Detector optimization in Muon Scattering Tomography

Maxime Lagrange on behalf of the **TomOpt authors***

Third MODE Workshop on differentiable programming for experiment design - Princeton University 24-26 July

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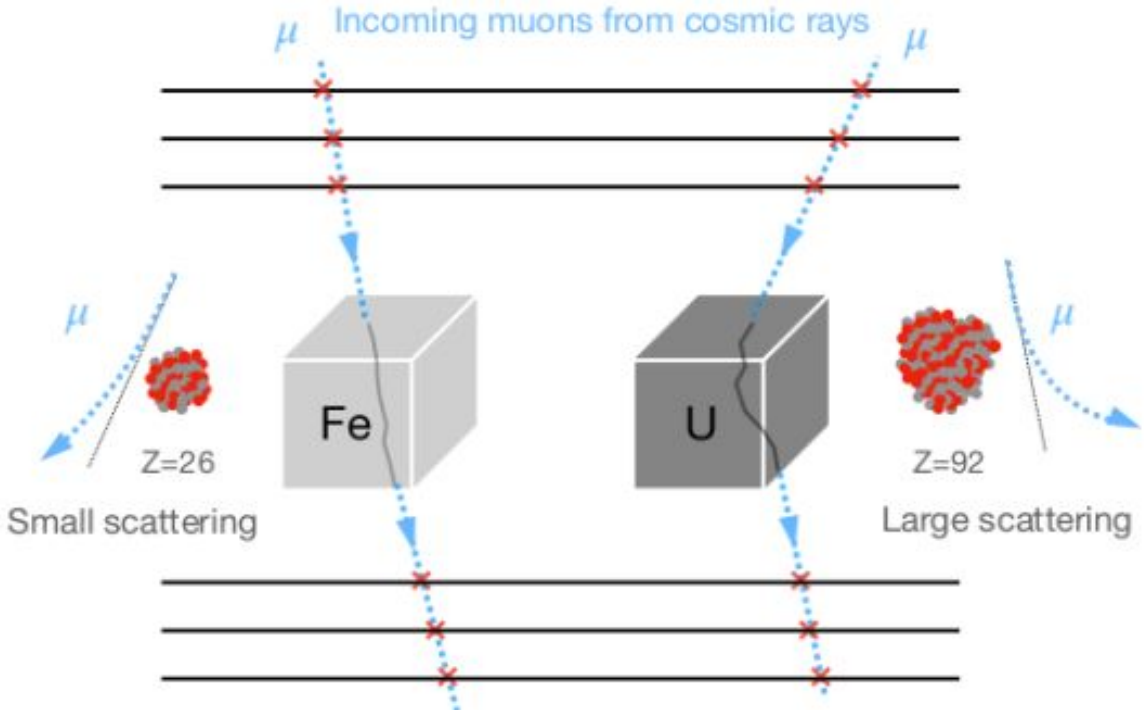
Muon scattering tomography: concept



Aim: Imaging inner structure of objects

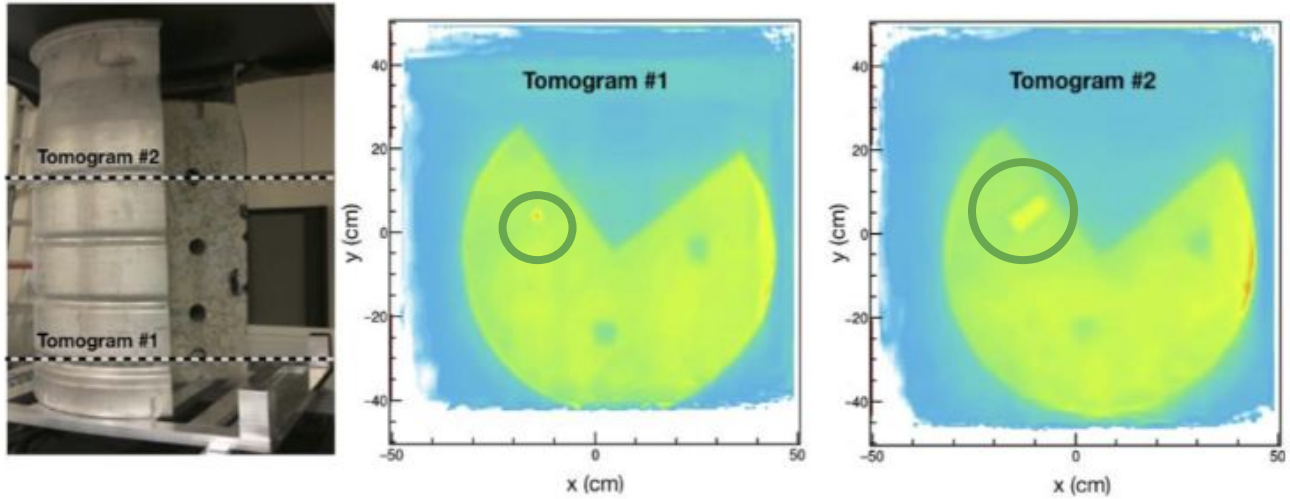
Signal: Deflection between incoming and outgoing muon tracks

Acquisition time: few minutes - few days

Nuclear Industry

Nuclear waste characterization

(University of Glasgow)



Illustrations from: "Muon Imaging Applications for Nuclear Waste Management and Decommissioning"

Constraints
Logistic

Target performance
Accurate material identification

Silent Border MST scanner for border guard

Cosmic Ray Tomograph for Identification of Hazardous and Illegal Goods hidden in Trucks and Sea Containers

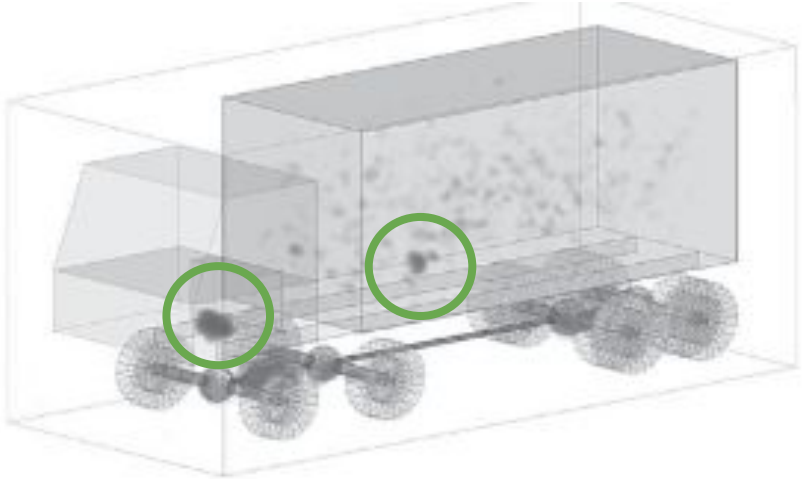


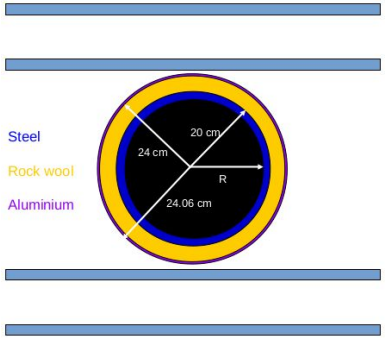
Illustration from "Muography of different structures using muon scattering and absorption algorithms"

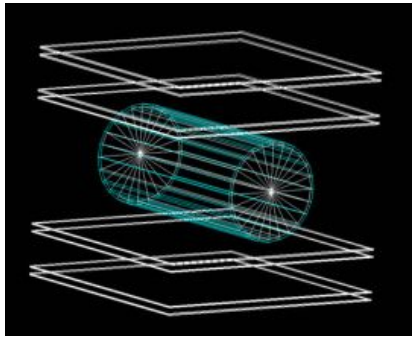
Constraints	Target performance
Short **acquisition time**	**Anomaly detection**

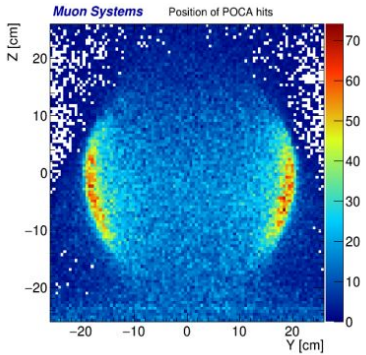
Industrial scanning solutions

MUON systems

1 - Measurement of the width of an insulated pipe



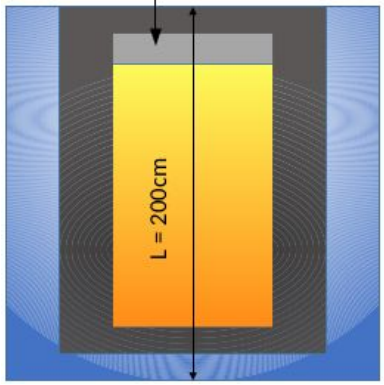


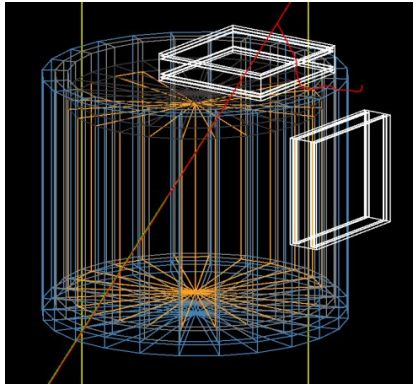


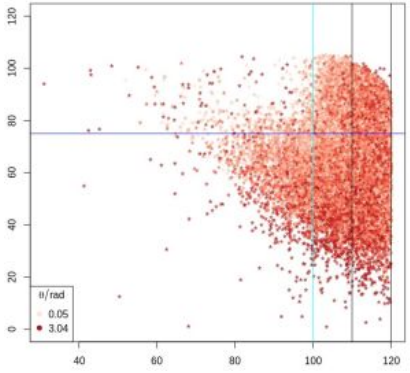
Illustrations from "Non-destructive testing of industrial equipment using muon radiography"

2 - Estimation of slag on a furnace laddle

unknown amount of waste







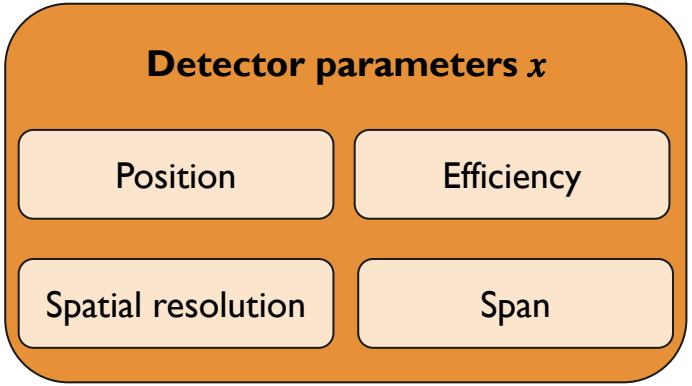
Target performance
Anomaly detection

Constraints
Portability, logistic

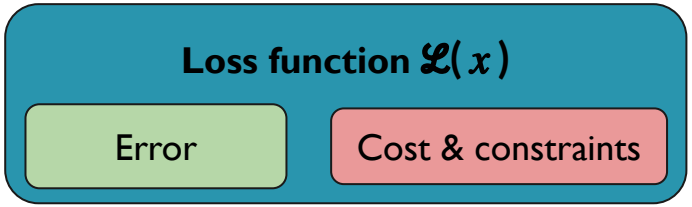
I - Introduction to TomOpt

Optimizing a detector for a desired task

What to **act** on?



