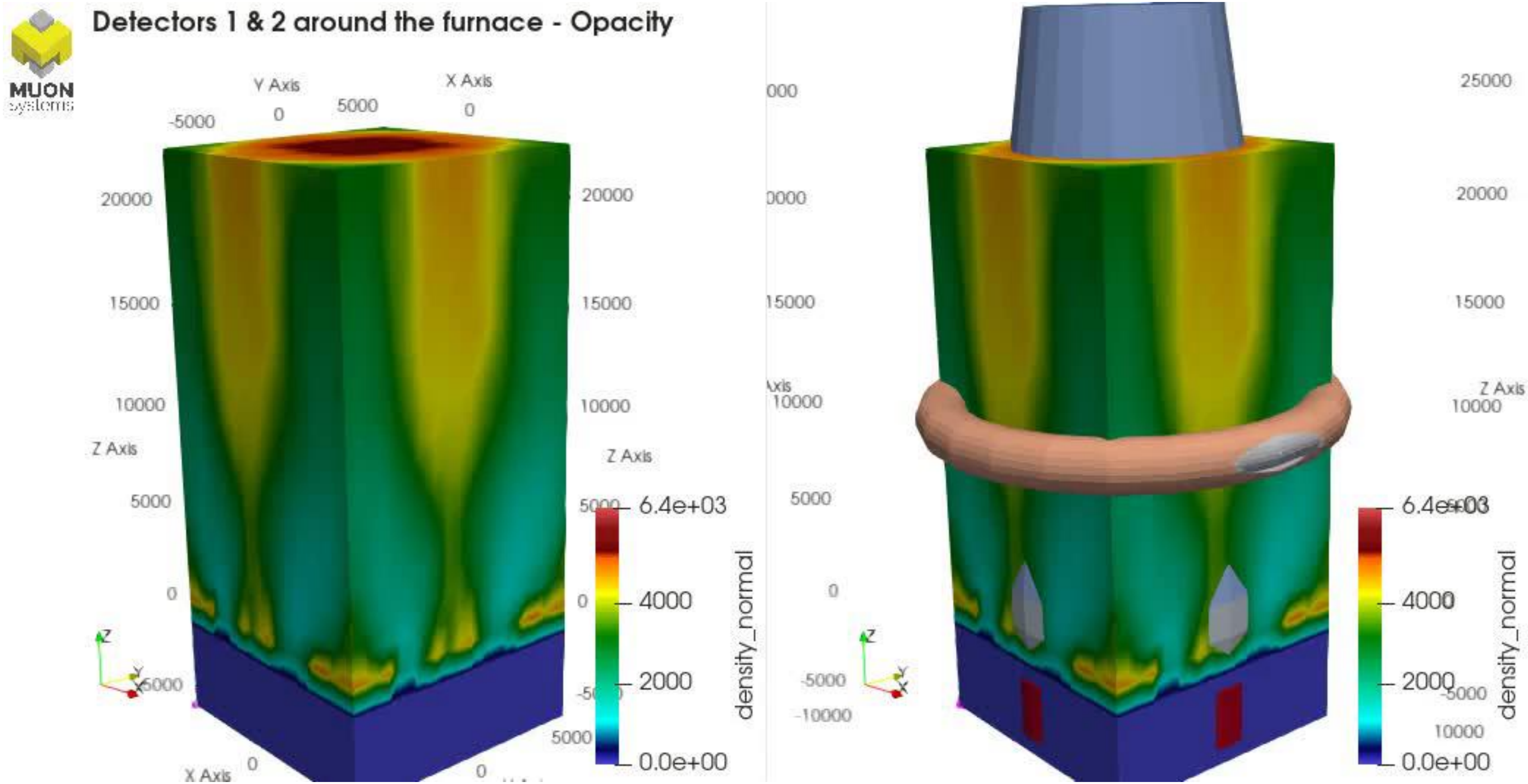
Open-sky With-Pyramid Transmission



Transmission tomography: blast furnace

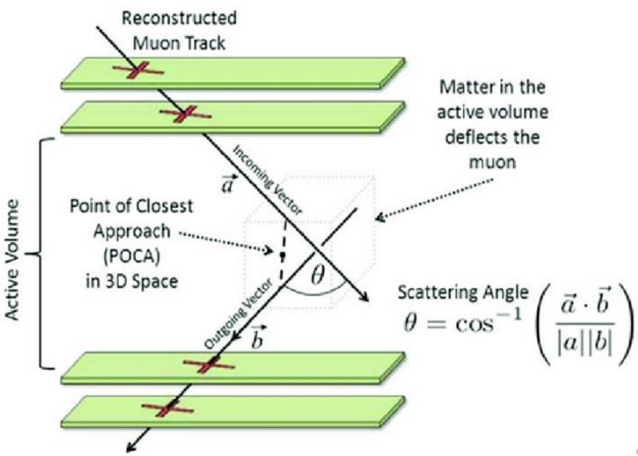


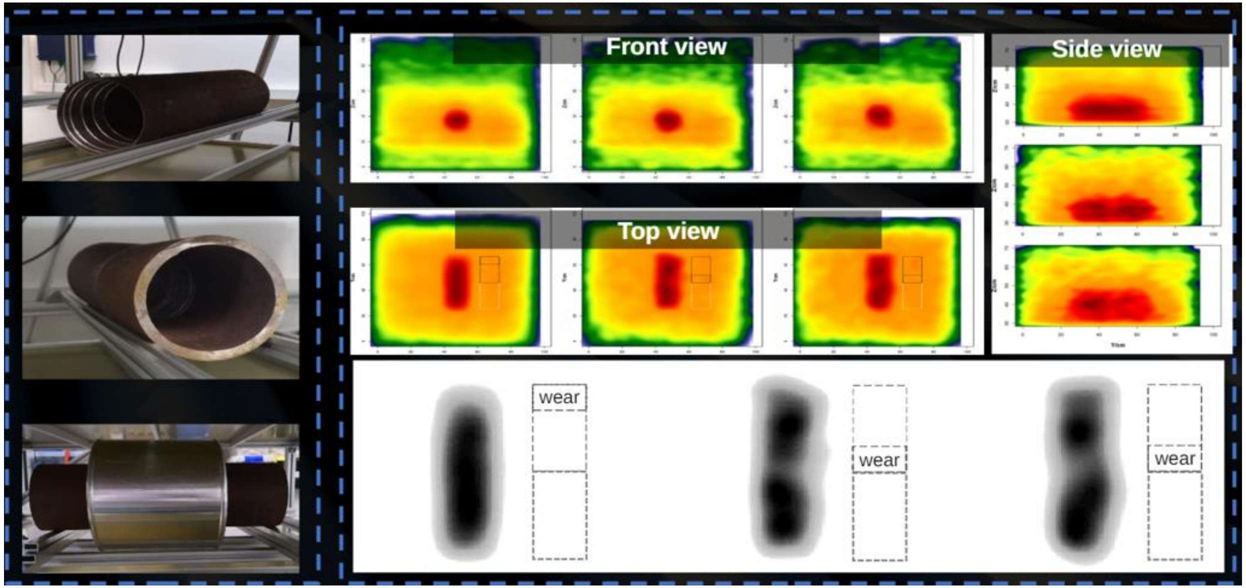

Transmission tomography: blast furnace



Scattering tomography: Point-Of-Closest-Approach

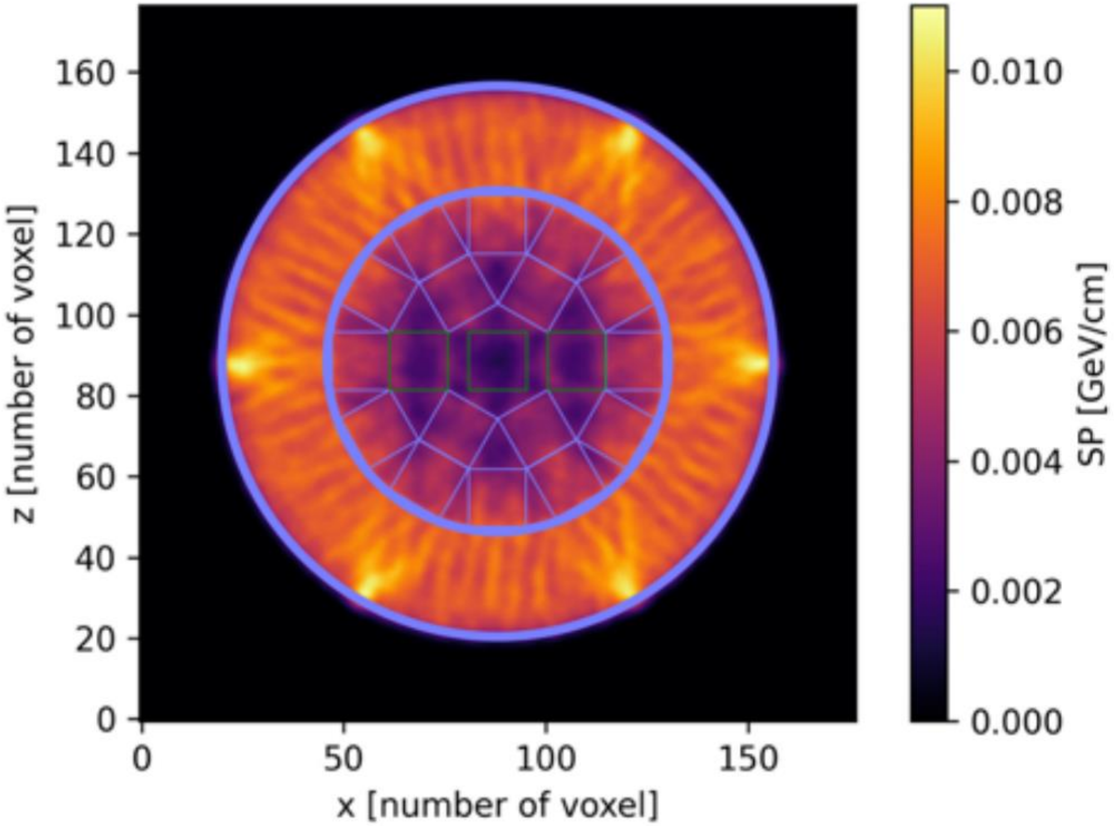
- This simple algorithm is one of the most widely used for scattering muography
- The algorithm makes two fundamental assumptions (which are known to be non-true in general)
  - The scattering takes place in a single point of the target
  - The point of closest approach of the incoming and outgoing trajectories is the scattering point





Scattering tomography: nuclear fuel cask

- Project MUTOMCA: monitoring a nuclear fuel cask in Germany



Artificial intelligence: boosting tomography

- The variety and power of AI algorithms can be applied to tomography at different levels

Design	Inference	Reconstruction	Simulation	Intuition
Hardware design	**Inverse problem solution**	**Object reconstruction**	**Simulation generation**	**Denoising**
• Differential programming	• Regressive ANN	• Neuromorphic computing	• Generative networks	• Autoencoders

Design of hardware: differential programming

- One fundamental aspect of muon tomography is the design of tomographic hardware
