Artificial Intelligence applied to the spectro-identification of radioelements in a complex radiological environment

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Thesis supervisor: Geoffrey DANIEL[2],
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1. Recap spectroscopy

Recap Spectroscopy

Google: *investigation and measurement of spectra produced when matter interacts with or emits electromagnetic radiation.*

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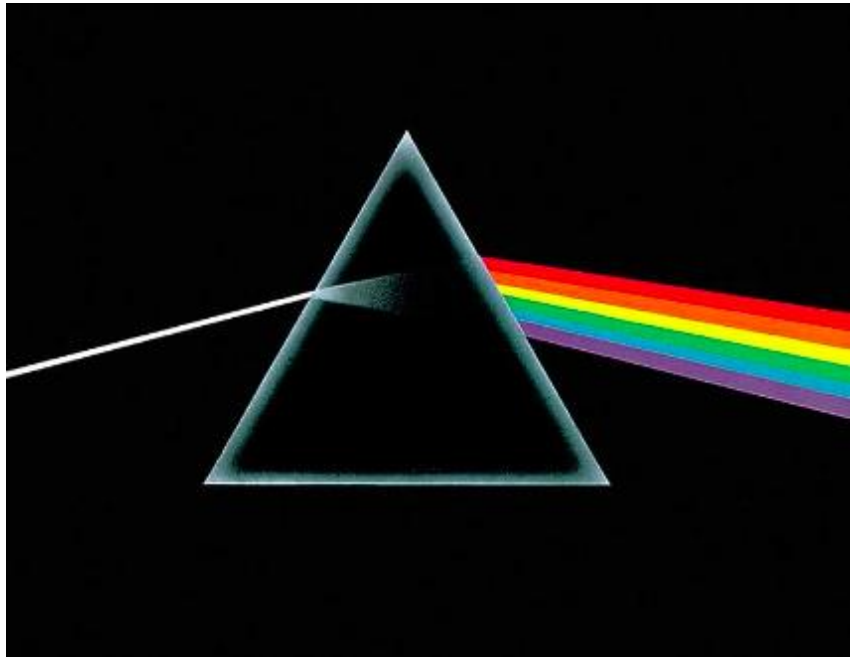
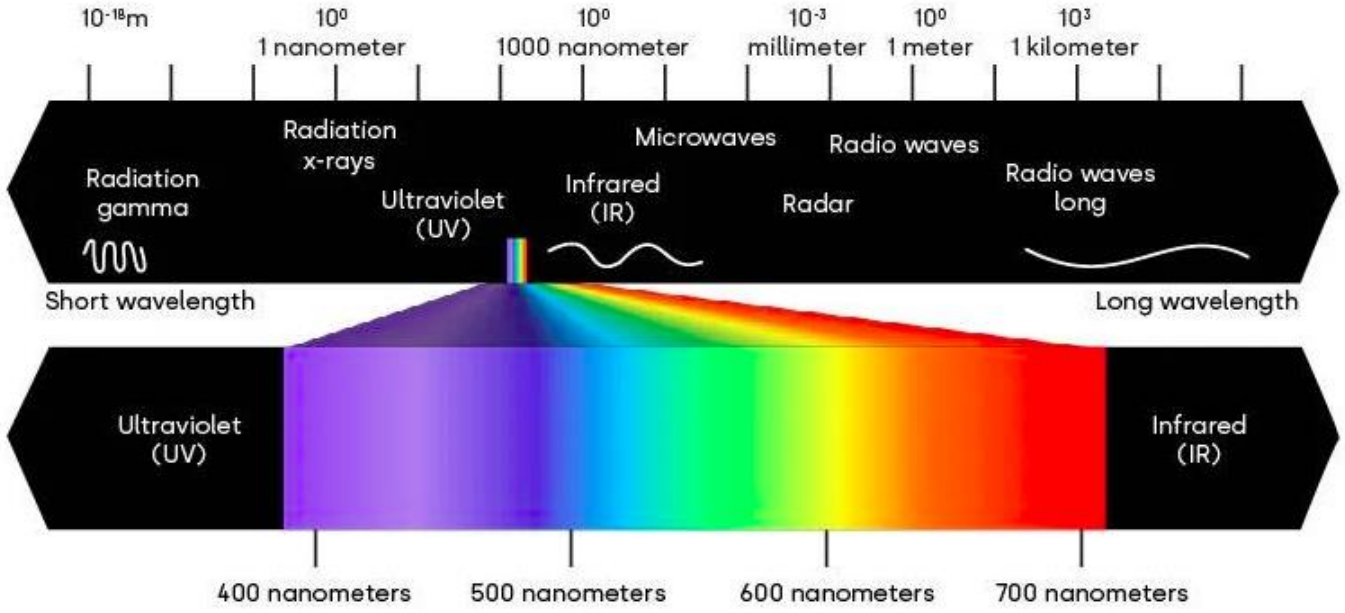


Visible spectrum



Recap Spectroscopy – X-ray and Gamma wavelength

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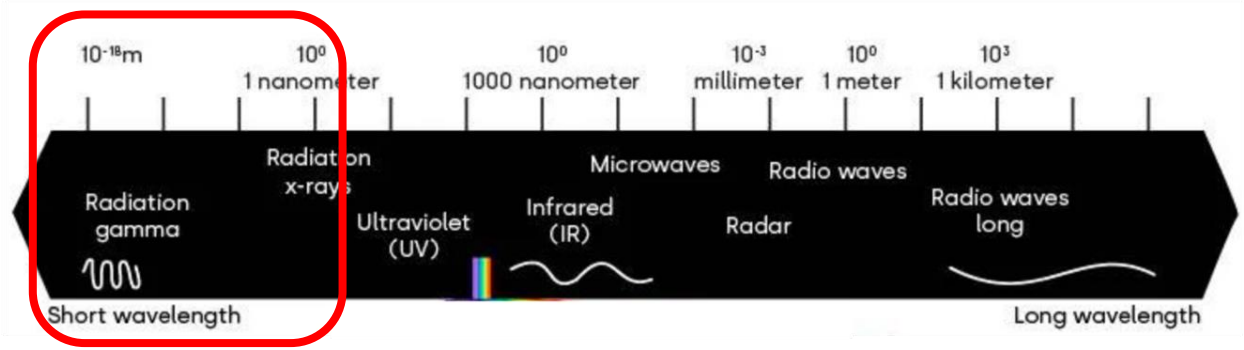

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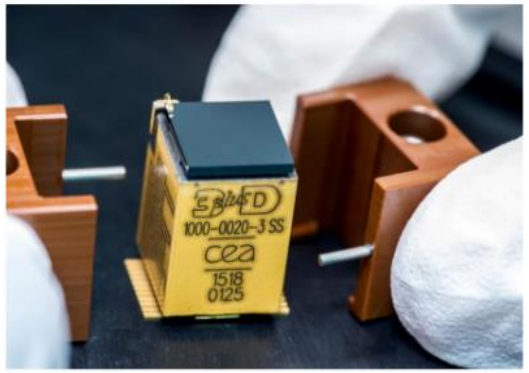

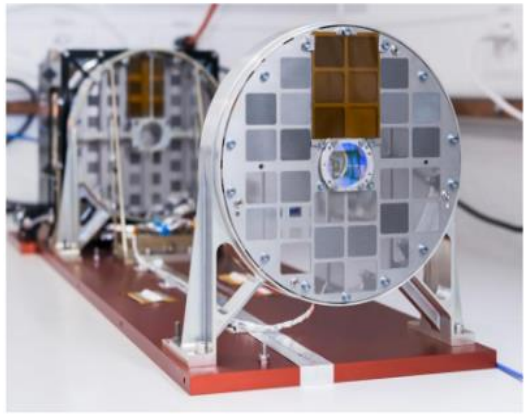

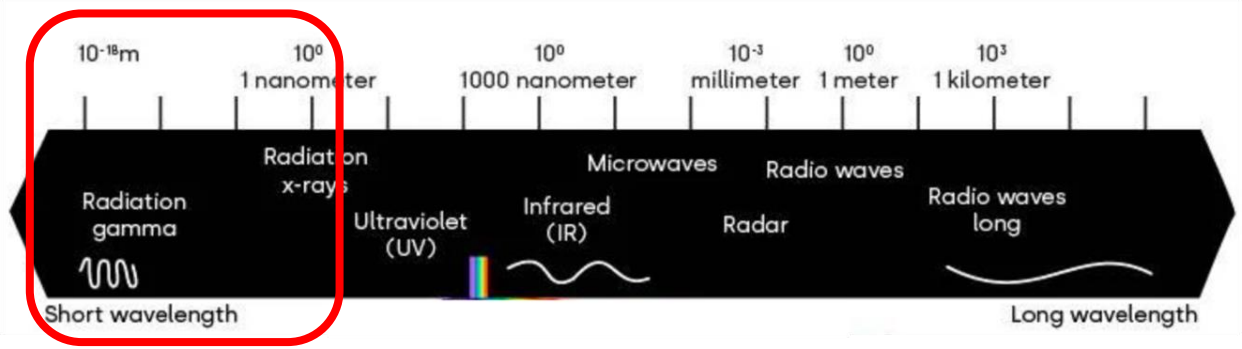

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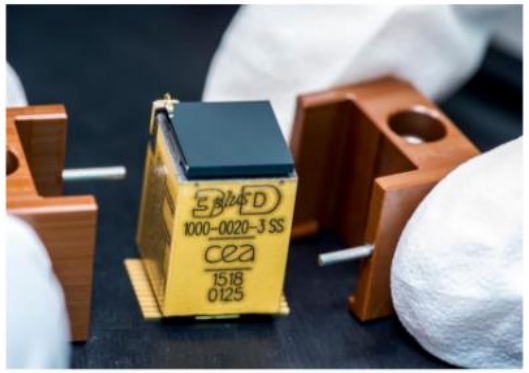
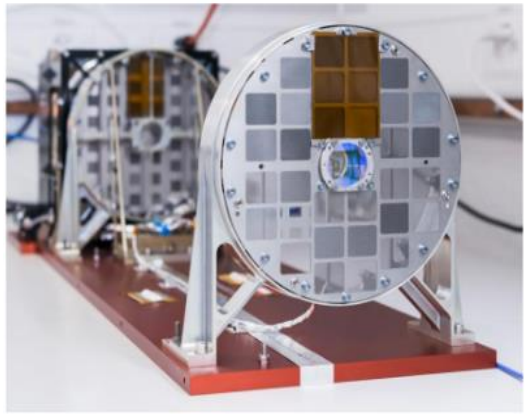


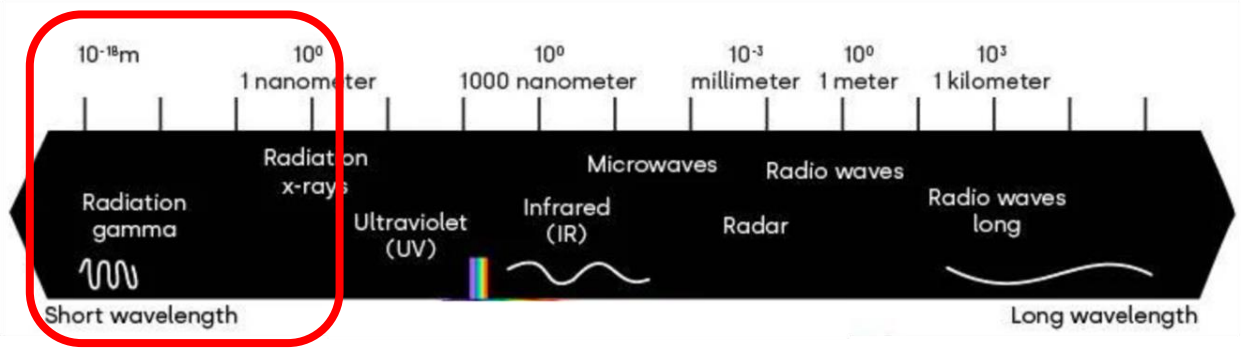


Light-matter interaction Physics:

PE effect

Compton scattering

Pair creation



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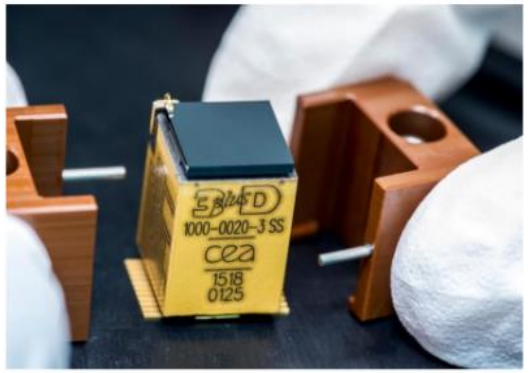

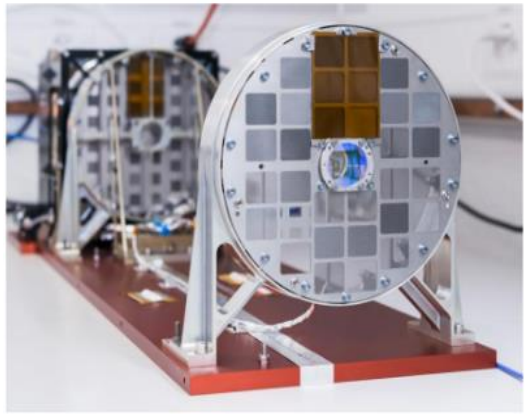

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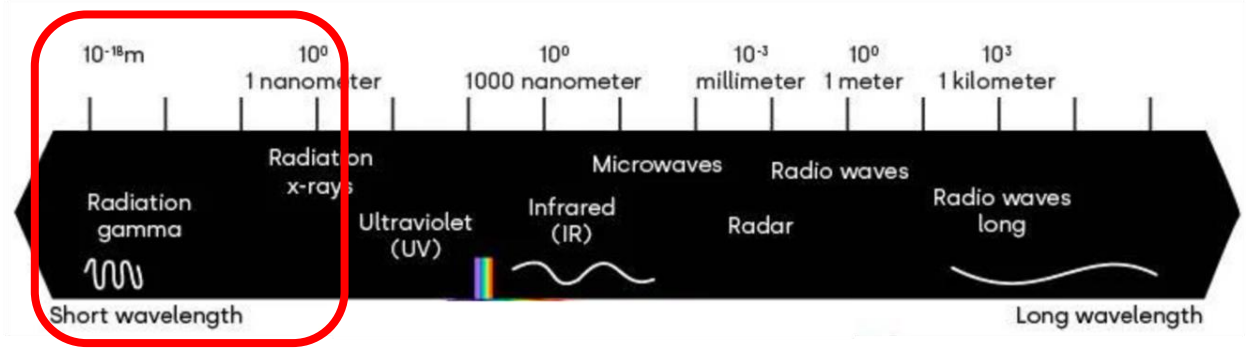

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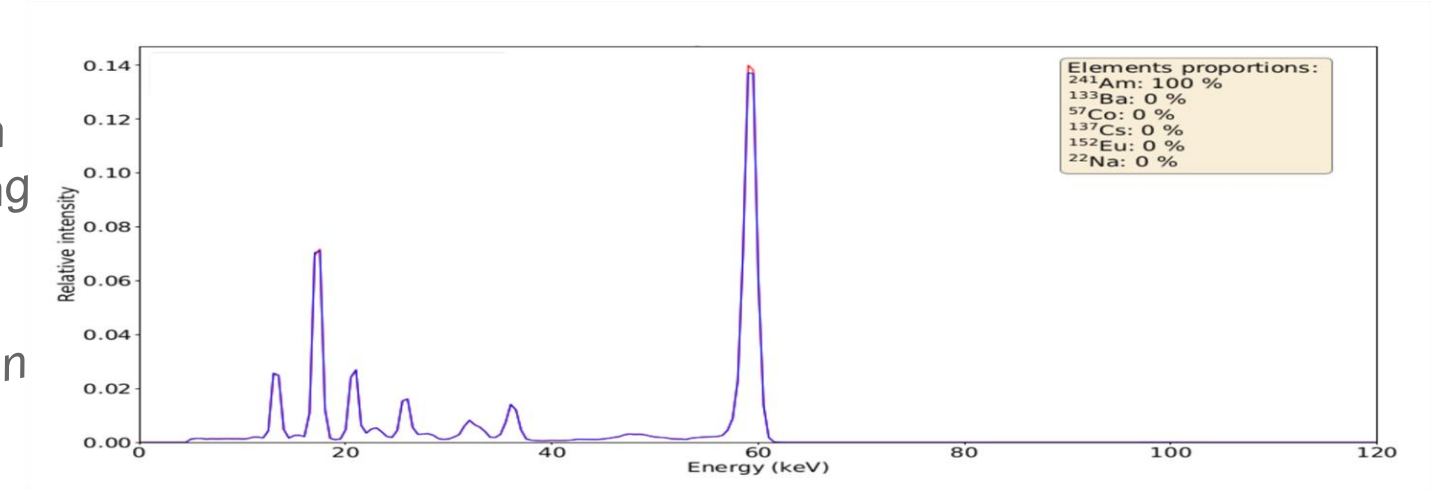


The detector
Caliste

- **CdTe** semi-conductor crystal
- **Miniature** pixelated **spectro**-imager
- First developments for **astrophysical** application
- From space applications to **industrial** applications:
  - Medical application: breast tumor cells detection
  - **Nuclear safety application**