Minimizing **cost**, **constraints** and **error on prediction**



Optimization becomes a **minimization** problem

$$min\, \mathcal{L}(x)$$

"Finding the local-**minimum** of a **differentiable function**"

Iterative **gradient-descent** algorithm:

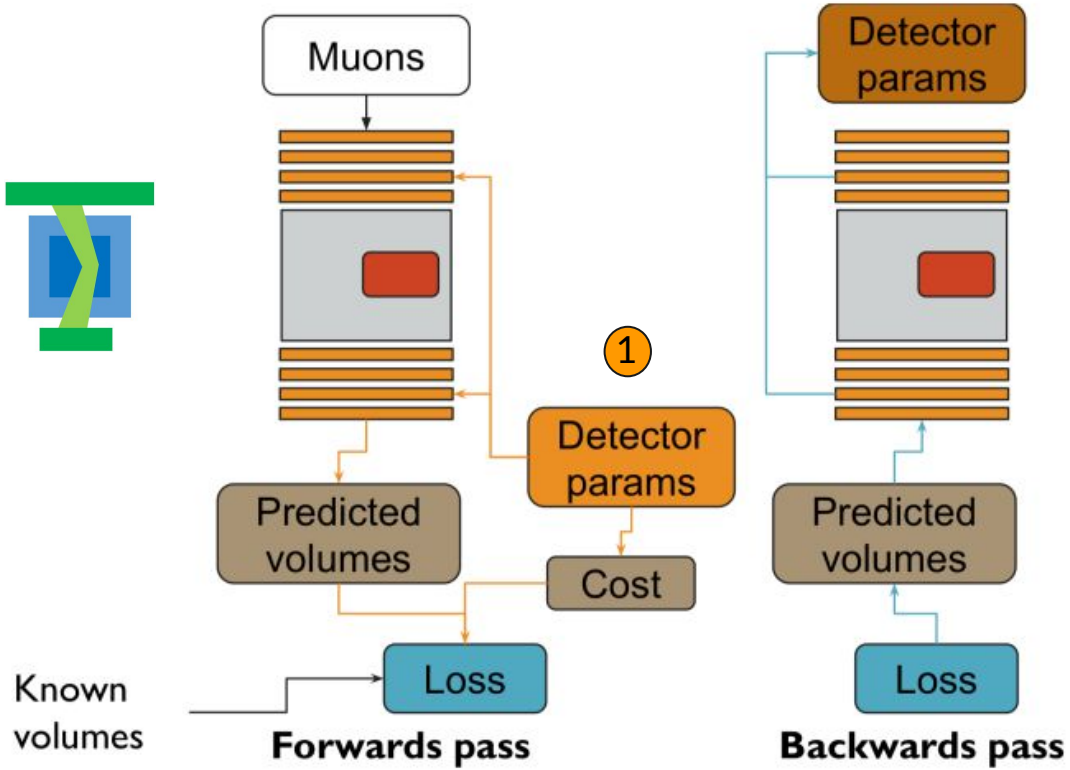
at iteration k:

$$x^{(k+1)} = x^{(k)} + \eta \, \nabla_x \mathcal{L}(x^{(k)})$$

Requires a **differentiable simulation pipeline**

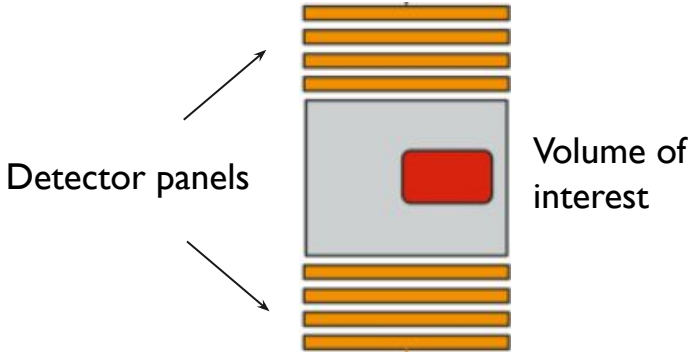
TomOpt: differentiable optimisation

TomOpt iteration routine



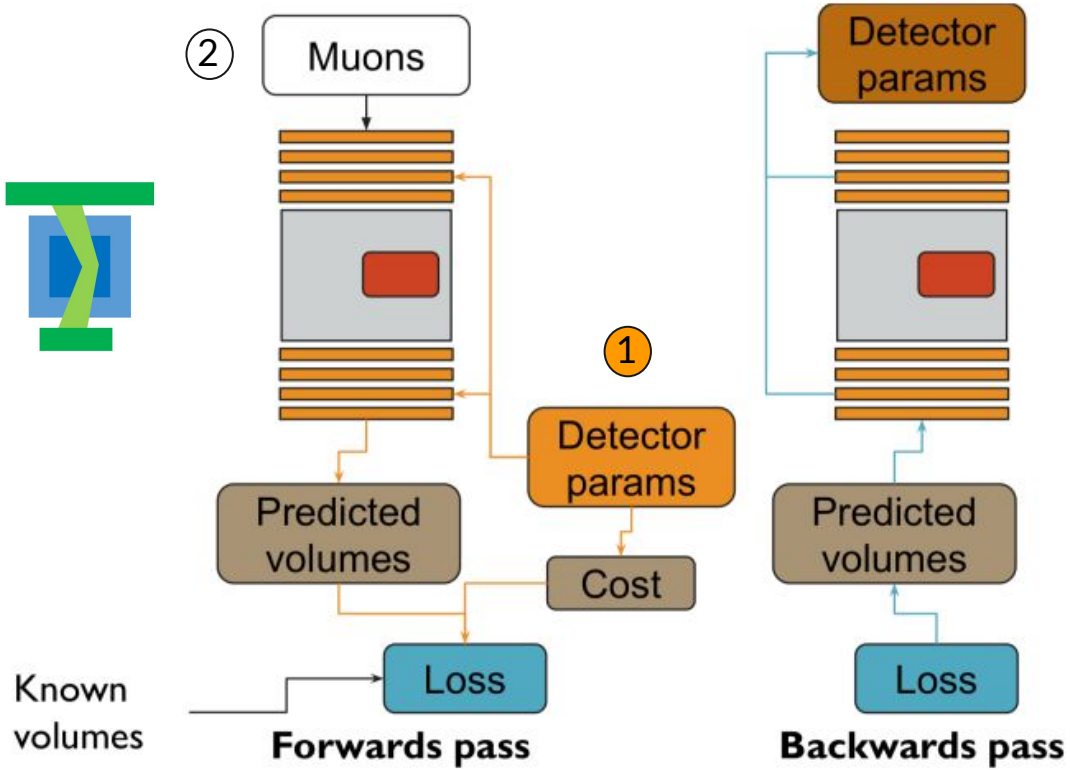
1. Initial **detector configuration**

- **Positions** x,y,z
- Spatial **resolution**
- **Efficiency**
- **Span** dx, dy

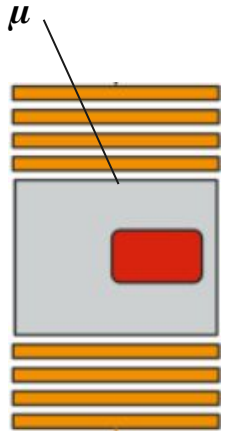


TomOpt: differentiable optimisation

TomOpt iteration routine

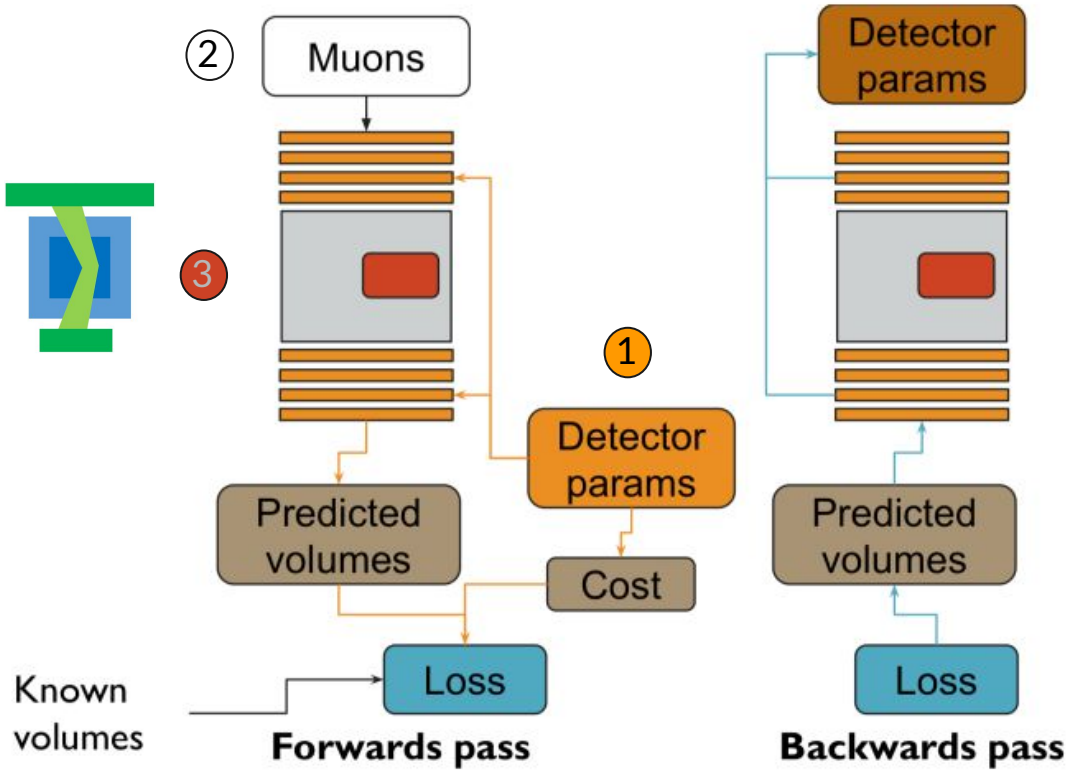


1. Initial **detector configuration**
2. **Cosmic** muon **source** sampled from literature

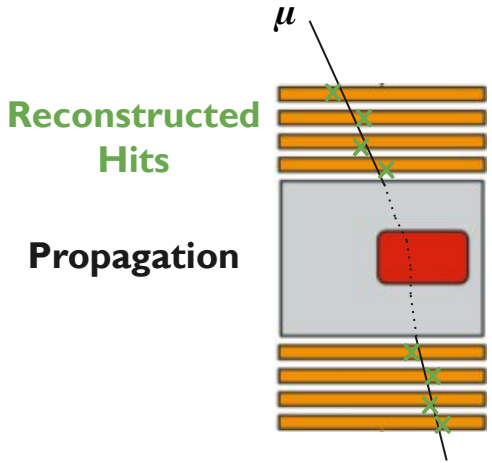


TomOpt: differentiable optimisation

TomOpt iteration routine



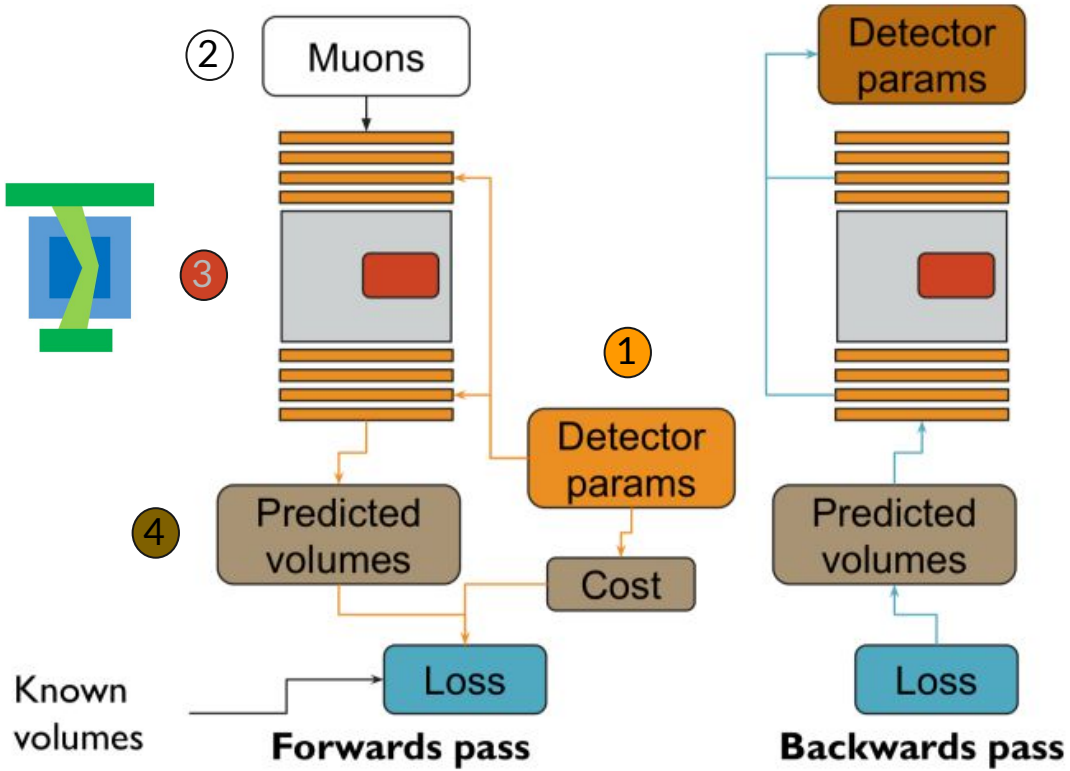
1. Initial **detector configuration**
2. **Cosmic** muon **source** sampled from literature
3. Muon **detection** and **propagation** through **matter**