- **Differential Programming (DP)** is an evolution of modern machine learning systems
- For example, a Neural Network, tries to find the minimum of a loss function using the gradients
  - These architectures are designed in such a way that getting the gradient is efficient
- PD is a new paradigm where all the elements of a program become differentiable
  - Then applying the derivative chain rule you can estimate the gradient of the program

$$program(x) \rightarrow \frac{\partial program(x)}{\partial x} = \frac{\partial program(x)}{\partial fN} \frac{\partial pfN}{\partial fN-1} \ldots \frac{\partial pf1}{\partial fx}$$

Program(x)

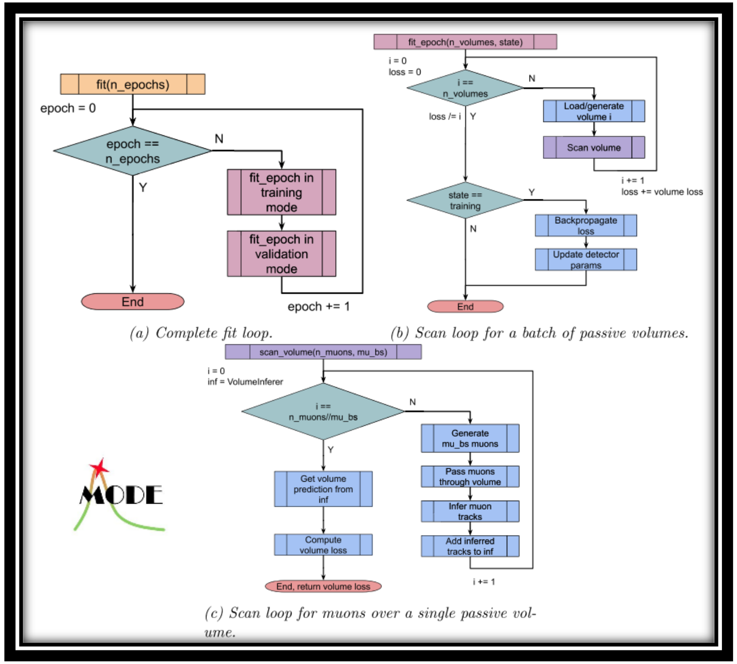
```
y1 = f1(x)
y2 = f2(y1)
y3 = f3(y2)
…
yn = fn-1(yn-2)
return yn
```

Program(x)

```
y1, dy1 = f1(x), df1(x)
y2, dy2 = f2(y1), df2(y1)
y3, dy3 = f3(y2), df3(y2)
…
yn, yn-1 = fn-1(yn-2), dfn-1(yn-2)
return yN, df1*df2*df3….*dfn-1
```

Design of hardware: TomOpt

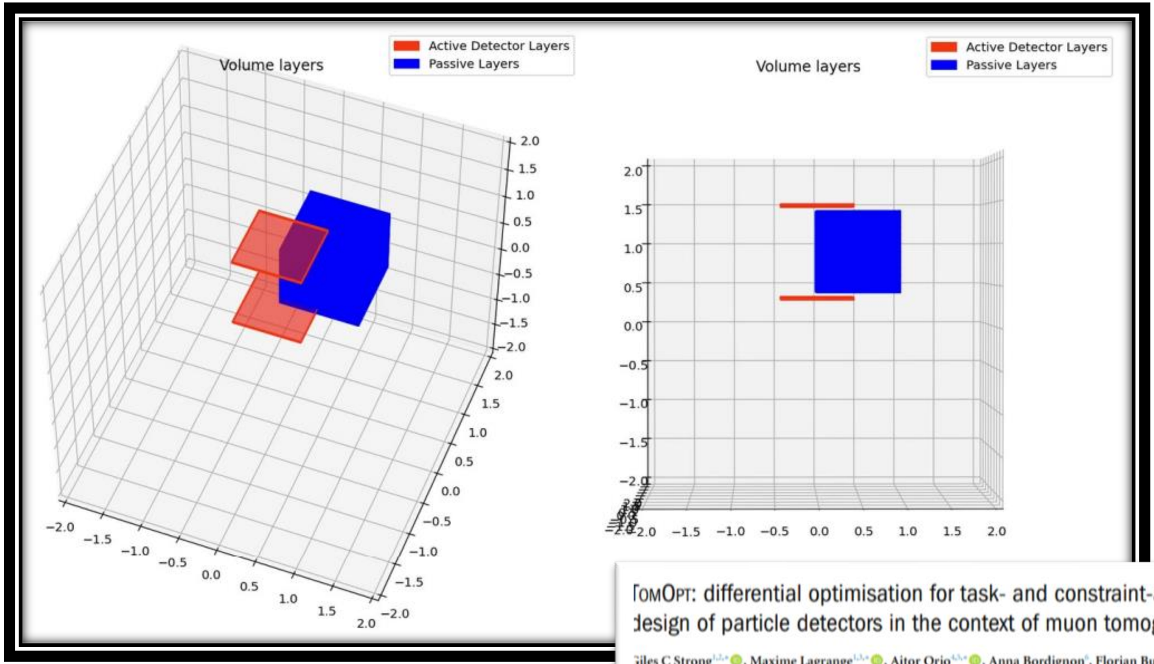
- TomOpt is a DP software to **optimize the best possible design for a muon detector**
  - It considers an specific problem: estimating the location of the metal-slag interface in a laddle
  - Takes into account: resolution, size of detectors, position, sizes, and cost



(a) Complete fit loop.

(b) Scan loop for a batch of passive volumes.

(c) Scan loop for muons over a single passive volume.

