Machine Learning Prediction of Pebble History and Nuclide Concentration in PBRs

April 24, 2024

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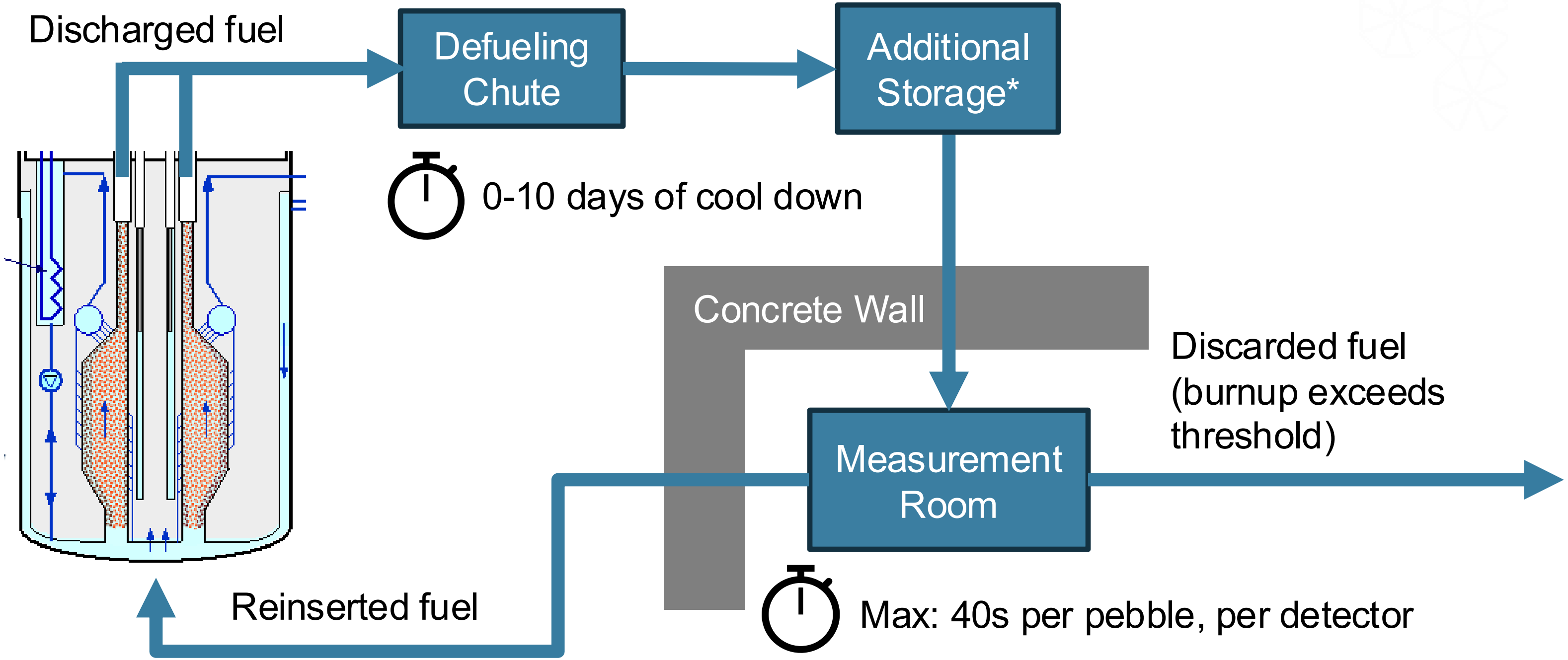
Pebble Assessment

- Objective: Simulate a realistic detected gamma spectrum from a gFHR fuel pebble and use ML to make predictions with it
- Challenges and Considerations:
  - About 2,300 pebbles leave the core a day, giving us about 40 seconds max to measure each pebble
  - Even with decay times of up to several days, pebbles emit on the order of 10^{13} gammas per second
  - For a detector, this could lead to serious dead time without prohibitively expensive shielding
- Can ML provide an edge over regression approaches?