Caliste Family

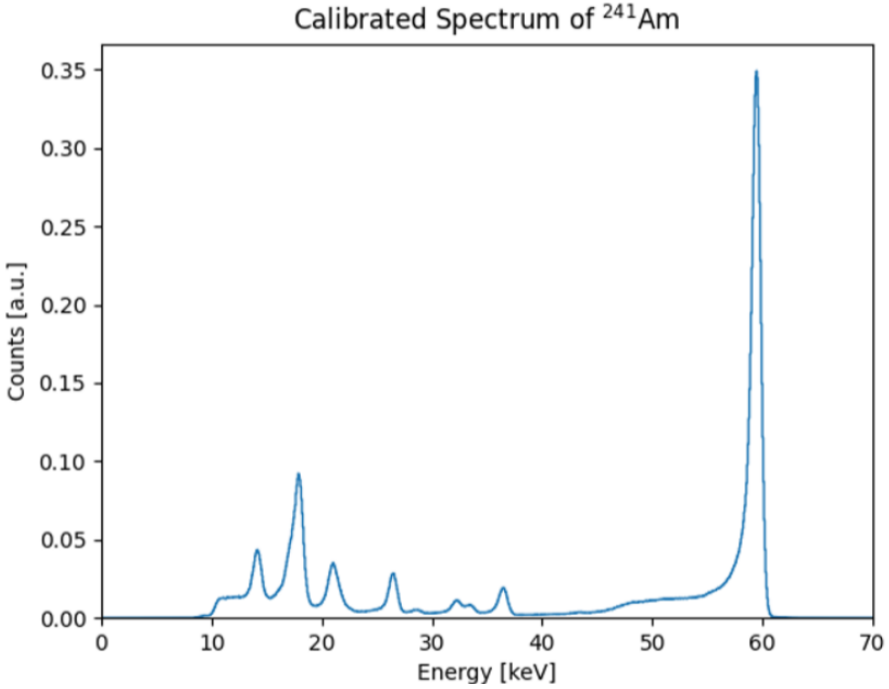
The detector
Caliste – O

- Pixelated detector 16 x 16 pixels
  - 800 μm pixel pitch
  - 2 mm crystal thickness
  - Surface: 2 cm²
  - Other versions available
- **High energy range**
  From 2 keV to 1 MeV
- *Spid-X* Energy resolution
  949±3 eV FWHM at 60 keV (1.6 %)
  10.2± 0.5 keV FWHM at 662 keV (1.5 %)
- **Capable of imaging and gamma spectroscopy**
  AI embedded model

Experimental data

Acquisition info
^{241}Am: 400 kBq

Spid-X Camera



2. Why Gamma Spectroscopy ?

Detector and why Gamma Spectroscopy

- Caliste - CdTe semiconductor crystal
- First developments for astrophysical application
- Solar Orbiter

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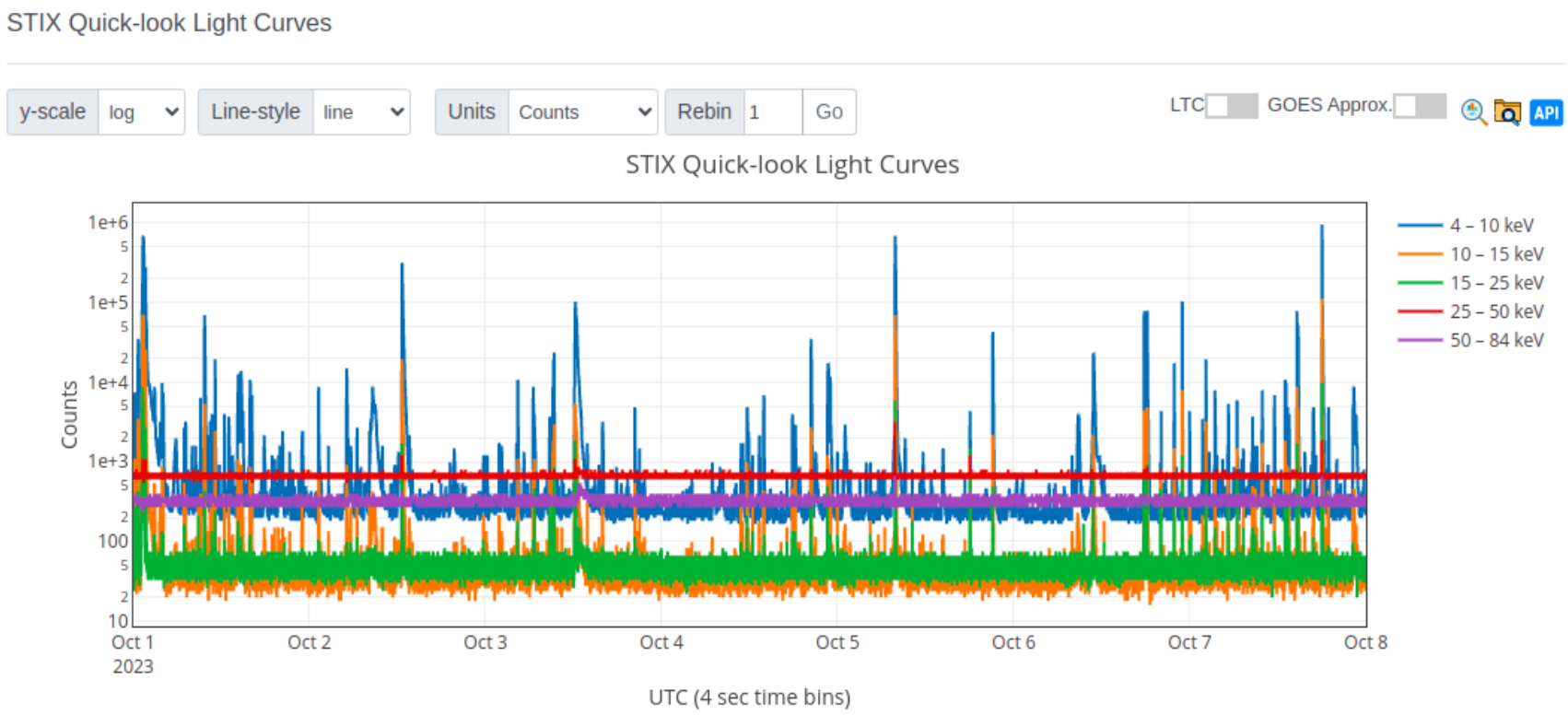
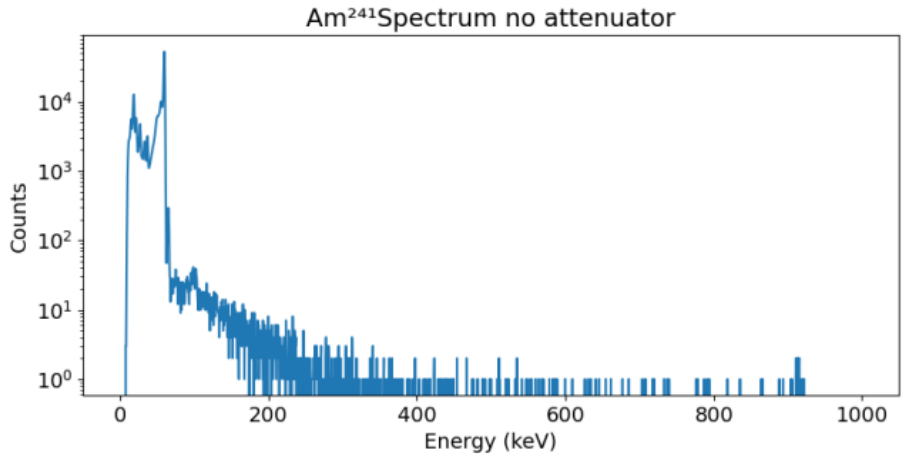


STIX Quick-look Light Curves
https://datacenter.stix.i4ds.net/view/ql/lightcurves#

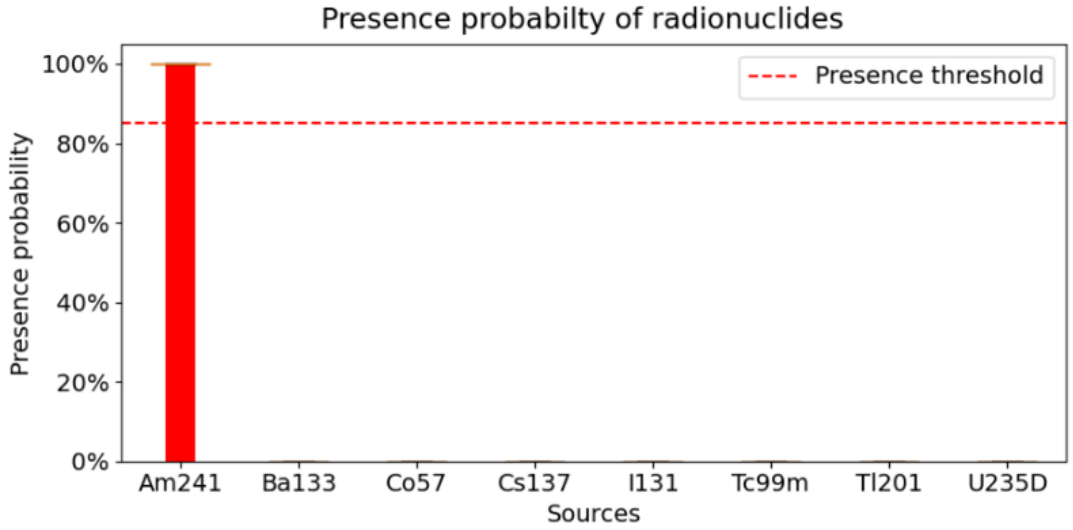
Detector and why Gamma Spectroscopy

- From space applications to industrial

Detector and why Gamma Spectroscopy

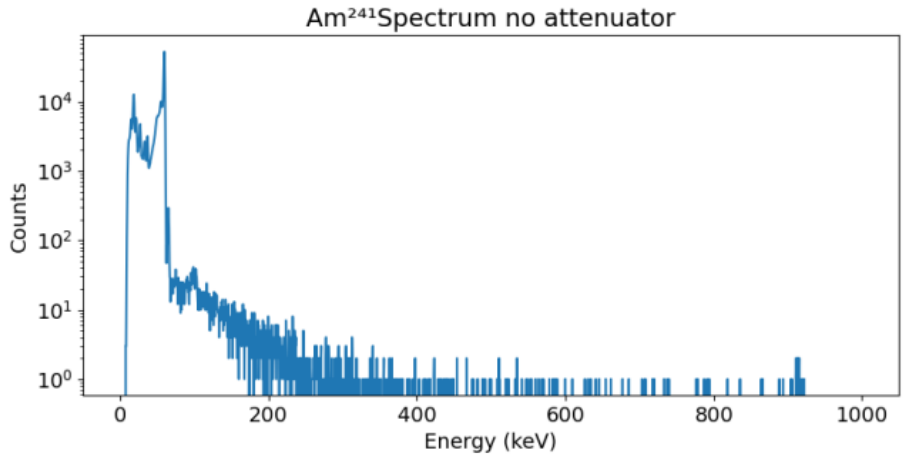


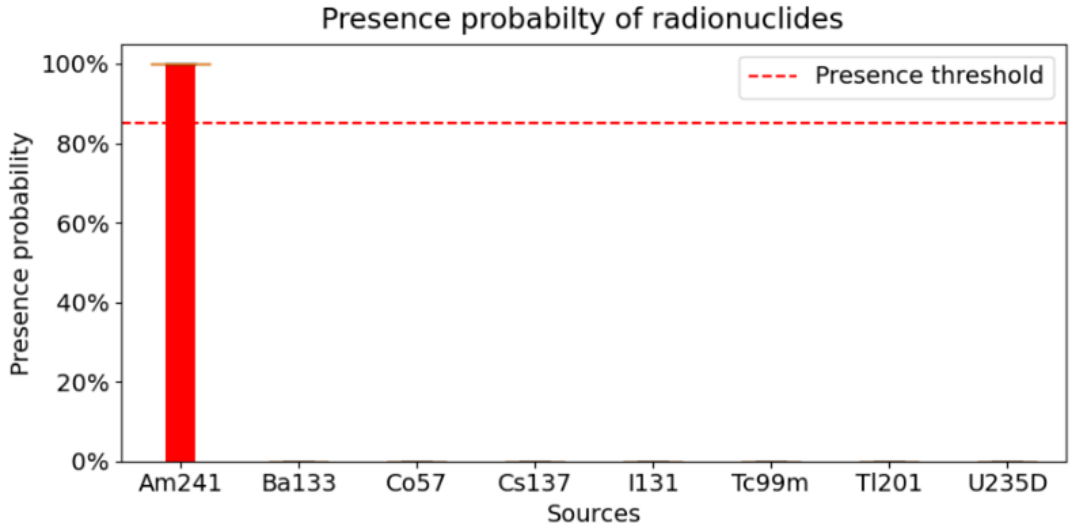
- From space applications to industrial

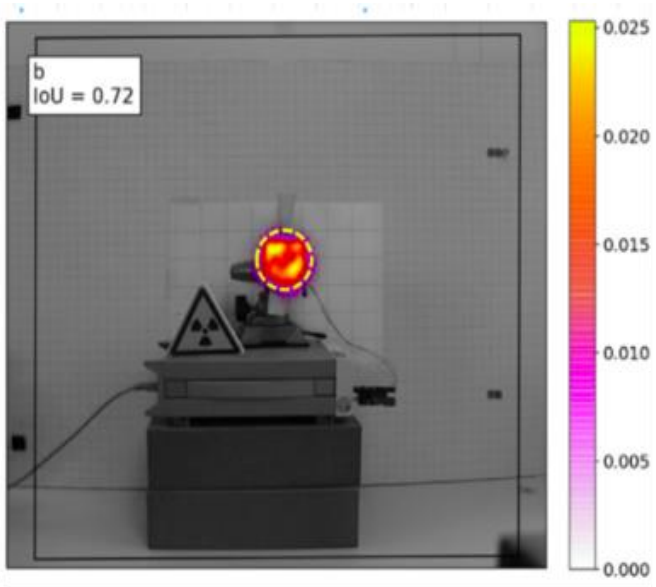


Detector and why Gamma Spectroscopy

- Imaging
- From space applications to industrial

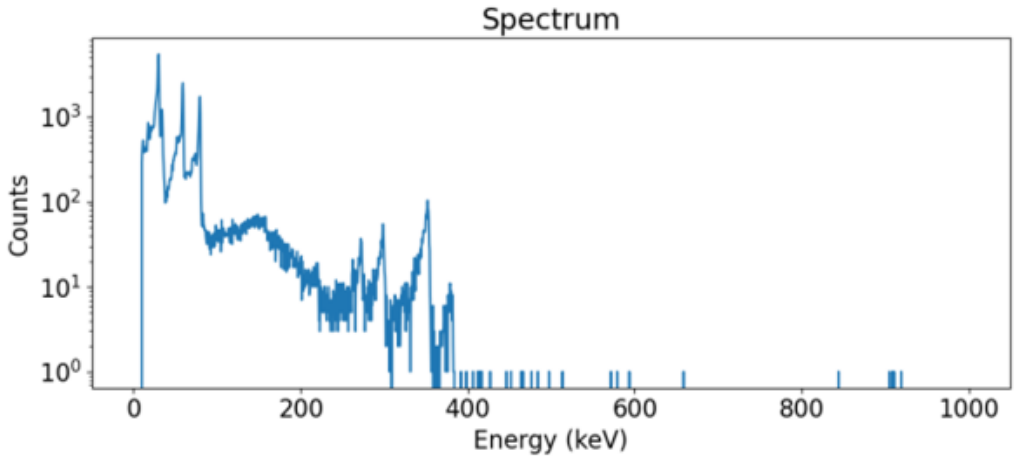






3. Where is AI ?

Gamma Spectroscopy identification with CNN



Acquisition info

^{241}Am : 400 kBq
^{133}Ba: 3.7 MBq
Distance from detector: ~2cm
Amount of photons: 7E+05

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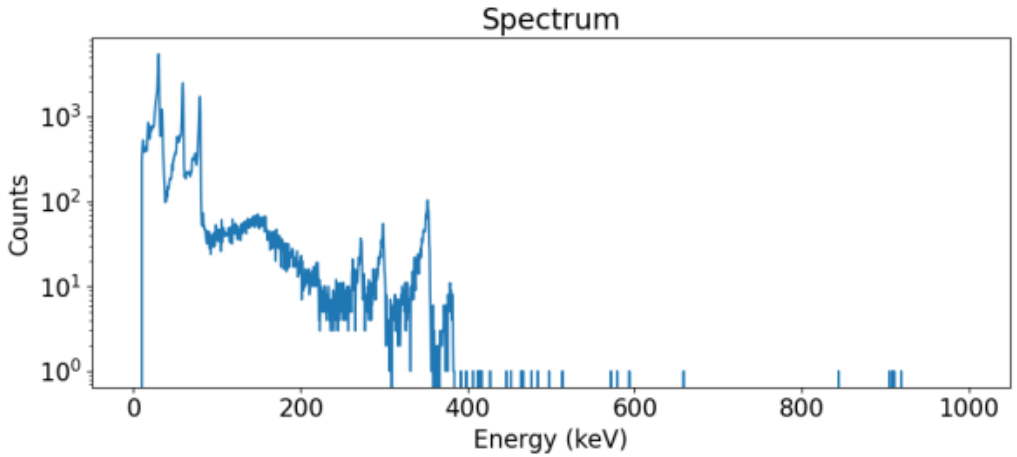

