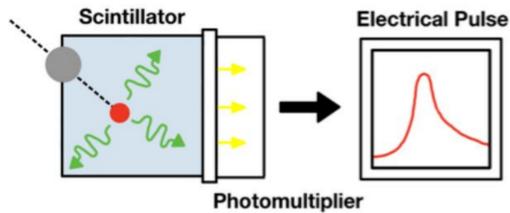


Performance of Simulated Detector Responses in Training Neural Networks for Neutron Spectrum Unfolding

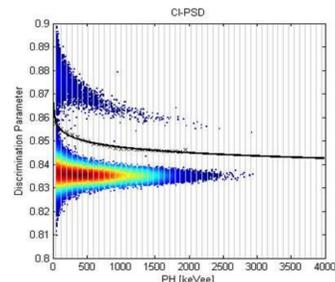
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Background



- Neutron energy spectra can be used as a fingerprint to identify radioactive sources.
- Organic scintillator detectors are commonly used to detect fast neutrons.
- When radiation interacts with an organic scintillator molecule:
 - Gamma radiation Compton scatters off of electrons.
 - Neutrons elastically scatter off of hydrogen (protons) and carbon ions.
- The carbon ring structures found in organic scintillators have delocalized electrons, which are excited by these recoiling particles to emit light.
- This light enters a photomultiplier tube, creating an electric pulse. These pulses are binned based on signal intensity, becoming the detector response function
- Different physical mechanisms cause distinct pulse shapes for light generated by scattering electrons vs scattering protons or carbon ions, as shown in the figure below [5]. Pulse shape discrimination can be used to filter for neutron radiation.

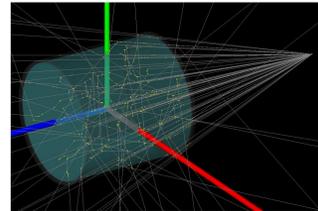


Motivation

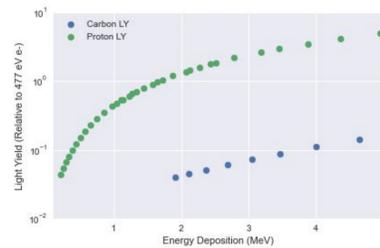
- Goal:** to train a neural network on simulated scintillator detector responses to unfold neutron energy spectra.
- Neutron energy spectra are used to detect radioactive materials for national security purposes, have medical applications in radiation dosimetry, and are crucial to monitoring nuclear reaction rates.
 - Traditional algorithms for neutron spectrum unfolding, such as iteratively solving the Fredholm integral equation, are extremely computationally expensive.
 - Neural networks only need to be trained once, and can then unfold detector responses instantly with potentially better accuracy

Simulation of Detector Response Functions

- Geant4 is used to simulate a 5 cm x 5 cm cylinder of EJ-309 organic scintillator. The cylinder is exposed to monoenergetic neutrons, and the energy deposition of the recoiling protons and carbon ions is tracked.



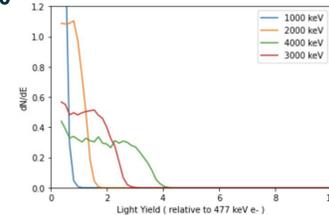
- Experimentally determined light yield data is used to calculate the expected light yield given the energy deposition [3]:



- A normally distributed variable is added to the light yield, to account for statistical variability in light production and photo-electron conversion [2]:

$$\sigma_L(L) = 2.335L\sqrt{\alpha^2 + \beta^2/L + \gamma^2/L^2}$$

- The resulting light yield for a mono-energetic neutron source gives the detector response function for that energy. 400 monoenergetic detector responses are simulated, with energies spaced evenly between 1 and 20,000 keV

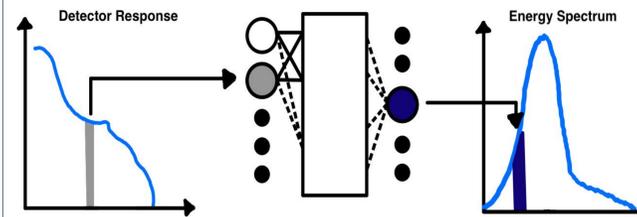


- To simulate the detector response of a neutron source with an arbitrary neutron energy spectrum, a weighted sum of the 400 monoenergetic responses is performed. ϕ_E is the Eth detector response and R_E is the relative proportion of that energy within the neutron energy spectra:

$$D_i = \sum_{E=1}^{400} \phi_E R_E$$

Design of the Neural Network

- The input layer has one neuron per bin in the detector response function, and the output layer has one neuron per bin in the energy spectrum.



