Gamma-ray spectrometry of fission fragments : ML analysis of multi-dimensional spectra

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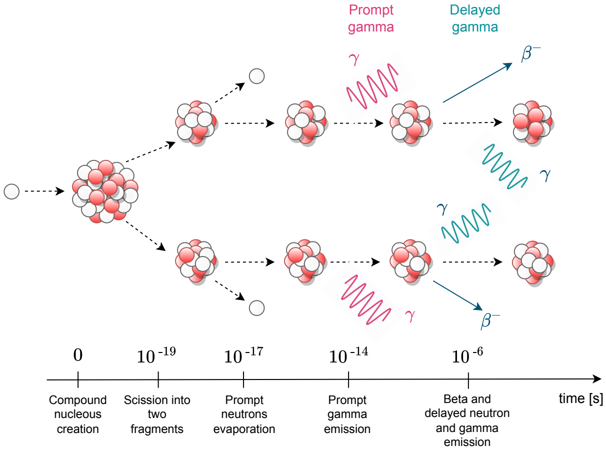
Gamma rays and the nuclear fission process



Compound nucleous creation

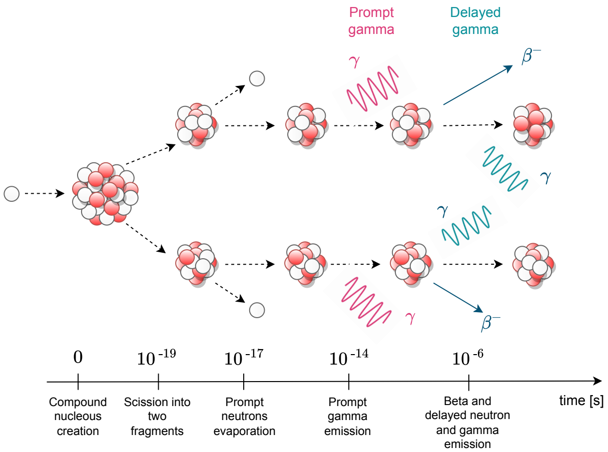
Scission into two fragments

Prompt neutrons evaporation

Prompt gamma emission

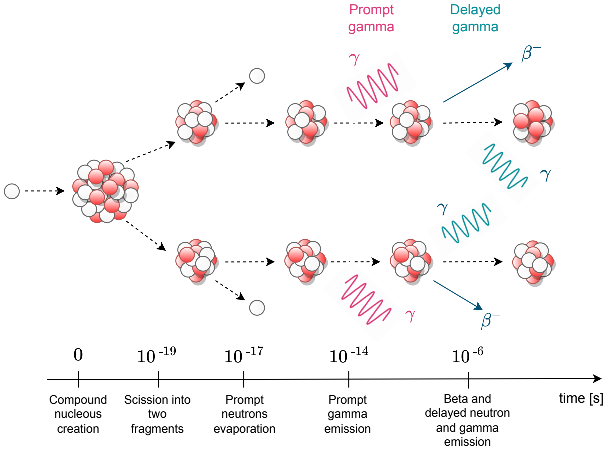
Beta and delayed neutron and gamma emission

Gamma rays and the nuclear fission process



- prompt gamma rays emitted by fission fragments
- delayed gamma rays emitted during beta decay

Gamma rays and the nuclear fission process



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Interest of gamma-ray spectroscopy

- Probe the intrinsic properties of the fragments
- Compare the desexcitation process with simulation
- Nuclear data

The FIPPS spectrometer

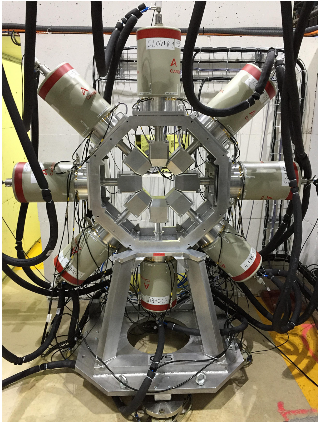

Figure: 8 of the 16 germanium spectrometers

The neutron source

- nuclear reactor located at Laue-Langevin Institute (ILL)

The *active* target (Kandzia et al., 2020)

Uranium 235 diluted in a scintillating liquid
Interest : gamma-rays emitted after a fission can be discriminated

The detection system (Michelagnoli et al., 2018)

Composed of two parts :