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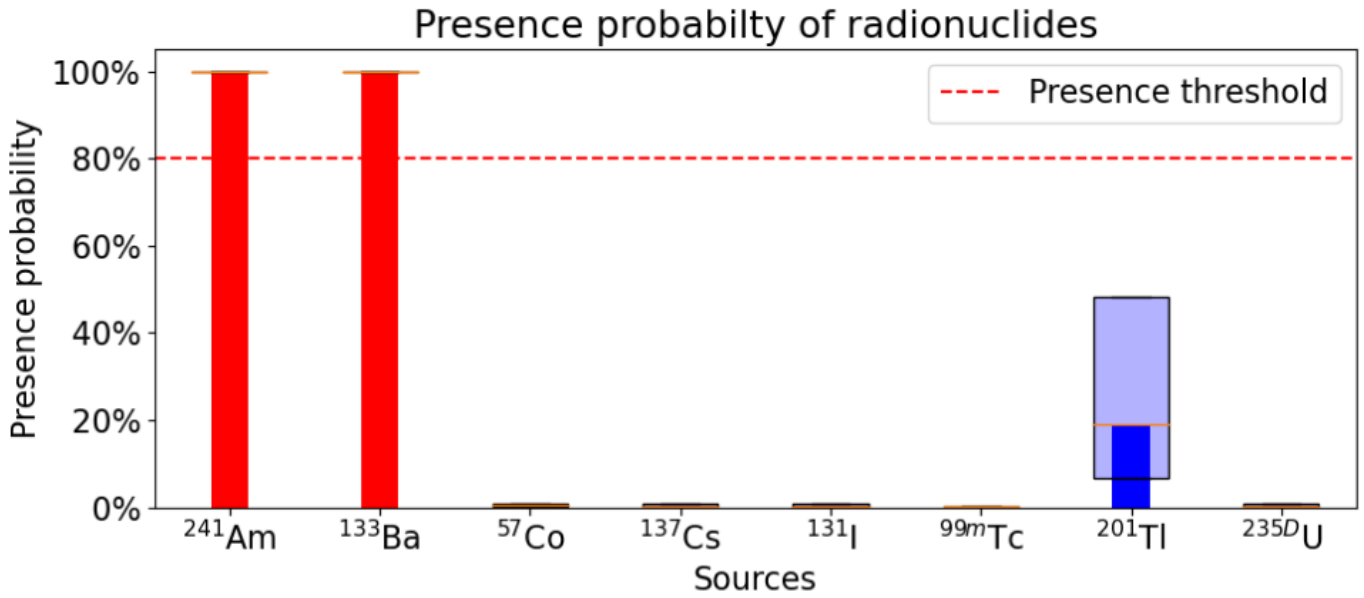
SpecID
AI model

Convolutional Bayesian Neural Network



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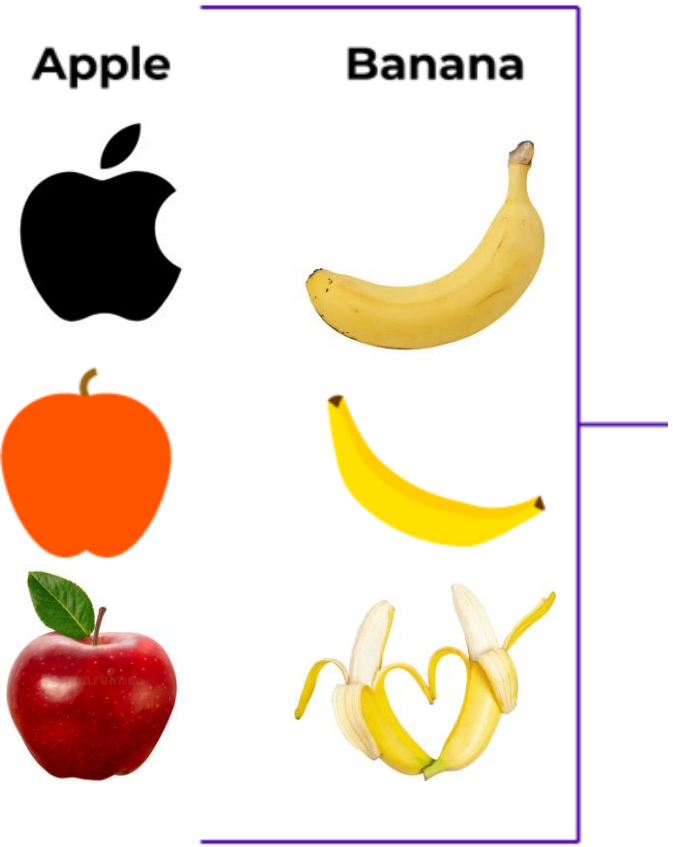
How ?

Supervised – Classification

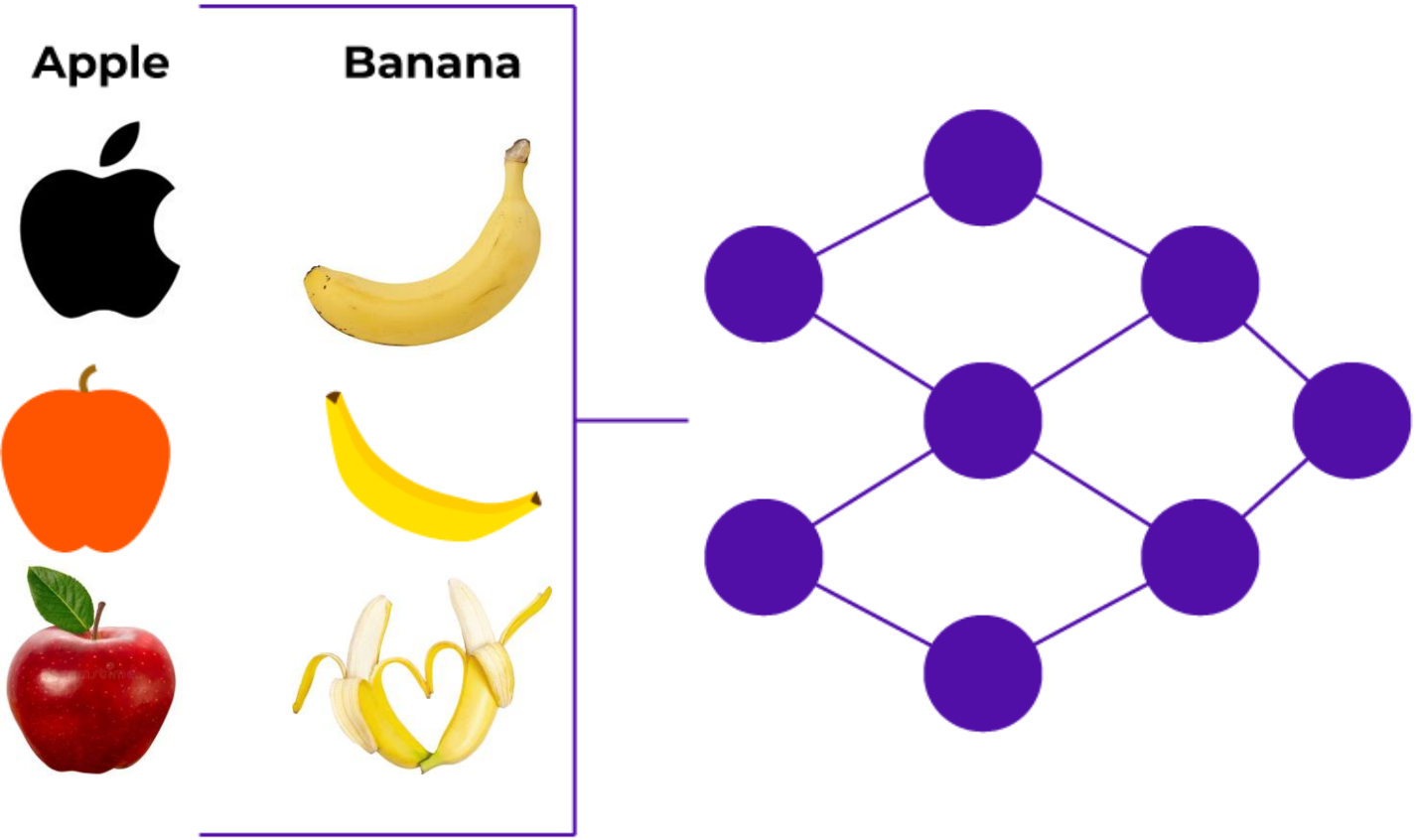
Training Data



Supervised – Classification

Training Data

ML Algorithm



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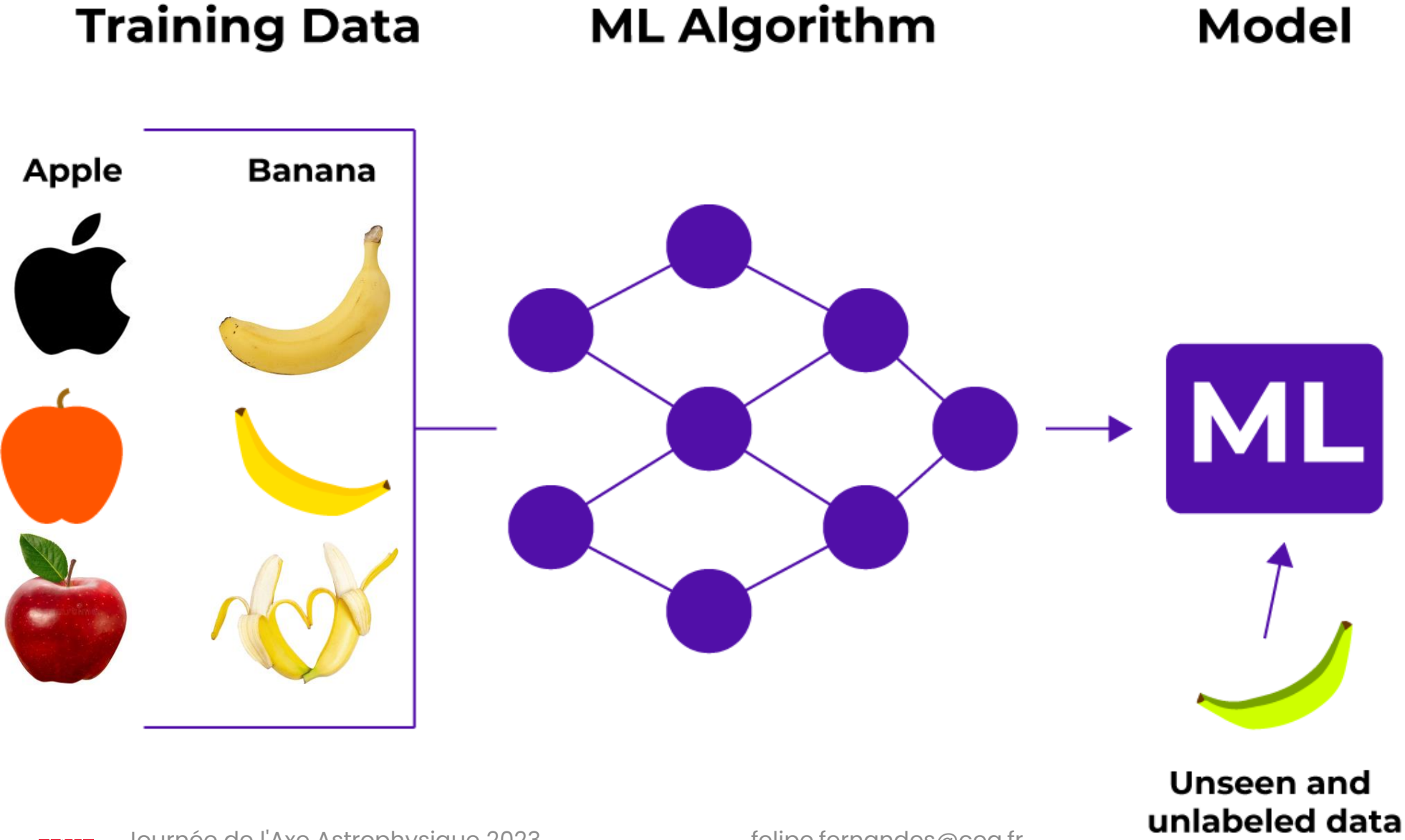

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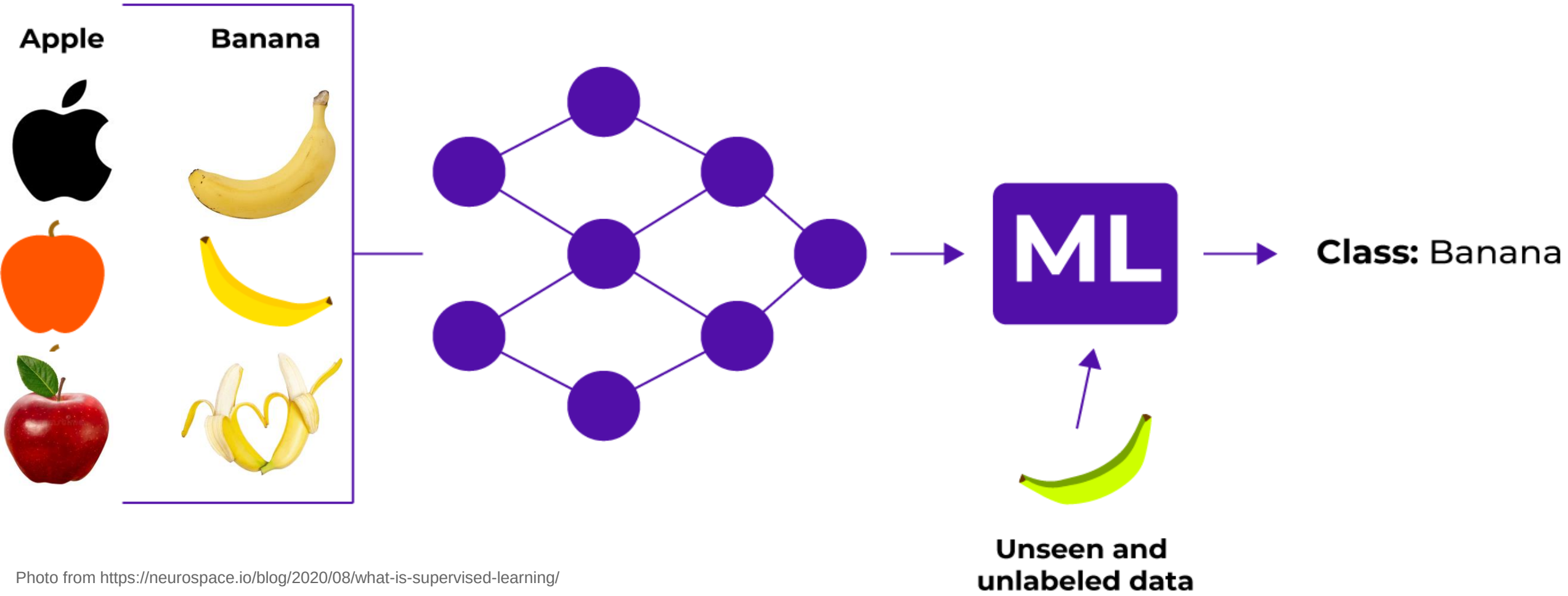
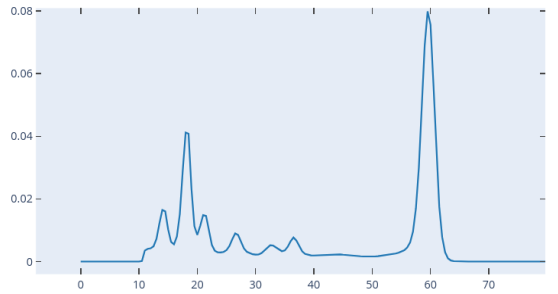


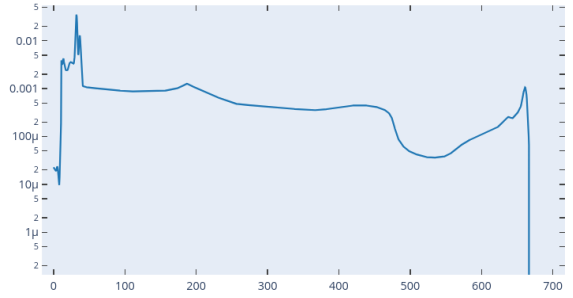
Photo from https://neurospace.io/blog/2020/08/what-is-supervised-learning/

Supervised – Classification

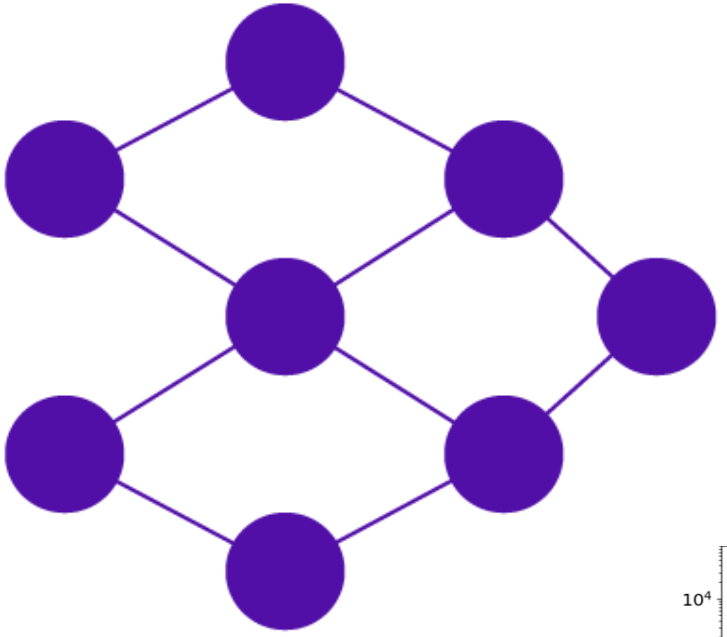
Training Data | **ML Algorithm** | **Model** | **Prediction**

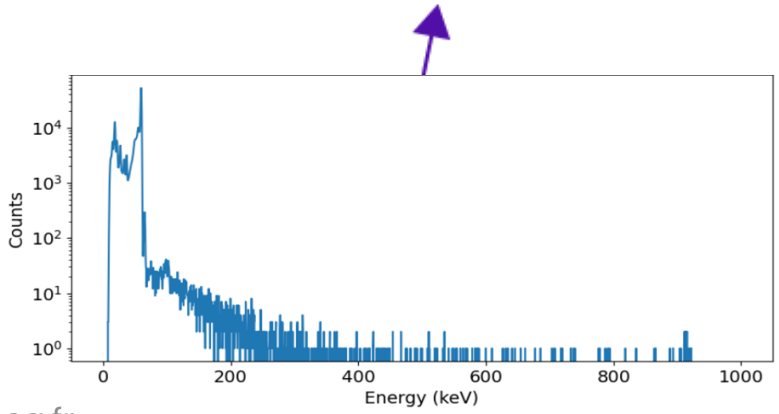


Am 241 Monte Carlo DRM simulated data, Relative intensity X energy (keV)



Cs 137 Monte Carlo DRM simulated data, Relative intensity (log) X energy (keV)