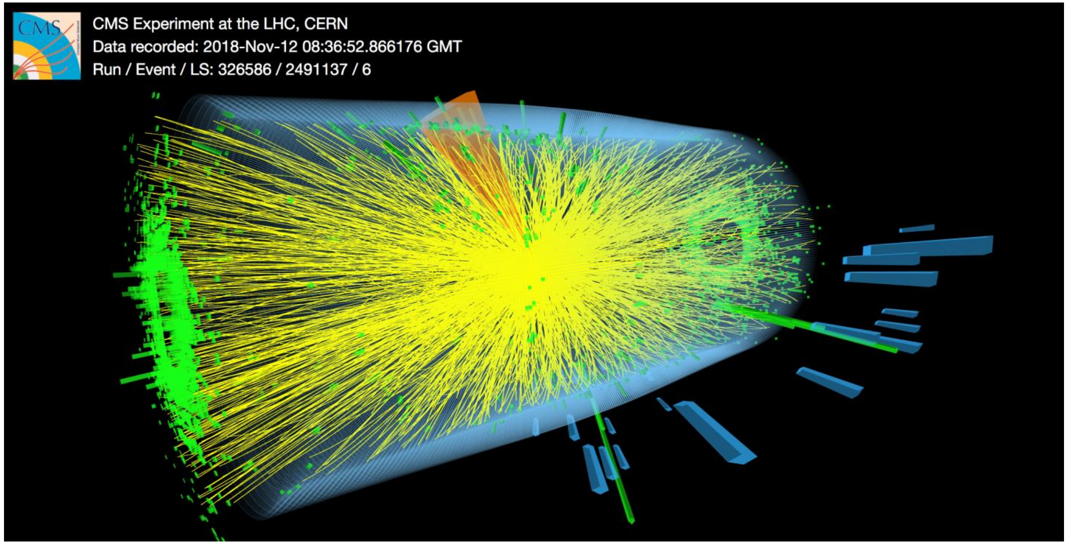


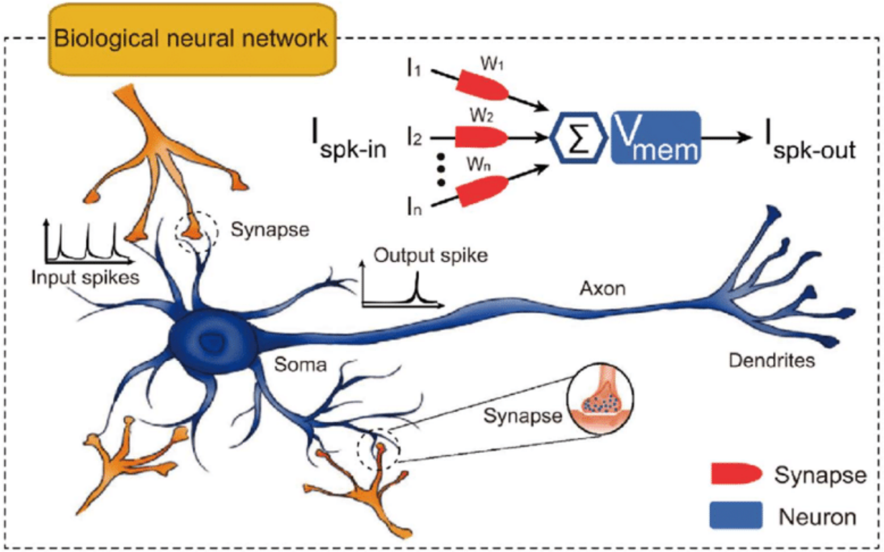
TomOpt: differential optimisation for task- and constraint-aware design of particle detectors in the context of muon tomography

Giles C Strong, Maxime Lagrange, Aitor Orio, Anna Bordignon, Florian Bury, Tommaso Dorigo, Andrea Giammanco, Mariam Heikal, Jan Kieseler, Max Lamparth, Pablo Martínez Ruiz del Árbol, Federico Nardi, Pietro Vischia and Haitham Zaraket

Track reconstruction: neuromorphic computing

- Particle tracking consist in the reconstruction of the trajectories from the “hits” left in the detectors
- Many traditional strategies: Kalman Filters, Gaussian Sum Filters, Machine Learning approaches, etc
- For proton tomography is crucial to use the time information of the hits -> **neuromorphic computing**
- Realistic implementation of neurons communicating through actual impulses or spikes

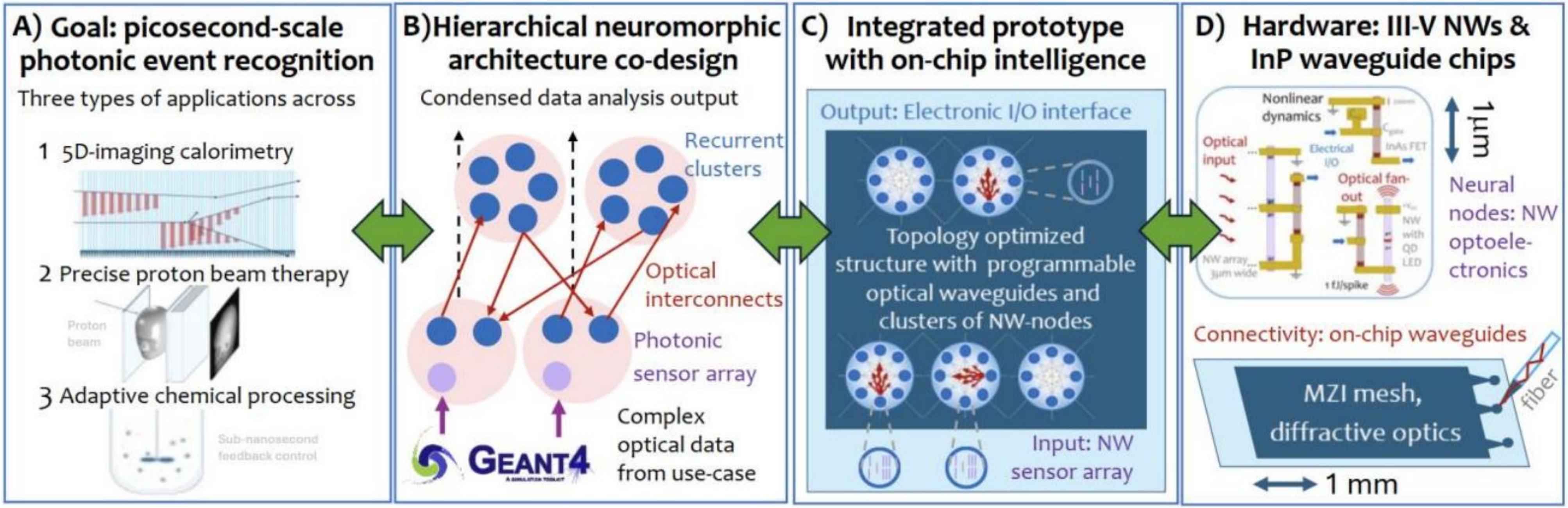




Track reconstruction: neuromorphic computing

- Starting the **Phinder Project** in which we are building a photonic neuromorphic chip based on nanotubes
- One of the use cases is to solve the tracking of protons in the context of proton tomography
- The position and time of the particle hits are encoded in the neuron impulses
- The network learns to associate hits to tracks and estimates the track parameters

