Unfolding a neutron energy spectrum using a trendfilter

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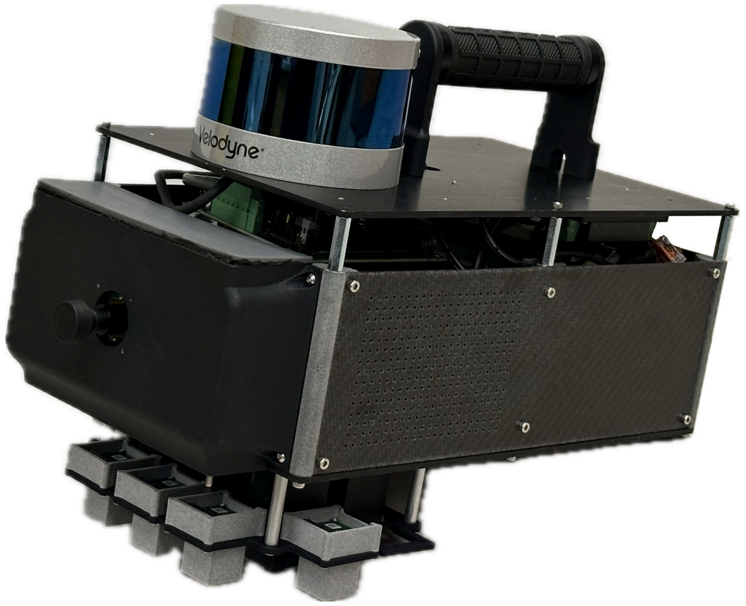
Introduction

- Aim: Develop an algorithm to unfold a neutron spectrum from measurements
    - Caveat: The neutron source can be an unknown mixture of sources. No prior
- Use cases: Free moving neutron mapping in nuclear facilities
- Technical challenges:
    - No prior and no stopping criterion (except a tolerance on matching measurements)
    - Noisy observations (short dwell times and low neutron counts per channel)
- Test cases: Watt and (α, n) spectrum (synthetic data); experimental data
- Measurements: Plastic scintillator (EJ-276D) w/ pulse-shape discrimination
    - Contains trapezoidal filters for fast and slow energy components
    - Provides neutron energies and a metric for gamma / neutron discrimination

Use cases

- Background
  - LBNL has developed a series of free-moving handheld radiation mapping systems called Localization and Mapping Platforms or LAMPs
  - Our project is developing data analysis methods for the new FastNeutronLAMP (FastN LAMP)
    - CLLBC and EJ-276D detectors (12x total)
    - Focuses on energetic neutron mapping
    - New data acquisition system can perform coincident timing at 10ns



(Above) FastNLAMP

(Below) Photo and LAMP Compton imaging data product of LAMP-identified hold-up in glovebox air outlet at SRNL Pu-238 facility

Use scenario: When nuclear inspectors (e.g., IAEA or NNSA Office of Nuclear Verification) enter an unknown site, **can we localize and provide rudimentary information on neutron sources?**

- Is measured spectrum consistent with (α,n) or fission?
- (still to work through) Can multiplicity/arrival times be leveraged to further constrain neutron source characteristics?

The unfolding problem

- Linear inverse problem: $F = [R]P$, $[R]$ :: detector response matrix
  - F(e) : detector counts in M energy bins
  - P(e): neutron energy spectrum on N bins; M > N usually
- Reconstruction problem: $F^{(obs)} \sim \text{Poisson}([R]P)$; estimate $\hat{P}$
- Issues:
  - $F^{(obs)}$ has limited information on P; need to inject exogenous information (prior)
  - $F^{(obs)}$ ca be noisy due to low counts in many energy bins
- Our solution:
  - Assumption: P(e) is smooth & can be approximated well by a piece-wise linear curve
  - The piece-wise linear approx. can be computed using a trendfilter

Trendfilter

- Trendfilter: a generalized lasso solution for under-defined system $Y = [A]X$
  - $\min_{x_i} C = \|Y - [A]X\|_2^2 + \lambda\| [D]X \|_1, X = \{x_i\}, Y = \{y_j\}$
  - [D]: centered finite difference matrix for second derivative
  - λ: penalty for curvature; estimated via cross-validation
  - Assumption: Formulation implies Gaussian noise
- Algo: Minimizes locations with curvature i.e., creates line segments
  - λ controls the penalty – larger λ implies fewer points with curvature i.e., fewer, large line segments
- Our predictor-corrector construction: Our algo builds on the trendfilter
  - Predictor step: Use an approximation of trendfilter for Poisson noise to get a starting guess $P^{(pred)}$
    - $P^{(pred)}$ may have elements < 0
  - Corrector step: Use ridge regression (in terms of $\phi = \log P^{(corr)}$) to get $\hat{P}$ that is always > 0

Our algorithm with non-negativity enforcement

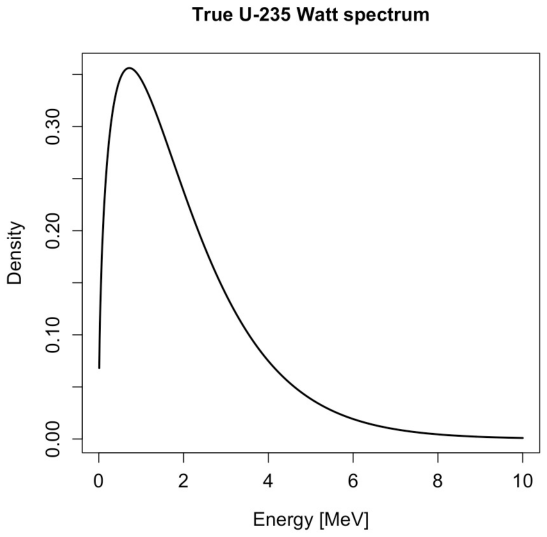
- Predictor step: Trendfilter approximation for Poisson noise, to get a "good" $P^{(pred)}$
  - $\min_{p_i} C_1 = \left\| \left(F^{(obs)} - [R]P^{(pred)}\right) ./ \left(\sqrt{F^{(obs)}}\right) \right\|_2^2 + \lambda_1 \| [D] P^{(pred)} \|_1$
    - ./ is element-wise division
  - $P^{(pred)}$ so obtained can be negative; non-negativity has to be enforced
- "Corrector" step: Enforce non-negativity
  - $P_{guess}^{(corr)}$ obtained by replacing –ve $P^{(pred)}$ elements with linear interpolations from +ve neighbors
  - Ridge regression: $\min_{\phi_i} C_2 = \left\|F^{(obs)} - [R]P^{(corr)}\right\|_2^2 + \lambda_2 \| [D] P^{(corr)} \|_2^2$
    - $\phi_i = \log_e p_i^{(corr)}$; optimizing in terms of ϕ_i enforces $p_i^{(corr)}$ to be always > 0
    - λ_2 keeps the spectrum close to piece-wise linear, as in the predictor step
  - Solved with L-BFGS to get $\hat{P}$