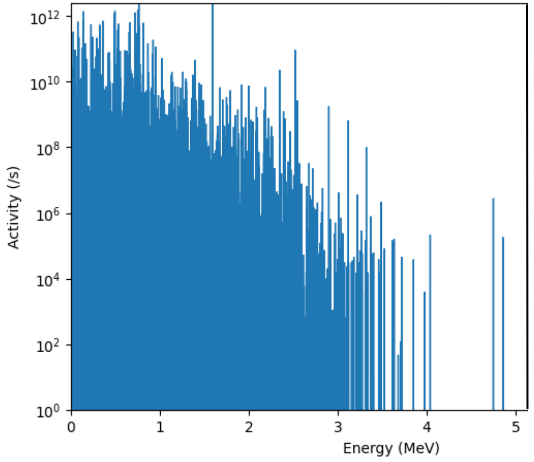
Hypothetical Burnup Measurement System



Detected Spectrum Generation

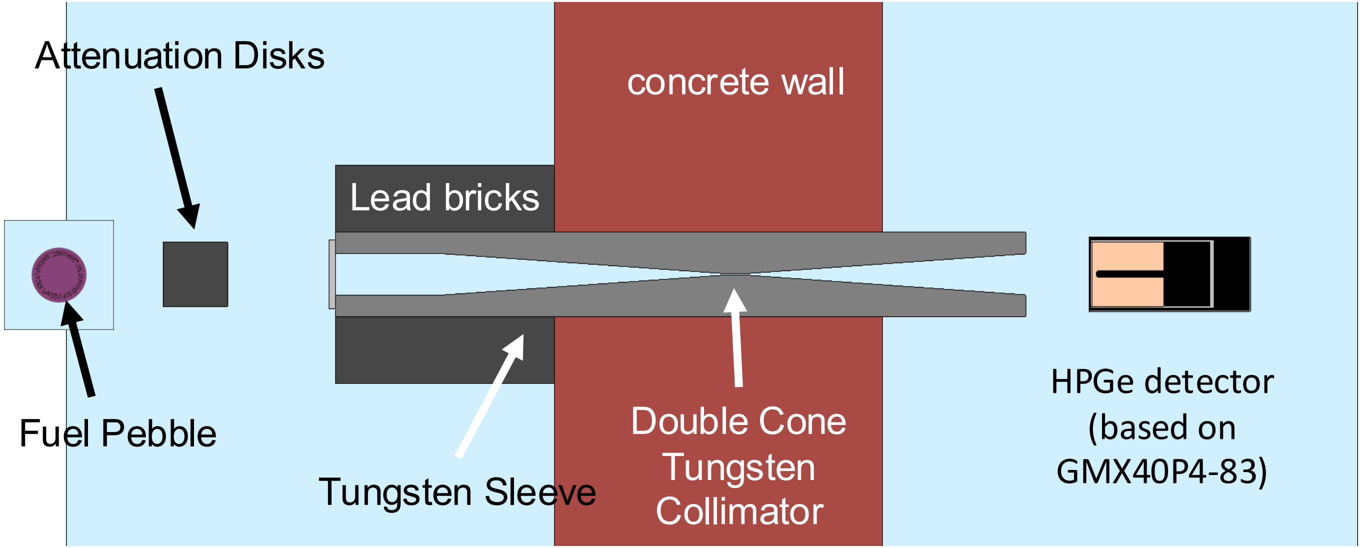
Emitted Gamma Source Generation

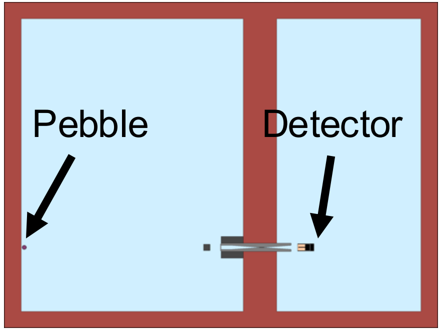
- Discharge compositions used to generate spectra
  - Unique, pebble-level data from HxF
  - Kairos Power gFHR at equilibrium
- Different decay times between 0 and 10 days
  - 120 second variance applied
- Spectra produced in Serpent
  - Decay step (neutron mode)
  - Gamma source (photon mode)