EIC Pathfinder

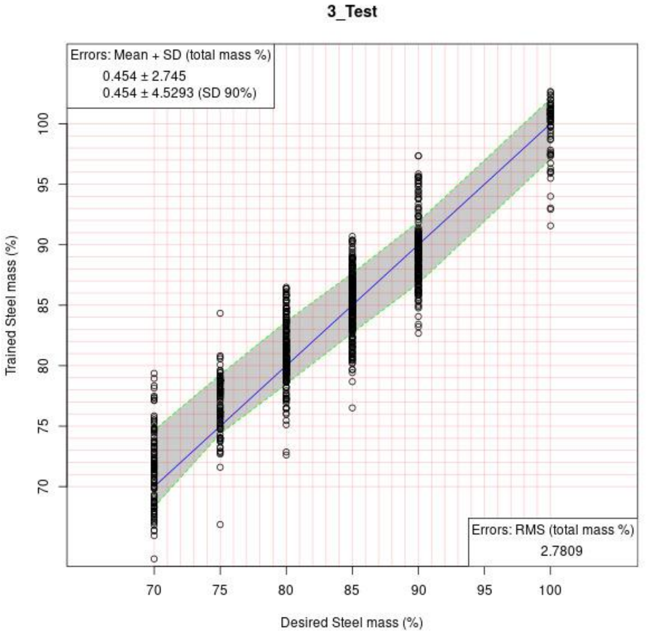


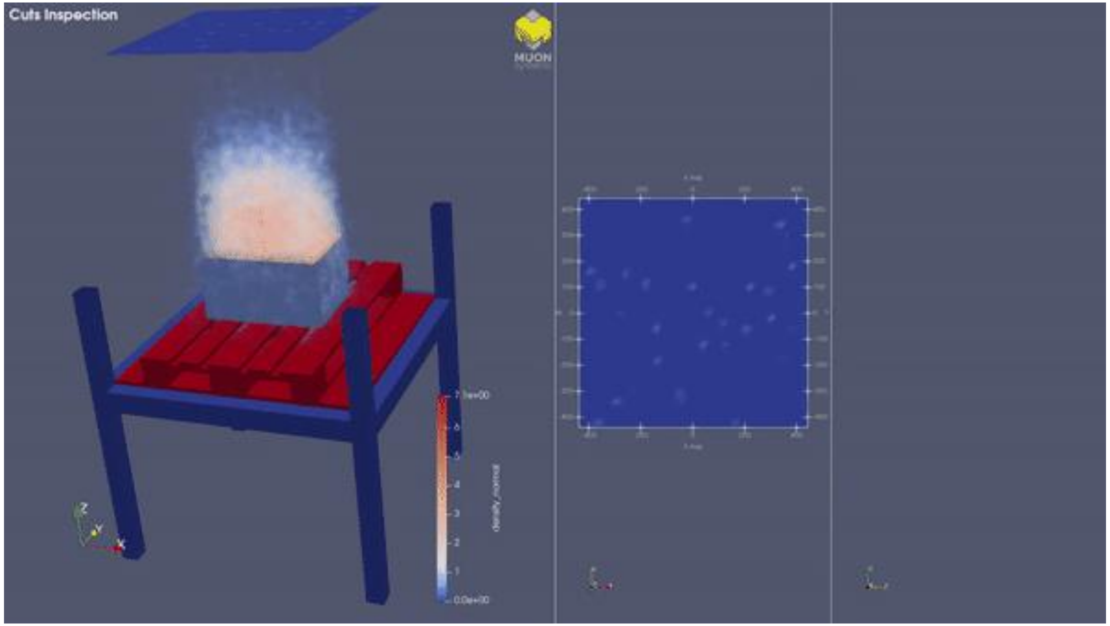
Prediction: metal scrap

- Scrap providers often try to cheat on their actual load by adding sand, concrete, tires, etc to the scrap
- This is bad for foundries for two reasons:
  - They are overpaying the scrap (typically traded as a function of the weight)
  - Strange objects may be dangerous or destructive for the melting process
- Testing the performance of a muon scanner to estimate average density and detect anomalies


Prediction: metal scrap

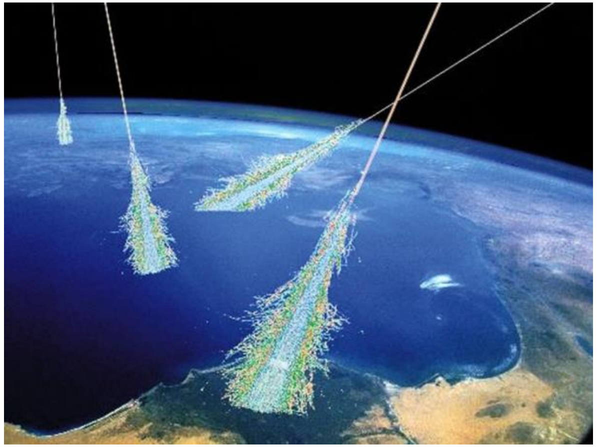
- Neural network in regression mode trained to infer the percentage of steel in the mixture
- Input to the network based on quantiles of the angular and spatial deviations
- Trained for a large variety of different combinations and steel percentages
- Mixing real data with simulated data for the training (see last part of the talk)





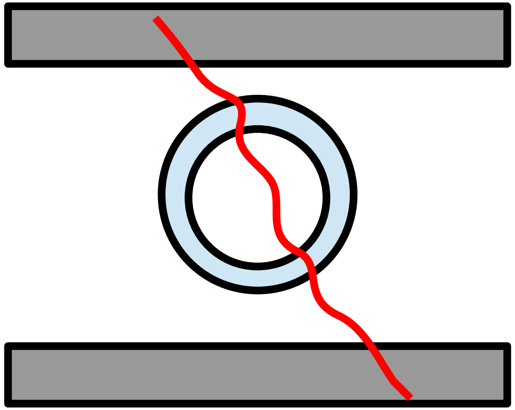
Simulation: passage of particles through matter

Muon flux generation



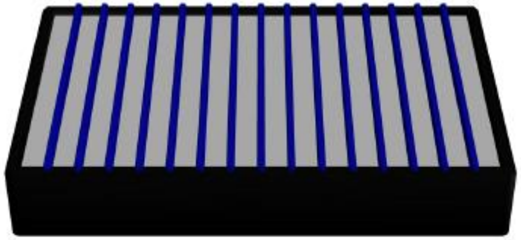
- Most generators parametrize the muon flux as a function of altitude/latitude etc
- This part is usually relatively fast
- CRY is a good example

Muon propagation through matter



- Implementation of energy loss and multiple scattering at least
- Can be very time consuming specially for complex geometres
- GEANT4 very precise on this

Detector simulation



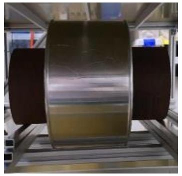
- A model of the detector response has to be considered for precise MC simulation
- This part can be critical and it is typically difficult to implement
- No general récipes, every detector needs its own model

Simulation: passage of particles through matter

- Our testing setup is based on the inference problem of the wear of an insulated pipe
- Simulator target: predict the segment in the lower detector provided the segment in the upper detector
- Caveat: for these simulations detectors are considered to be perfect

Pipe corrosion

Measure of the wear:
1mm resolution
1 min exposure



Upper detector

$x_1, y_1, v_{x1} = \mathrm{atan}(\theta_{x1}), v_{1y} = \mathrm{atan}(\theta_{y1})$

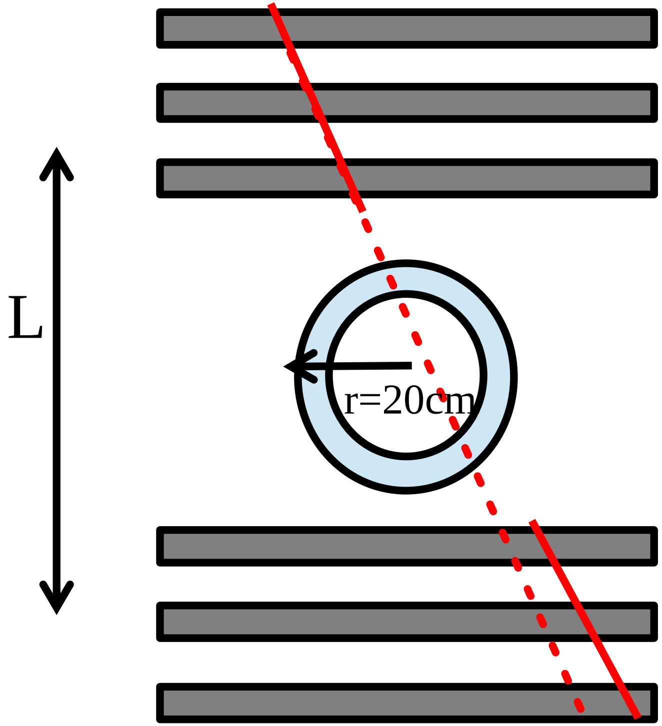
Lower detector

$x_2, y_2, v_{x2} = \mathrm{atan}(\theta_{x2}), v_{2y} = \mathrm{atan}(\theta_{y2})$

Target variables

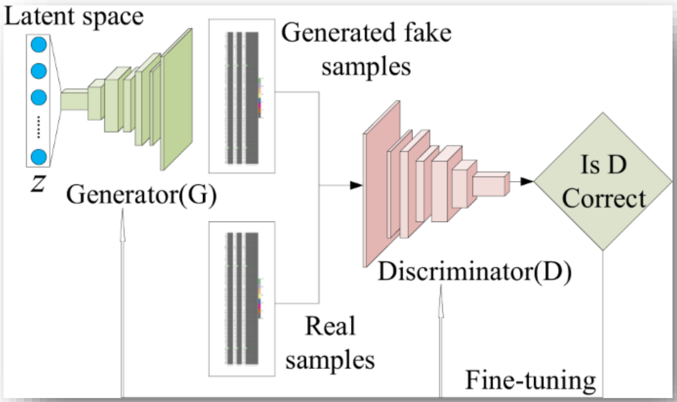
$\Delta x = x_2 - L\, v_{x1} - x_1$ $\Delta y = y_2 - L v_{y1} - y_1$

