Investigating the modelling of delayed gamma from nuclear fission with the help of multi-dimensional gamma spectroscopy

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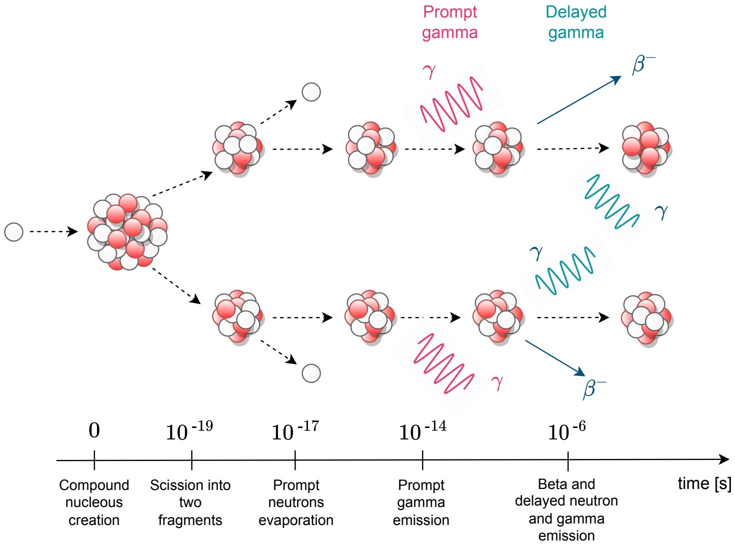
Neutron induced fission



- Gamma rays : photon produced by the radioactive decay of a nucleus
- energy : 100 keV - 8 MeV

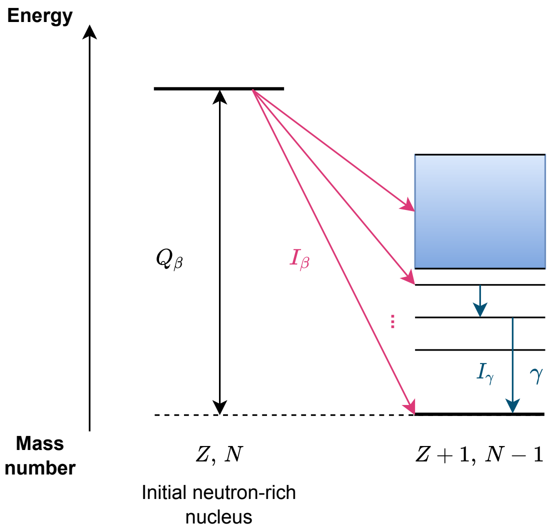
Beta decay for neutron-rich nuclei

β^- decay :

$$\boxed{{}^{A}_{Z}\mathrm{X} \longrightarrow {}_{Z+1}^{\ \ A}\mathrm{Y} + e^- + \bar{\nu}_e}$$

$$Q_\beta = E_{e^-} + E_{\bar{\nu}_e} + E^*$$

I_β gives the probability that the Y nucleus is produced at a given excited state



How to get I_β ?

- I_β can be estimate from I_γ thanks to gamma spectroscopy
- *pandemonium effect* : missing transitions and bias in intensities

Objective of the thesis

provide experimental verification of fission-delayed gamma-ray modelling
Include:

- beta decay process
- fission fragment deexcitation

but strongly depends on the *speed* of the analysis of the data we have

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Description of the experimental setup

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The neutron source

- experimental nuclear reactor
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uranium 235 diluted in a scintillating liquid

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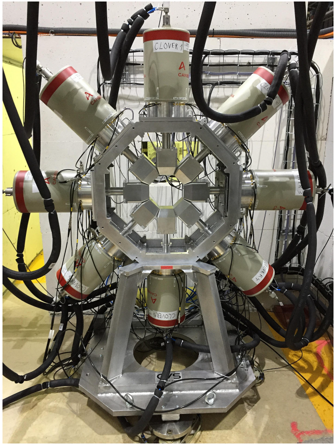
The detection system (FIPPS gamma-ray spectrometer)

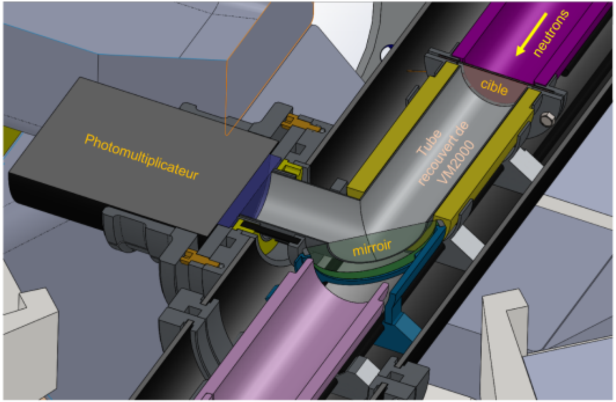
Composed of two parts :