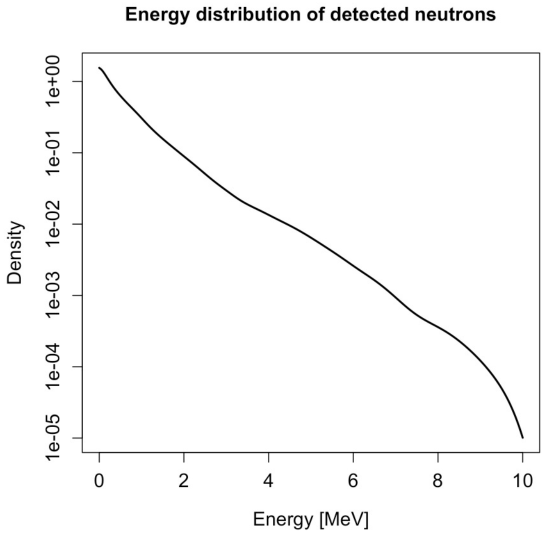
CV and making $[R]$

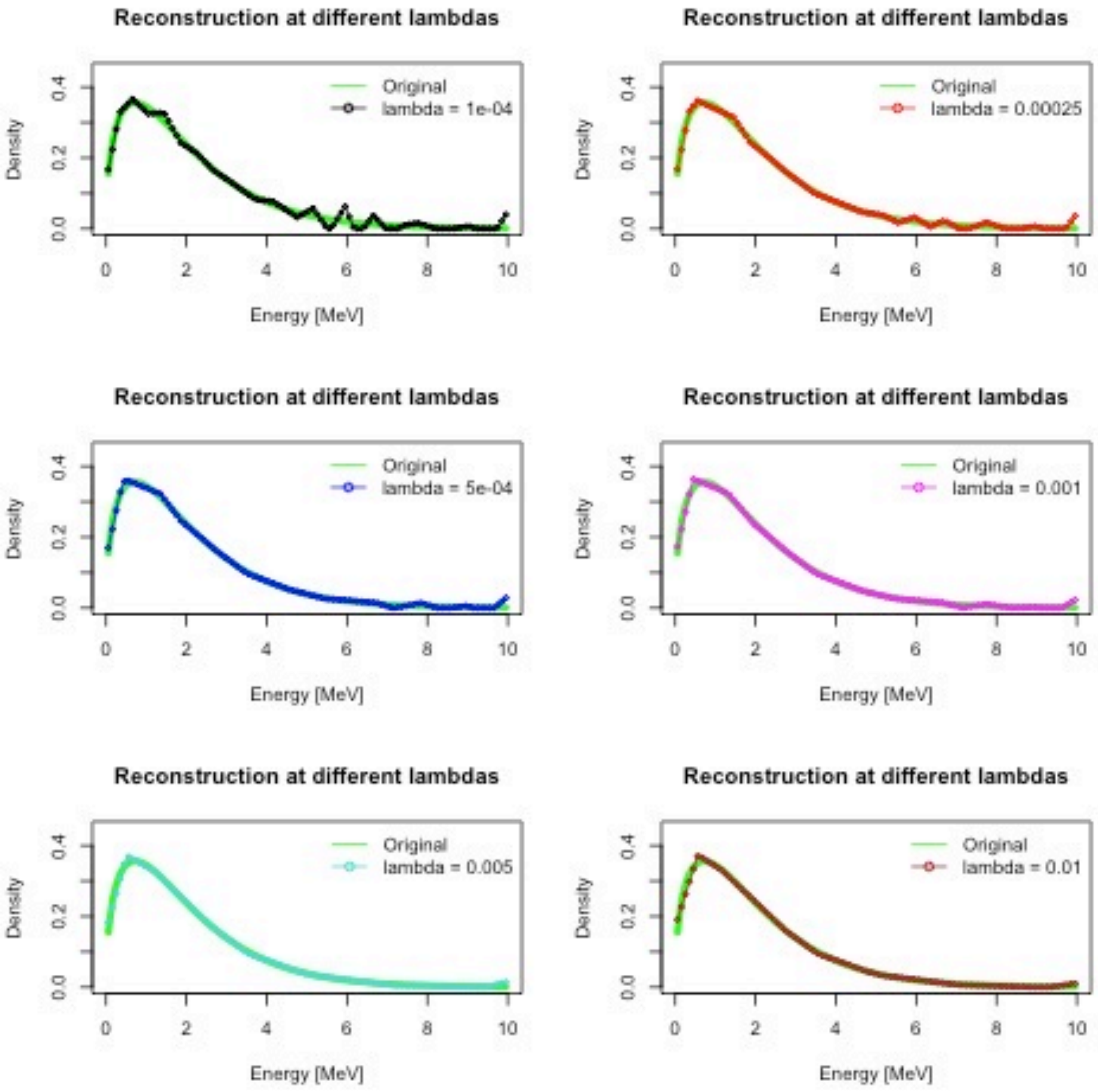
- Cross-validation (CV): A range of λ is chosen i.e., $\lambda \in (\lambda_{min}, \lambda_{max})$
  1. $F^{(obs)}$ is separated 80:20 into a learning set (LS) and training set (TS)
  2. For a given λ, use predictor-corrector and LS to get P_j'
  3. Using P_j' and TS compute $e_j = \sqrt{\left\|\left(F_{TS}^{(obs)} - [R_{TS}]P'\right)\right\|_2^2}$
  4. Repeat steps (1, 2) J = 30 times and compute $E(\lambda) = \left(\sum_j e_j\right)/J$
  5. Pick λ with min E(λ)
- Constructing $[R]$:
  - Made with MCNP
  - Energy deposition is calculated by parsing the ptrac files from mono-energy neutrons
  - Each scatter converted into light output via a fitted response and summed for a single deposition value.
  - Energy cutoff & gaussian energy broadening are also applied before being collated into the response matrix.

Test case 1 – Watt spectrum w/ synthetic data

- Specifics:
  - U-235 Watt spectrum
  - M = 1024 bins
  - N = 100 bins
- Synthetic data:
  - Poisson([R]P)
  - 5×10^6detections
- Reconstructions with different λ
- CV errors and picking λ_{best}







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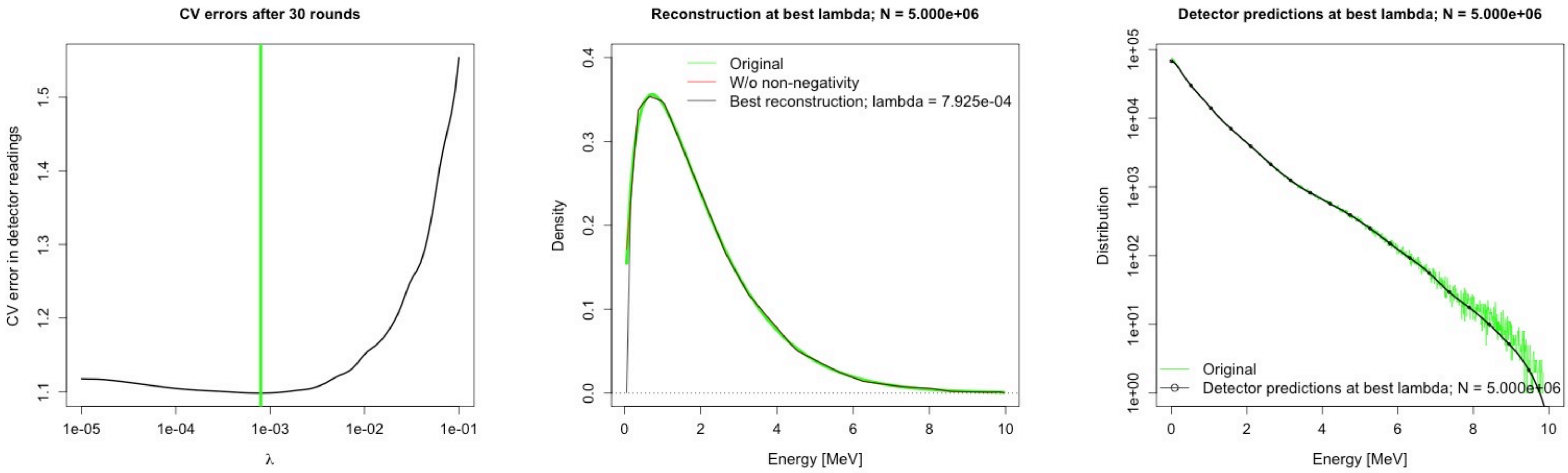
Test case 1 – Watt spectrum w/ synthetic data (cont’d)