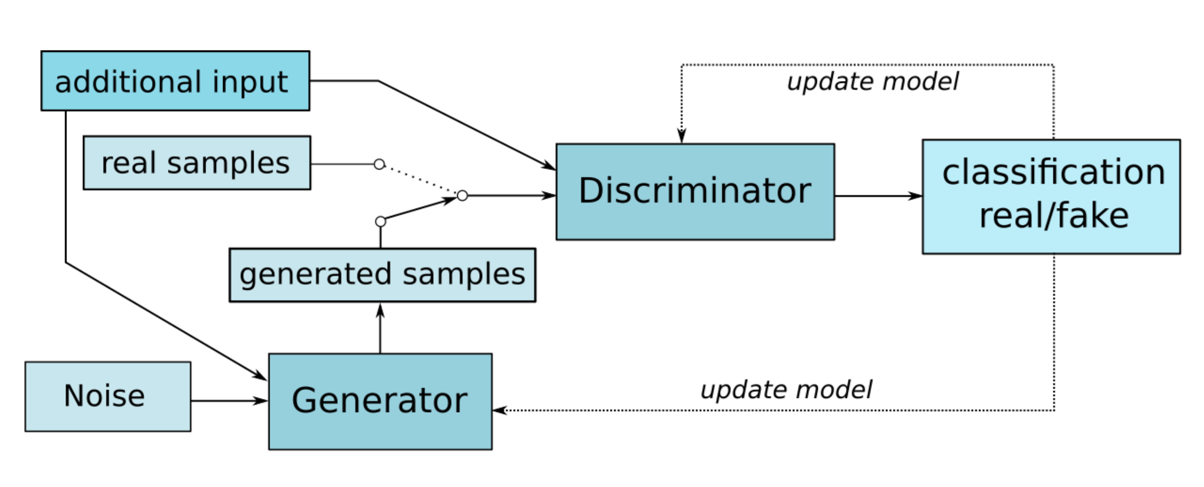
$\Delta v_x = v_{x2} - v_{x1}$ $\Delta v_y = v_{y2} - v_{y1}$



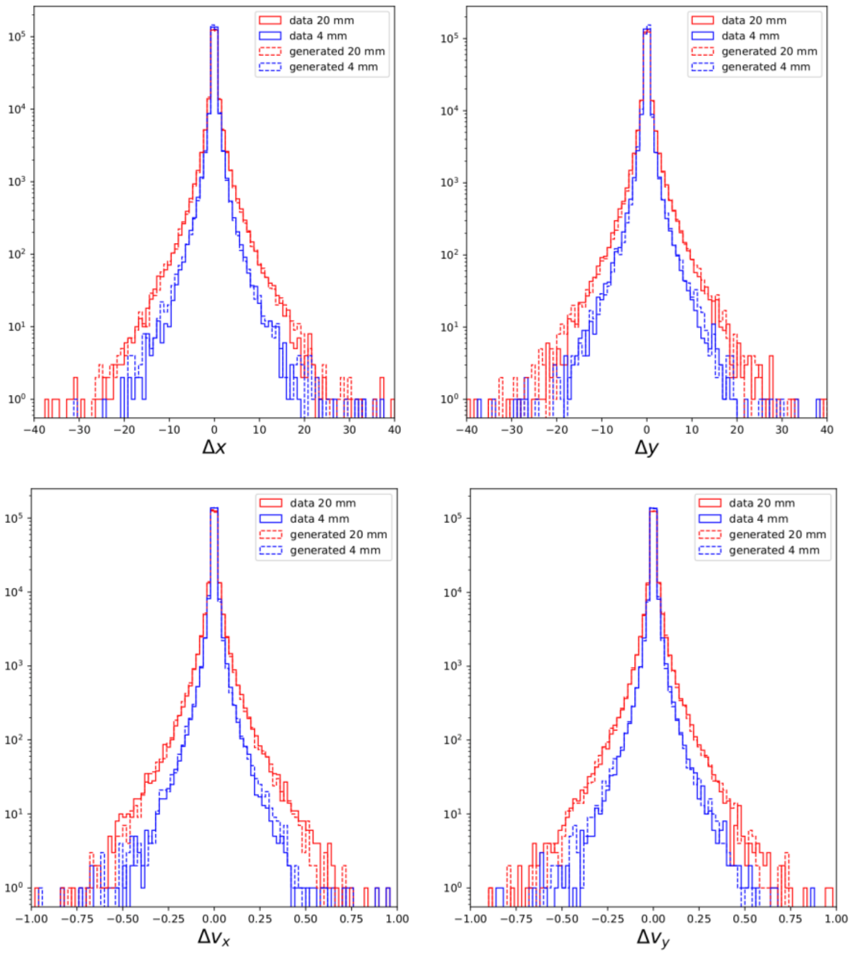
Simulation: passage of particles through matter

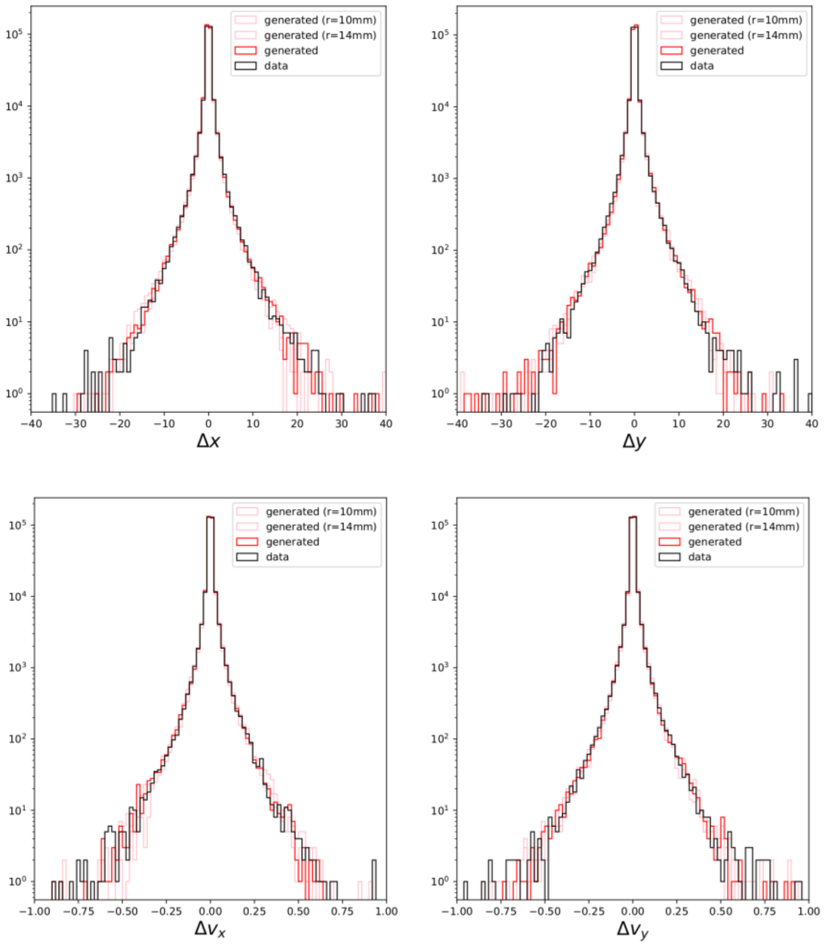
- Can we teach physics to a Deep Learning model?
- Based on a conditional Wasserstein GAN as follows:
  - Input 1: latent space (noise)
  - Input 2: pipe radius
  - Input 3: muon coordinates in the upper detector
- Predicts the muon coordinates in the lower detector