Class: Am 241

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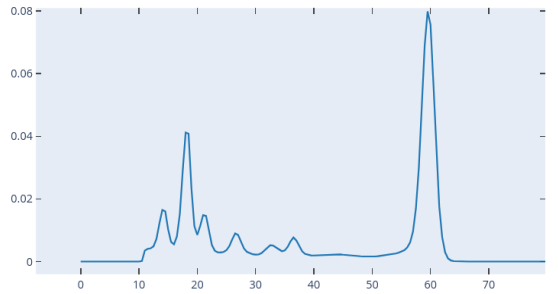
Supervised – Classification – Train data importance

Training Data | **ML Algorithm** | **Model** | **Prediction**



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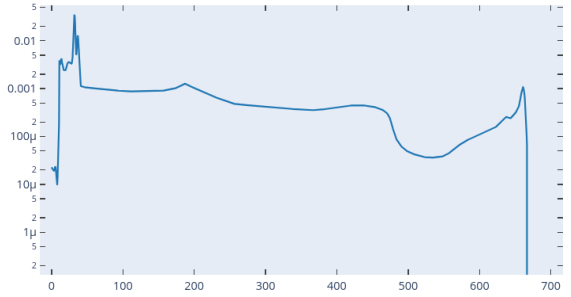

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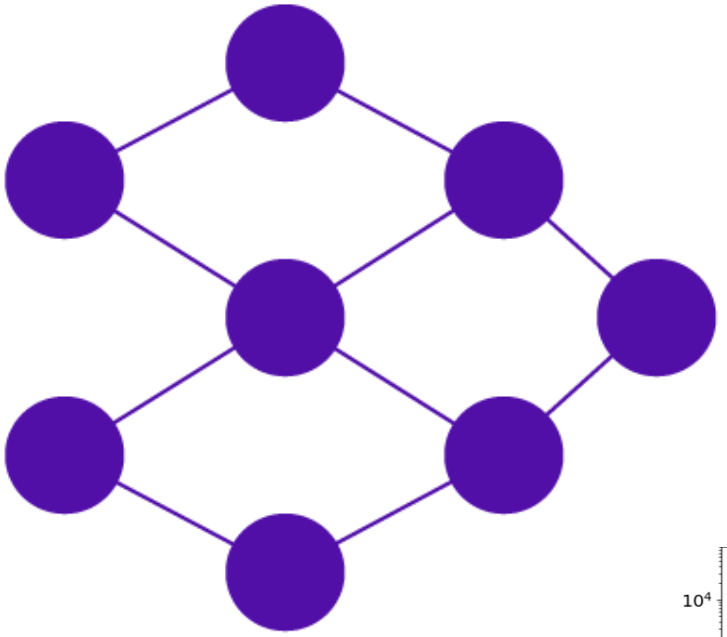
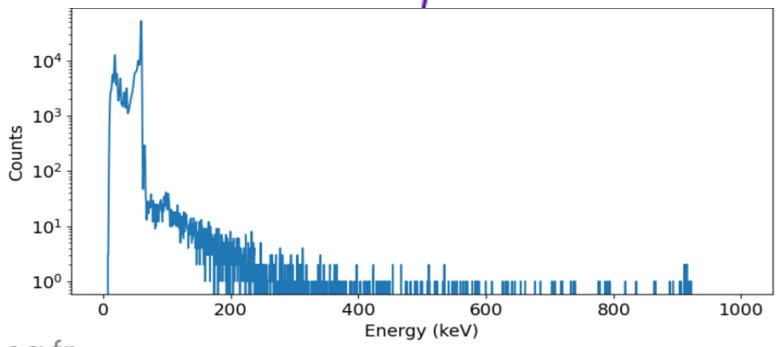


ML

Class: Am 241



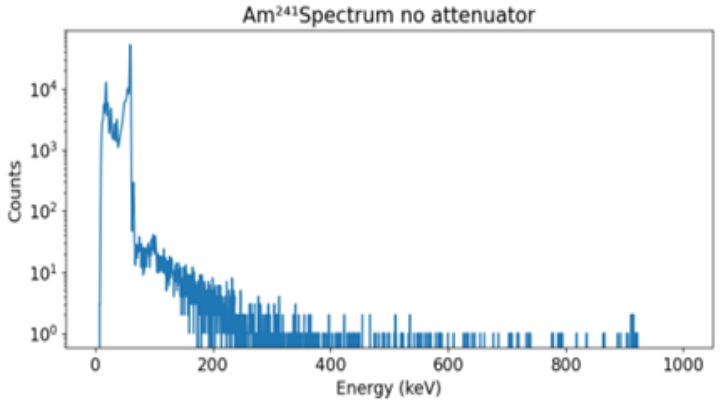
*"PDFs" MC generated -> Data Base creation by Poisson Sampling

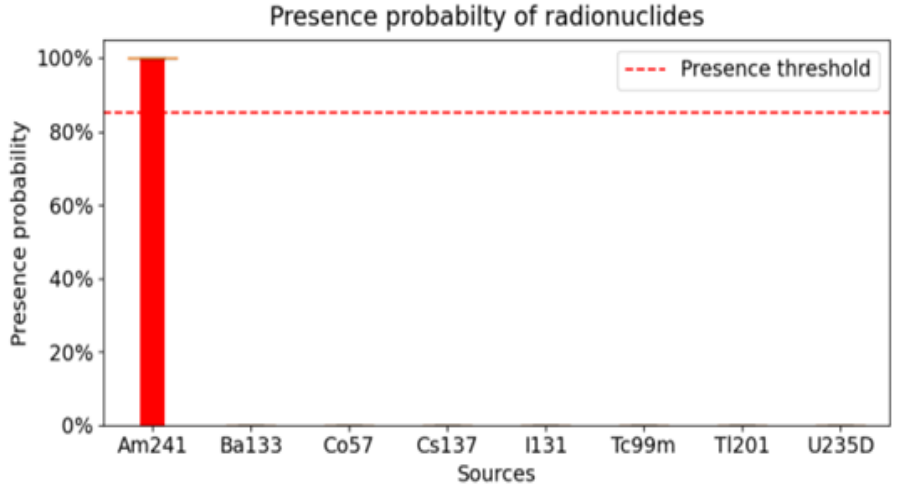
4. Issue on complex environments

Issue of loss of accuracy in complex environments
Shielded

Experimental data

Acquisition info
^{241}Am: 400 kBq
Distance from detector: ~2cm
Amount photons: 5.9E+05 and 2.7E+02





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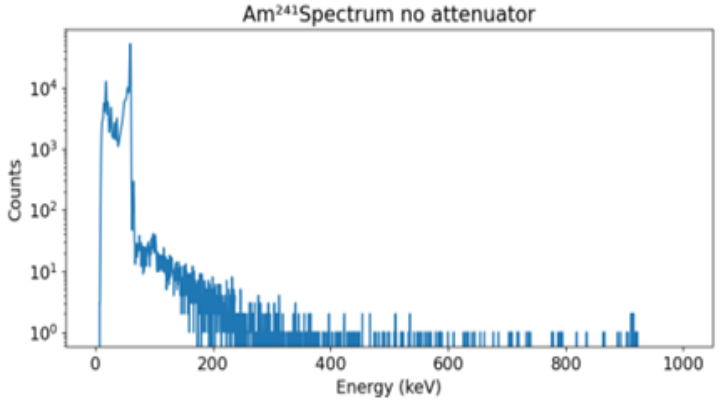
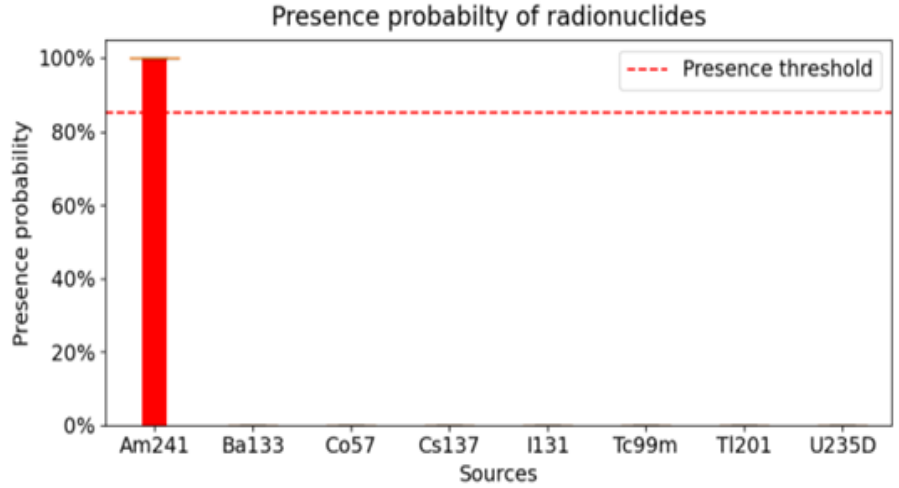
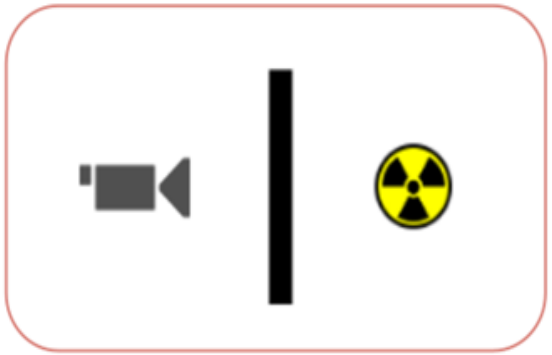
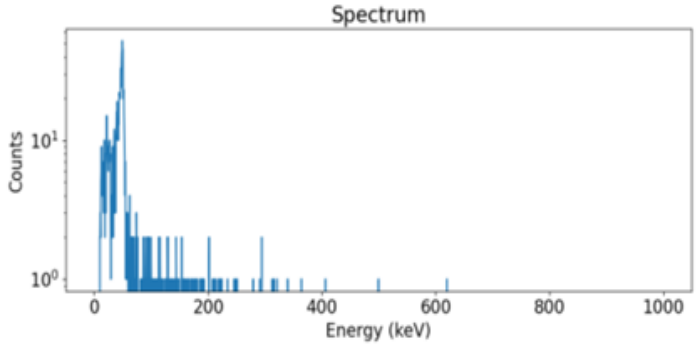
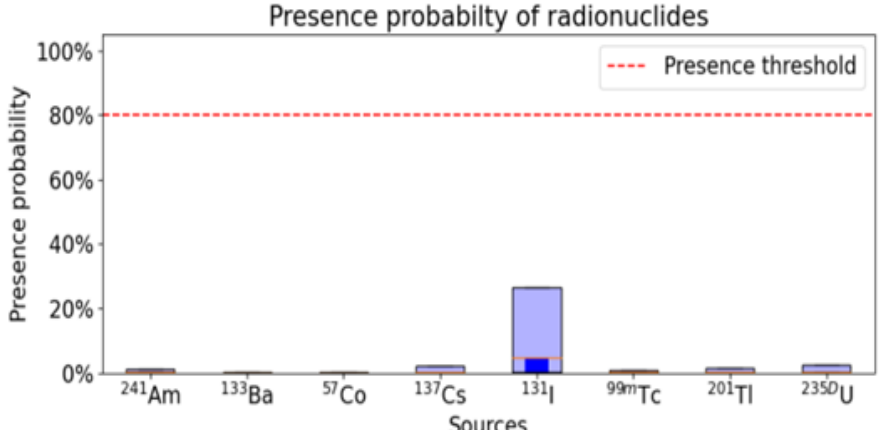