Custom made **differentiable** muon **detection** and **propagation** models

TomOpt: differentiable optimisation

TomOpt iteration routine

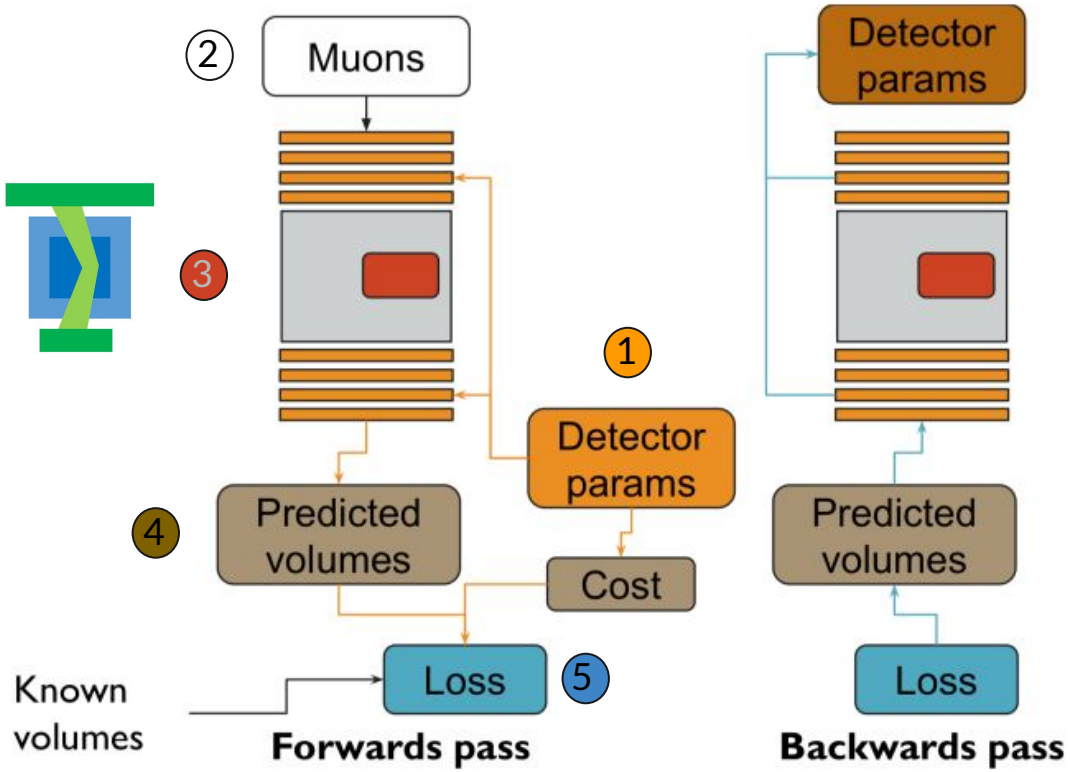


1. Initial **detector configuration**
2. **Cosmic** muon **source** sampled from literature
3. Muon **detection** and **propagation** through **matter**
4. Volume **prediction**

Using **reconstructed hits** and a given reconstruction **method, predict** the desired figure of merit

TomOpt: differentiable optimisation

TomOpt iteration routine



1. Initial **detector configuration**
2. **Cosmic** muon **source** sampled from literature
3. Muon **detection** and **propagation** through **matter**
4. Volume **prediction**
5. **Loss function** computation

Loss function $\mathcal{L}(x)$

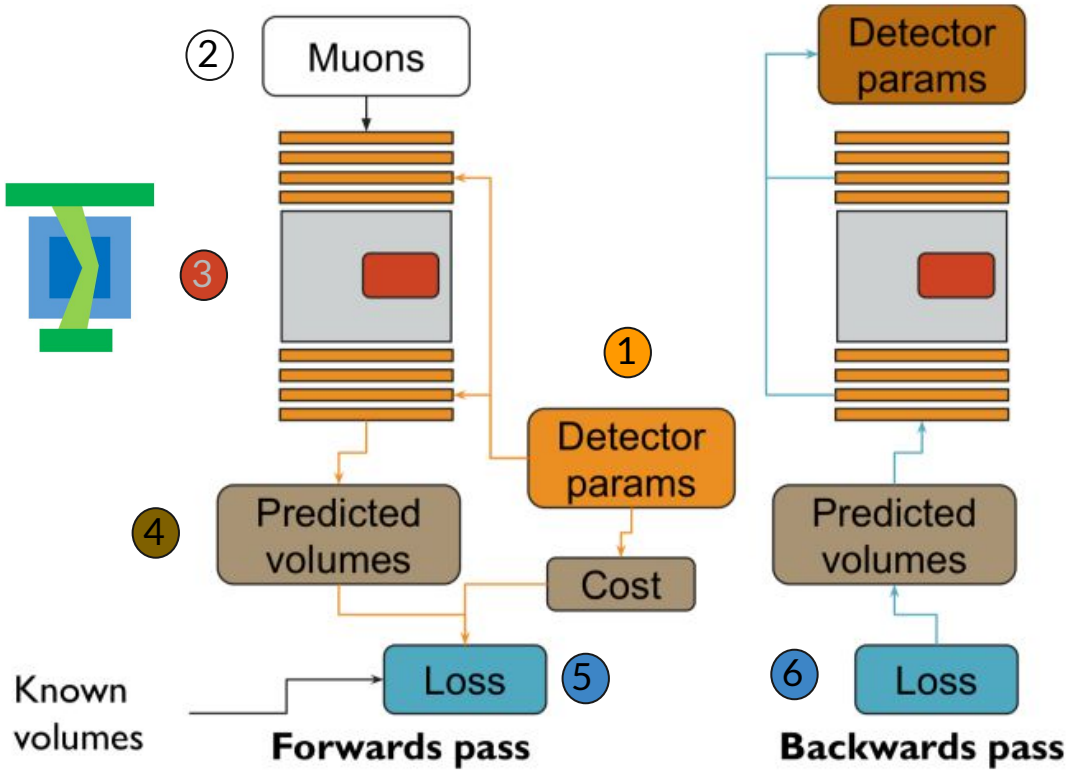
Error | **Cost**

Prediction ~ Simulated **truth**

$, external constraints

TomOpt: differentiable optimisation

TomOpt iteration routine



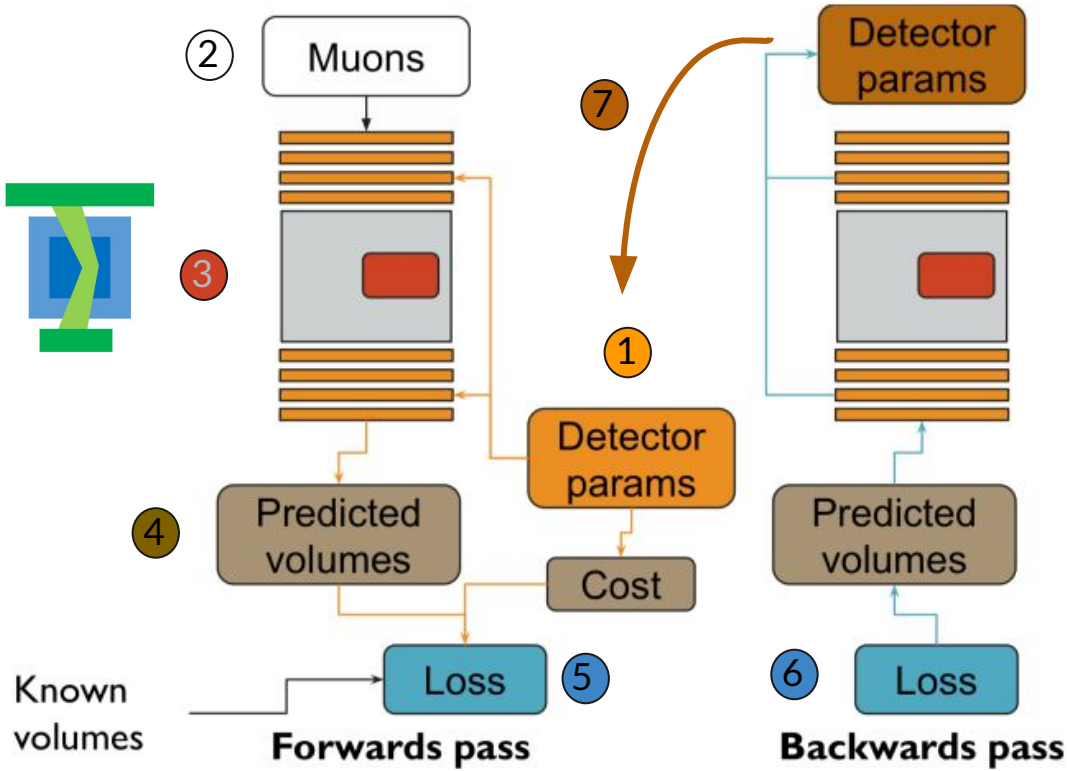
1. Initial **detector configuration**
2. **Cosmic** muon **source** sampled from literature
3. Muon **detection** and **propagation** through **matter**
4. Volume **prediction**
5. **Loss function** computation
6. Gradient-descent **optimisation**

$$x^{(k+1)} = x^{(k)} + \eta \cdot \nabla_x \mathcal{L}(x^{(k)})$$

Updated parameter — **Initial** parameter — **Loss** gradient

TomOpt: differentiable optimisation

TomOpt iteration routine



1. Initial **detector configuration**
2. **Cosmic** muon **source** sampled from literature
3. Muon **detection** and **propagation** through **matter**
4. Volume **prediction**
5. **Loss function** computation
6. Gradient-descent **optimisation**
7. Modified geometry used at step 1

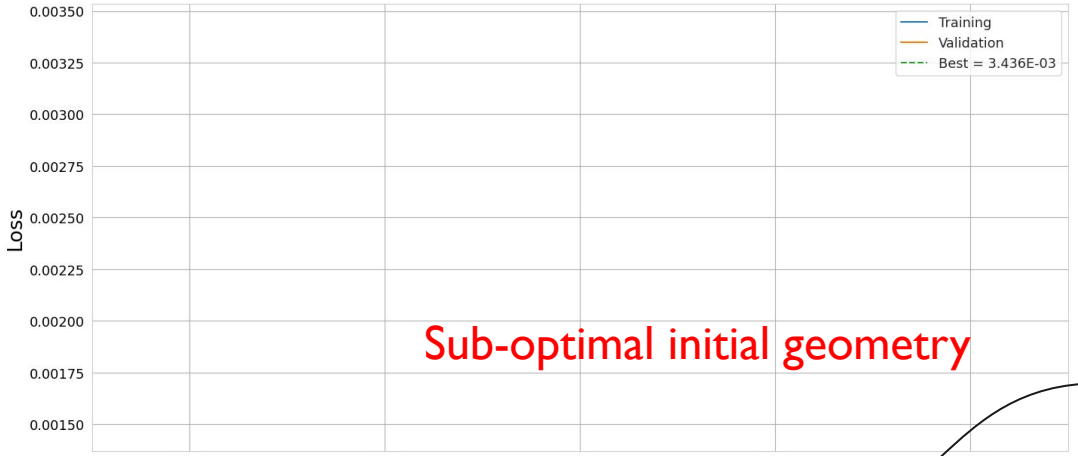
Repeat until **Loss function minimum** is found

II - TomOpt demonstration

TomOpt: X_0 inference performance driven optimisation

Loss function

$\mathcal{L}$



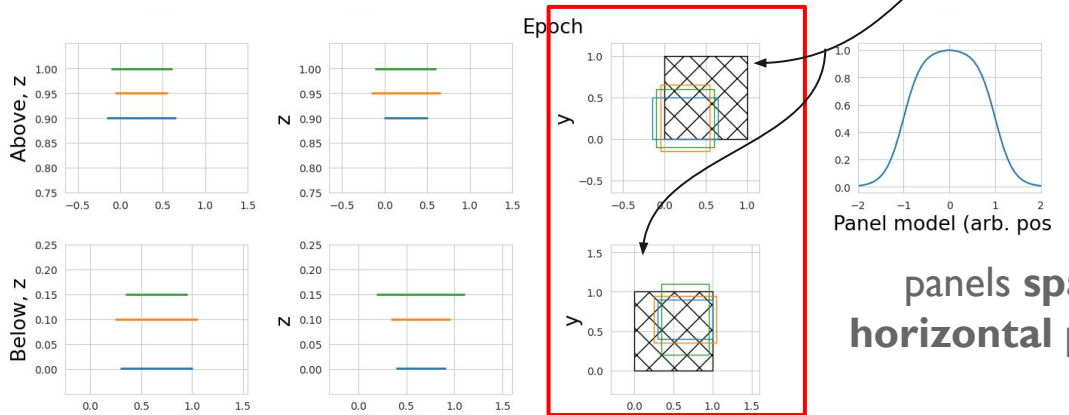
30 free parameters:

- x,y,z position
- xy span

Volume of interest

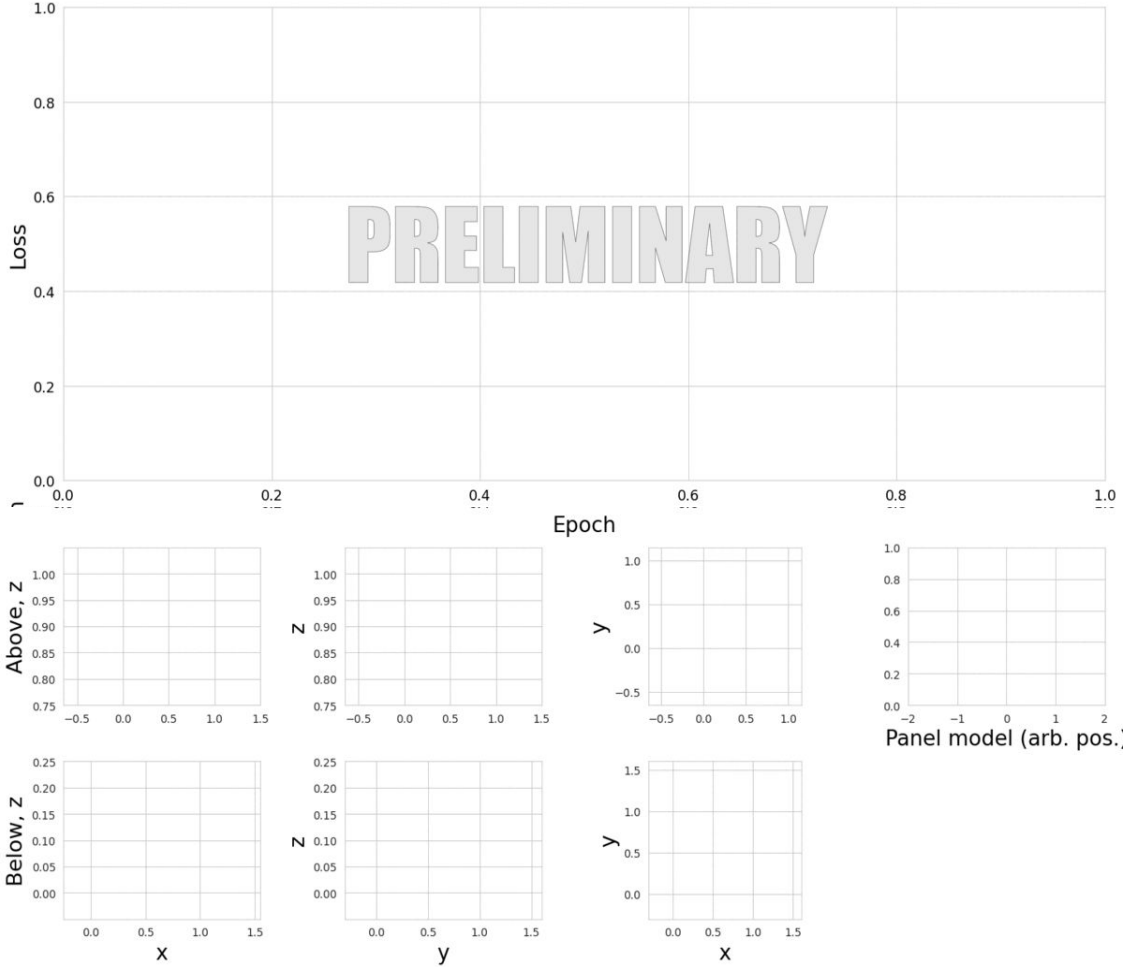
Upper panels vertical **placement**

Lower panels vertical **placement**



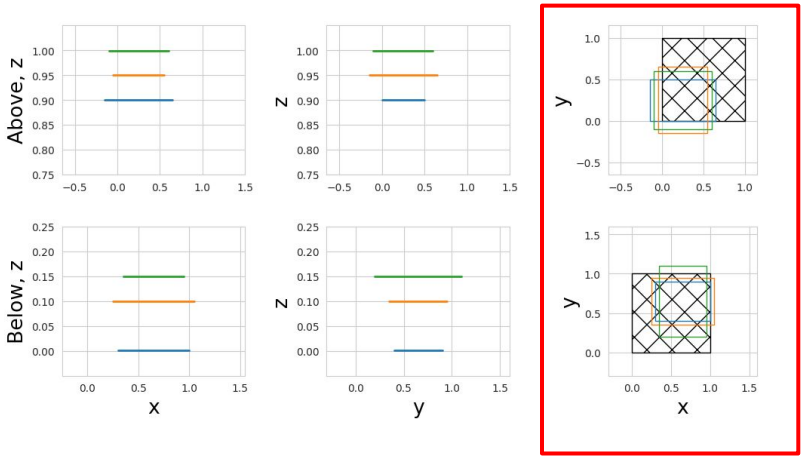
panels **span** and **horizontal** placement

TomOpt: X_0 inference performance driven optimisation



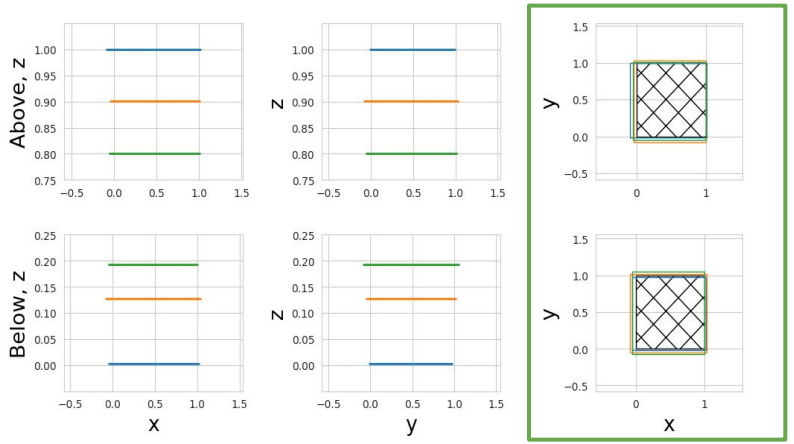
TomOpt: X_0 inference performance driven optimisation

Initial configuration



- Panels off centered in x and y
- Panels z placement grants poor angular resolution

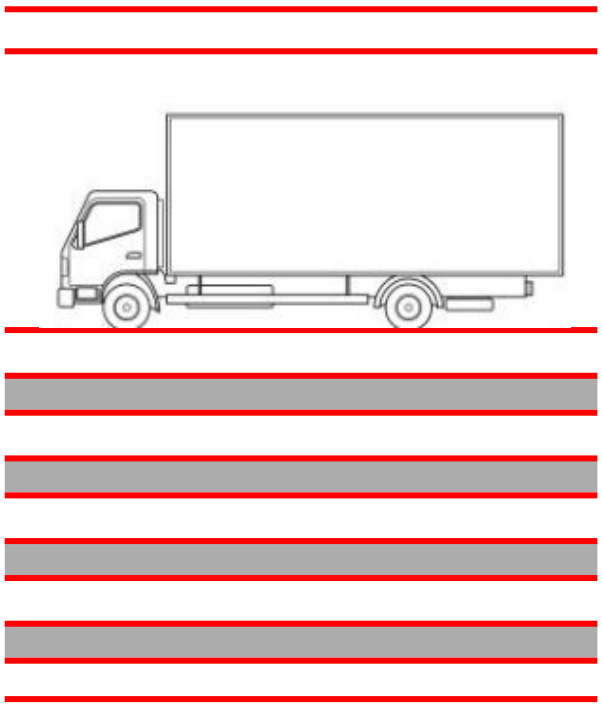
Final configuration

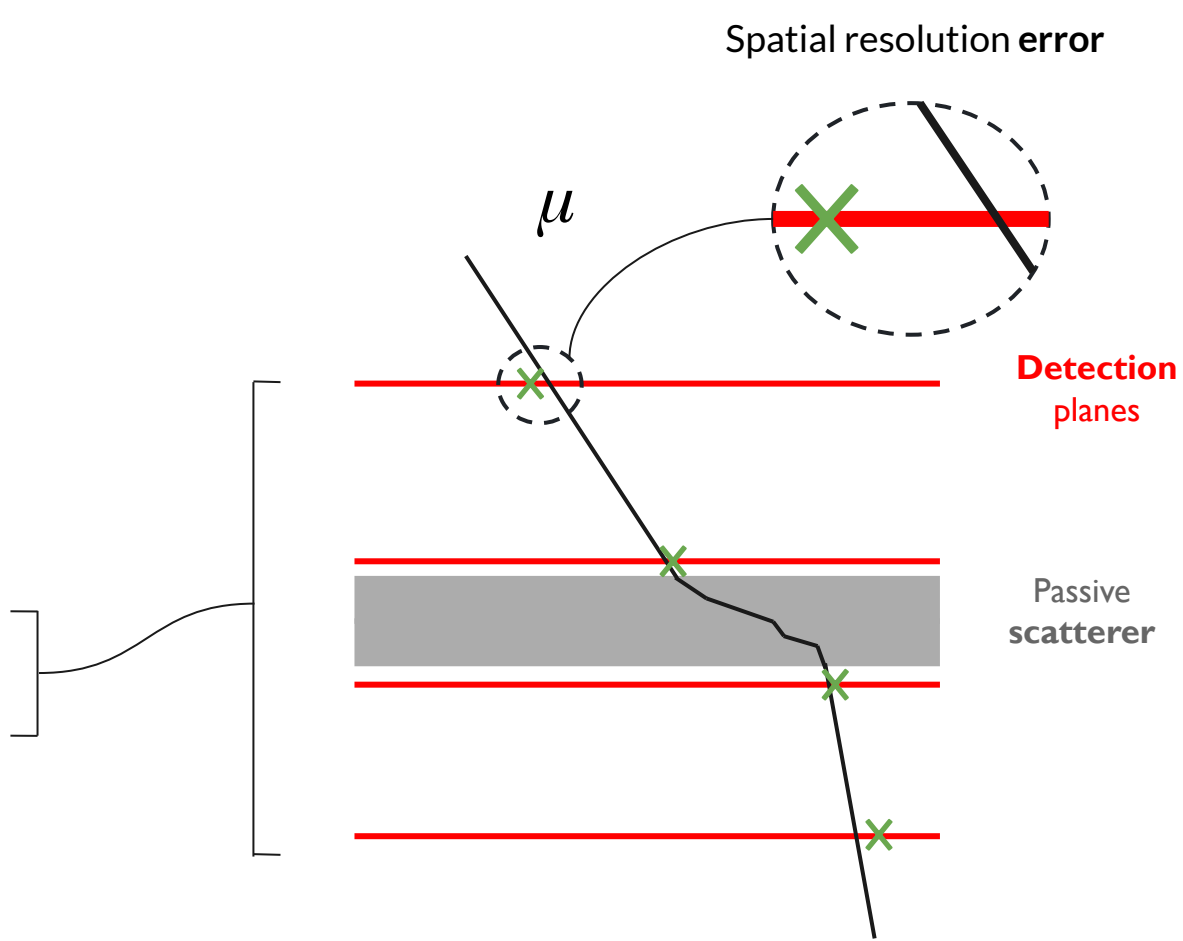


- Panels properly centered around object
- Panels z placement grants better angular resolution
- Acceptance is not ideal, must include acquisition time as a constraint

III - Momentum measurement module

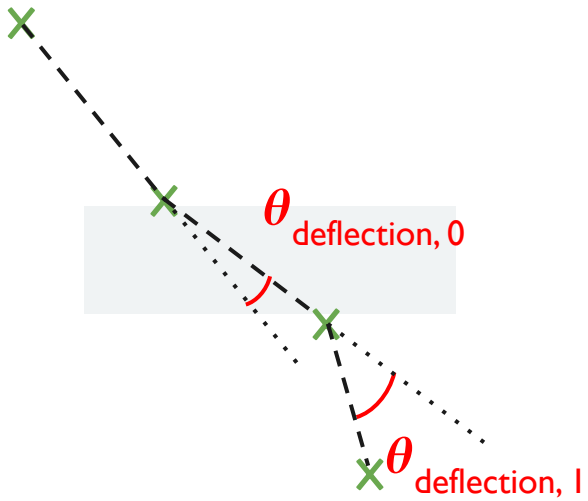
Momentum measurement module



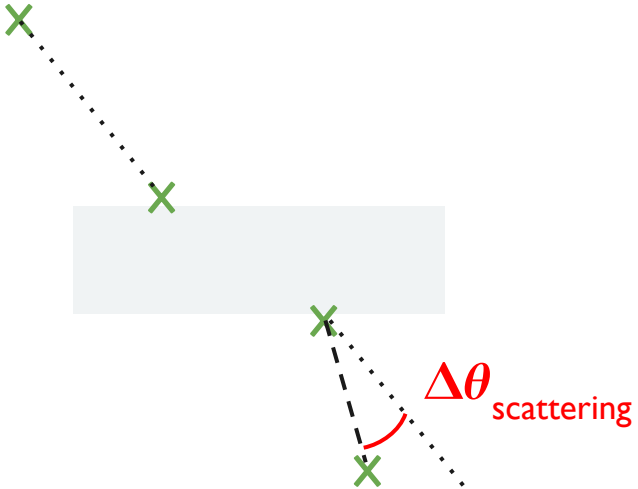


Momentum measurement module: input variables

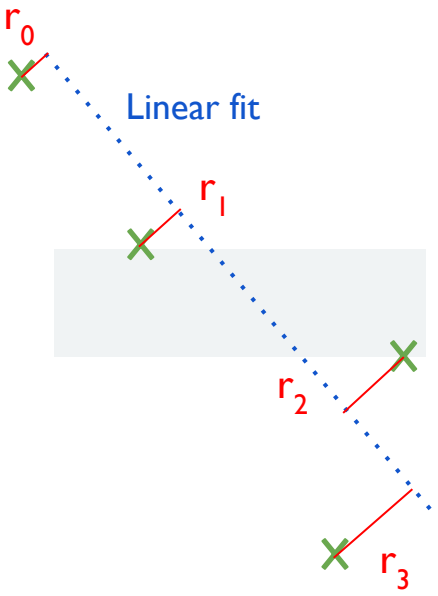
Deflection angles



Scattering angle



Fit residuals r



Momentum inference: DNN regression

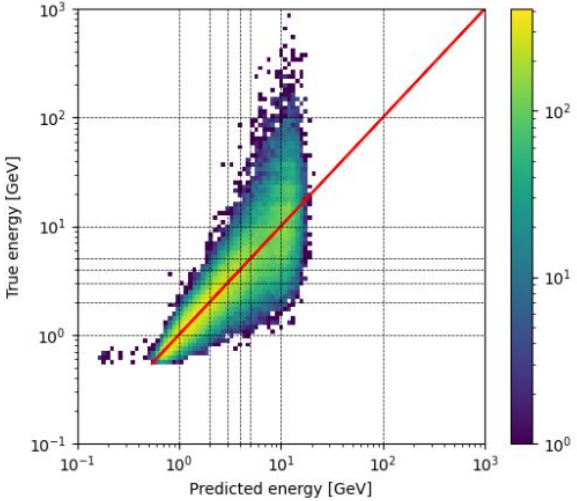
Input variable

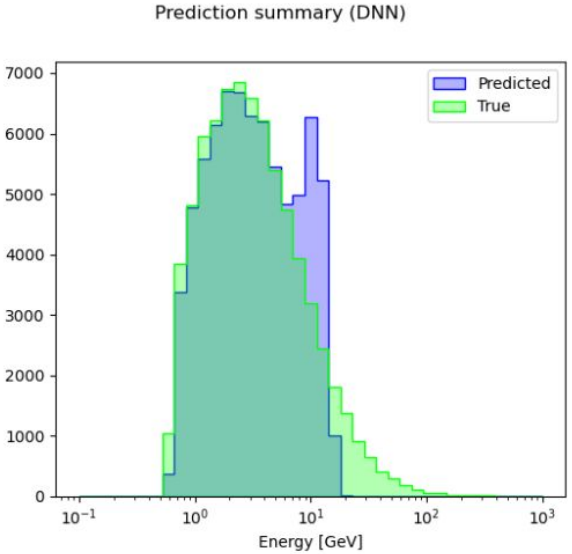
- 8 **deflection** angles
- 10 **residuals**
- 4 **scattering** angles