Simulation: passage of particles through matter

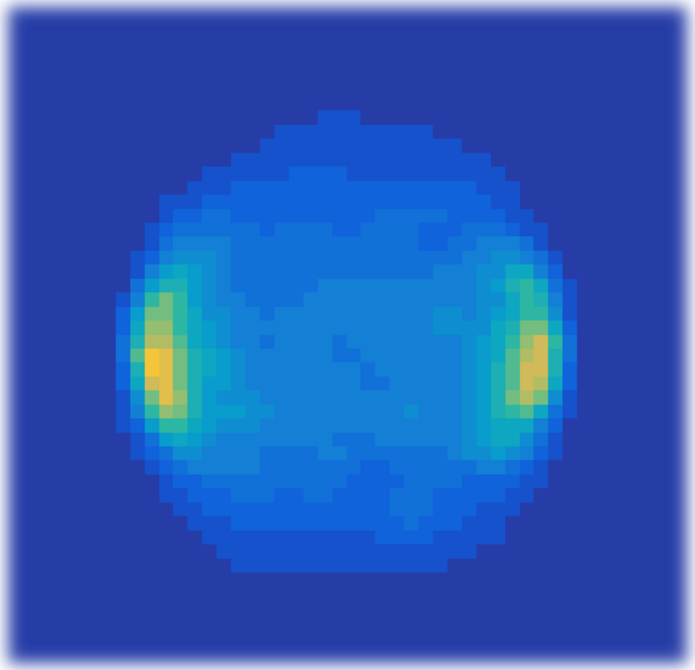




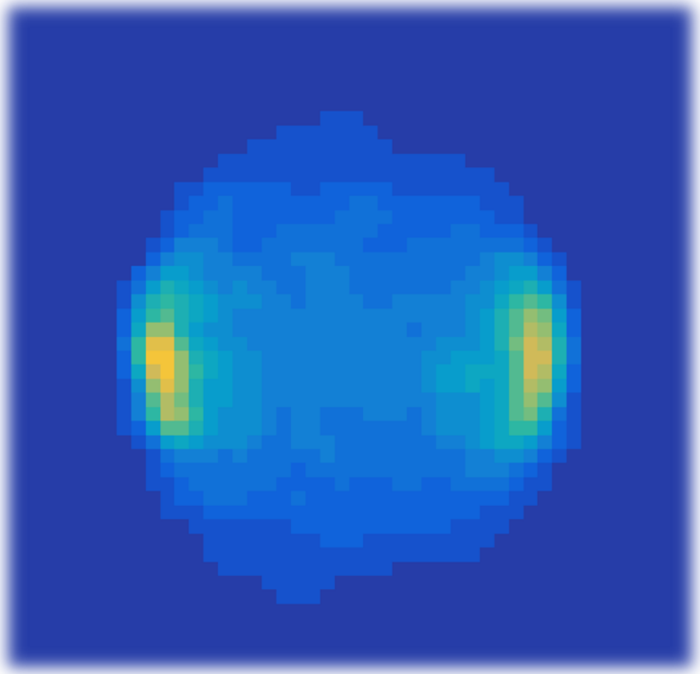
Simulation: passage of particles through matter

- To proof that we really need to see whether the GAN has “absorbed” the geometry
- First thing we can do is to see how the POCA estimation looks for this simulation

Geant4 generated - 16 mm thickness pipe



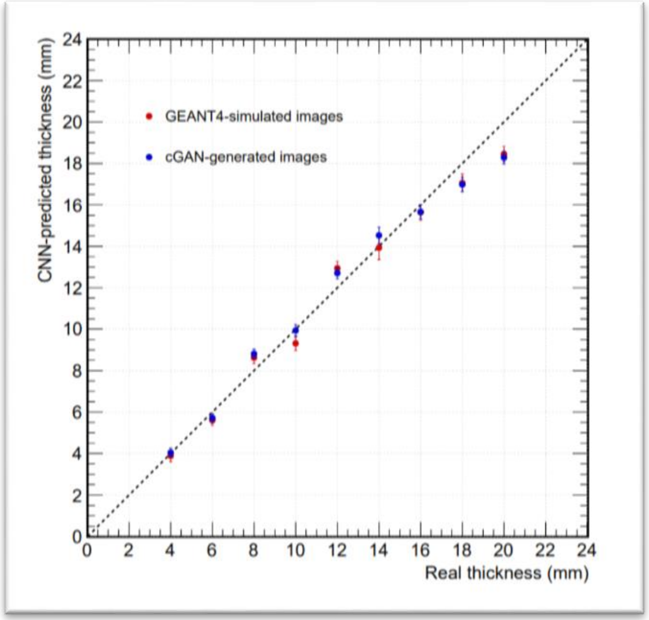
GAN generated - 16 mm thickness pipe

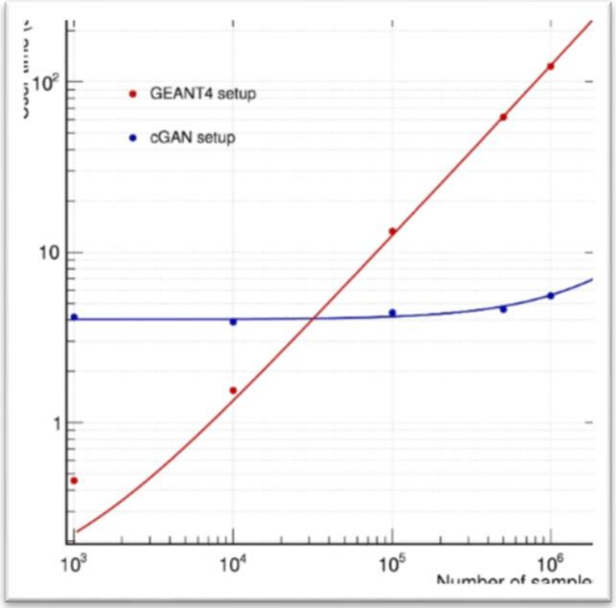


Simulation: passage of particles through matter

Instituto de Física de Cantabria

- A **convolutional neural network** has been trained to predict the pipe thickness based on POCA images
- Training dataset based on 90 POCA images per thickness (4, 6, 8, …, 18 mm thickness)
- Each POCA image is made with 300K muons based on CRY + GEANT4 simulation
- The CNN uses a RestNET50 with 4 additional dense layers with 1024, 512, 512 and 256