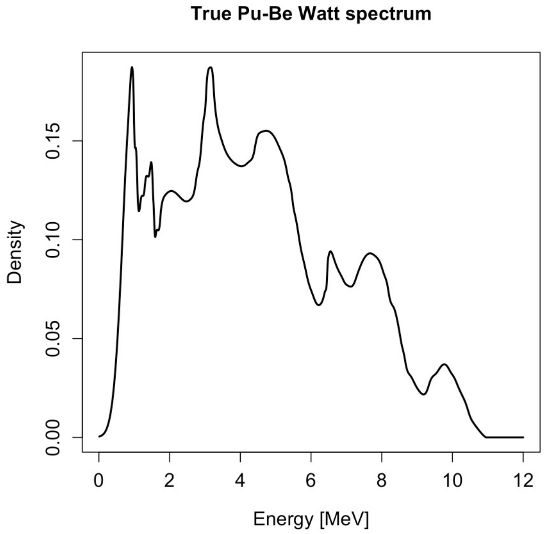


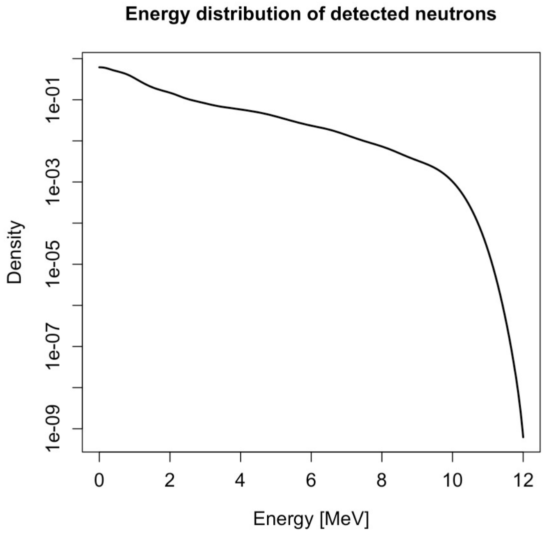
- Trendfilter leads to a spectrum that goes not go –ve
- Unfolded spectrum reproduces synthetic measurements well
- Jensen-Shannon distance = 7.9e-2

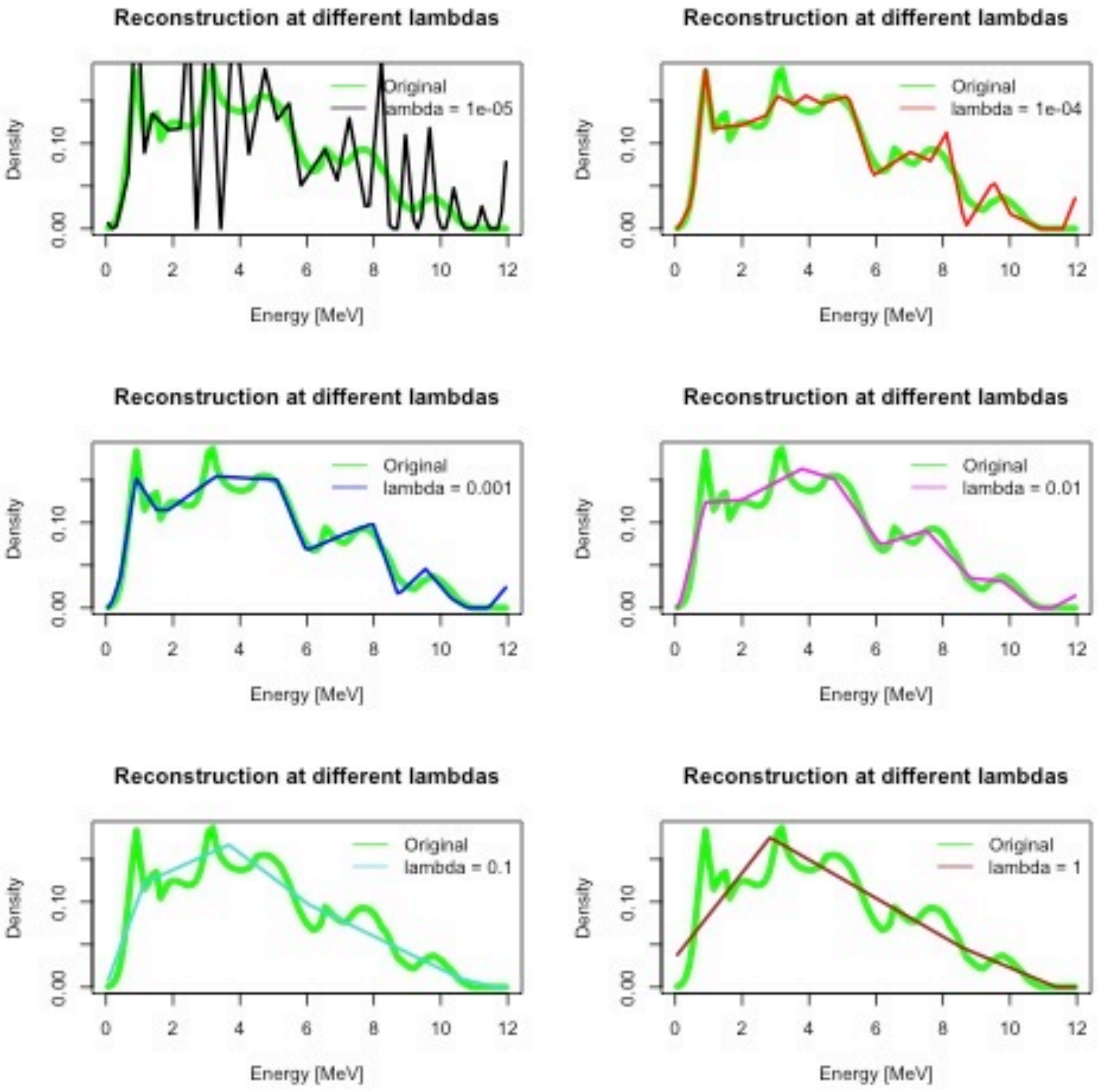
Projects/RDF22/src/point/ex08/fig07

Test case 2 – (α, n) spectrum w/ synthetic data

- Specifics:
  - Pu-α-Be spectrum
  - M = 1024 bins
  - N = 100 bins
- Synthetic data:
  - Poisson([R]P)
  - 5×10^6detections
- Reconstructions with different λ
- CV errors and picking λ_{best}