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

A look at the data

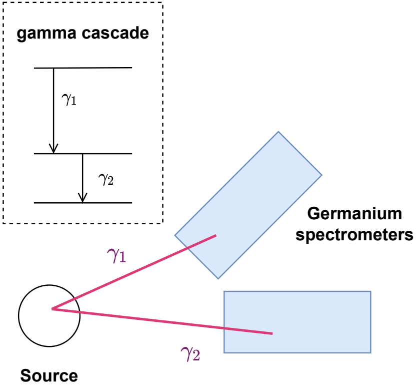

Figure: Measure of gamma rays in coincidence

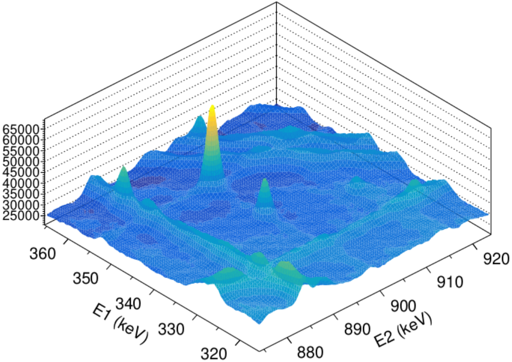

Figure: Zoom of the coincidence matrix on the region that corresponds to the detection of 2 gamma rays following the beta decay of $^{132}\mathrm{Sn}$

What's the issue ?

Goal

Extract the intensity of one or several peaks on a given region

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Current analysis method

- gating, background subtraction and projection to work with 1D-histograms
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Better approach : fit directly the matrix

but :

- required complex fit model (designed *by-hand*)
- required a good first guess of the parameters

An automatic (or at least semi-automatic) procedure would be welcomed !

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Road map

DATA

- training, testing, evaluating : **?**
- benchmarking : simulated data from GEANT4 simulation
- comparison with classic fit methods : real data from calibration source ($^{152}\mathrm{Eu}$)

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CNN but which type ?

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Architectures

CNN but which type ?

The rest

- what about uncertainty quantification ? and how to deal with the uncertainty in the input histograms ?
- how can we introduce prior knowledge in the analysis ?

Example of a synthetic 2d-histogram

Requirements

- closely imitate experimental data
- cover the *space* of possible histograms

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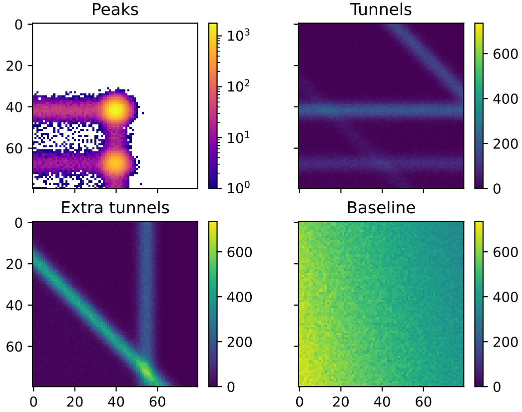

Figure: Example of a synthetic 2D-histogram

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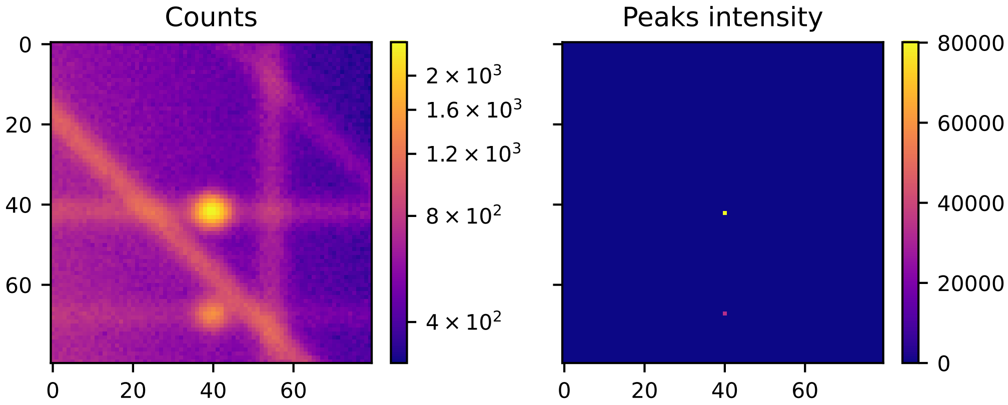
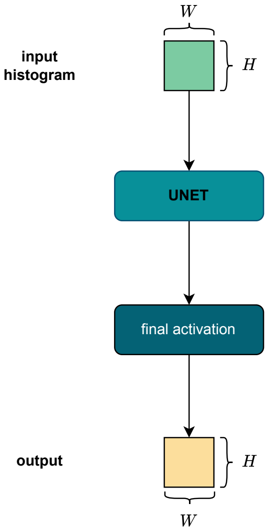
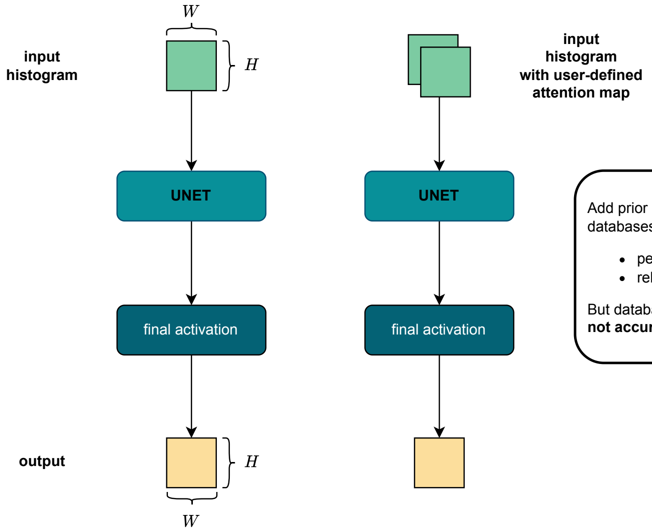