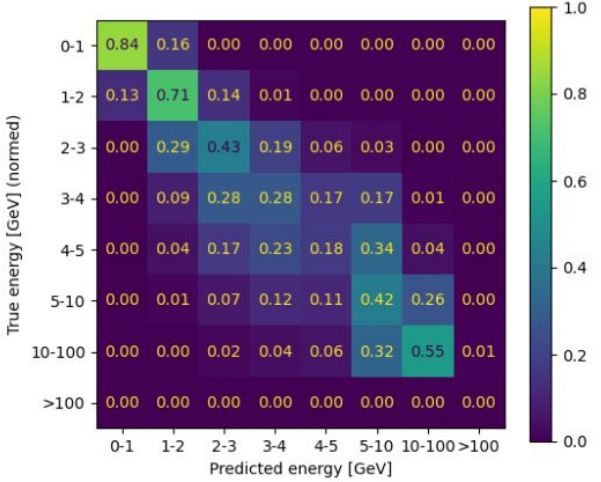
2mm spatial resolution

Inference method

- **DNN**
- Three 64 neurons layers
- Infer on $\log(p)$

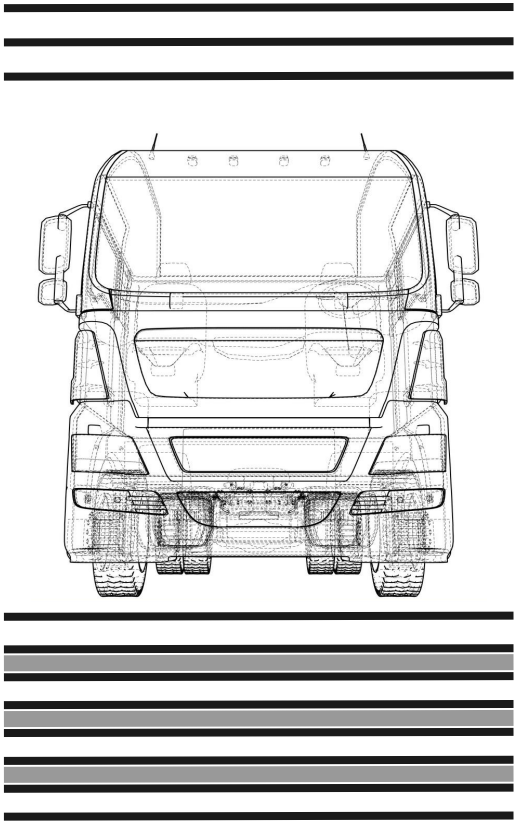






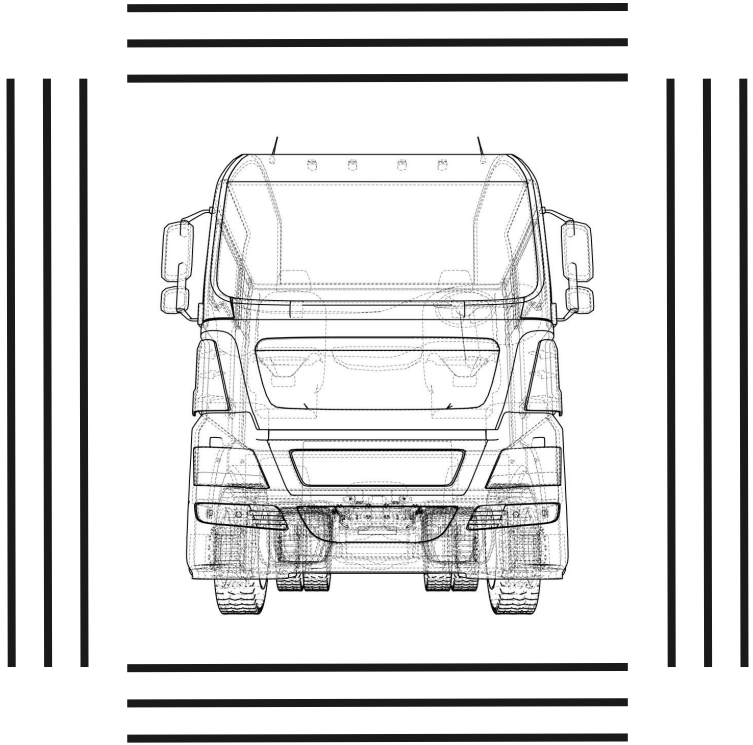
Question TomOpt will answer

Is it worth it to add a muon energy spectrometer to the detector?



momentum measurement module

OR



IV - Conclusion

CONCLUSION

- **TomOpt optimises** detector configuration for **specific** Muon Scattering Tomography **tasks**
- **TomOpt** offers a **differentiable** MST **simulation pipeline**
- As long as **differentiability** is preserved, it can be **adapted** to **any tasks**

In the future

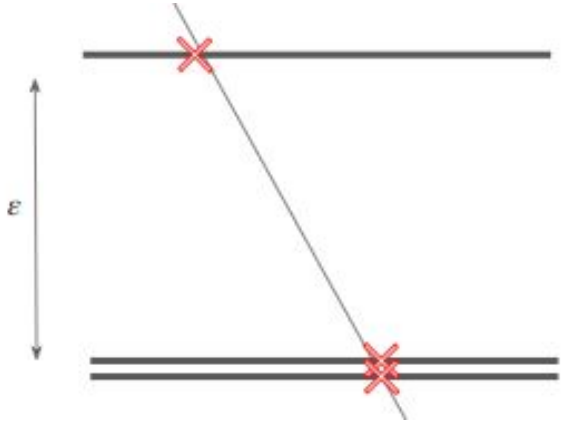
- **Open source release** of the software
- **Publication incoming!**
- **Include momentum measurement sub-detector** in the optimisation chain
- Don't hesitate to contact us!

Contact: *maximelagrange98@gmail.com*

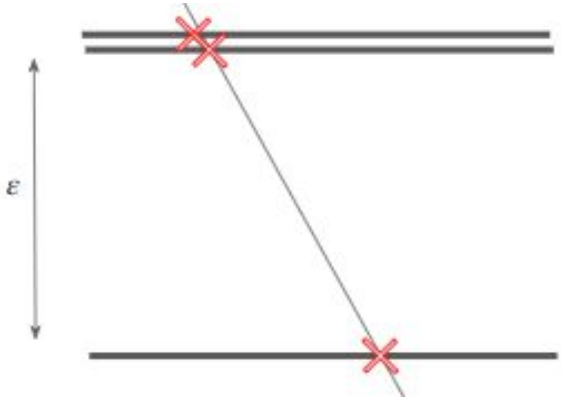
BACKUP SLIDES

Detector z placement: effect on POCA precision

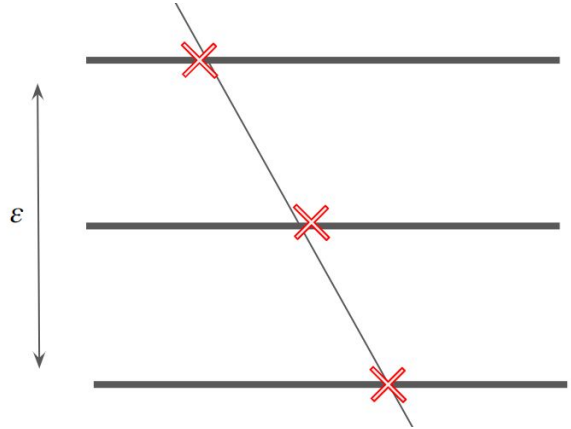
Scenario A



Scenario B



Scenario C



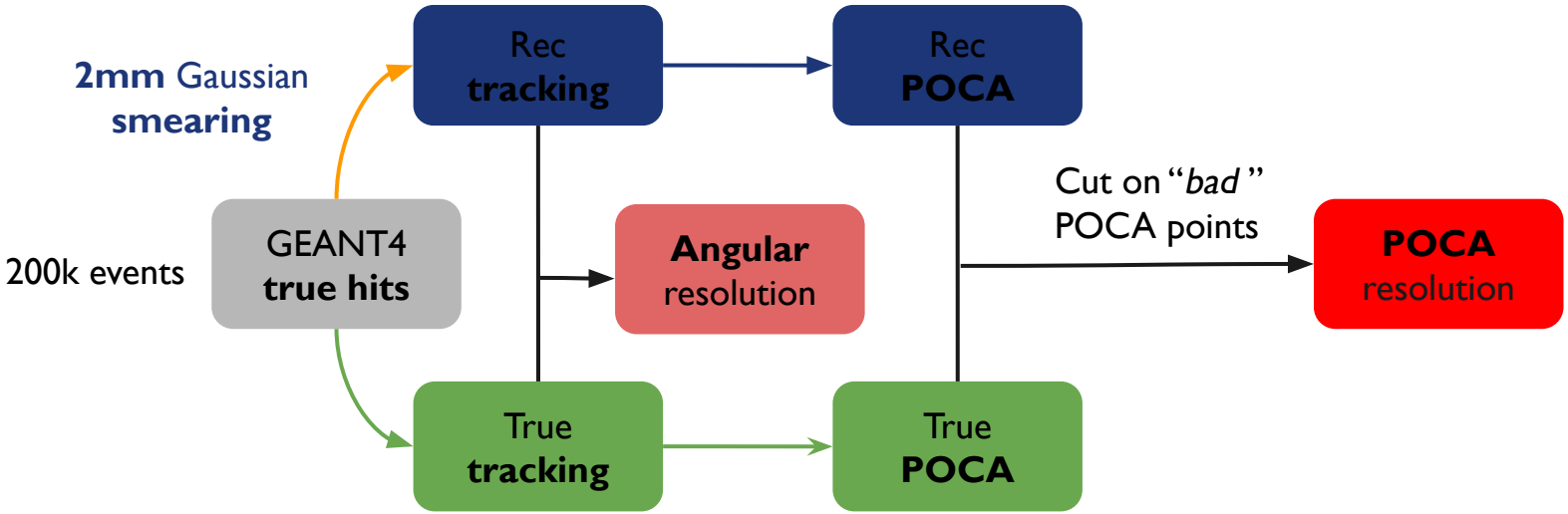
Configuration:

- $\mathcal{E}$ = 30cm
- Spatial resolution = 2mm

Question:

- Which scenario gives the best **precision** on **POCA** points **location**?
- Associated **angular resolution**?