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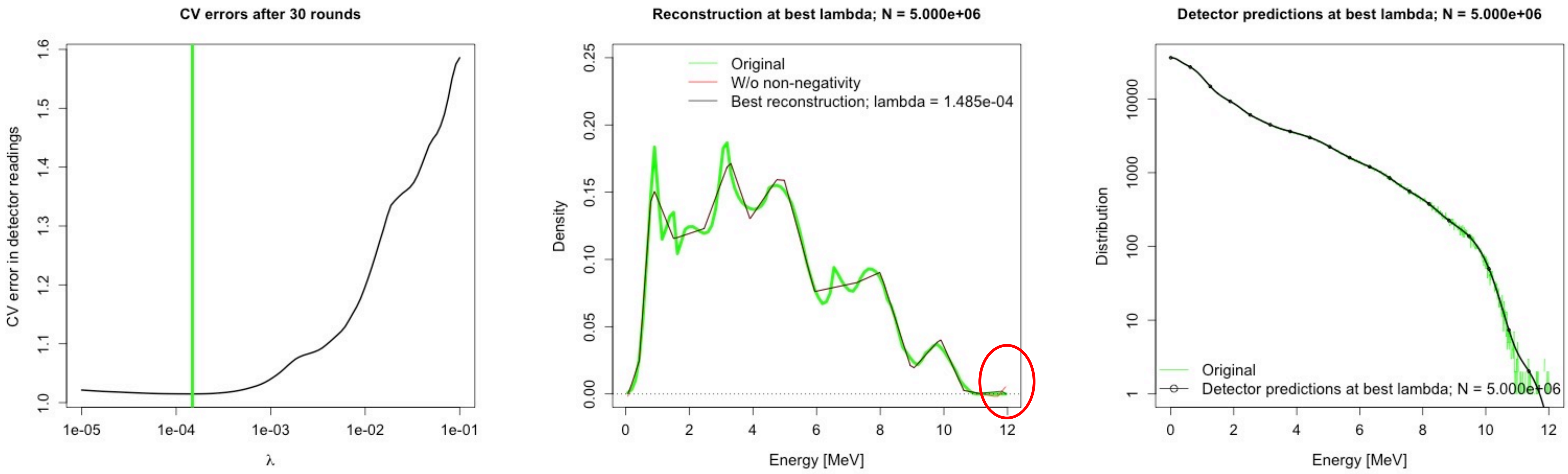
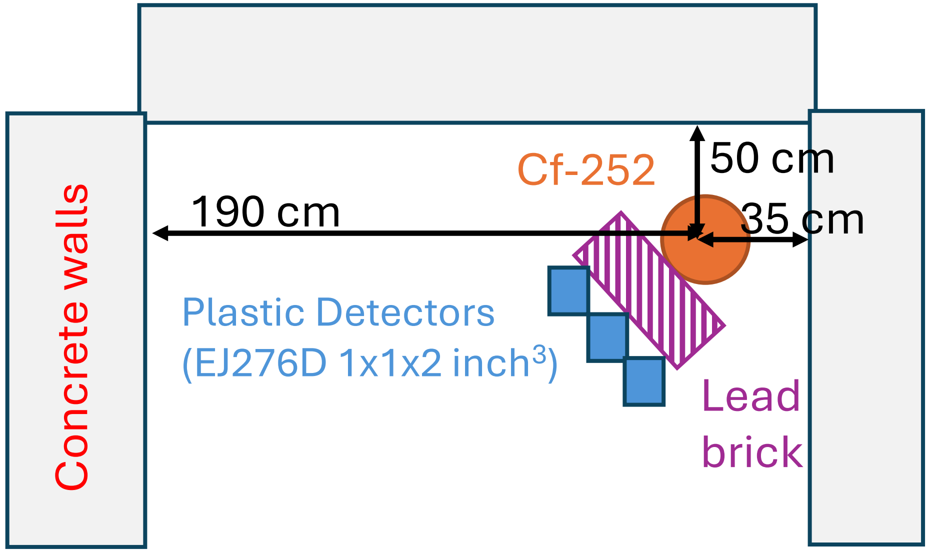
Test case 2 – (α, n) spectrum w/ synthetic data (cont'd)



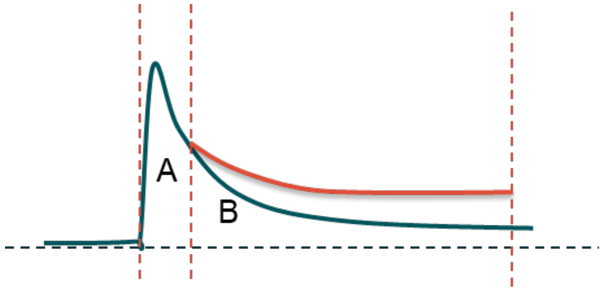
- Trendfilter leads to a spectrum that goes –ve; non-negativity enforcement fixes it
- Residual error at the high-energy end
- Unfolded spectrum reproduces synthetic measurements well
  - Jensen-Shannon distance = 1.462e-2

Projects/RDF22/src/point/ex09/fig07

Test case 3 - the experiment

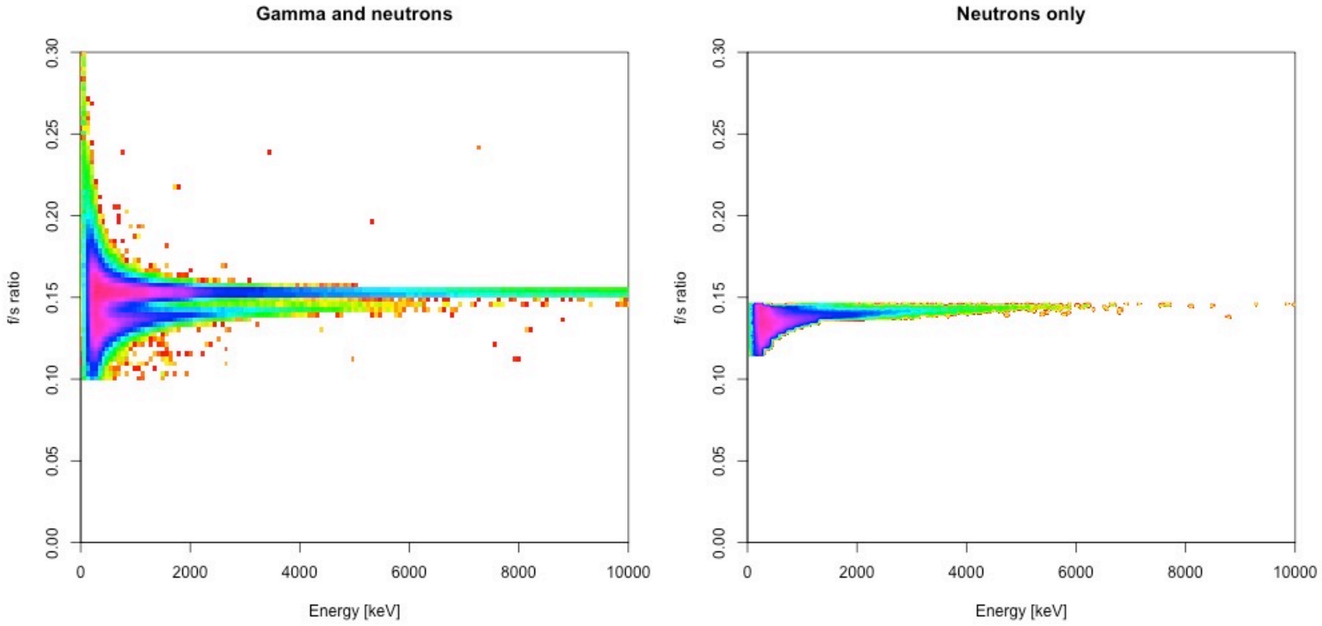


- Experimental setup:
  - Cf-252 inside a poly container; plastic detector (EJ-276D)
  - pulse shape discrimination by metric fast/slow ratio

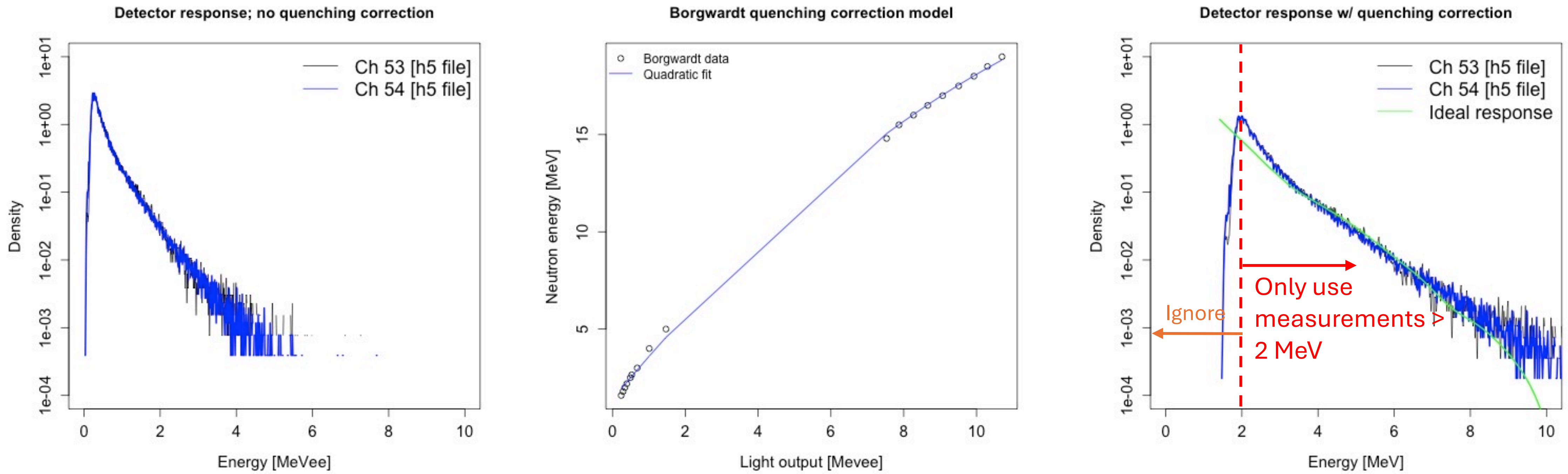


- Tail-to-total: area_tail / area_total = B/(A+B)
- fast/slow = A / (A+B)