The architectures : 3 flavors



The architectures : 3 flavors

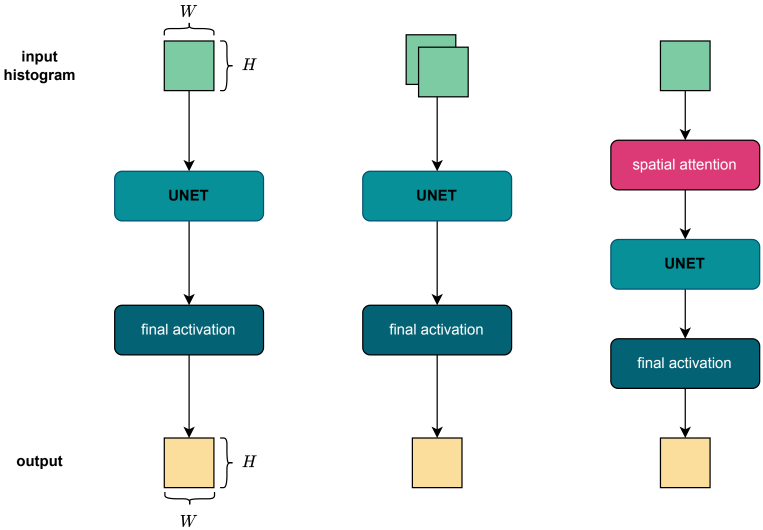


Add prior knowledge from nuclear databases

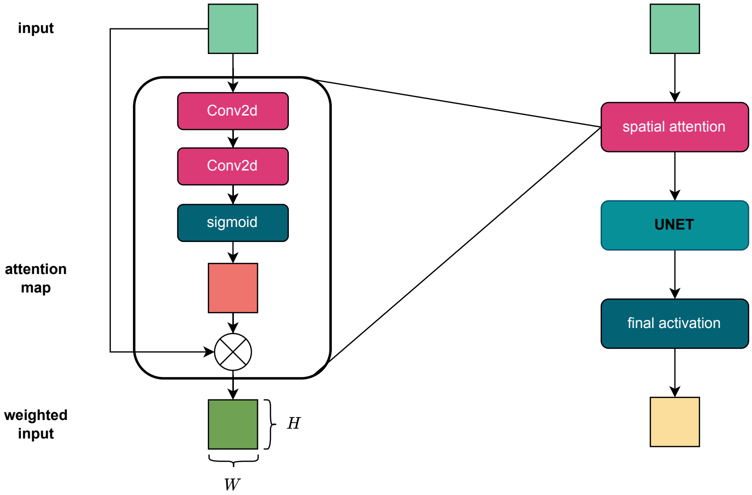
- peaks' positions
- relative intensity

But databases **incomplete** and **not accurate**

The architectures : 3 flavors



The architectures : did you say attention ?



Results on relative loss

- training on 2 million histograms
- 10 epochs
- Adam and cyclic LR scheduling
- weighted loss function:

$$\mathcal{L} = \alpha \, \mathcal{L}_P \, (y,\, \hat{y}) + (1 - \alpha) \, \mathcal{L}_Z \, (\hat{y})$$