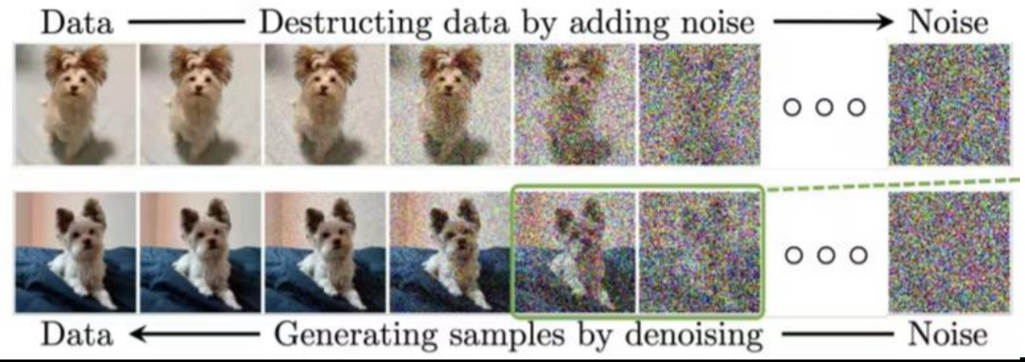




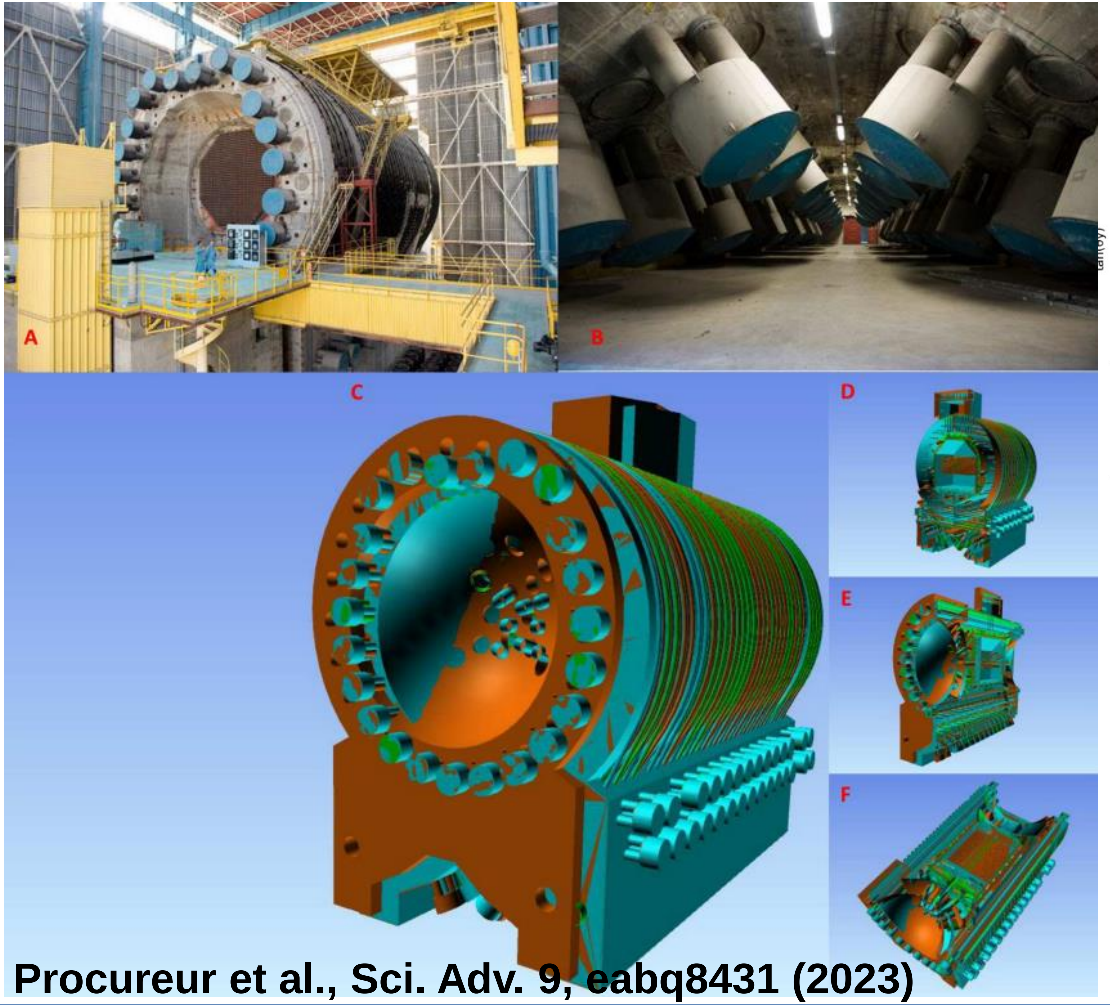
10.1016/j.engappai.2025.112357

Denoising techniques

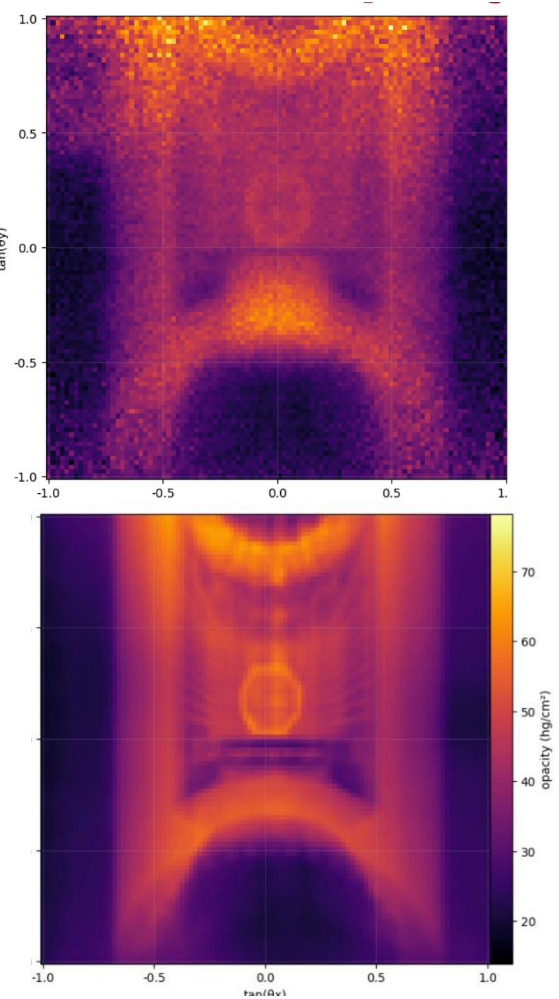
- A well-known problem in tomography is the fact that images are noise and can contain artifacts
  - Noise is due to the statistical nature of quantum processes and/or electronic noise
  - Artifacts appear because of the limitations and assumptions made for the imaging algorithms
- Removing the noise is possible if there was a high exposition to images with the same kind of noise
- Convolutional Neural Networks can be used to distinguish and eliminate the noise
- There is a large variety of methods that can do this:
  - Some of them are based on diffusion models
  - GAN networks can also be trained to do this



Denoising techniques: G3 reactor



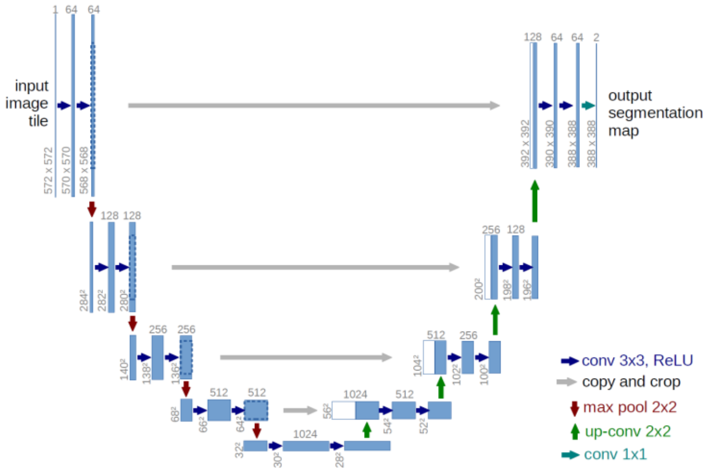
Procureur et al., Sci. Adv. 9, eabq8431 (2023)

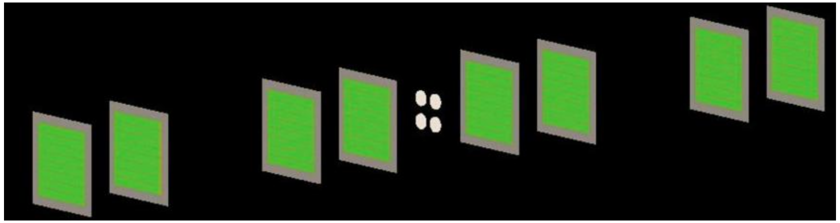


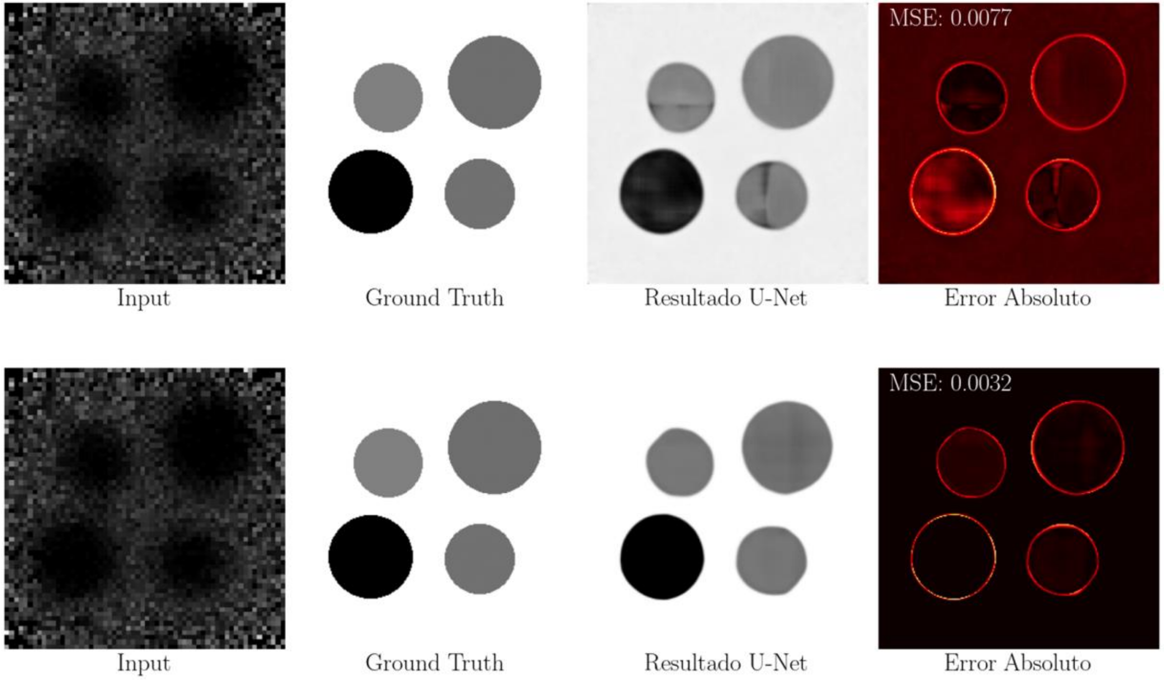
U-NET architecture trained with simulations that implement variations of the nominal geometry

Noise reduction in proton tomography

- Application of **U-NET** to reduce noise level and remove artifacts in proton tomography
- Work in the context of a project to develop and test a **proton tomography telescope based on LGADs**







Thank you!