- Gamma/neutron classifier
  - Counts divided into different energy bins
  - Two Gaussian peaks fitted each bin
  - A threshold set at intersection of two peaks.
    - neutron : fast/slow < threshold
    - gamma : fast/slow > threshold



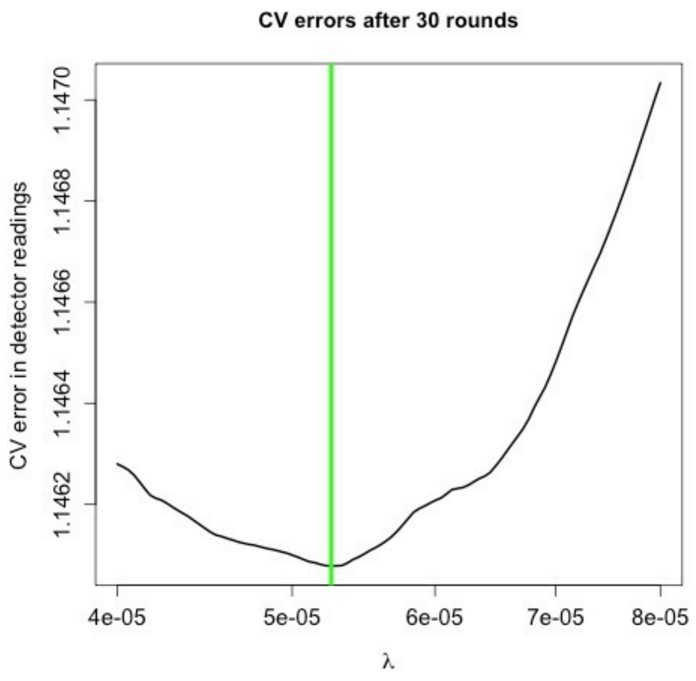
Post-processing data

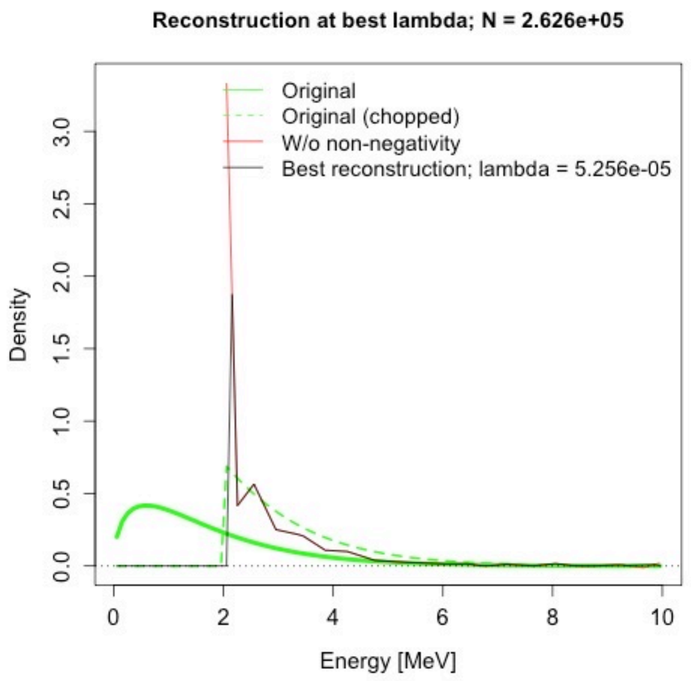


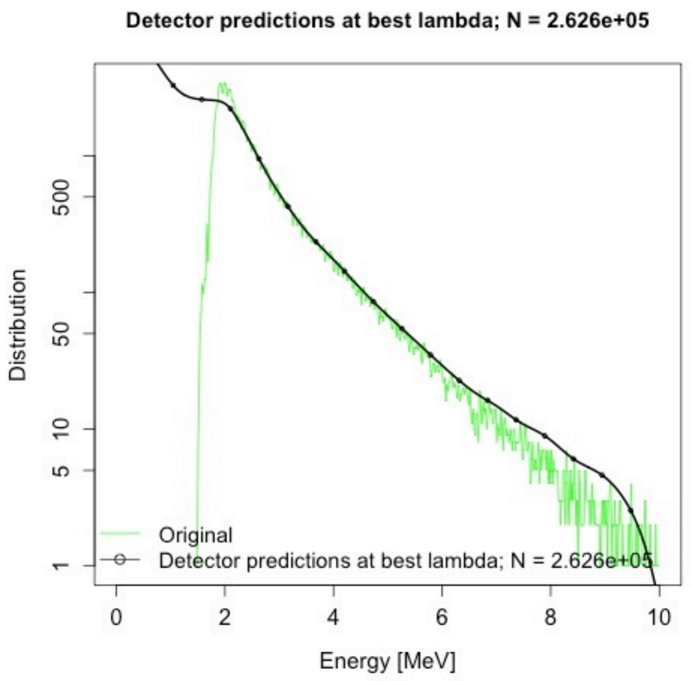
- Detections (scintillation light energy) in [0.6, 5.3] MeVee; 262,574 neutron detected
- Quenching model = Borgwardt, 2025 data (light energy v/s proton energy), fitted with quadratic
  - https://scintillator.lbl.gov/psd-plastic-scintillator-quenching-data/
- Quenching removes an important part of the spectrum below 2 MeV
  - We will underestimate the spectrum in the [2, 6] MeV range

Projects/RDF22/src/point/ex13/

Test case 3 – Watt spectrum from measurements







- Not being able to access any neutron counts < 2 MeV causes big deviation from true Cf-252 spectrum
- If limiting to E > 2 MeV and normalizing accordingly, not too bad
  - However, we underpredict spectrum in [2, 6] MeV range as we don't have access to measurements in [0, 2] MeV
- Reproduction of detector measurements too high at high-energy end

Projects/RDF22/src/point/ex13

Conclusions

- Have a predictor-corrector algo that unfolds neuron spectra
  - Doesn’t need any priors; works for an arbitrary spectrum, regardless of complexity
  - Only assumption: spectrum is smooth and admits piecewise-linear approx
  - Well-defined stopping criterion for the unfold
  - Builds on trendfilter (or generalized lasso for under-defined linear inverse problems)
- Shortcomings:
  - Our experimental data did not allow full testing and exercise of algo
  - Will always lag (in accuracy) algos that can exploit prior information
- Next steps: Hunt for better (α, n) and Watt spectrum measurements
- Not shown:
  - Degradation of unfold as number of detector channels and neutrons detected decrease