Attenuated by 2mm of lead

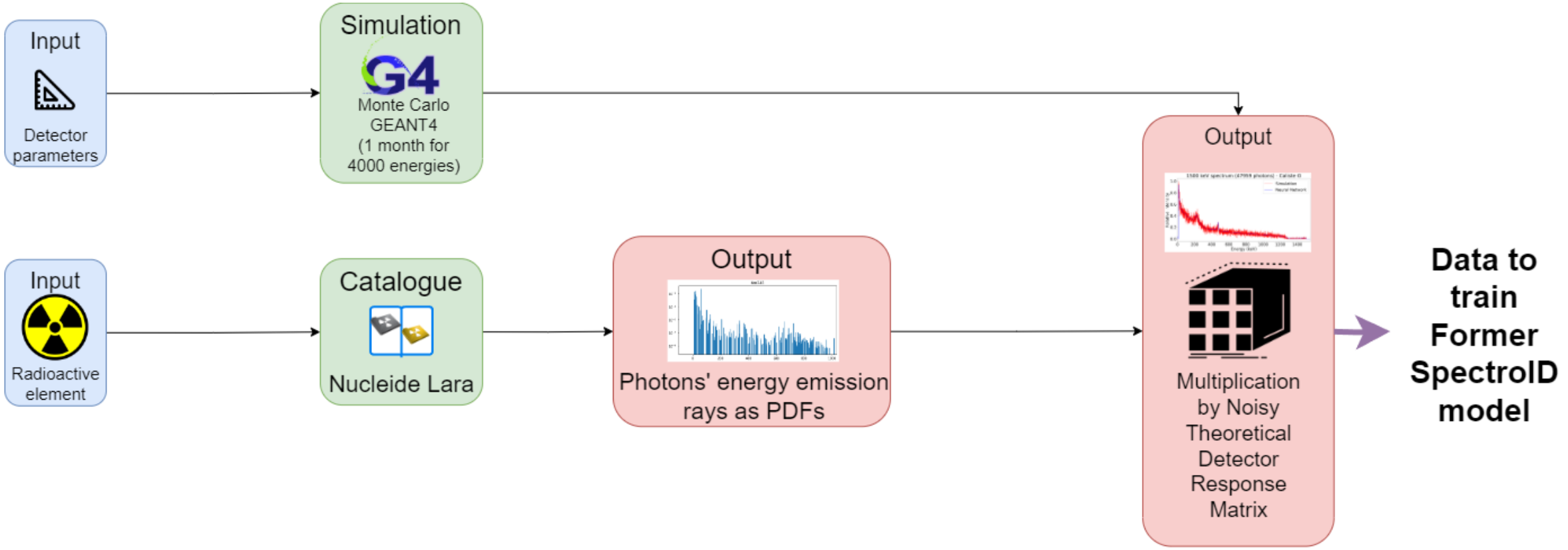


5. Proposed Solution?

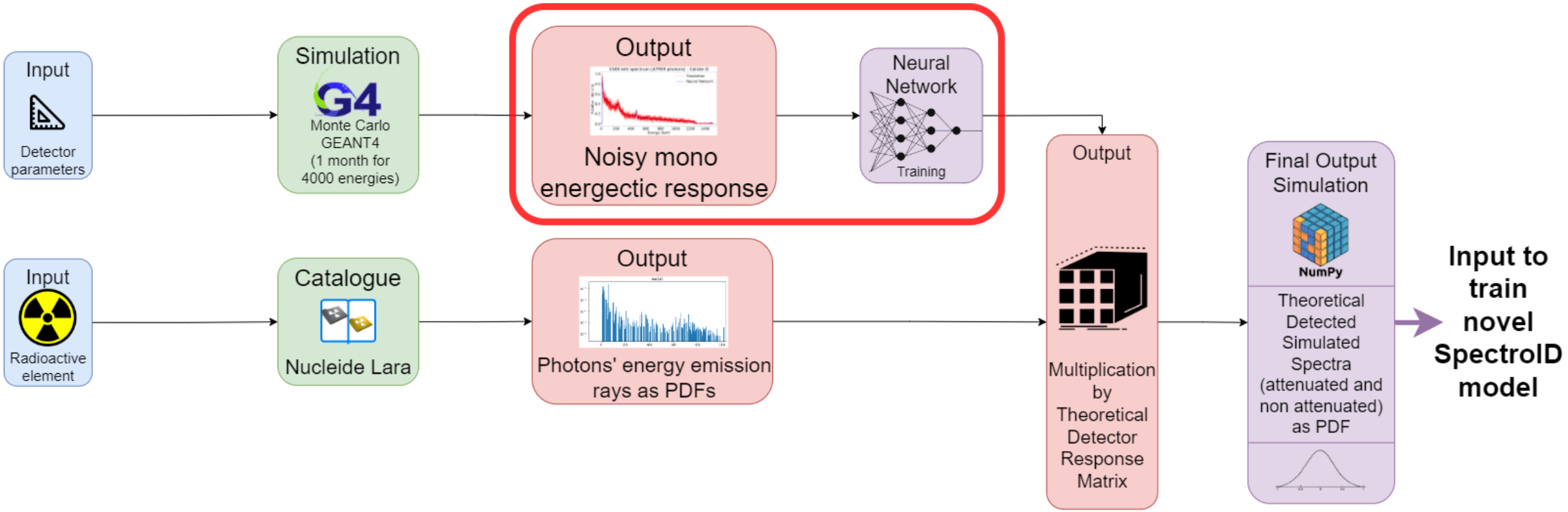
AI – based advancements

Data generation

Proposed Solution
Former model pipeline

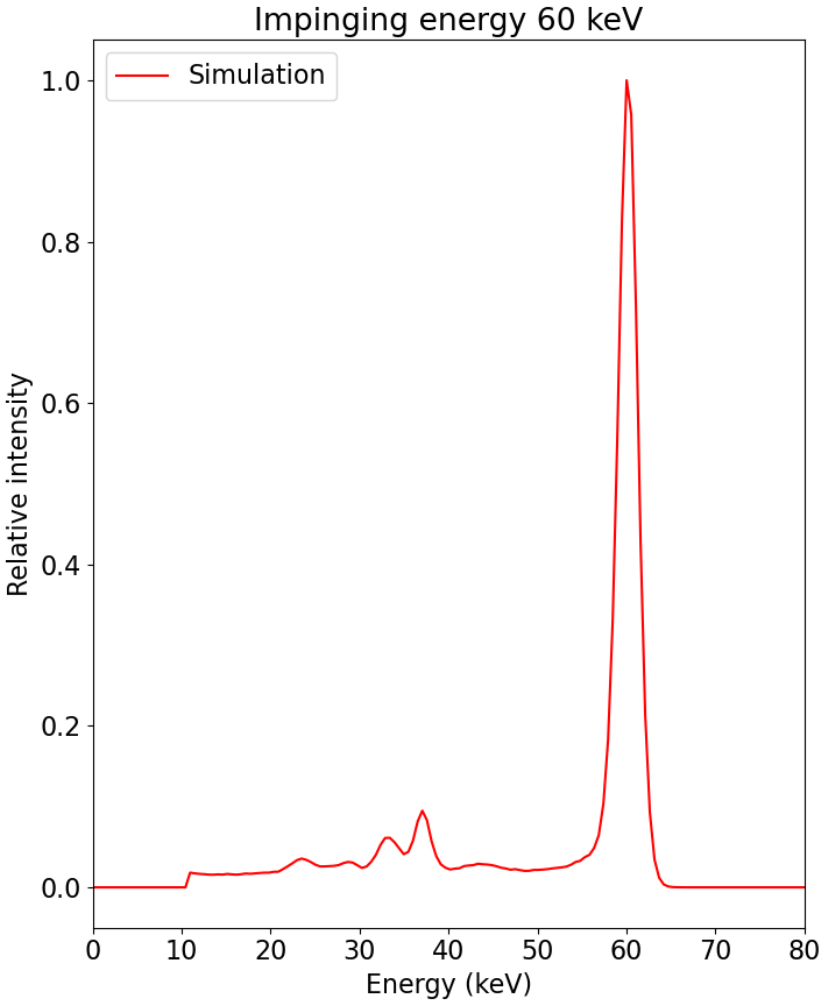


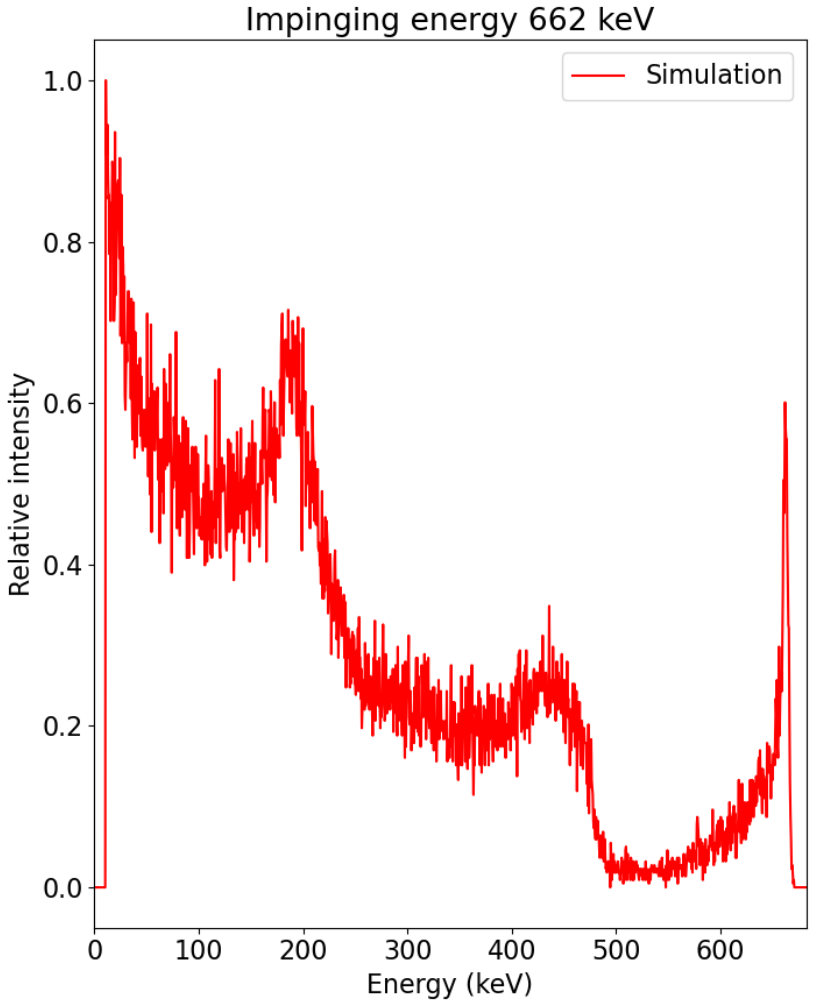
Proposed Solution
Mono energetic response (accelerating MC)

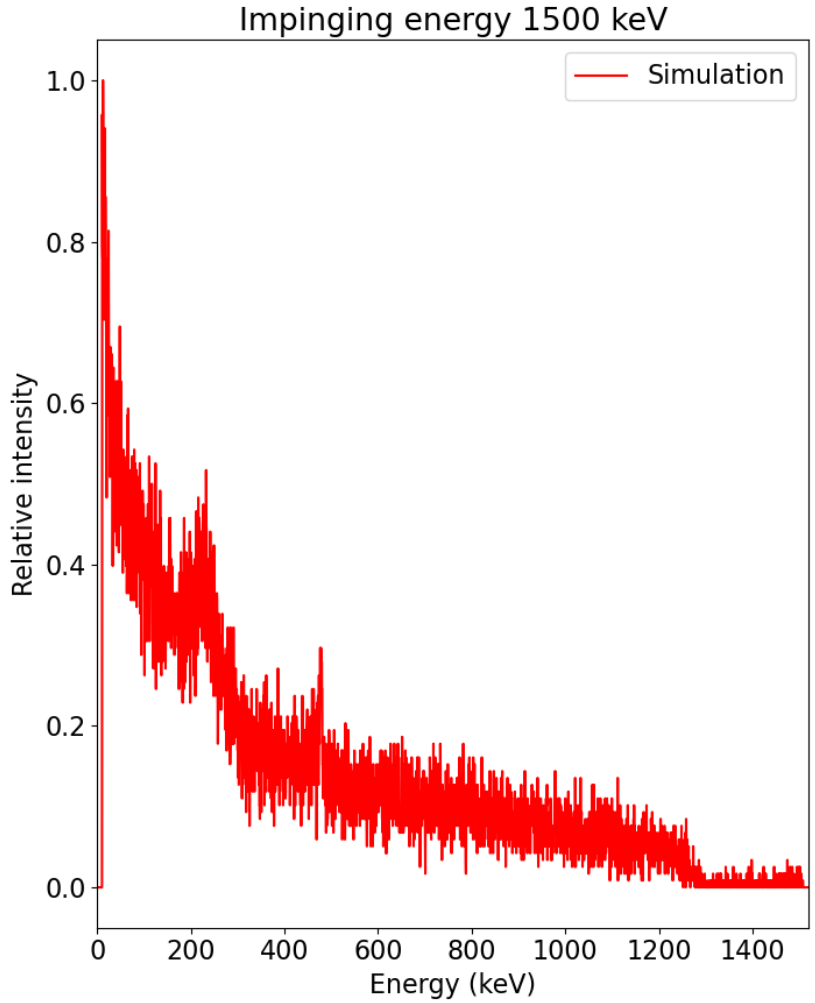


Proposed Solution
Mono energetic response (accelerating MC)

simulation







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Mono energetic response (accelerating MC)

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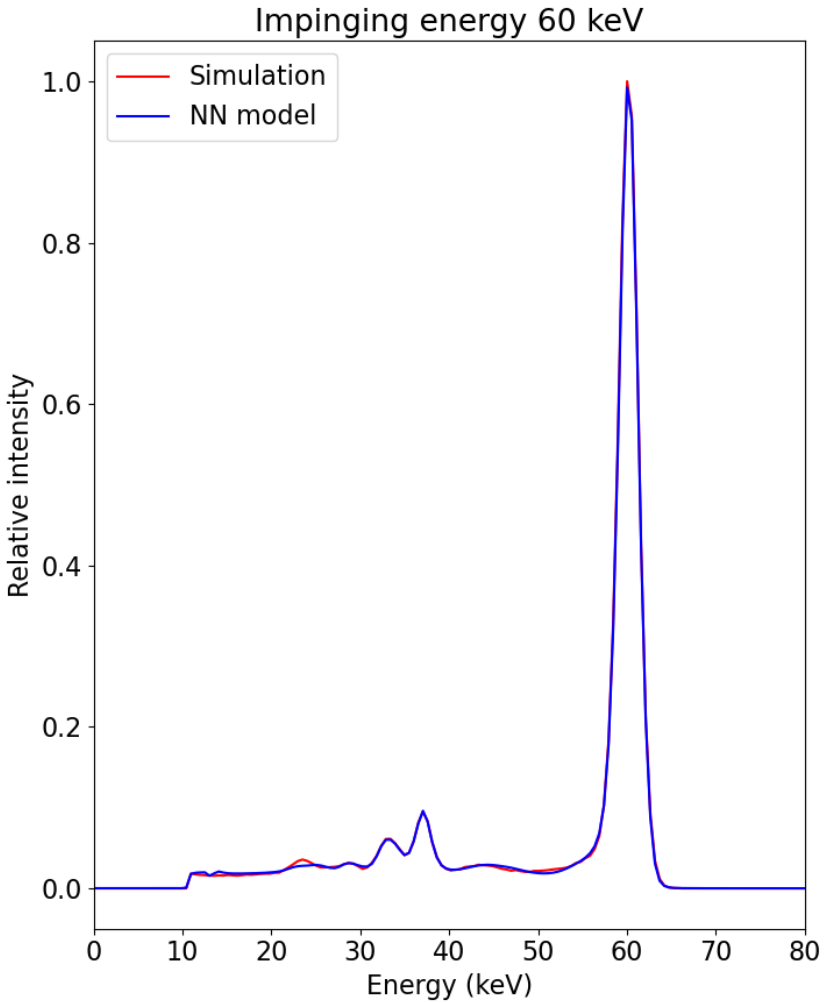
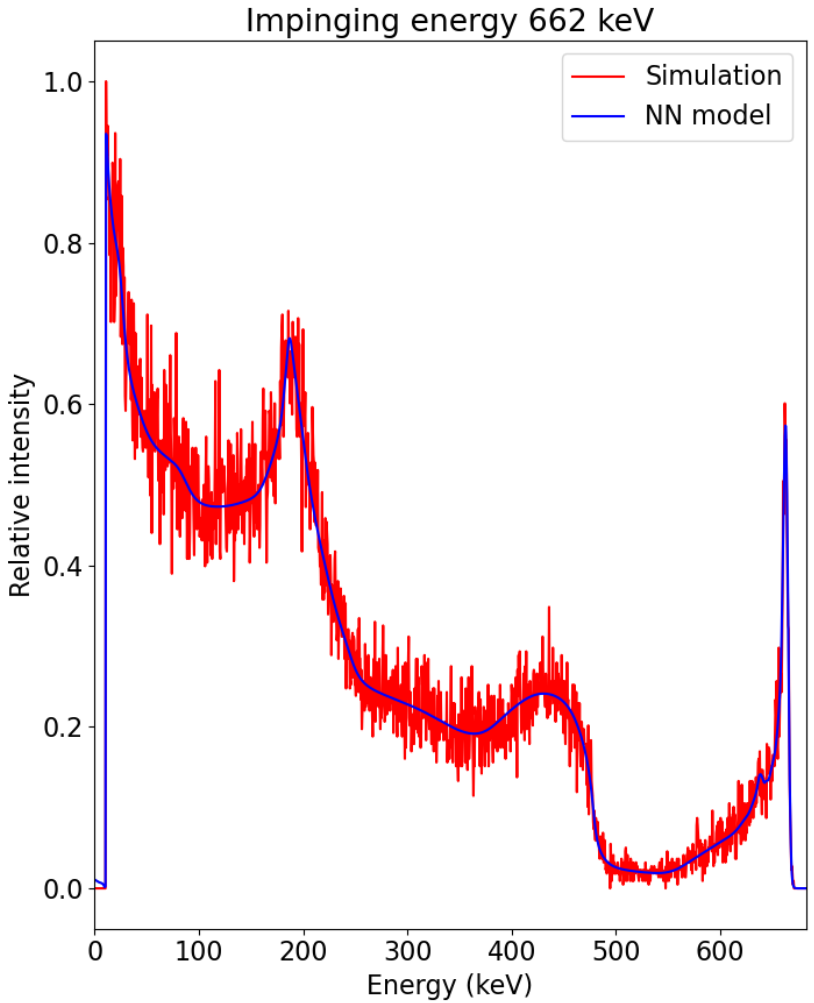
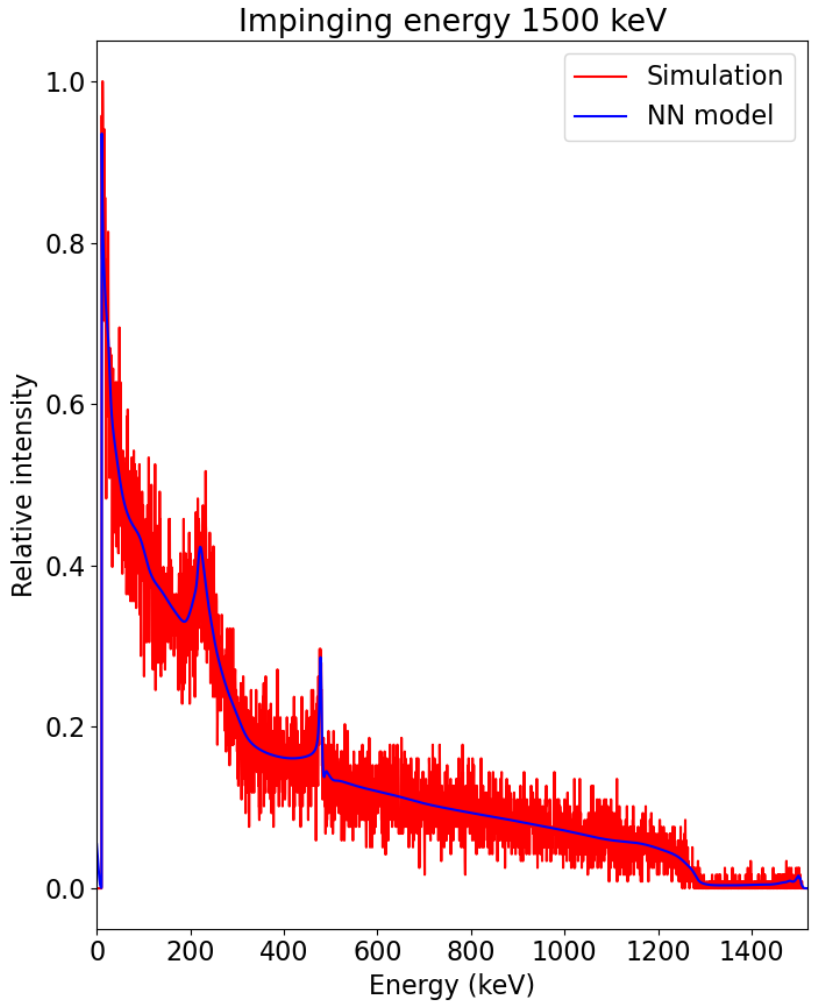
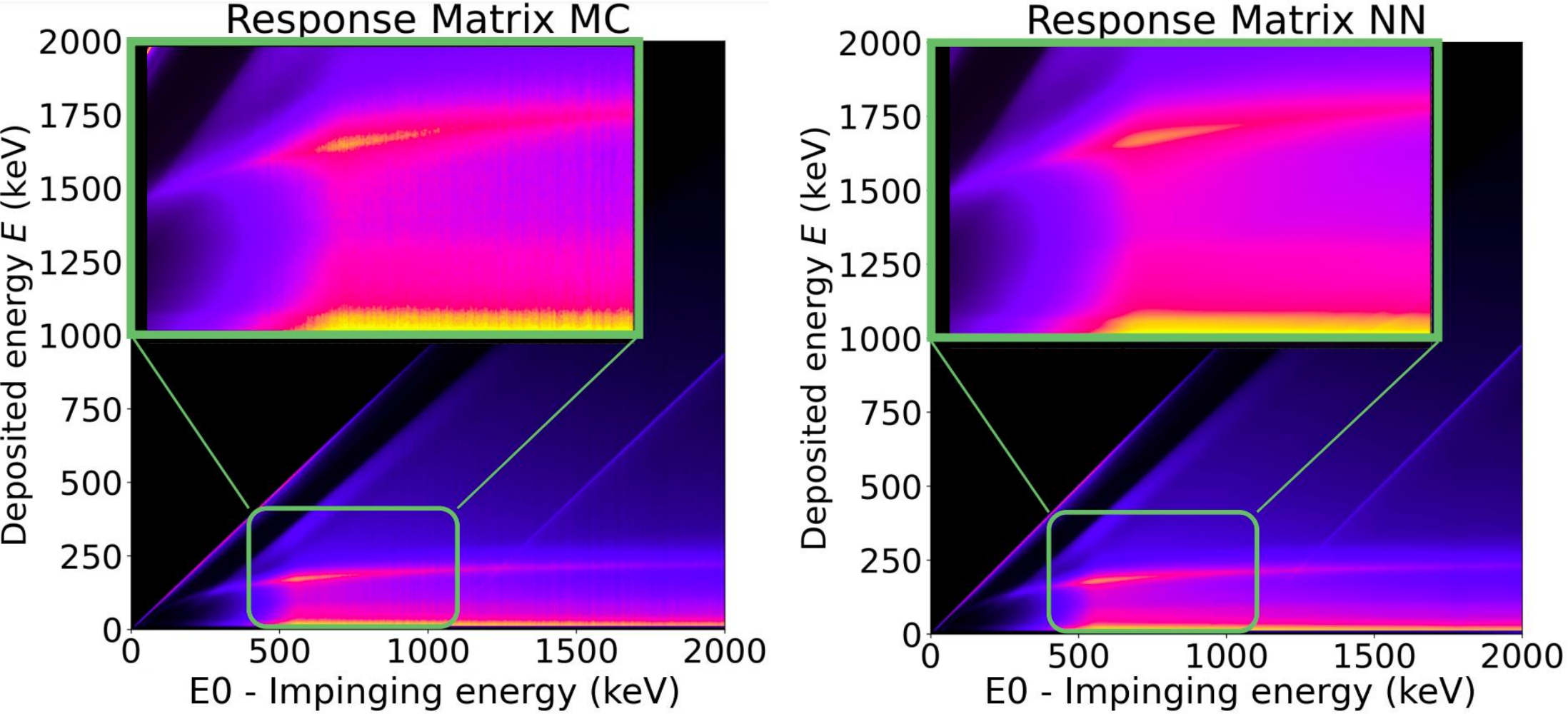