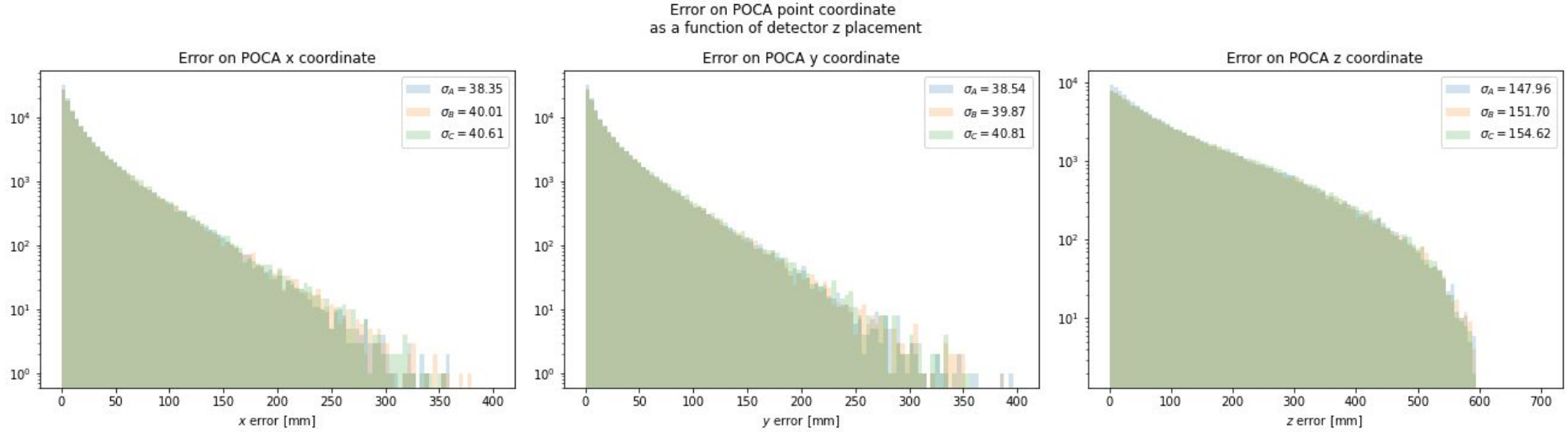
Detector z placement: effect on POCA precision measurement



Angular resolution = std(θ_{true} - θ_{rec})

POCA resolution$_{x,y,z}$ = std(**POCA**$_{x,y,z\ true}$ - **POCA**$_{x,y,z\ rec}$)

Detector z placement: effect on POCA precision results

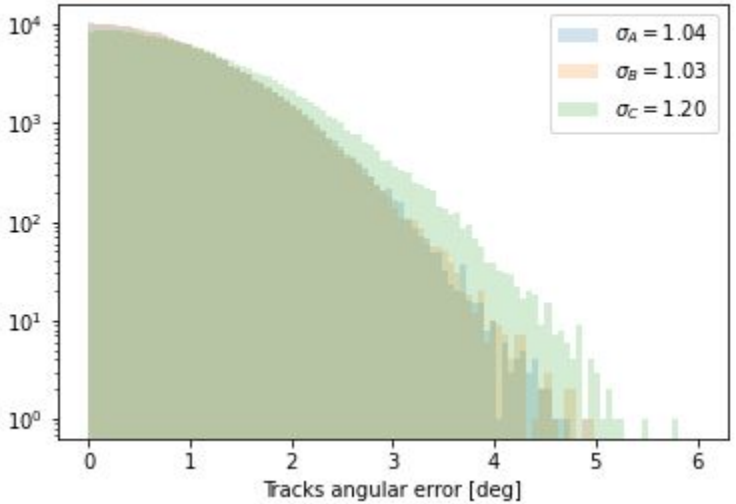


Resolutions	$POCA_x$	$POCA_y$	$POCA_z$
A	38.35	38.54	147.96
B	40.01	39.87	151.70
C	40.61	40.81	154.62

Scenario A has a ~3.5% $POCA_{xy}$ and ~2.5% $POCA_z$ **better** precision **than B**!

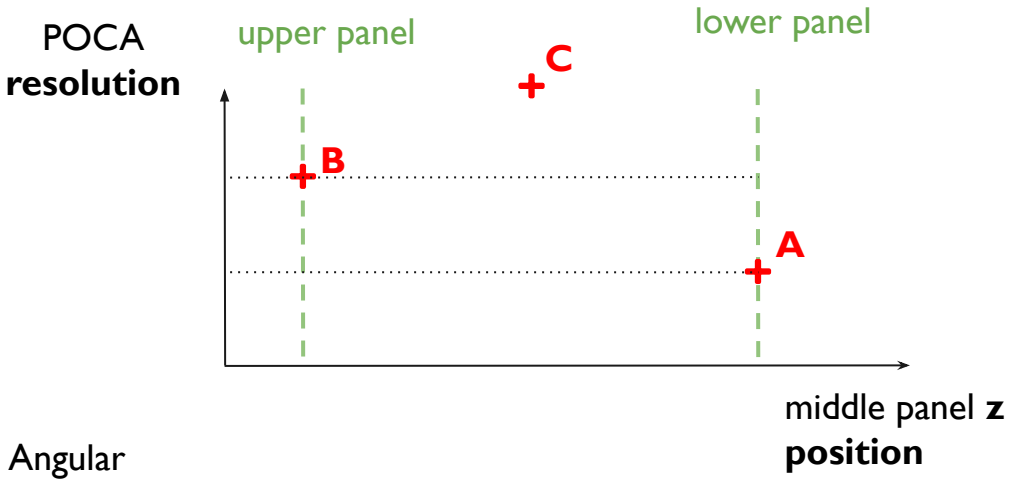
Scenario A has a ~5.5% $POCA_{xy}$ and ~4% $POCA_z$ **better** precision **than C**!

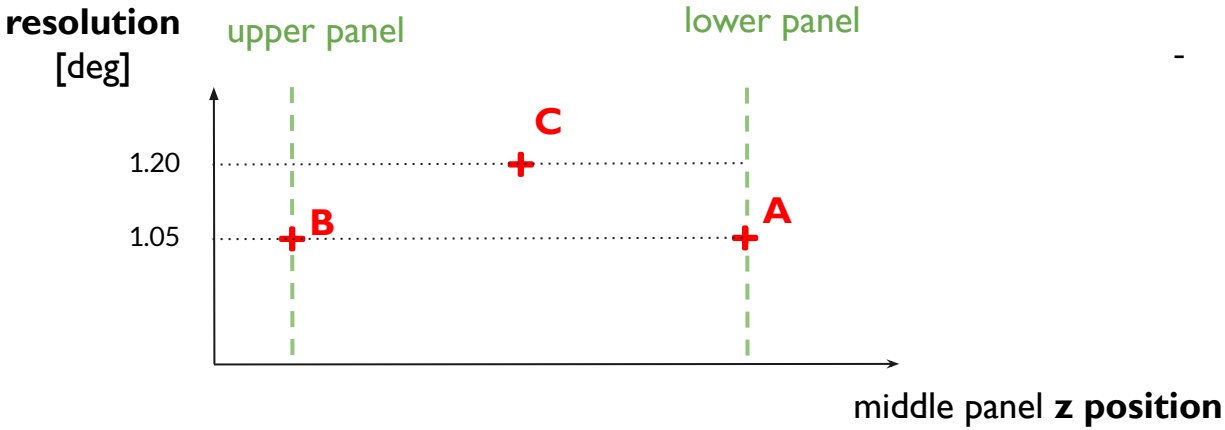
Detector z placement: effect on angular resolution



Scenario A and **B are equivalent**, and have a ~13% better **angular resolution** than **scenario C!**

Detector z placement: conclusions

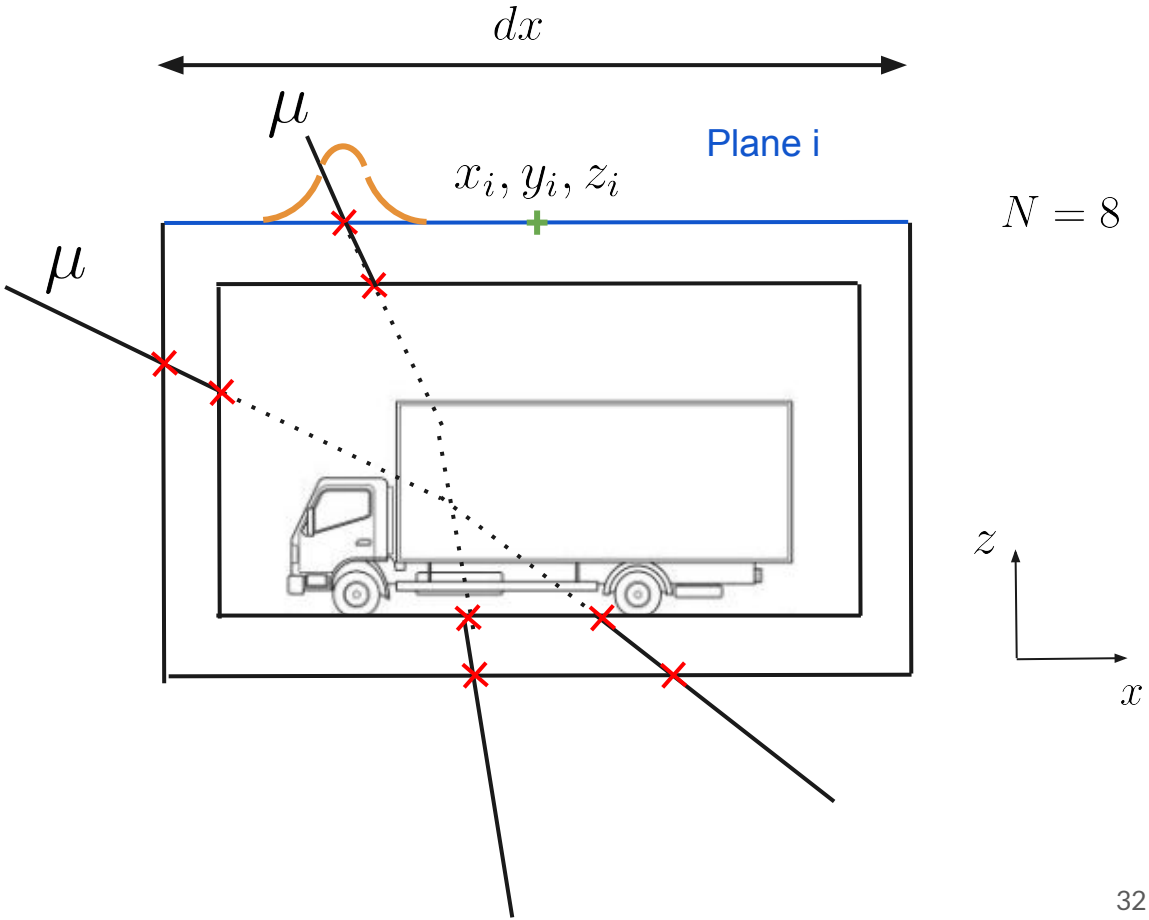




- Now must study **gradients behaviour** between **A, B** and **C**
- Difference between those scenario can be observed with **low spatial resolution** (2mm) and **large number of muons** (200k)
- Is **TomOpt sensitive** to this?

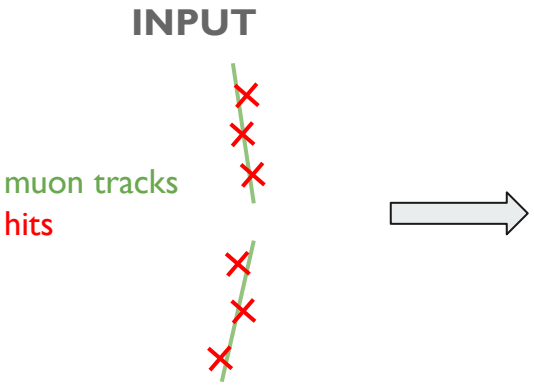
Hardware parameters

Number of detection planes	N
Placement	x_i, y_i, z_i
Dimension	dx, dy
Spatial resolution	$\sigma_{x,y}$
Efficiency	ϵ
Technology	RPC's Scintillators MicroMegas

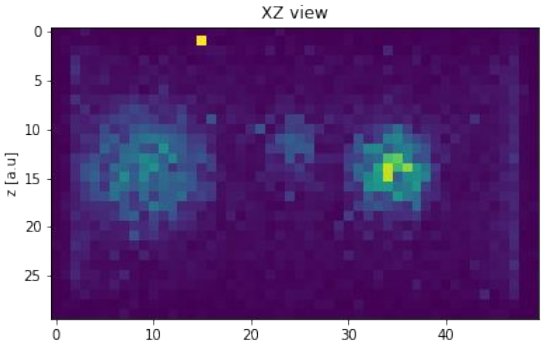


Software parameters

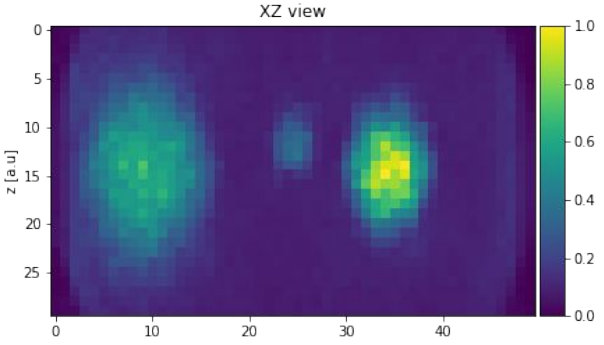
I - Reconstruction algorithm (POCA, ASR, Maximum Likelihood, Binned Clustered Algorithm, etc..)