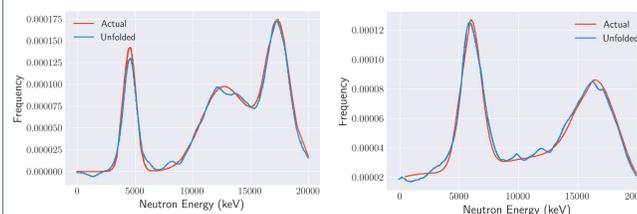
- Three hidden layers, with Leaky ReLU used as the activation function.
- Neurons per layer and Leaky ReLU activation value determined through Bayesian hyper-parameter optimization.

Data Engineering Using IAEA Data

- To determine how to optimally generate simulated detector response data, an IAEA technical report was used containing known neutron energy spectra, the corresponding Bonner sphere response functions, and a fully solved Bonner sphere response matrix [4].
- From this we developed an algorithm which randomly placed Gaussian-shaped peaks to generate realistic neutron energy spectra. Bayesian hyper-parameter optimization was used to determine optimal parameters for the algorithm, such as the mean and deviation in the width, height, and number of peaks to place.

Performance of Neural Network on Simulated Detector Response Functions

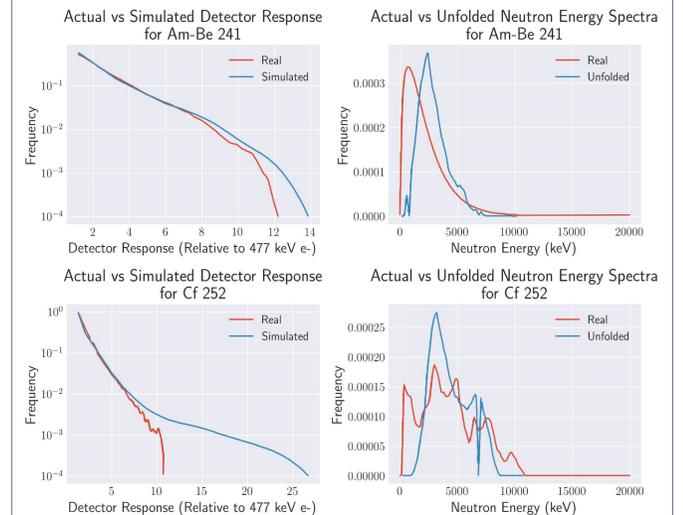
- The neural network is able to unfold simulation data with an average NRMSE of 3.3%, which is accurate enough to capture the important qualitative features of the neutron energy spectra.



- This is primarily a sanity check – there is sufficient information contained in a detector response for the neural network to unfold the energy spectra. The primary sources of error should instead be due to disagreement between simulations and measurements.

Performance of Neural Network on Real World Data

- Real-world Am-Be and Cf-252 detector responses were used to evaluate the accuracy of the simulated detector response function and the performance of the neural network [1].
- The geometry of the detector used by Bai et al. deviates significantly from the geometry of our simulated detector.



- The unfolded Am-Be 241 spectrum has an NRMSE of 43.8% and the unfolded Cf 252 spectrum has an NRMSE of 24.9%
- There are many unknowns about the experimental setup of these real-world response functions, so we are unsure if these discrepancies are due to simulation error.
- We will soon take our own detector response measurements to narrow down possible sources of error.

References

- [1] Bai, Huaiyong, et al. "Simulation of the Neutron Response Matrix of an EJ309 Liquid Scintillator." <https://doi.org/10.1016/j.nima.2017.12.072>.
- [2] Laplace, T. A., et al. "Simultaneous Measurement of Organic Scintillator Response to Carbon and Proton Recoils." <https://doi.org/10.1103/PhysRevC.104.014609>.
- [3] Dietze, G., and H. Klein. "Gamma-Calibration of NE 213 Scintillation Counters." Nuclear Instruments and Methods, July 1981.
- [4] Compendium of Neutron Spectra and Detector Responses for Radiation Protection Purposes: Supplement to Technical Reports Series No. 318. IAEA, 2001
- [5] Pulse-Shape Analysis & Pulse-Shape Discrimination – Detection for Nuclear Nonproliferation Group. <https://dnng.engin.umich.edu/research/research-projects/pulse-shape-analysis-pulse-shape-discrimination/>