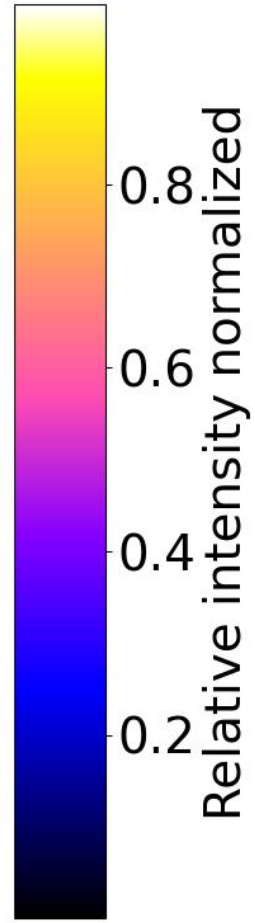




Proposed Solution
Mono energetic response – Response Matrix

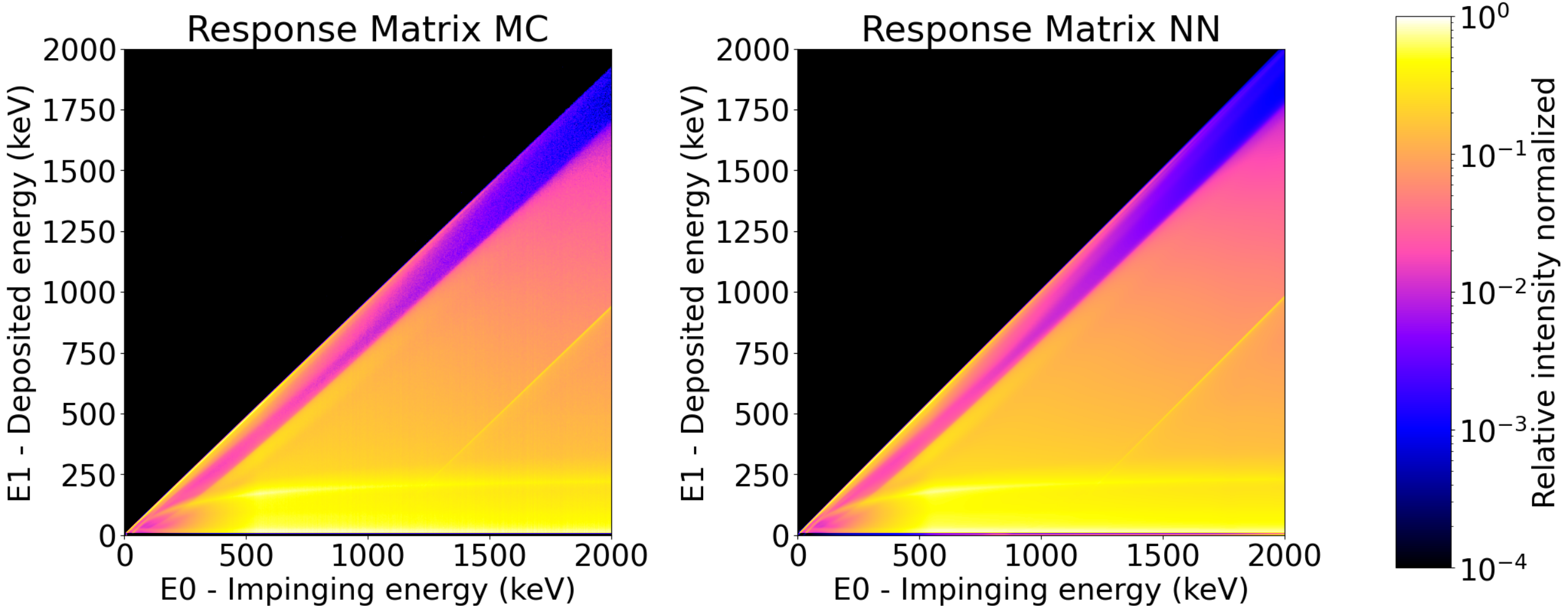
simulation



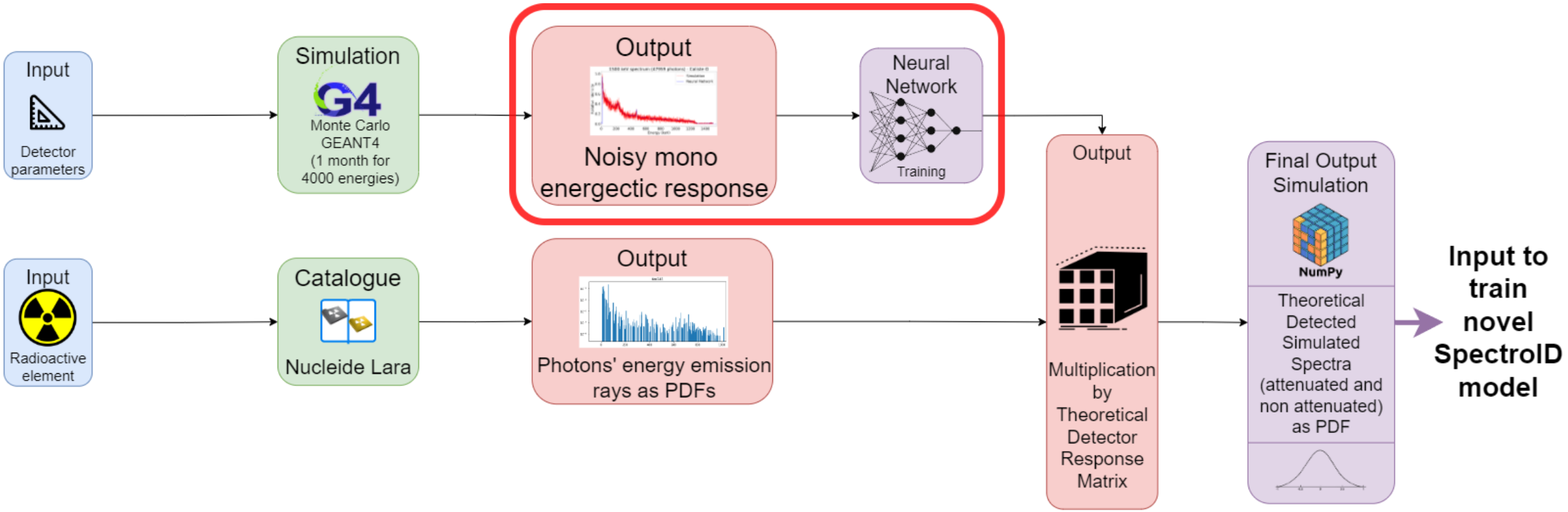


Proposed Solution
Mono energetic response – Response Matrix (log)

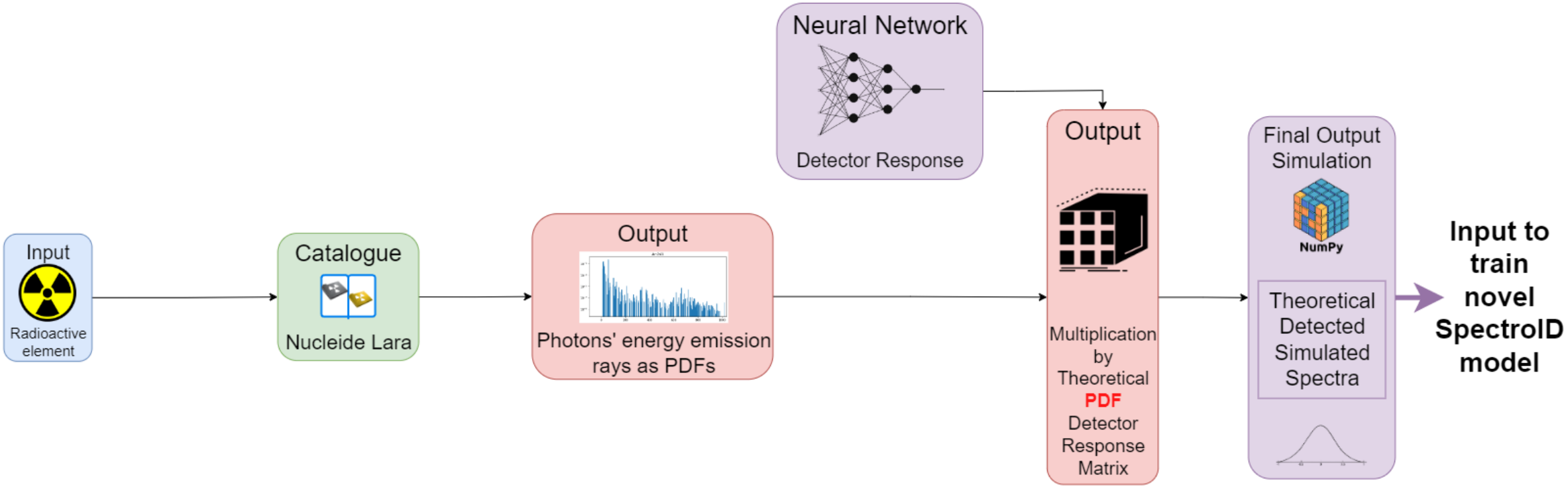
simulation



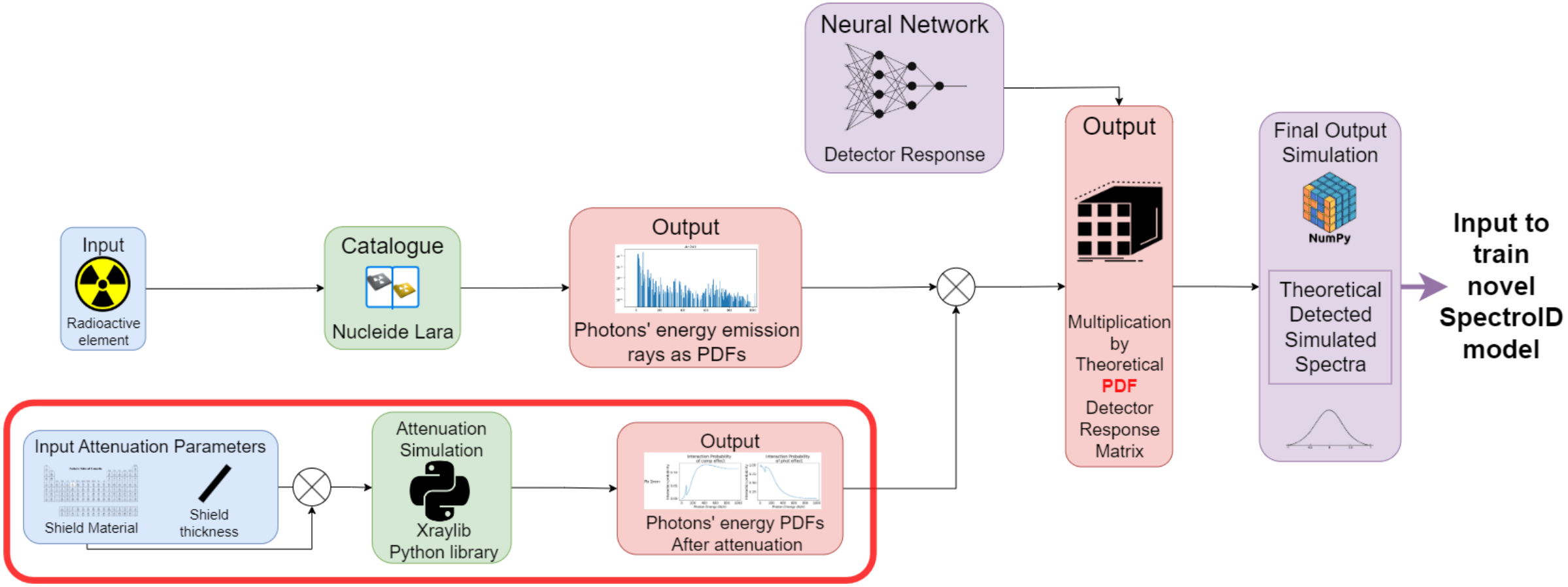
Proposed Solution
Mono energetic response (accelerating MC)



Proposed Solution
Mono energetic response (accelerating MC)

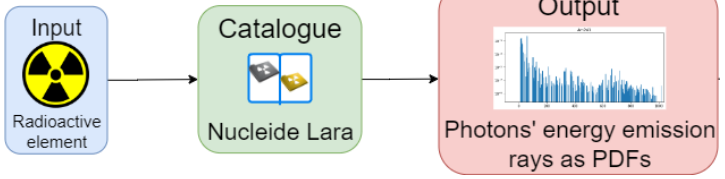


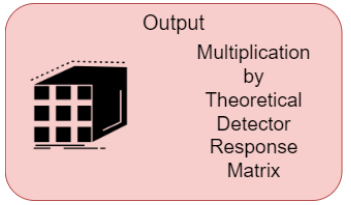
Proposed Solution
Physical modelization

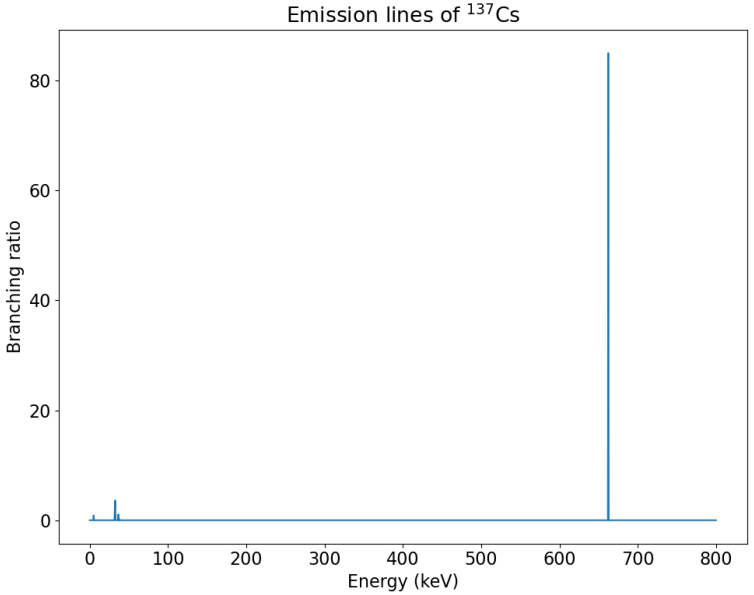


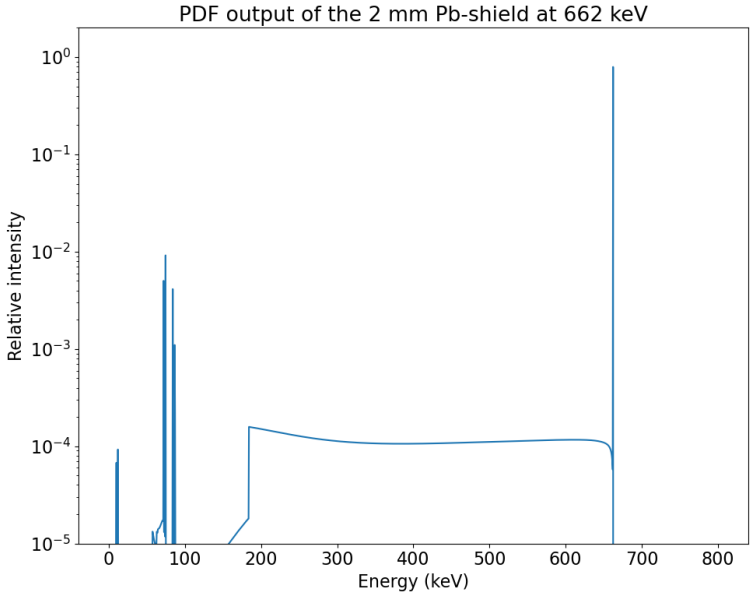
Proposed Solution
Physical modelization - Spectrum result