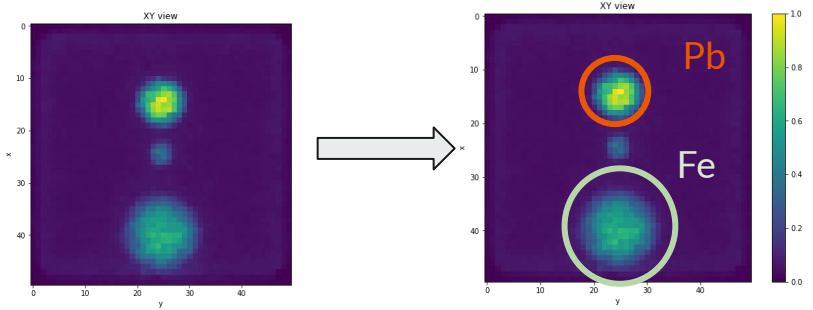
a - Point Of Closest Approach (POCA)



b - Angle Statistic Reconstruction algorithm (ASR)



II - Material classifiers



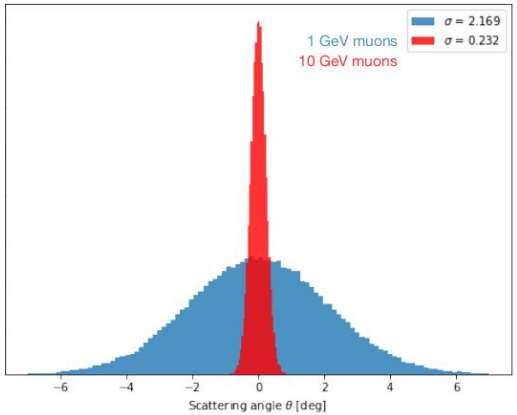
Typical MST reconstruction parameters

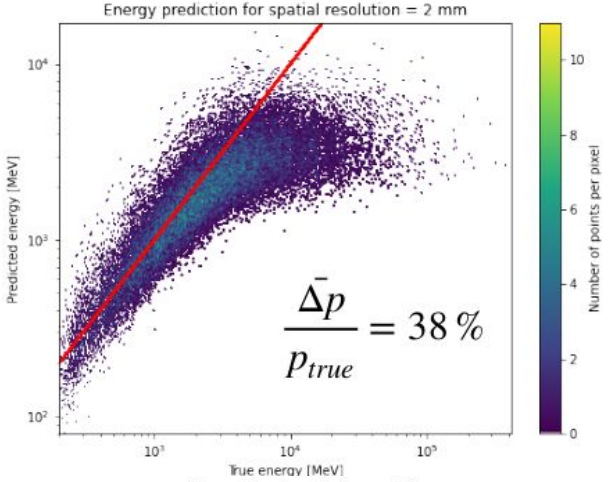
- Cuts on scattering angles
- Noise reduction sensitivity

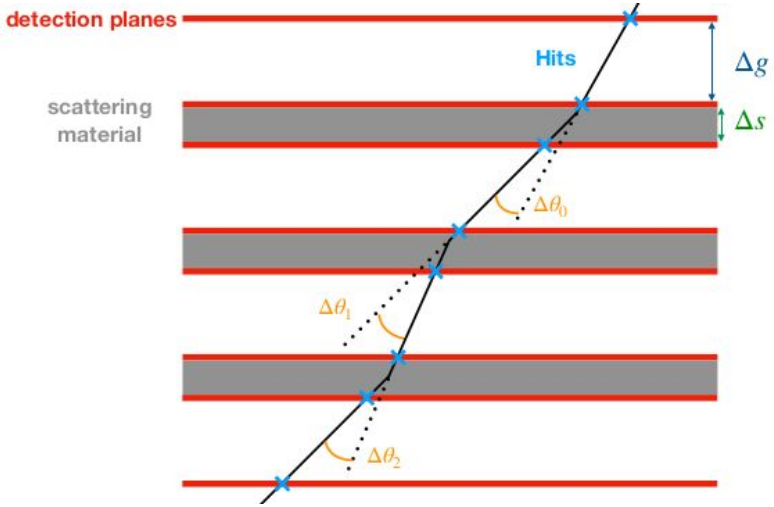
Muon momentum measurement

Muon **scattering amplitude**

$$\propto \frac{1}{p}\sqrt{\frac{x}{X_0}}$$





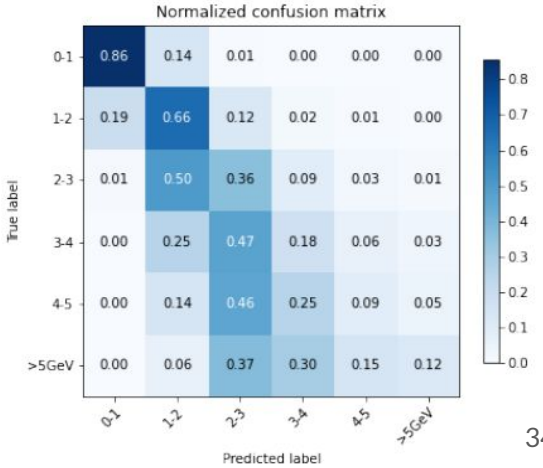


Scattering angle measurement

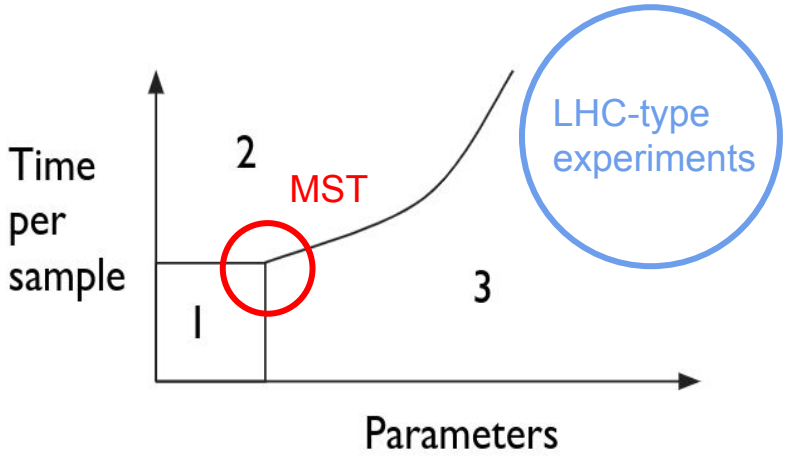
$$\theta_{RMS} = \frac{1}{3}(\theta_1^2 + \theta_2^2 + \theta_3^2)$$

Multiple Coulomb scattering model

$$p = \frac{13.6MeV}{\theta_{RMS}}\sqrt{\frac{x}{X_0}}$$



Parameter space in MST



1. Grid/random search
2. Bayesian optimisation, Simulated annealing, genetic algorithm, particle swap optimisation, …
3. Gradient-based optimisation: Newtonian, gradient descent, BFGS, …

Hardware

- Tracking system **technology** (RPC's, scintillators, micromegas, drift tubes, etc..)
- **Spatial resolution**
- **Efficiency**
- **Tracking system** (# planes, dimensions, geometry)

Software

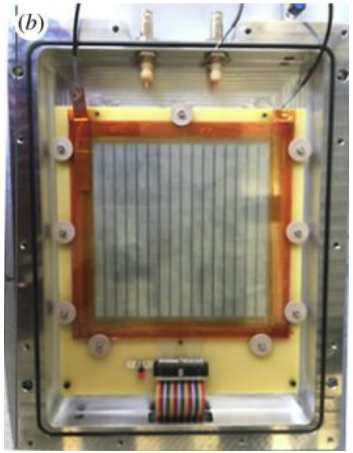
- **Reconstruction algorithms**
- **Material classifiers**
- **Image recognition, clustering**

Detector parameters and cost

Given its design and technology choices, how to estimate detector cost?

Local cost γ

Cost specific to the technology used



Sealed RPC prototype in development at UCLouvain

Local cost γ

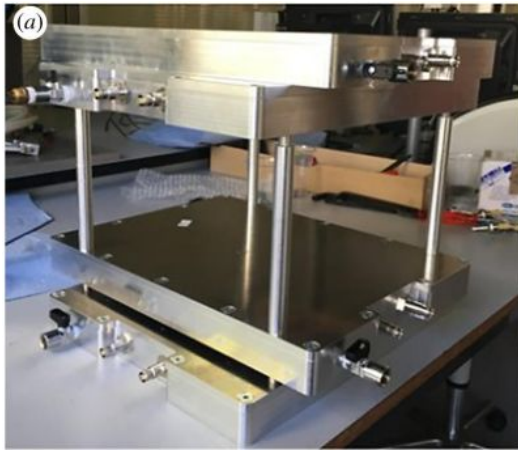
$$\gamma_{technology} = \gamma(x)$$

with x the performance properties of the given technology e.g time, spatial resolution, efficiency

$$\gamma\,[\,m^{-2}.readout^{-1}\,]$$

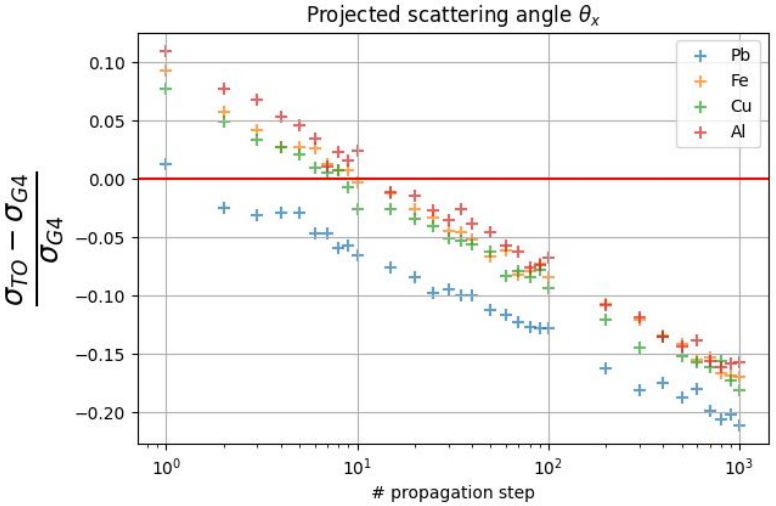
Global cost C(γ,φ)

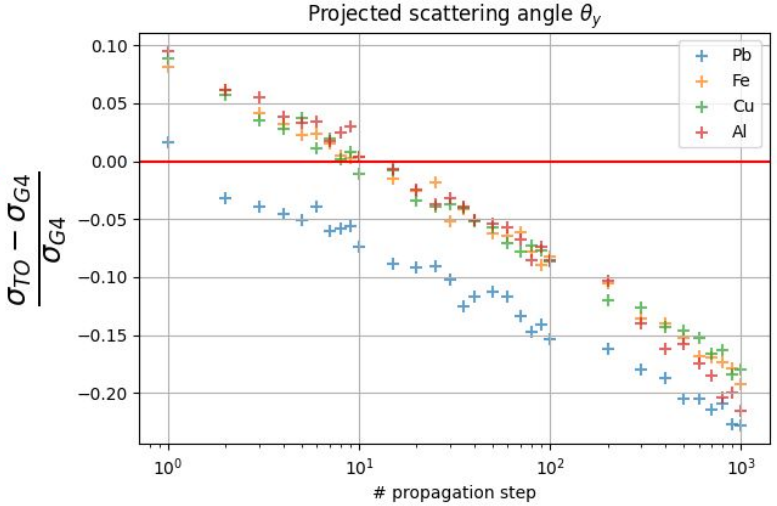
Describe overall detector conception

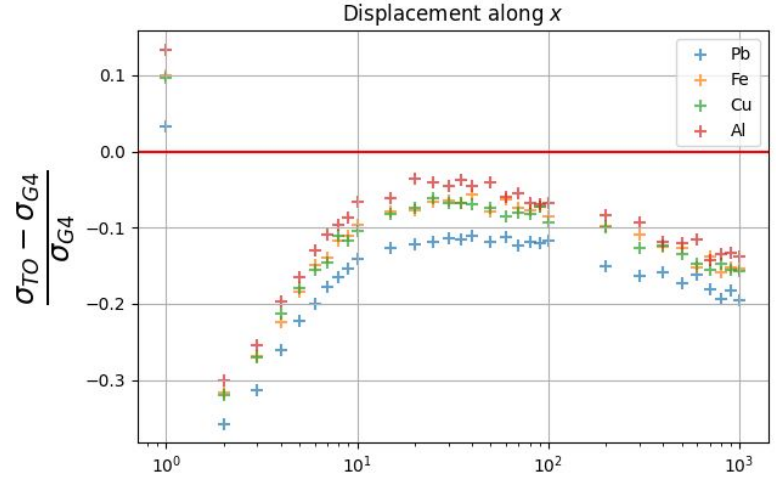


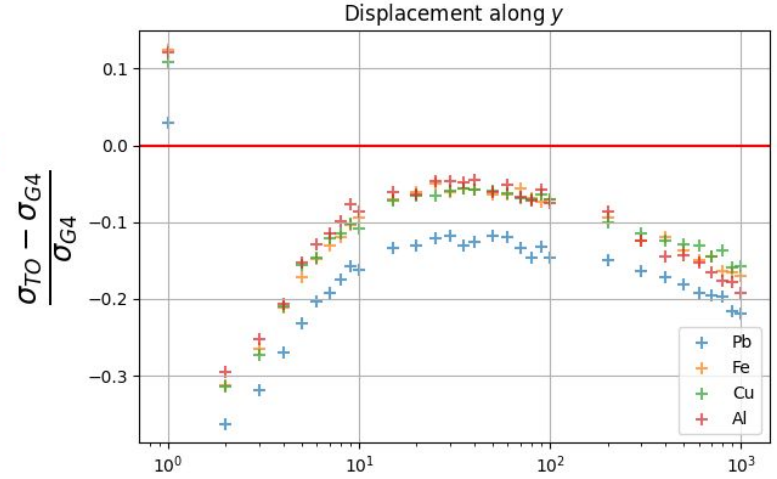
Portable muoscope in development at UCLouvain