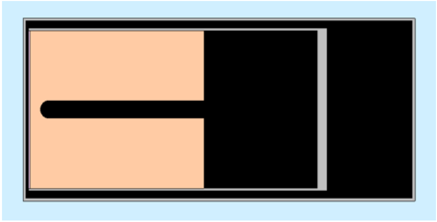


Detector Model (HPGe)

Total pebble distance	250 cm
Collimator Length	54 cm
Detector Dimensions	6.06 x 6.69 cm
Photopeak Efficiency @ 1MeV	2.19 x 10^{-8}

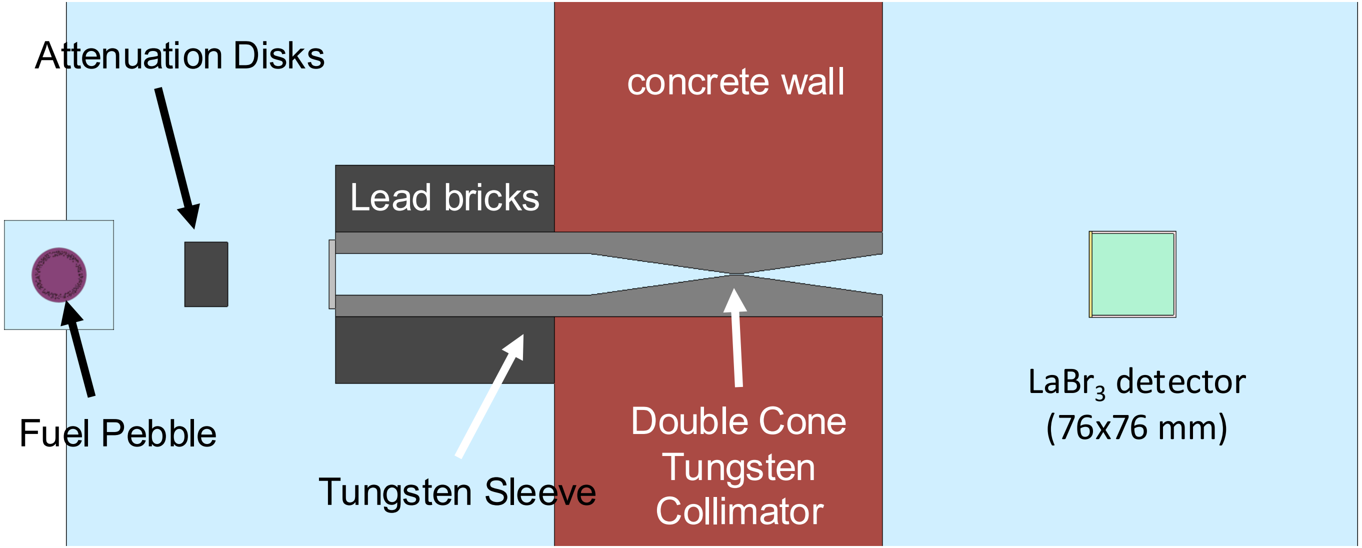


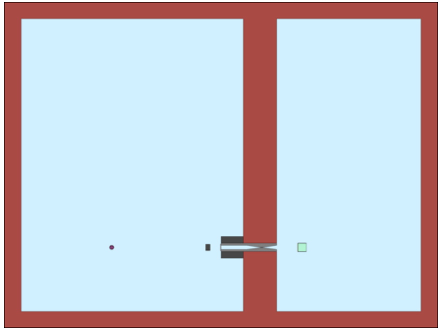


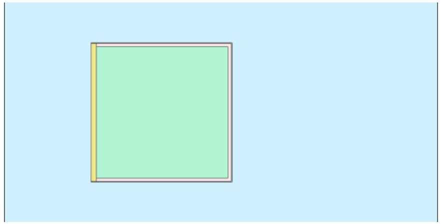


Detector Model (LaBr3)