- 16 high-purity germanium clover detectors (HPGe)
- Photo-multiplier : collect the light produced at the target

Description of the experimental setup



(a) 8 of the 16 germanium spectrometers



(b) The target and the light collecting system

Pre-analysis

Raw data treatment

- Validation of the *fission tag* (other PhD student) ✓
- Energy calibration (other PhD student and myself) ✓
- Time calibration (other PhD student) ✓
- Produce the coincidence matrix and cube ✓

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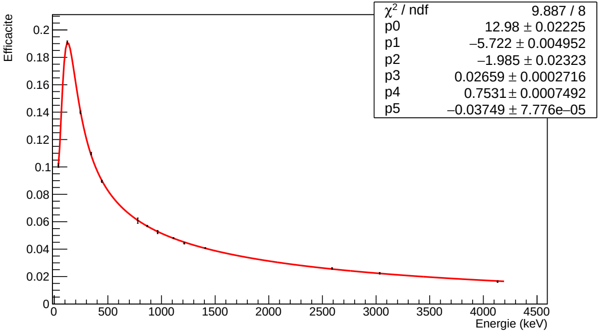
Detector properties

- dead time ✓
- efficiency ✓

Efficiency

- calibration source : europium 152
- relies on a good knowledge of the source's activity which was not easy to estimate
- relative uncertainty around $1\,\%$



Previous analysis

What has been done

- Independent fission yield for a dozen of fission fragments [a]
- the analysis relies extensively on peak fitting on 2d or 3d spectra to extract the number of measured gamma for a given transition
- the current methods are time consuming and the uncertainty can be large

[a] *The nuclear fission process in the light of prompt gamma-rays : measurement of thermal fission yields of U-235 on the FIPPS spectrometer*, P. Herran (2023)

Limitations

- we want to analyse hundreds of peaks with a good control on the uncertainty
- an automatic (or at least semi-automatic) procedure would be welcomed

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The motto of every programmer

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We are physicists, how can we introduce some physics ?

Which data to train the model ?

Problem

There is no labeled data available

Solution

We simulate our own data : synthetic data set

- Pro : full control
- Con : possible bias and missing things

New problem

How to truthfully reproduce the data we observe ?

Synthetic dataset : an example

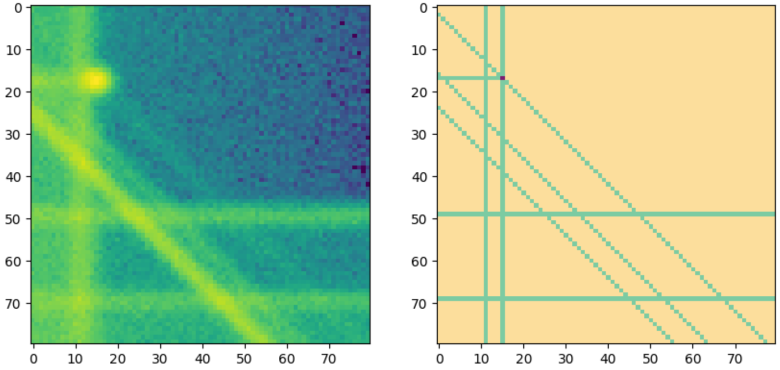
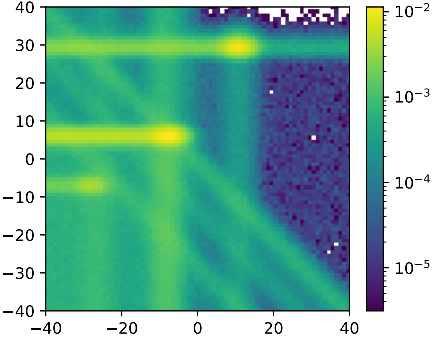
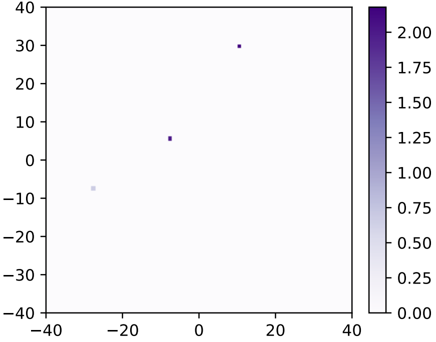


Figure: Example of a synthetic histogram with one peak with it corresponding mask (right)