50 GeV muon propagation through 50cm thick material block

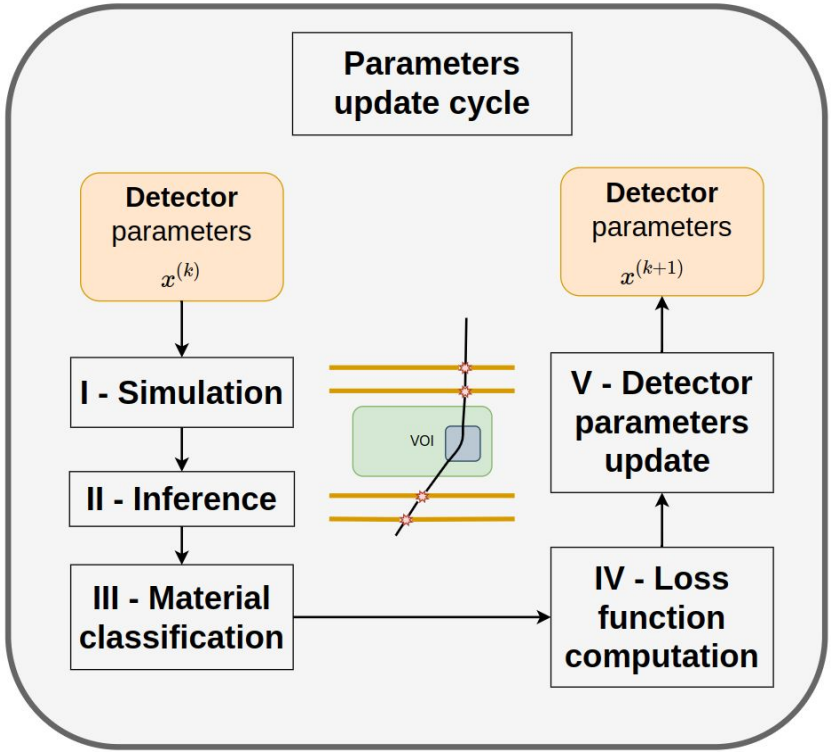


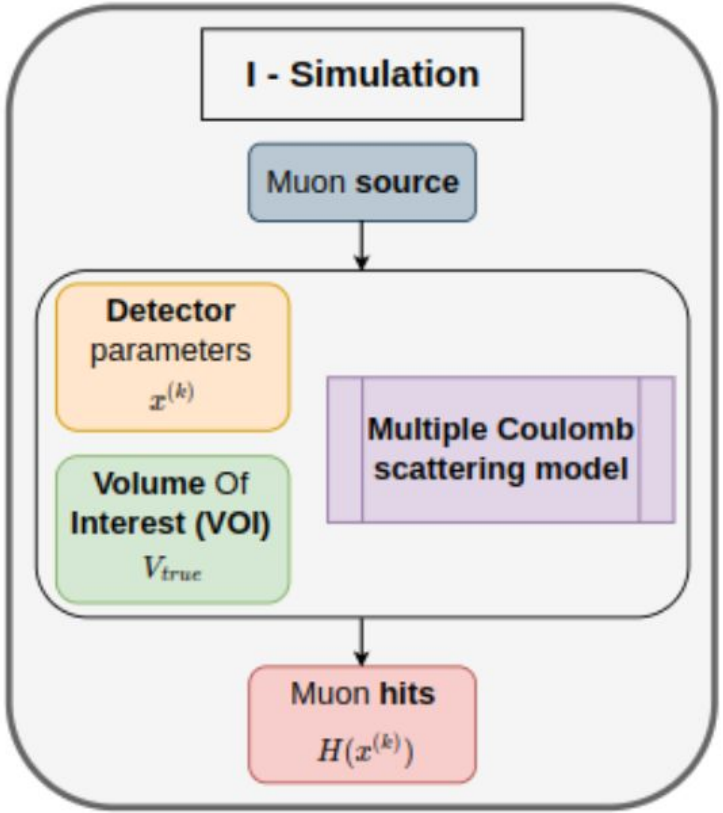




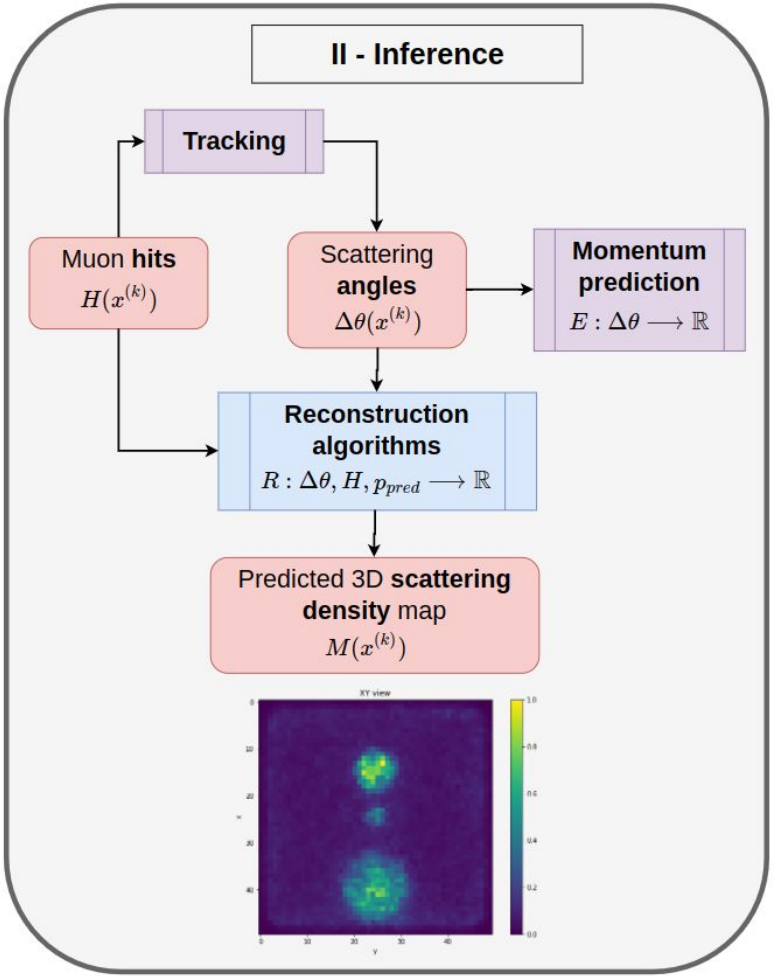


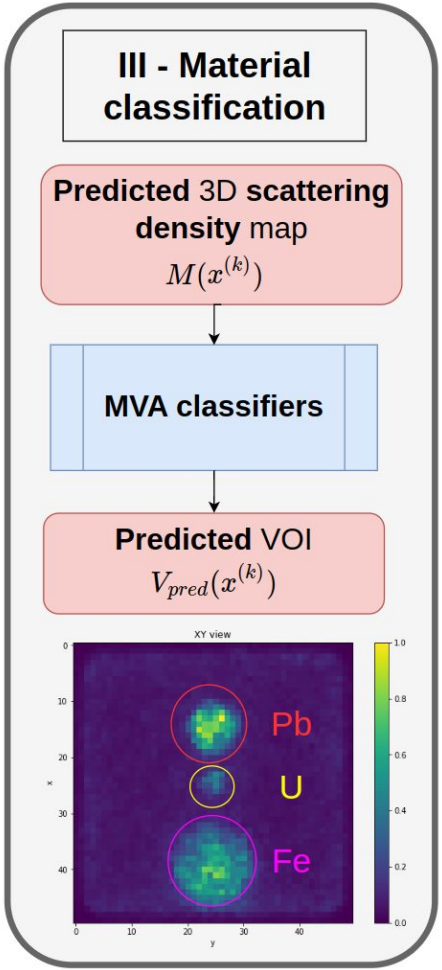
TomOpt


Parameters update cycle
Detector parameters $x^{(k)}$
I - Simulation
II - Inference
III - Material classification
VOI
Detector parameters $x^{(k+1)}$
V - Detector parameters update
IV - Loss function computation

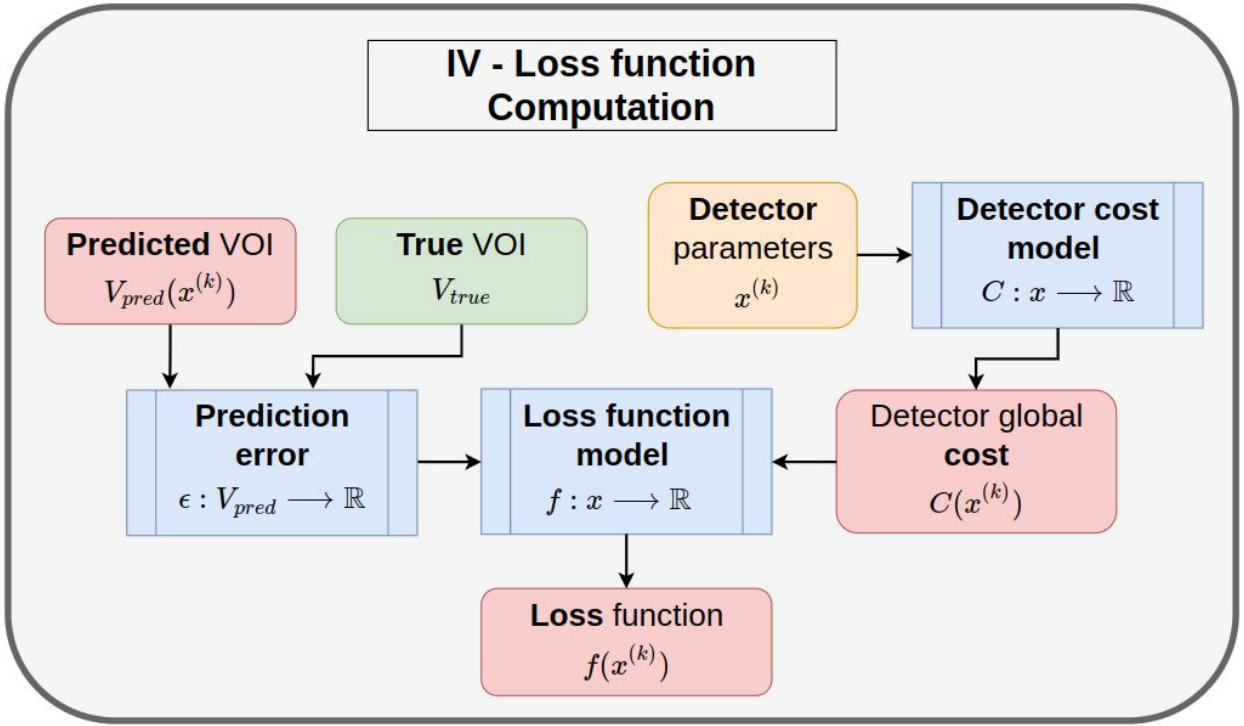

I - Simulation
Muon source
Detector parameters $x^{(k)}$
Volume Of Interest (VOI) V_{true}
Multiple Coulomb scattering model
Muon hits $H(x^{(k)})$

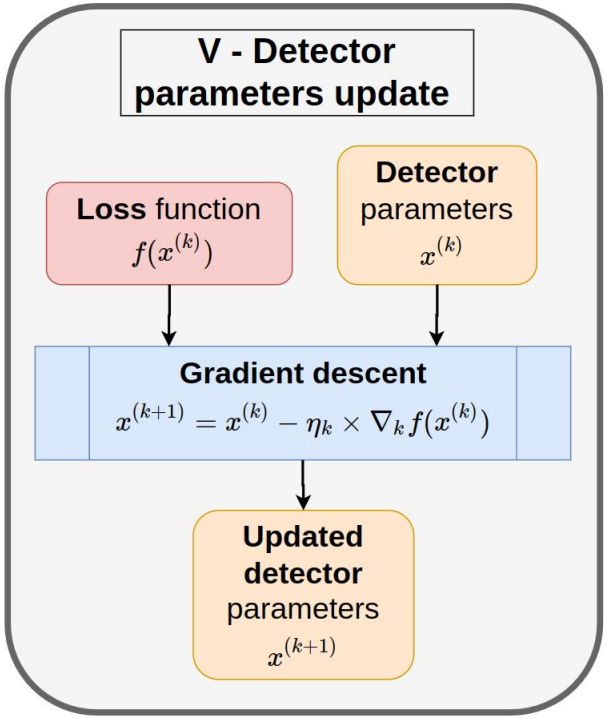
TomOpt


II - Inference
Tracking
Muon hits
$H(x^{(k)})$
Scattering angles
$\Delta\theta(x^{(k)})$
Momentum prediction
$E : \Delta\theta \longrightarrow \mathbb{R}$
Reconstruction algorithms
$R : \Delta\theta, H, p_{pred} \longrightarrow \mathbb{R}$
Predicted 3D scattering density map
$M(x^{(k)})$
XY view


III - Material classification
Predicted 3D scattering density map
$M(x^{(k)})$
MVA classifiers
Predicted VOI
$V_{pred}(x^{(k)})$
XY view
Pb
U
Fe

TomOpt


IV - Loss function Computation
Predicted VOI
$V_{pred}(x^{(k)})$
True VOI
V_{true}
Detector parameters
$x^{(k)}$
Detector cost model
$C : x \longrightarrow \mathbb{R}$
Prediction error
$\epsilon : V_{pred} \longrightarrow \mathbb{R}$
Loss function model
$f : x \longrightarrow \mathbb{R}$
Detector global cost
$C(x^{(k)})$
Loss function
$f(x^{(k)})$


V - Detector parameters update
Loss function
$f(x^{(k)})$
Detector parameters
$x^{(k)}$
Gradient descent
$x^{(k+1)} = x^{(k)} - \eta_k \times \nabla_k f(x^{(k)})$
Updated detector parameters
$x^{(k+1)}$