Total pebble distance	170 cm
Collimator Length	27 cm
Detector Dimensions	7.6 x 7.6 cm
Photopeak Efficiency @ 1MeV	1.87 x 10^{-7}





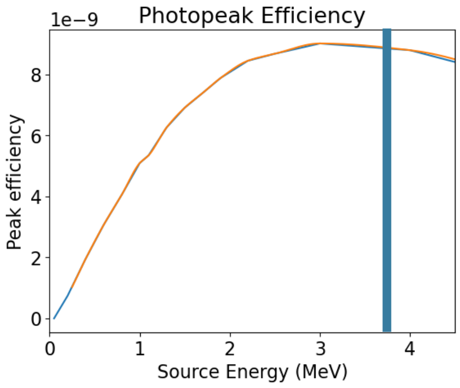


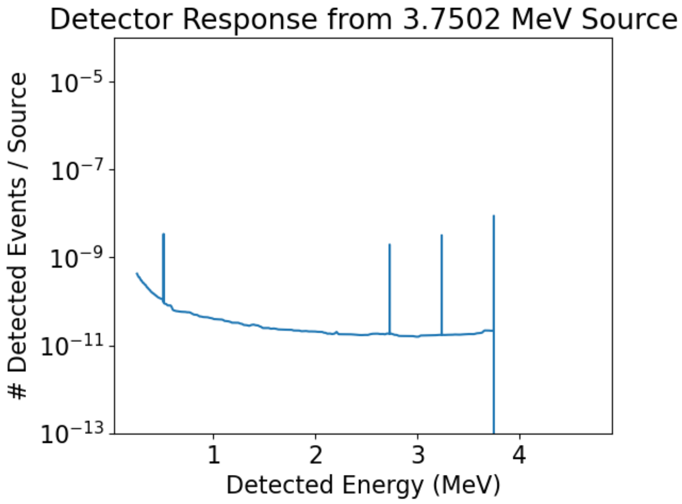
Detector Response Simulation: Tally

- Simulated at 16 different source energies
- Monoenergic source sampled from pebble
- Pulse height tally in detector crystal
- Energy bins in the tally are divided to capture different reactions:
  - Coarse bins (20–50 keV wide) for continuum
  - Very fine bins for discrete energies (photopeak, pair production, single and double escape peaks)

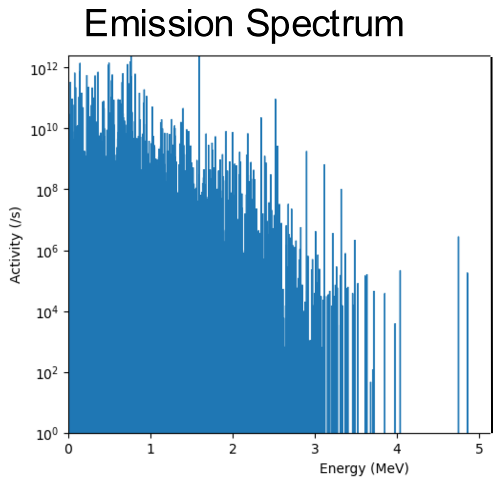
Detector Response Function

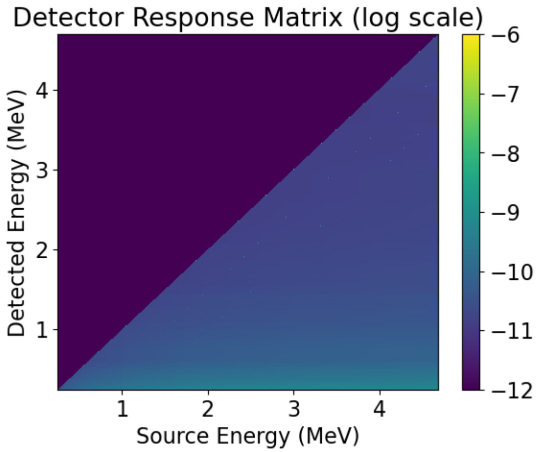
- 12000 channels from 0.25 MeV to 4.7 MeV
- Discrete peaks efficiencies are interpolated
- Continuum is fit with a RFR model