Acknowledgements

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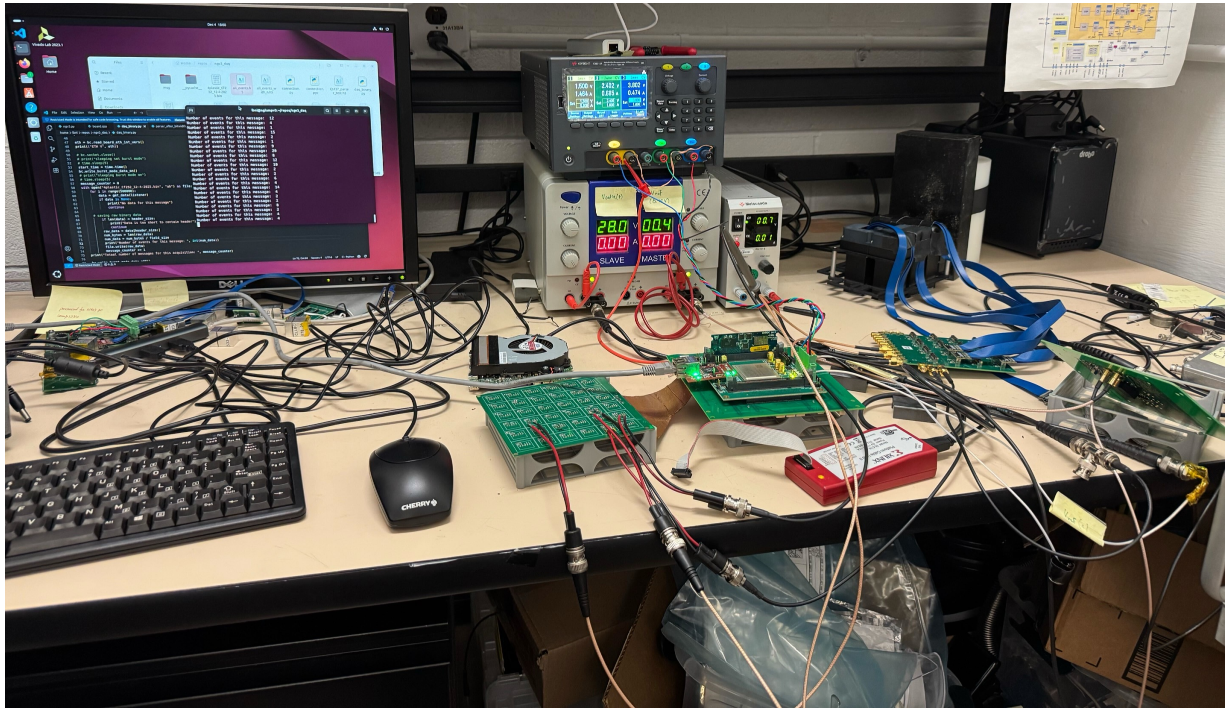
Experimental setup

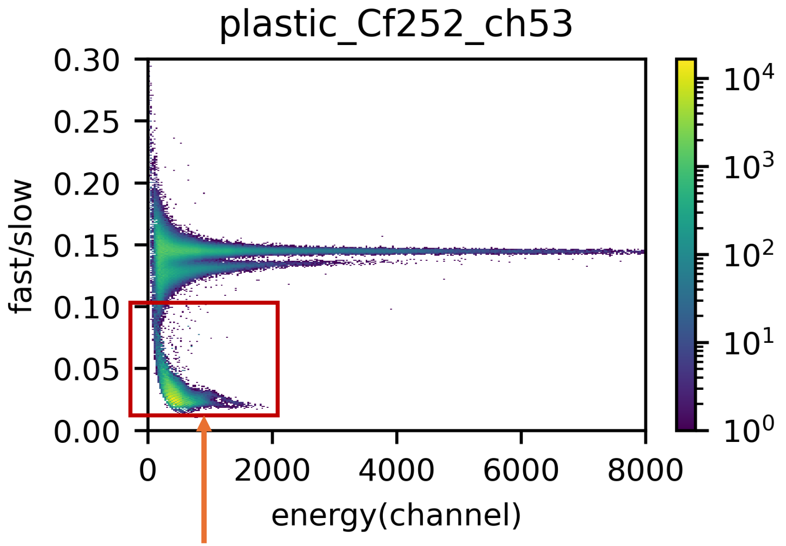
Overnight data acquisition: 4 plastic detectors with Cf-252

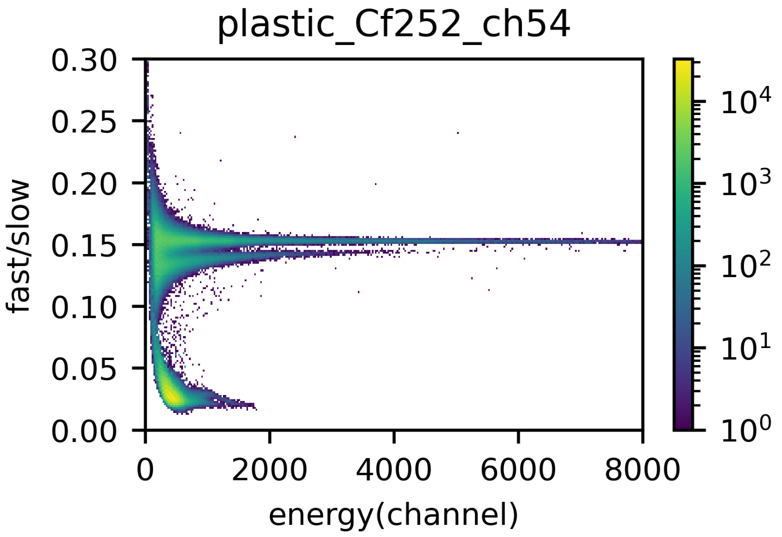
4 plastic detector used
3 of them has data output - 1 might have poor wire connection
500000 messages saved – took ~ 19 hours

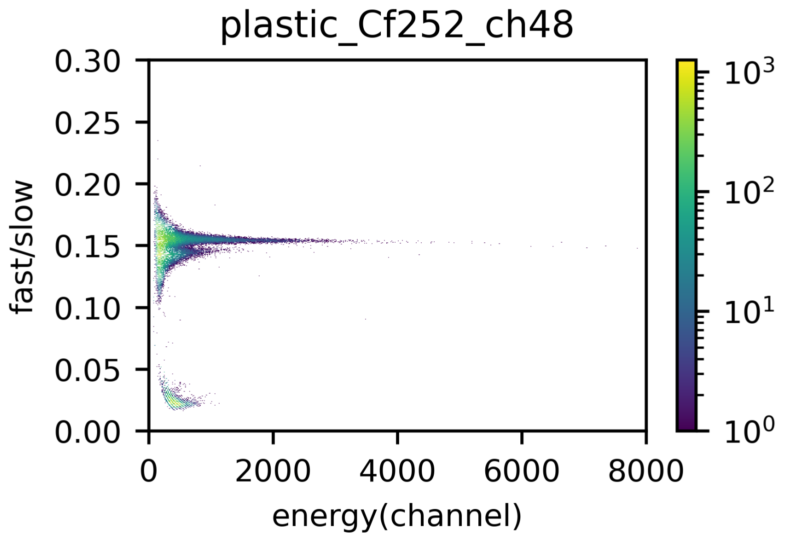


100 uCi at 2019-8-15
With half life of 2.645 years for Cf-252, activity at date of 12-5-2025 is 19uCi