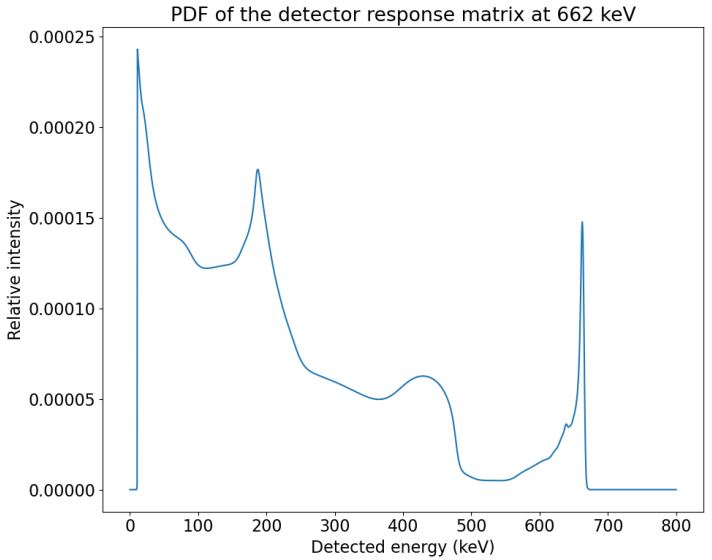
simulation

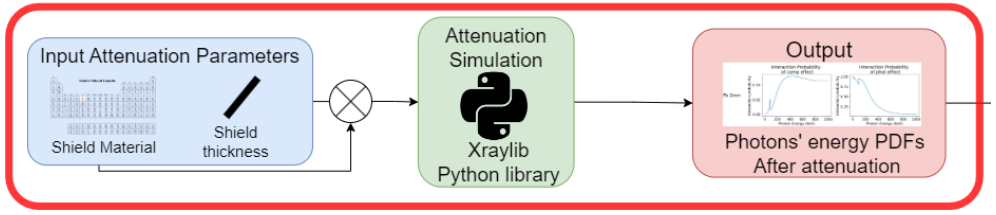






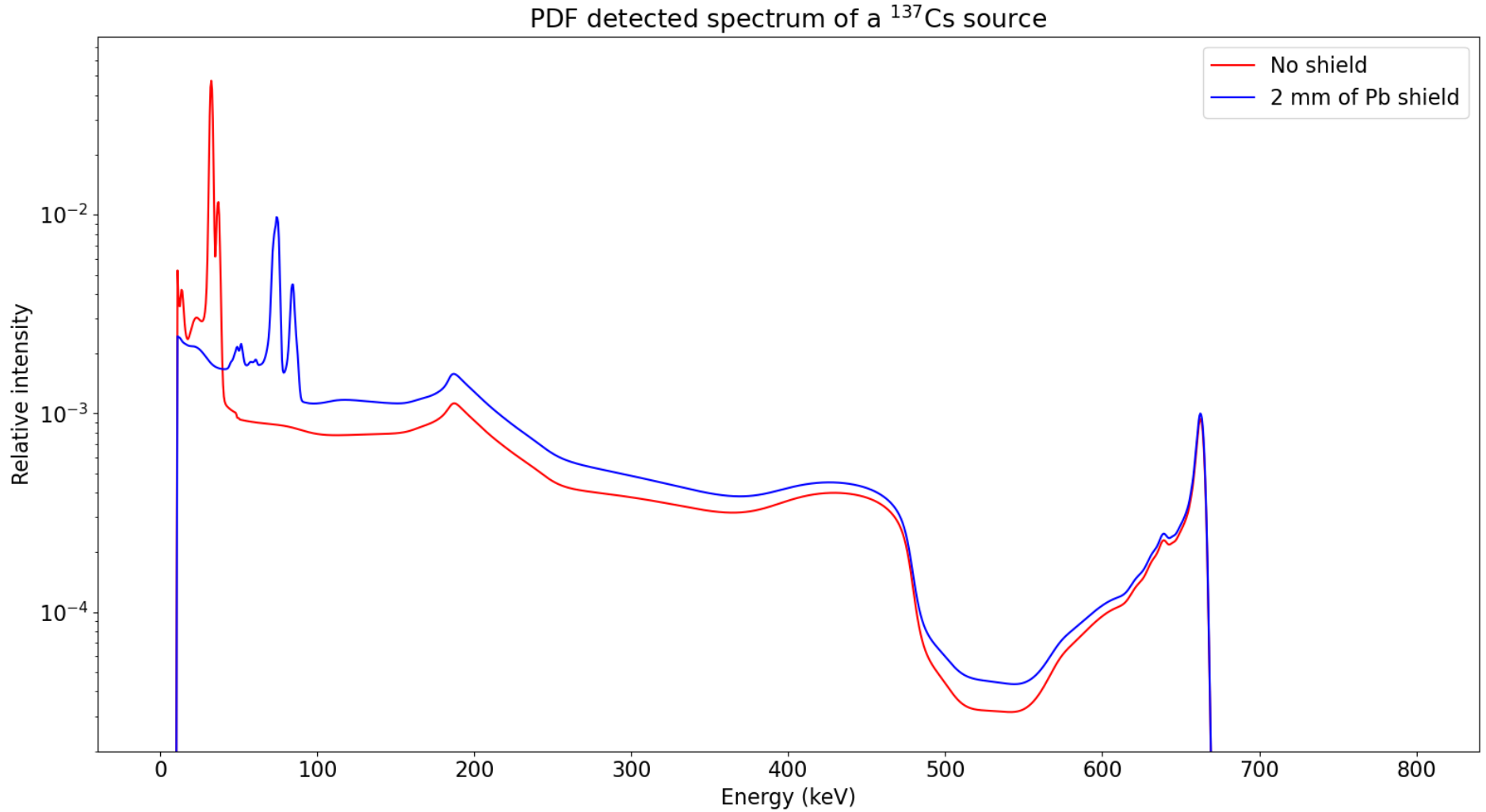






Proposed Solution
Physical modelization - Spectrum result

simulation



6. Model and results

Model and training

- **Convolutional Network Model**
  - Signal patterns
  - Characteristics extraction
  - Photoelectric and fluorescence peaks
  - Compton scattering structure
- Ending with perceptron identification
- Bayesian -> estimation of confidence

- **Online learning:**
  - Poisson sampling from theoretical PDFs
  - New samples every epoch
  - Random decalibration
  - Random combination of elements

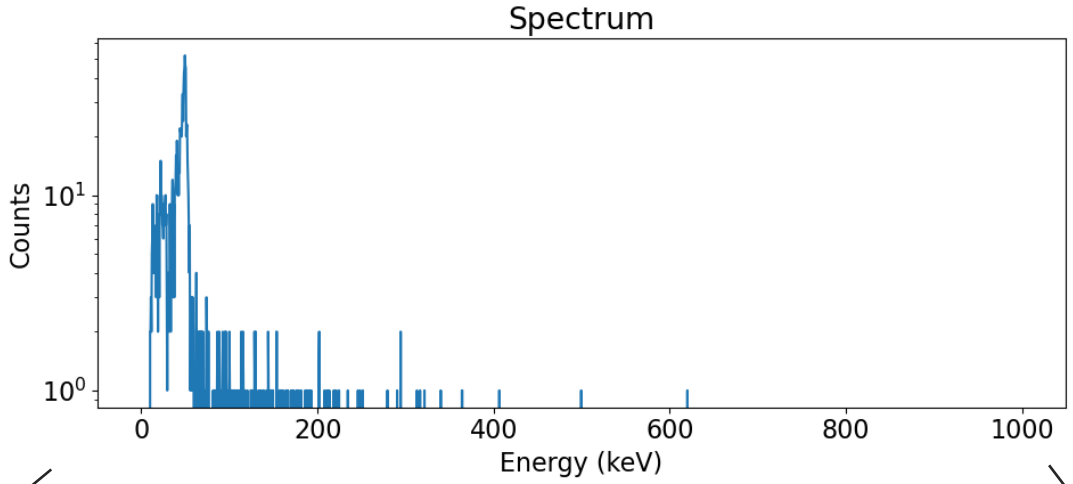
Results

^{241}Am behind 2 mm of lead

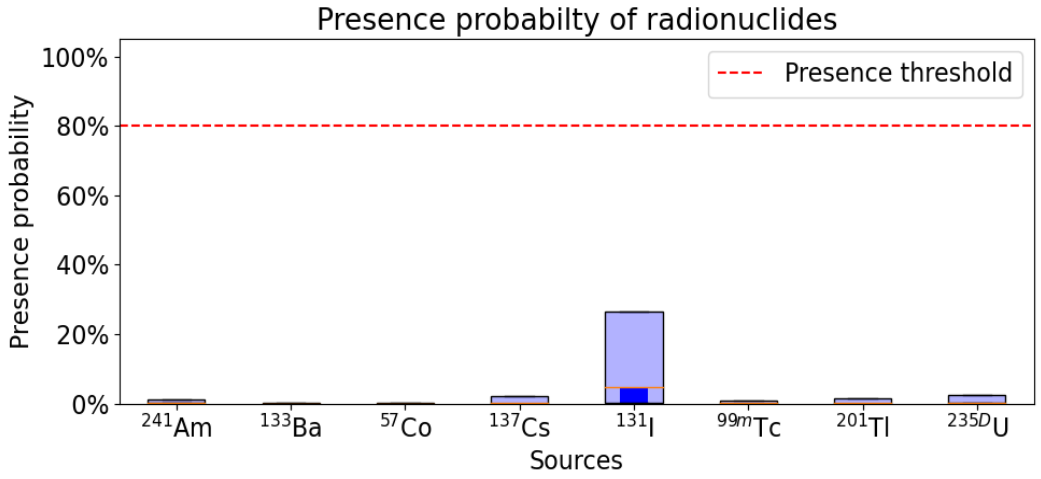
Experimental data

Acquisition info

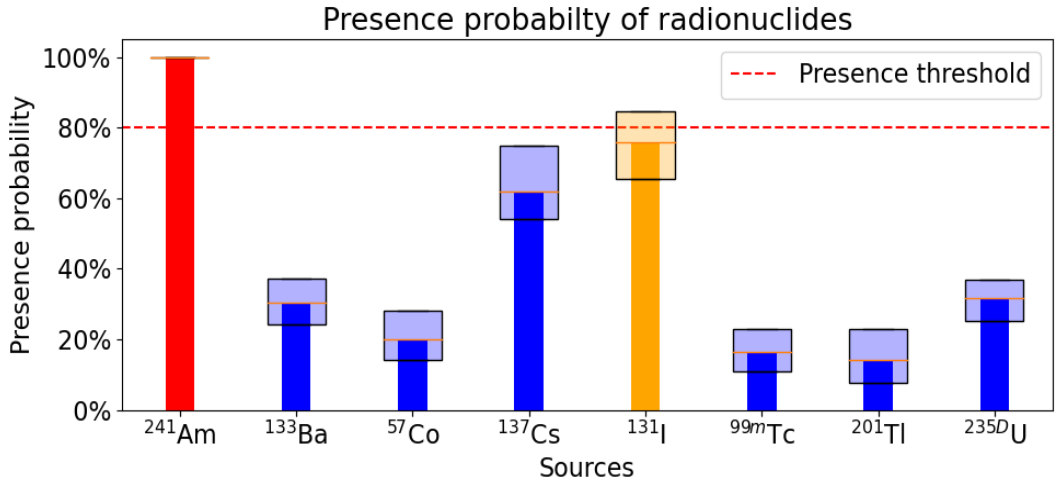
^{241}Am: 400 kBq
Distance from detector: ~2cm
Amount photons: 2.7E+02



Former model



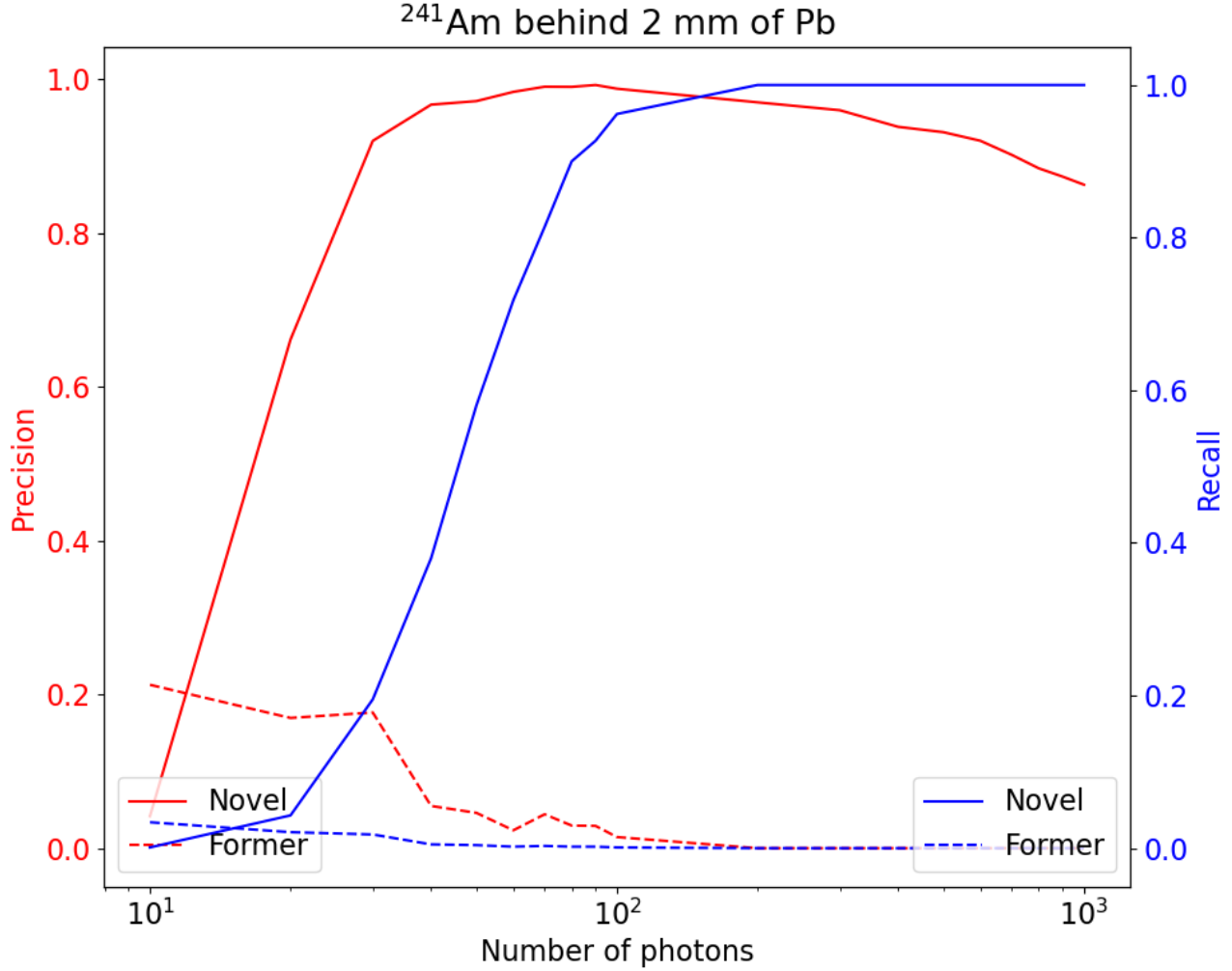
Novel model



Results
Performance by amount of photons

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Influence of False Positive



$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Influence of False Negative

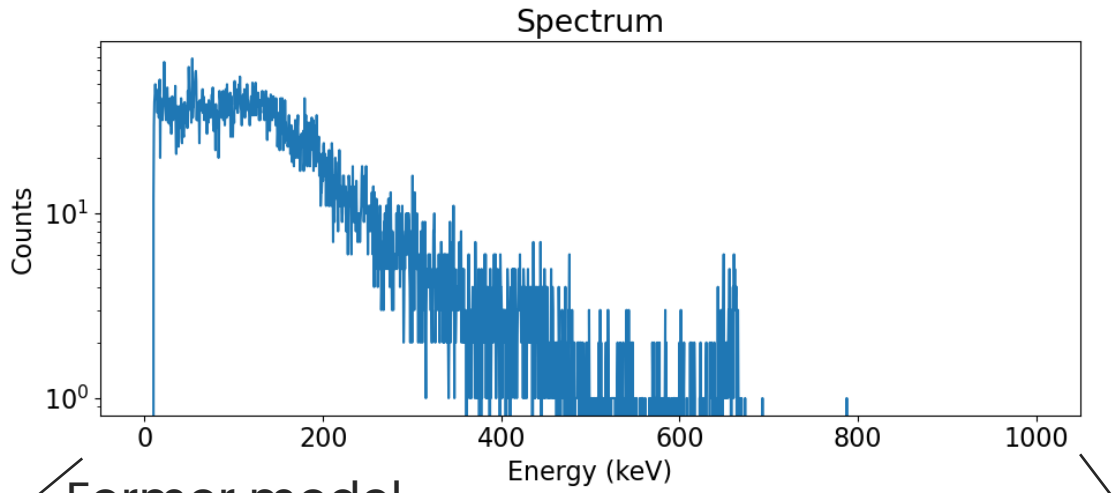
Results

^{137}Cs and ^{241}Am behind 42 mm of copper

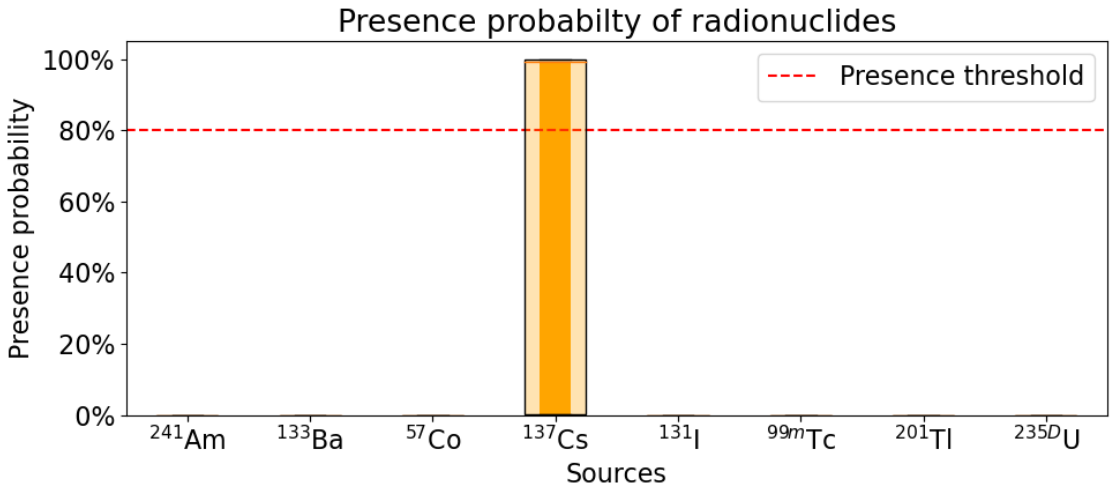
Experimental data

Acquisition info

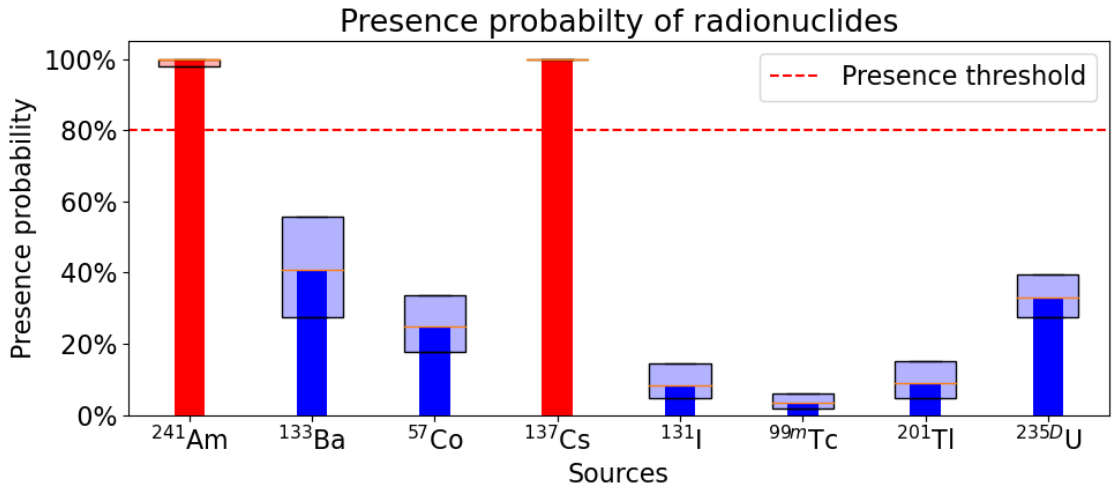
^{241}Am: 400 kBq
^{137}Cs: 3.4 MBq
Distance from detector: ~6cm
Amount photons: 1.7E+04