The architecture : inputs and outputs



(a) Input : histogram with one or several peaks



(b) Expected outputs : peaks positions and intensities

Figure: Inputs and outputs of the neural network

The architecture : the network

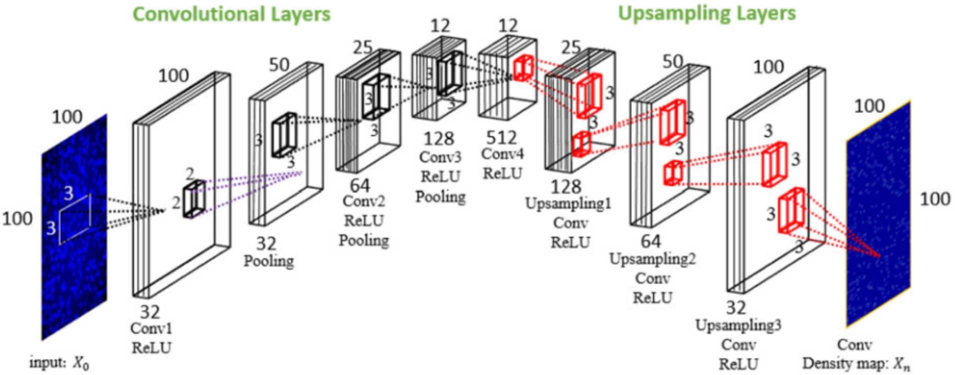


Figure: One of the implemented architecture. Inspired from Xie et al

Loss function

Two tasks : find the peaks locations **and** intensities

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Notations :

- $\hat{y} = (\hat{y}_{ij})$: output of the model
- $y = (y_{ij})$: the expected output
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And $\mathcal{F} = \hat{\mathcal{I}} \setminus \mathcal{I}$ the indexes of false positives

$$\boxed{\mathcal{L}(y, \hat{y}, \boldsymbol{\theta}) = \mathcal{L}_{\mathcal{I}}(y, \hat{y}, \boldsymbol{\theta}) + \lambda \cdot \mathcal{L}_{\mathcal{F}}(y, \hat{y}, \boldsymbol{\theta})} \tag{1}$$

$$\mathcal{L}_{\mathcal{I}}(y, \hat{y}, \boldsymbol{\theta}) = \sum_{\mathcal{I}} (\hat{y}_{ij} - y_{ij})^2 \qquad \mathcal{L}_{\mathcal{F}}(y, \hat{y}, \boldsymbol{\theta}) = \mathrm{card}(\mathcal{F})$$

Details

- input "augmented" with prior information on the peaks positions
- 2 architectures implemented using PyTorch
- models train on GPU on the CCIN2P3

First results

What metrics to measure the accuracy of the neural network ?

- Relative error : $\frac{y-\hat{y}}{y}$ where y is the expected peak intensity
- number of false positive

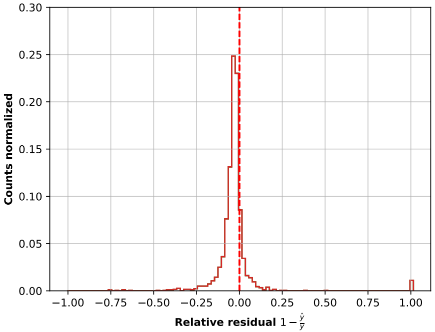

Figure: Distribution of the relative error for the test set

Question : what did we miss with this model ?

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Uncertainties in the inputs

statistical variation of the content of each bin in the 2d spectra

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Uncertainties in the outputs

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Confidence of the model

uncertainties in the prediction of the neural network

Conclusion

What has be done so far ?

- FIPPS raw data treatment and determination of the efficiency of the FIPPS spectrometer with a relative uncertainty around 1%
- building of a generator of synthetic data to train and test machine learning models
- implementation, training and testing of two architectures of CNN

What's next ?

- uncertainty quantification
- test the robustness of the neural network
- test the neural network on real data and compare with classic fit method
- analysis of the FIPPS data

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^{136}Te levels

Objective

We want to measure the independent fission yield of tellurium 136.

How ?

by counting the number of gamma rays emitted by a ^{136}Te nucleus and measured by the spectrometer.