Raw data before processing





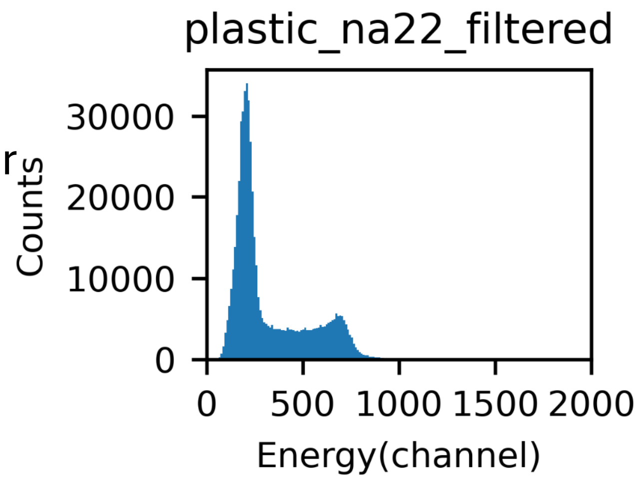


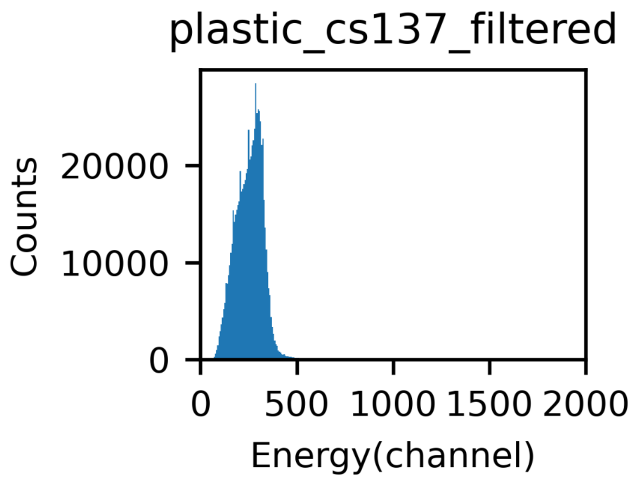
- Abnormal counts (noises) due to imperfect pole-zero cancellation
- Simply discard those counts by setting fast/slow>0.1 (0.1 is selected manually)

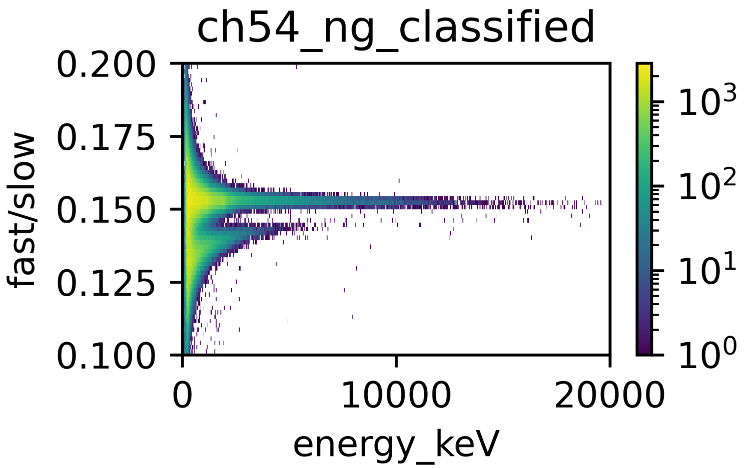
- The fast/slow band position for different detectors are different.
- Ideally, neutron gamma separation should be performed for individual detector, not for combined data from all detectors

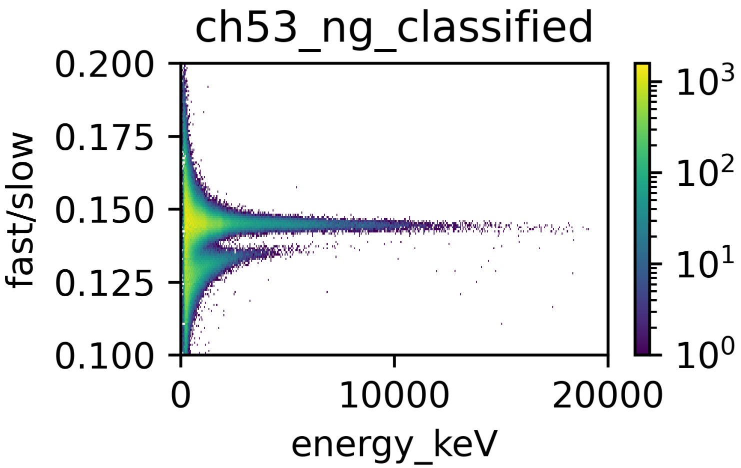
Energy calibration using Na-22 and Cs-137

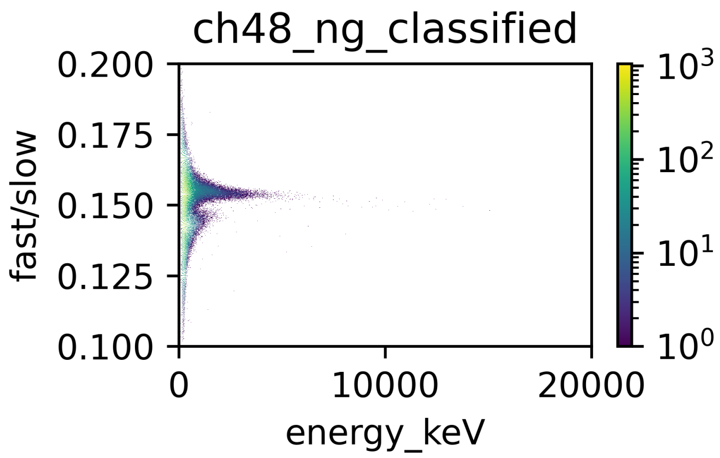
- Gamma energy spectrum of Na-22 and Cs-137 were acquired for ch54
- Linear fitting using the Compton edge energies (478 for Cs-137; 341 and 1062 for Na-22) and corresponding channel positions were performed
- Energy(keV) values for all 3 detectors, ch53, ch54 and ch48 were obtained using the linear fitting results of ch54. (using energy calibration of ch54 for other detectors is not very accurate, but it should be reasonably good.)











Neutron gamma classification

Method for n/g classification:

- The counts are divided by separate energy bins (number of bins manually determined)
- In each energy bin, two Gaussian peaks are fitted to the fast/slow values. (GaussianMixture from sklearn.mixture is used)
- Values with extreme fast/slow are excluded from the fitting and labeled “excluded”, because they can lead to bad fitting.
- The fitted two Gaussian peaks are plotted to inspect if the fitting agree with the actual data.
- A threshold is set at the intersection between the two fitted Gaussian peaks. Events with fast/slow value smaller than the threshold is labeled “neutron” and events with fast/slow value larger than the threshold is labeled “gamma”
- The probability that a neutron event has fast/slow value larger than the threshold and the probability that a gamma event has fast/slow value smaller than the threshold are calculated.

The energy bins and results related to Gaussian fitting is as follows.

	Energy_bin_Min	Energy_bin_Max	Threshold	FOM	mu1	mu2	sigma1	sigma2	w1	w2	Probability:neutron(Left Peak smaller mu)>Threshold	Probability:gamma(Right Peak larger mu) <Threshold
0	0.0	200.0	0.149122	0.359595	0.141796	0.156802	0.010195	0.007525	0.510262	0.489738	0.236195	0.153722
1	200.0	250.0	0.146971	0.478475	0.140350	0.155407	0.007962	0.005401	0.380845	0.619155	0.202809	0.059152
2	250.0	300.0	0.146630	0.609904	0.140852	0.155423	0.005372	0.004773	0.268849	0.731151	0.141059	0.032712

FOM is figure-of-merit that quantify the separation of the two Gaussian peak

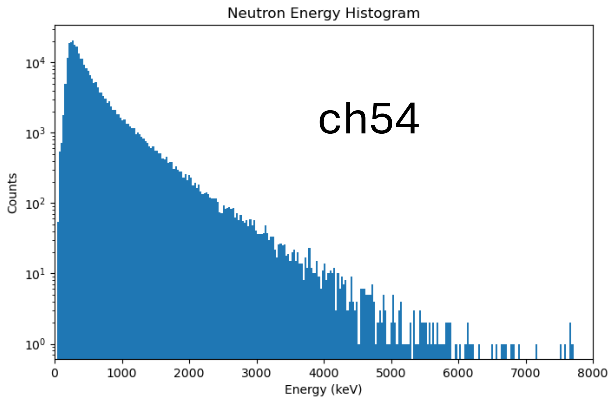
Neutron gamma classification

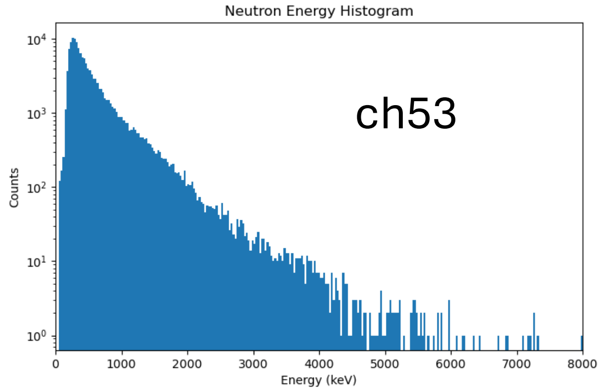
Example of the data after neutron gamma classification