Former model



Novel model



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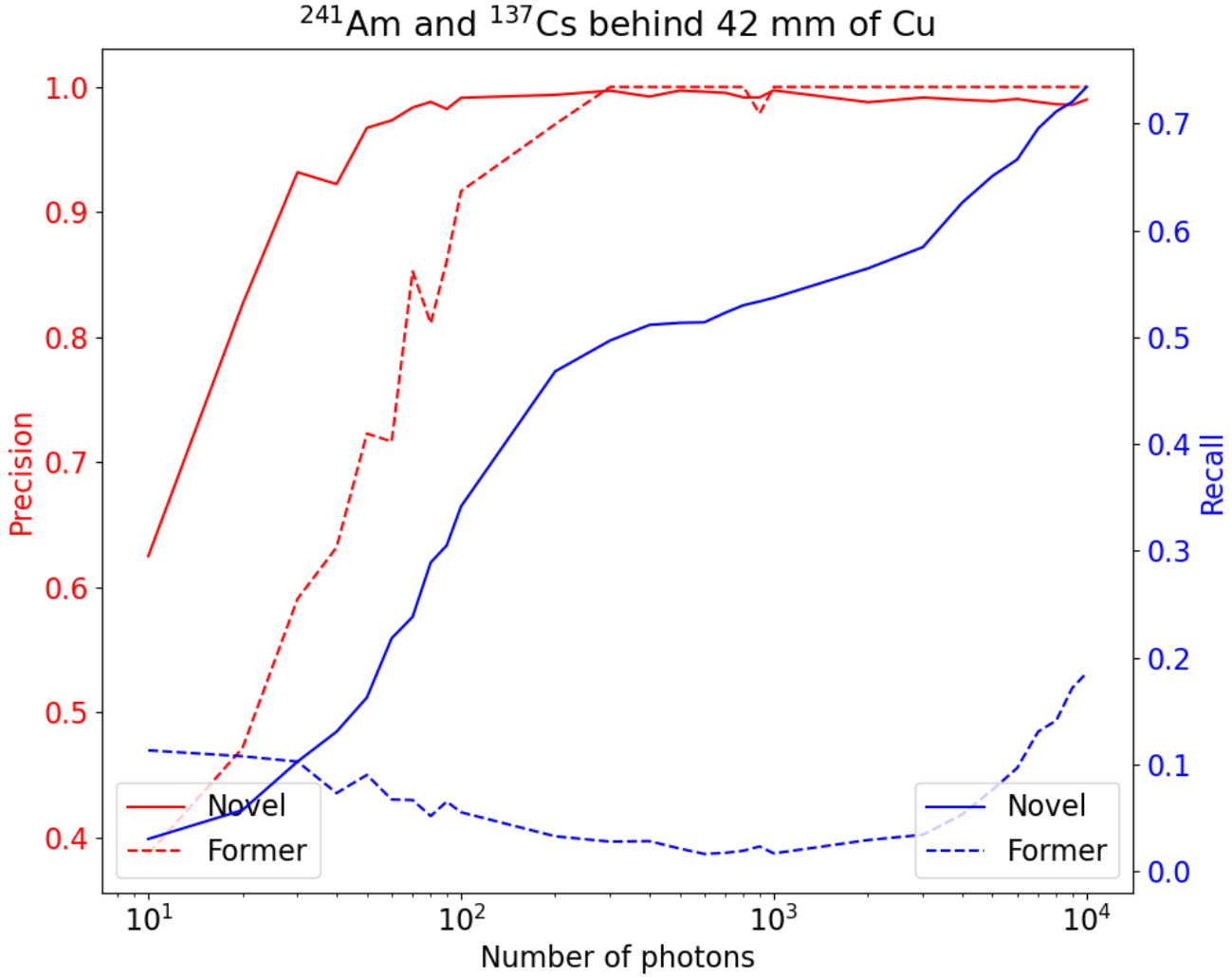
$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Influence of False Positive



$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Influence of False Negative

7. Conclusions, applications and next steps

Conclusions and further applications

- Training data proved to solve some attenuation issues
- No performance was lost
- Artificial data generation achieved prior objective

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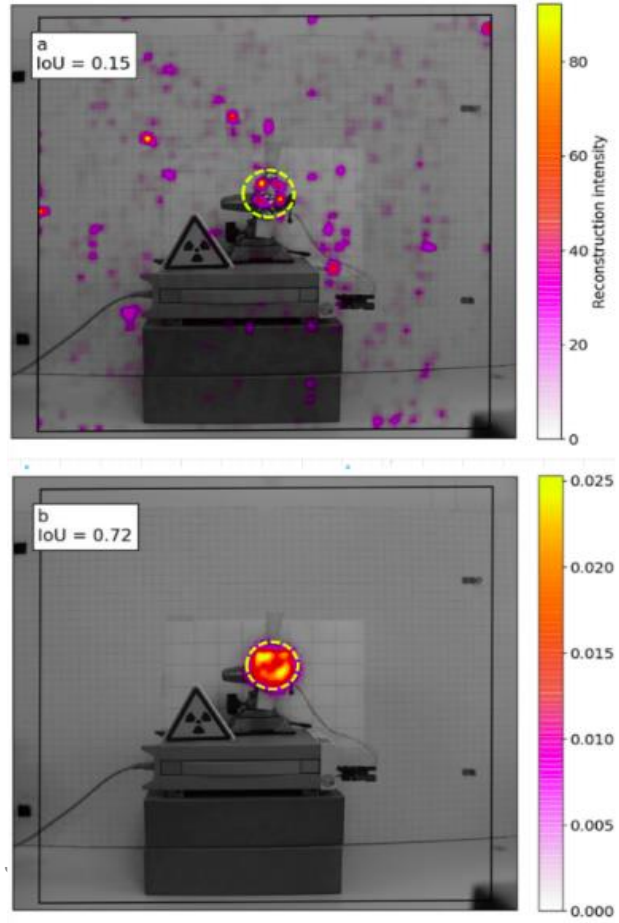

- Other applications
  - Imaging

Conclusions and further applications

- Training data proved to solve some attenuation issues
- No performance was lost
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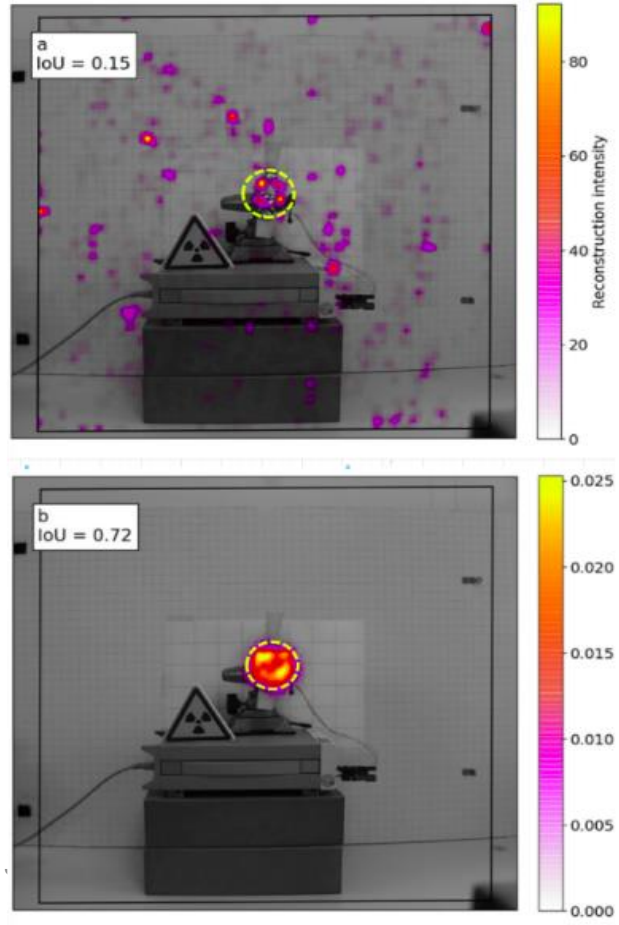
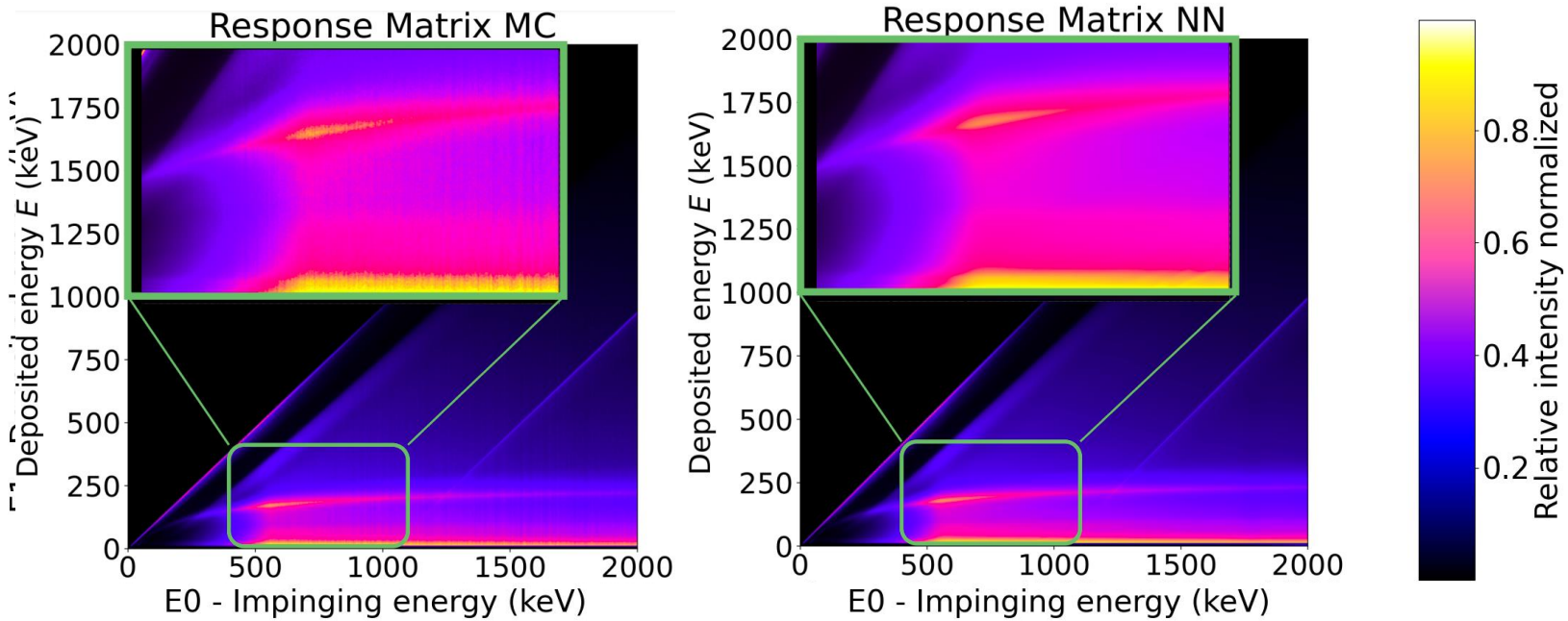
- Other applications
  - Imaging
  - Faster Detector Response Matrix compared with MC





Conclusions and further applications

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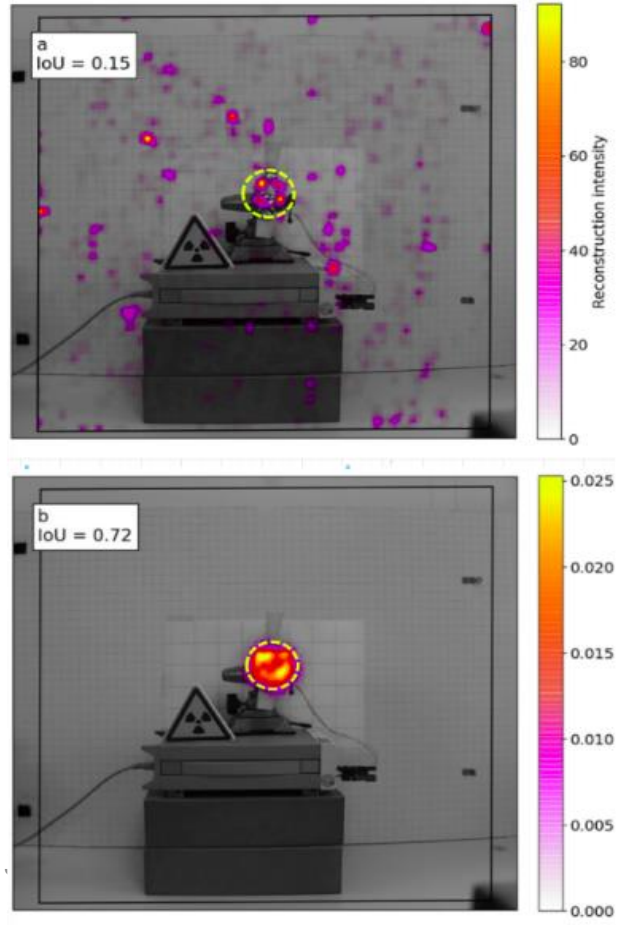
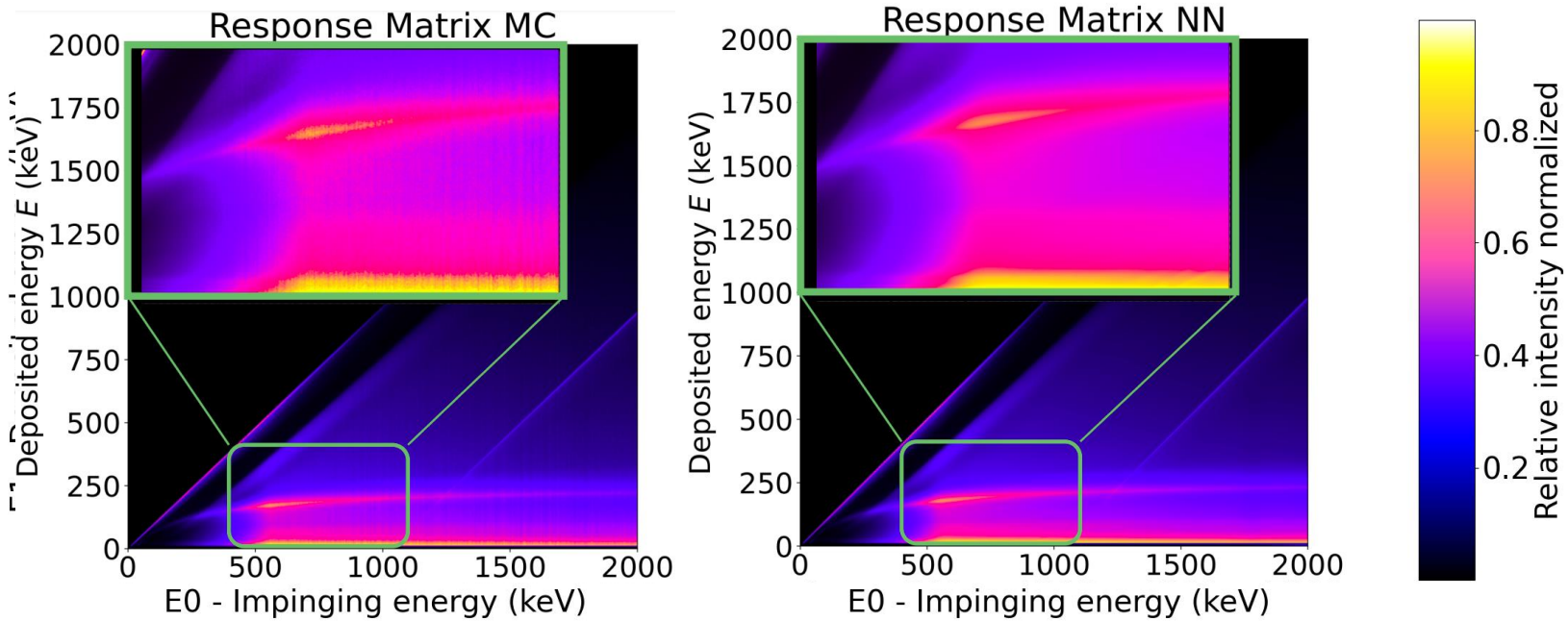


- Other applications
  - Imaging
  - Faster Detector Response Matrix compared with MC
  - Spectrum Reconstruction
  - Etc…



Conclusions and next steps

- Training data proved to solve some attenuation issues
- No performance was lost
- Artificial data generation achieved prior objective

- Optimization of results
- Implement physical modelization over 800 keV
- Add more elements on the pool
- Identify attenuators
- Predict the percentage of radioelements
- Launch MC simulations to evaluate
- Set metrics to be used on manuscript

Merci

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