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Workshop – Hands on exercise

Hand-on exercise

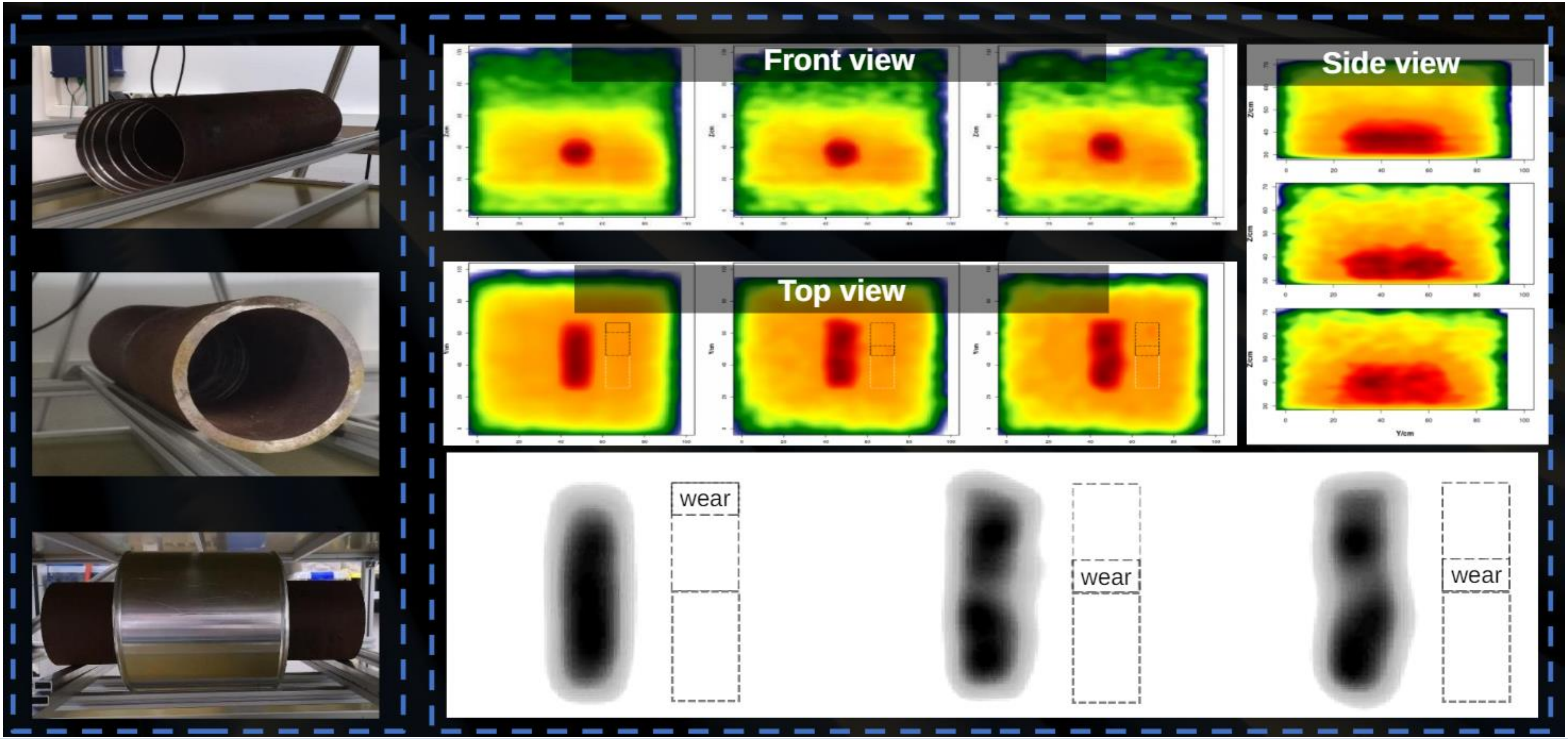
- Instead of another (boring) talk we are proposing a hands-on exercise of muon tomography
- We have prepared datasets and a jupyter notebook where you will run yourself an application
- You can find the notebook at:

https://tinyurl.com/4kbyfxbf

- Please, make a copy of the google collab notebook and run an instance of your own
- Make sure that you run in T4GPU mode since you will be running a relatively large CNN

What is this about?

- We will be working on the problem of determining the wear of the inner walls of a gas pipe



The setup (a reminder)

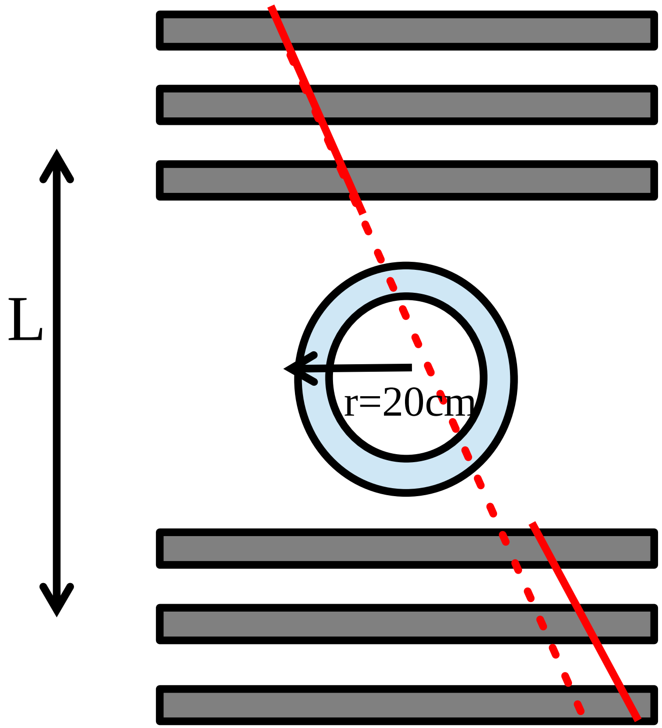
- The datasets you will be using contain the position and direction of muons in the upper and lower detector

Upper detector

$x_1, y_1, v_{x1} = \mathrm{atan}(\theta_{x1}), v_{1y} = \mathrm{atan}(\theta_{y1})$

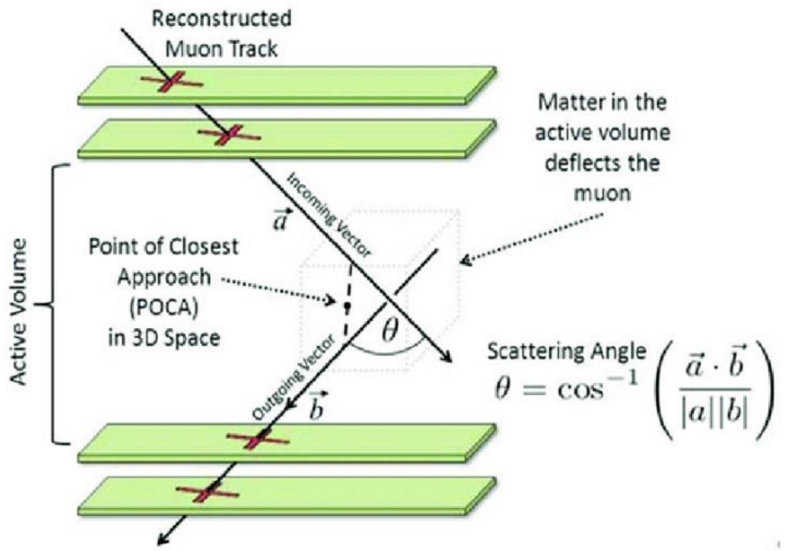
Lower detector

$x_2, y_2, v_{x2} = \mathrm{atan}(\theta_{x2}), v_{2y} = \mathrm{atan}(\theta_{y2})$



Scattering tomography: Point-Of-Closest-Approach

- This simple algorithm is one of the most widely used for scattering muography
- The algorithm makes two fundamental assumptions (which are known to be non-true in general)
  - The scattering takes place in a single point of the target
  - The point of closest approach of the incoming and outgoing trajectories is the scattering point



The goal

- In the notebook you will have to:
  - Apply the Point-Of-Closest-Approach algorithm to a couple of datasets
  - Produce the corresponding tomographical projections
  - Tune the binning and the limits of the algorithm to get the best possible image
  - Answer the questions
  - Smooth the images using a Kernel-Density Function technique
  - Use a previously trained CNN in order to predict the actual inner radius of the pipes
  - You will do it for two types of images: generated with GEANT4 and generated by our GAN
  - Answer the questions