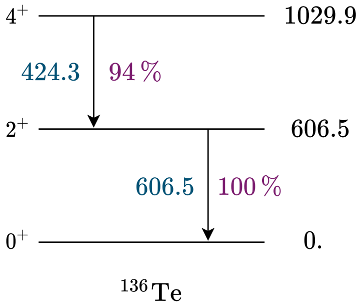


Figure: Energy and transition for the first two levels of ^{136}Te

Aperçu de spectre 1d

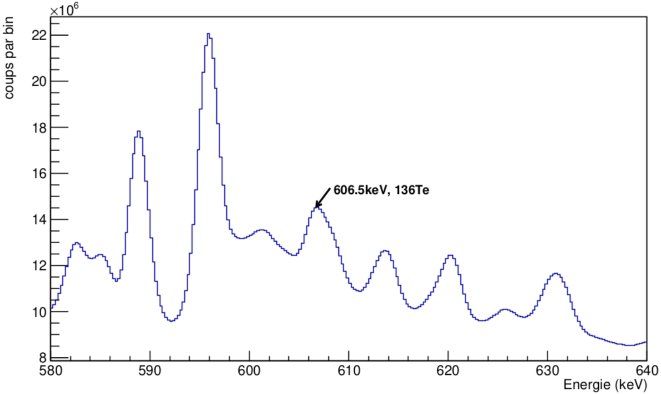


Figure: Zoom around 610 keV on the one full fission events spectrum from FIPPS

Coincidence matrix

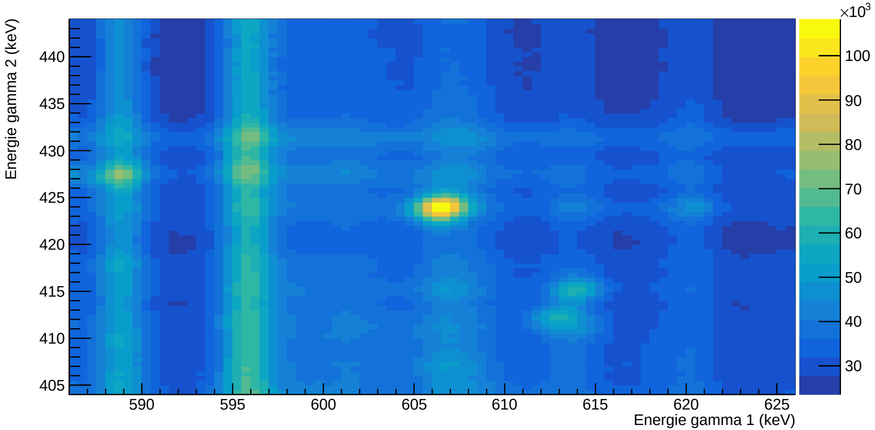
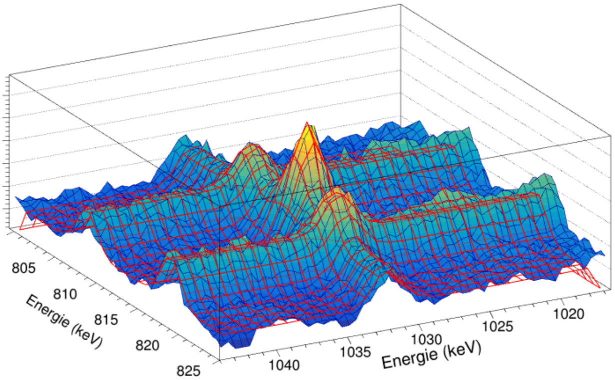


Figure: Region around the peak of interest on the coincidence matrix for fission events

Example of a fit of a peak on the matrix



- Required complex fit model
- Goodness-of-fit difficult to estimate

Projection and fit

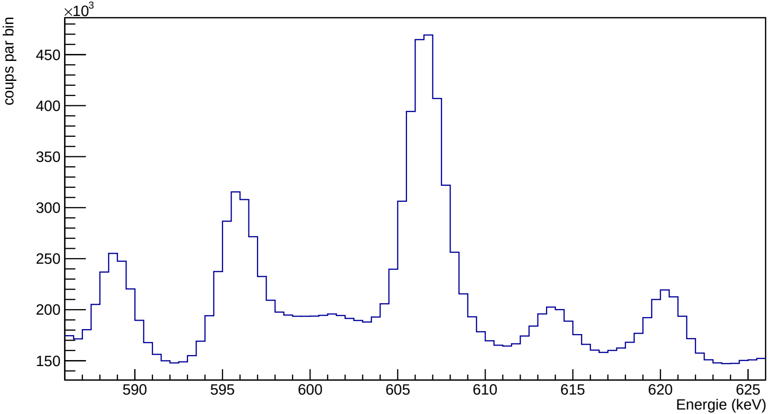


Figure: Projection of the previous histogram after applying a selection on the y-axis between 421 and 424 keV

What already exist

- Détection de pics : Kensert et al. 2022 (chromatographie)
- Ajustement de pics en 1d : Park et al. 2021 (photo émission), Abdel-Aal 2002
- ML et spectroscopie gamma : Kamuda et al. 2020, Daniel et al. 2020
- architectures : U-Net Ronneberger et al. 2015, SE (Squeeze and Excitation)

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