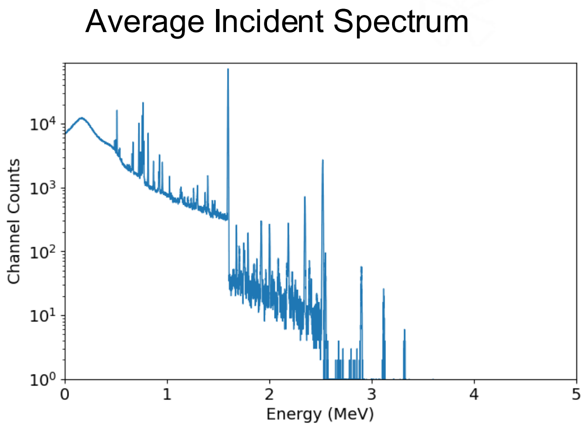




Detector Response Matrix







Dead time and pile-up

40s measurement time with 0.4s standard deviation

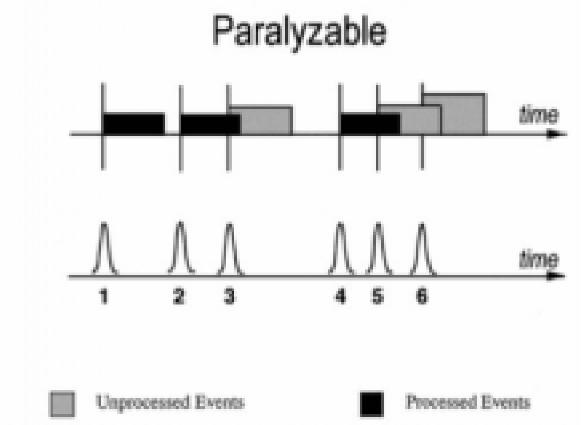
With average count rate *R* and measurement time *t*:

- Sample total counts *N~Poisson(Rt)*
- Sample *N* energies *E* from average spectrum
  - Gaussian broadened
- Sample *N* waiting times *t~Exp(1/R)*

Events arriving:

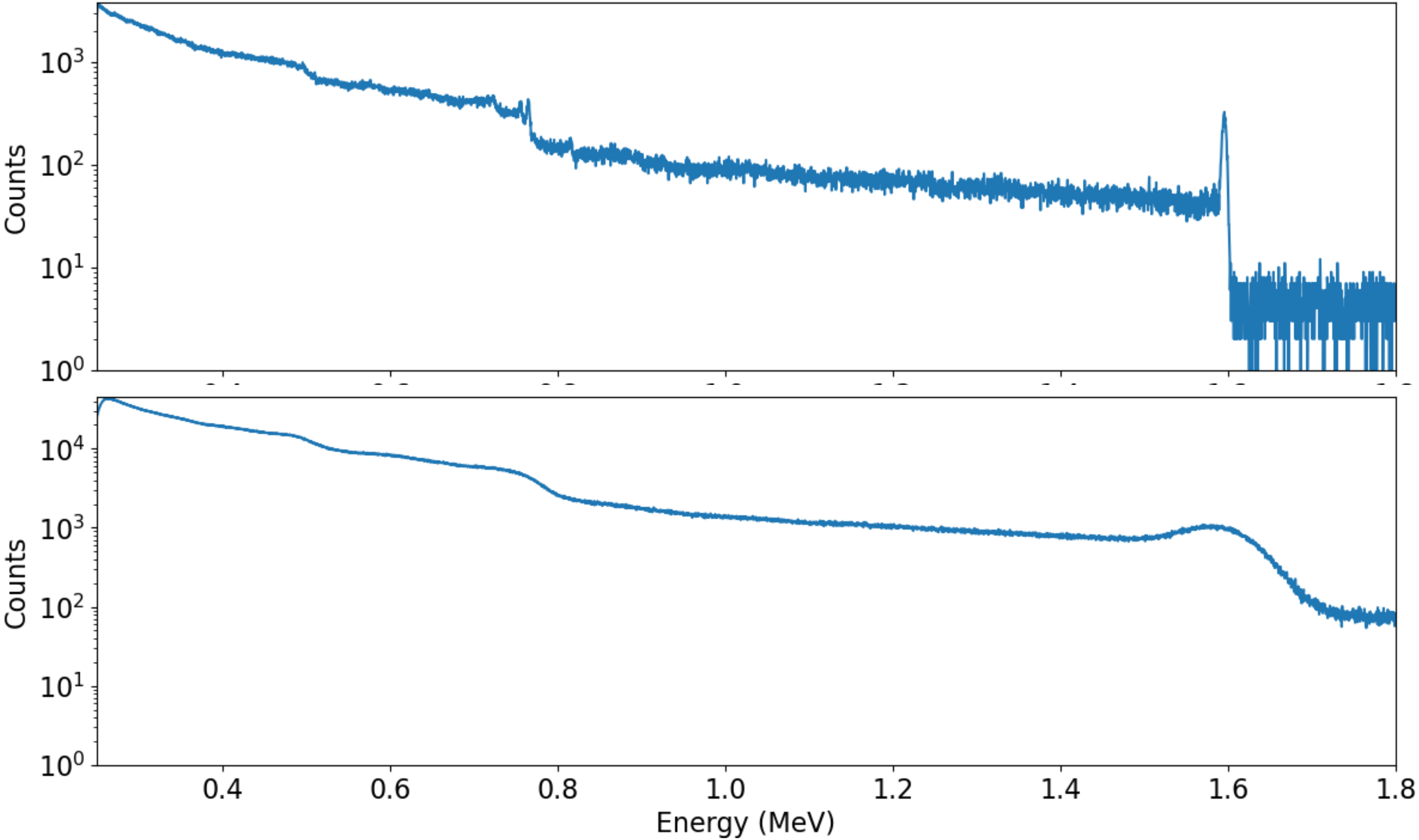
- during peaking time are summed
- during dead time are rejected
- after are recorded normally

HPGe Dead Time	6 μs
LaBr3 Dead Time	0.016 μs



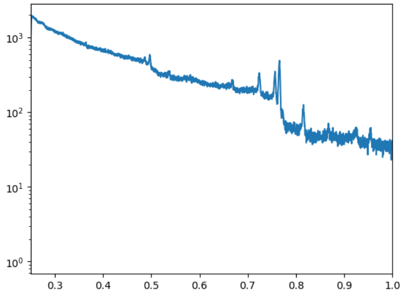
HPGe
(5d decay)

LaBr3
(1d decay)



Pebble Prediction

Pebble Assessment: Two Layers

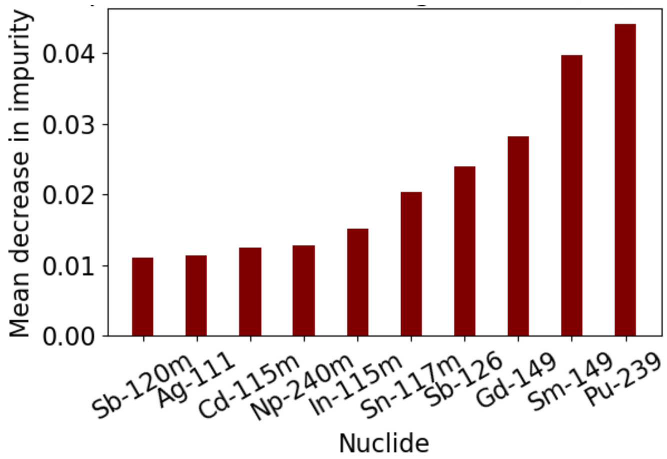


→ ML Models → Nuclide Concentrations → ML Models → History Parameters

Nuclide Feature Importance (Ideal)