target is > 0

target is 0

- $\mathcal{L}_P = \mathcal{L}_Z =$ MSE, $\alpha = 0.8$

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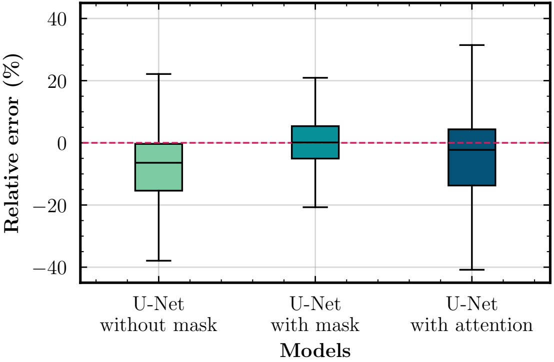
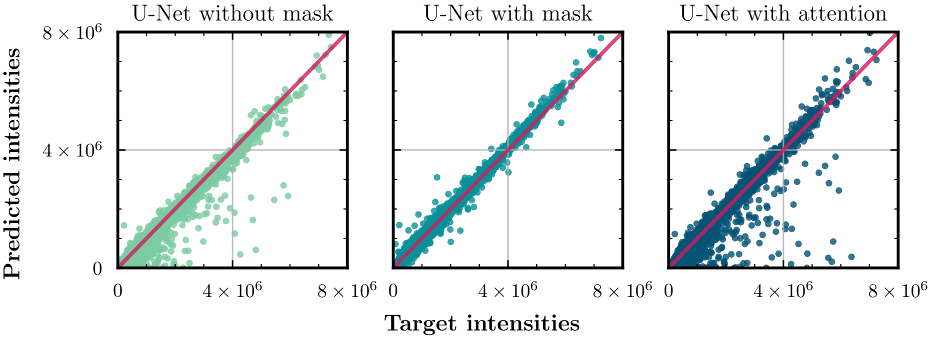


Target and prediction comparison



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Statistical uncertainty in the inputs

input histogram

c_{ij}

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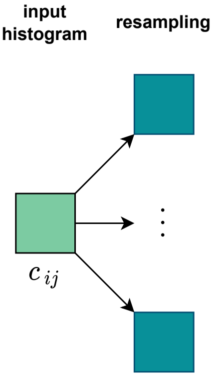
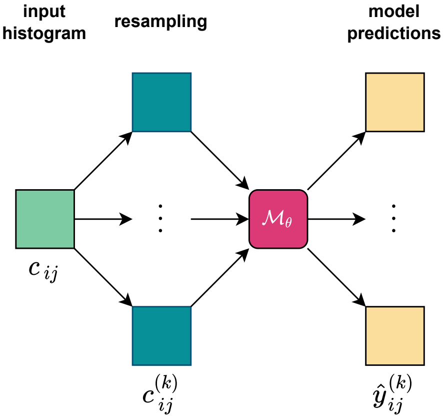


Assumptions :

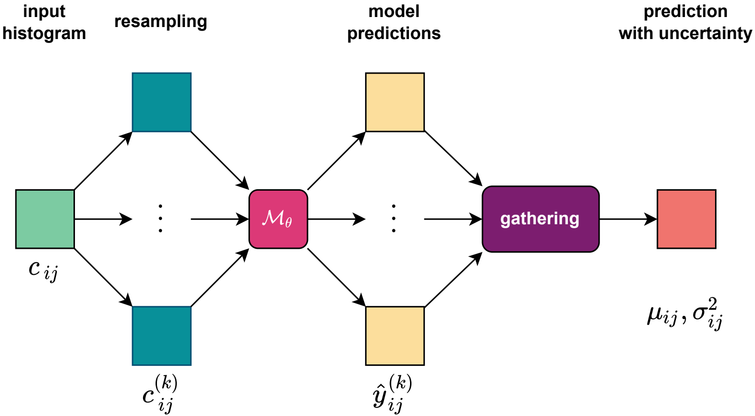
- the number of counts in the bin $(i,\ j)$ follows a Poisson distribution
- bins are **NOT** correlated

for each bin, k samples are drawn in $\mathcal{P}(c_{ij})$

Statistical uncertainty in the inputs



Statistical uncertainty in the inputs



Conclusion and perspectives

What has be done so far

- synthetic dataset
- implementation of 3 architectures
- first characterization

What's next ?

- model uncertainty
- comparison to classic fit method
- application to the real data

References I

F. Kandzia, G. Belier, C. Michelagnoli, J. Aupiais, M. Barani, J. Dudouet, C. E. Düllmann, Ł. Iskra, M. Jentschel, Y. Kim, et al. Development of a liquid scintillator based active fission target for fipps. *The European Physical Journal A*, 56(8):207, 2020.

C. Michelagnoli, A. Blanc, E. Ruiz-Martinez, A. Chebboubi, H. Faust, E. Froidefond, G. Kessedjian, M. Jentschel, U. Köster, P. Mutti, et al. Fipps (fission product prompt γ-ray spectrometer) and its first experimental campaign. In *EPJ Web of Conferences*, volume 193, page 04009. EDP Sciences, 2018.