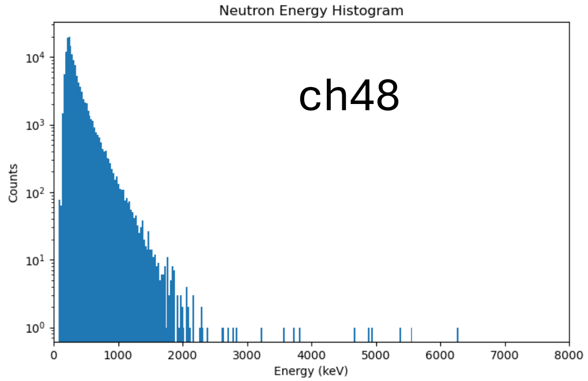
	energy	timestamp	channelID	fastEnergy	fast/slow	timestamp_unwrapped	energy_keV	label
0	42	6513871	54	8	0.190476	0.100213	32.718813	gamma
1	960	8318060	54	146	0.152083	0.127970	1360.310293	gamma
6	169	1321673	54	26	0.153846	0.020333	216.383430	gamma
7	687	5584766	54	101	0.147016	0.085919	965.503677	gamma
14	142	5014863	54	22	0.154930	0.077152	177.336621	gamma

Note: the timestamp_unwrapped may not be correct, because only 24 bits were used that a rollover could be missed

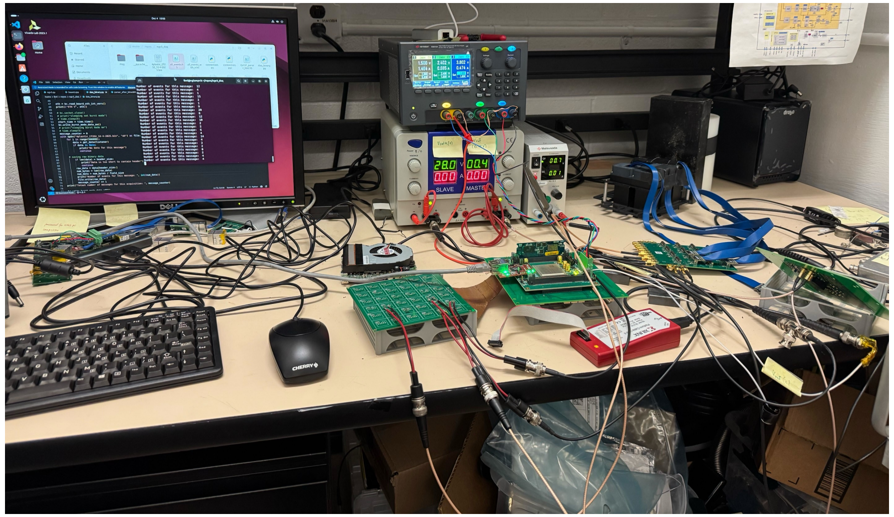
Neutron energy spectrum for 3 detectors after neutron/gamma classification

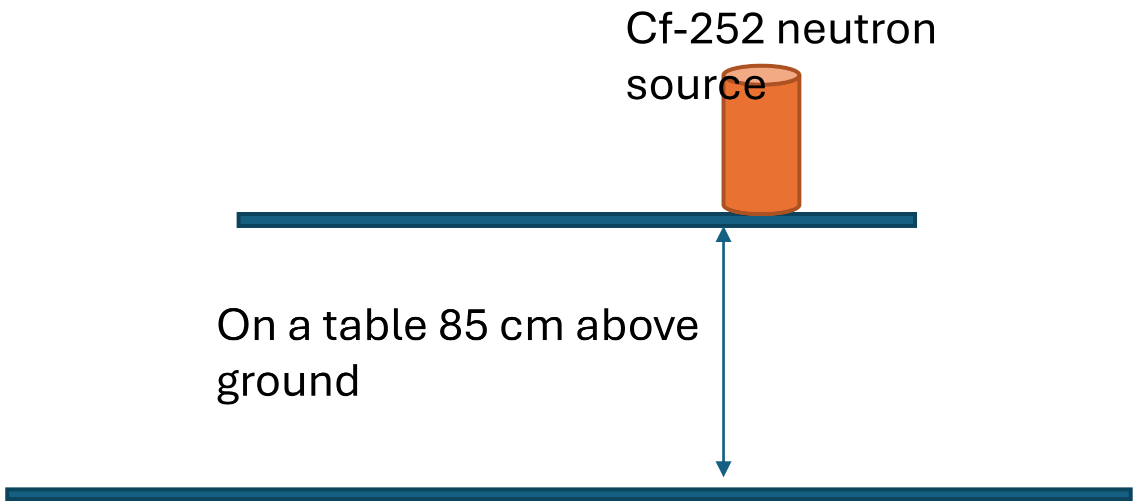




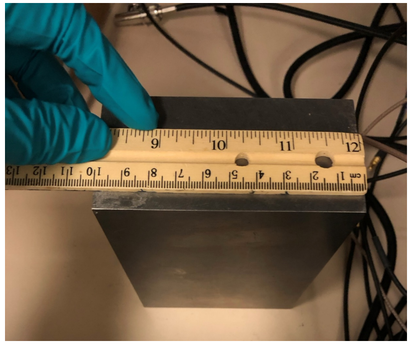


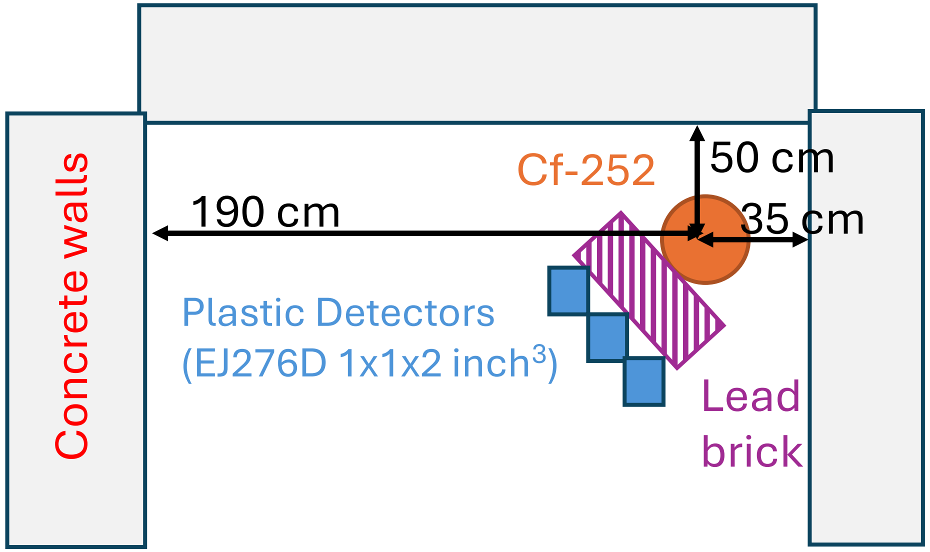
A simple geometry showing the environment for the data acquisition





- Lead brick dimension





- Cf-252 source Dimension
- Cf-252 is placed inside a polymer jig (probably polyethylene)