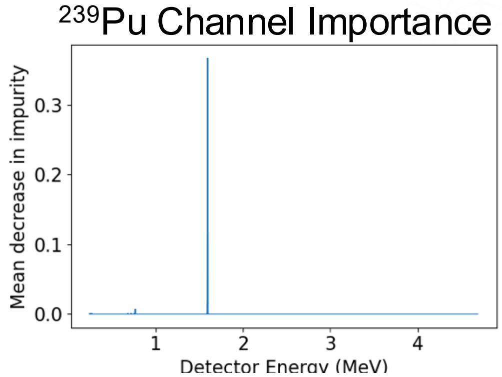
- A Random Forest Regressor (RFR) model is trained for each history parameter using *actual* concentrations from Serpent
- Informs which nuclides we need to predict
- Highlights physical trends and correlations

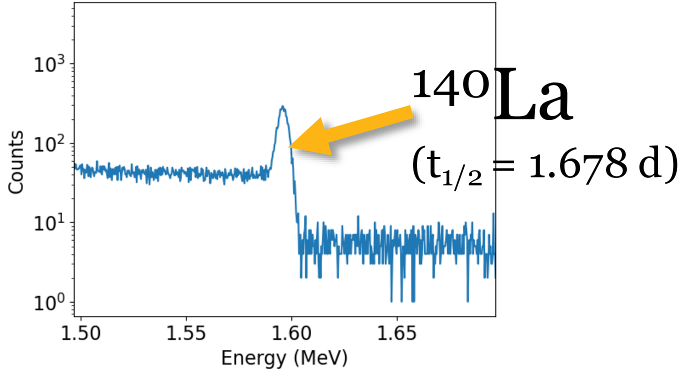
Nuclide Importance for Thermal Fluence on Last Pass



Spectrum Feature Importance

- For each nuclide, a RFR is fit using the actual spectral data
- The most important channels are determined
- Then, a NN model is trained and its hyperparameters optimized using only useful channels
- Rarely determined by that nuclide's own decay gammas





Final Model Training

- Neural Networks are optimized for each history parameter using the predicted important nuclides
- Number of hidden layers and layer sizes are coarsely optimized in large grid search

Random Forest Regressor Parameters

Max Depth	14
# Estimators	1000
Min. Feature Split	1
Bootstrapping	True

Neural Network Parameters

# Epochs	300
Batch Size	256
Activation	ReLU
Learning Rate	0.001
Network Sizes tried	(8, 2), (64, 8), (128, 16), (36)

History Metrics Performance

R^2 accuracy of model (HPGe – 40s measurement – 5d decay)

	LR on full Spectrum	NN on pred. nuclides	RFR on actual nuclides
%FIMA (burnup)	0.8021	0.9740	1.0000
Residence Time	0.8003	0.9671	0.9999
Passes	0.7974	0.9691	0.9999
Avg radial path on last pass	-1.9720	0.6643	0.9554
Thermal fluence on last pass	-3.9159	0.5576	0.8468

Baseline Detected Idealized

History Metrics Performance

R^2 accuracy of model (LaBr3 – 40s measurement – 1d decay)

	LR on full Spectrum	NN on pred. nuclides	RFR on actual nuclides
%FIMA (burnup)	0.7770	0.9856	1.0000
Residence Time	0.5851	0.9888	0.9999
Passes	0.5825	0.9848	0.9999
Avg radial path on last pass	-1.8001	0.8969	0.9554
Thermal fluence on last pass	-6.2175	0.8369	0.8468
	Baseline	Detected	Idealized

Conclusions & Final Work

- Conclusions
  - Machine learning offers greater accuracy than linear regression
  - Timing resolution is more important than energy resolution
  - HPGe detectors may be prohibitively expensive to run
- Future Work
  - Explore other detector choices & further optimize setup
  - Run different measurement times (multiples of 40s)
  - More extensive ML model optimization

Thank you!

Acknowledgements

- Professor Kai Vetter for insight on detector setup and modeling
- Berkeley Research Computing program at the University of California, Berkeley for providing the Savio computational cluster resource (supported by the UC Berkeley Chancellor, Vice Chancellor for Research and Chief Information Officer).