

# Uranium Enrichment Measurements Using an Artificial Neural Network

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## **Introduction and Problem Statement**

- When would we want to know uranium enrichment
  - Enrichment and fuel fabrication plants
  - Waste characterization
  - Homeland security activities







# **Introduction and Problem Statement**

- Uranium enrichment algorithms should be able to
  - Use a Nal detector
    - Greater efficiency over HPGe
    - Does not require mechanical cooling
    - Cheaper
  - Operate in the hands of a non-expert
    - Operate in a range of detector calibrations
    - Operate in areas with unknown background
  - Operate quickly without sacrificing accuracy







## **Proposed Solution**

- Artificial Neural Networks (ANNs)
  - Biologic inspired mapping from  $\mathbb{R}^{N} \to \mathbb{R}^{M}$
  - Each neuron is a weighted sum of the previous layer passed through a nonlinear function
    - Knowledge stored in weights
- Benefit of using ANNs for isotope quantification in Nal spectra
  - ANNs can learn to incorporate abstract spectral features
  - Removes the need for user-defined heuristics







# **Proposed Solution**

- Our implementation
  - Input log-scaled spectrum
  - Output component contributions
  - Between 1 and 4 hidden layers
    - Additional hidden layers add capacity to the model







## **Published Work**

- Published work applying ANNs to isotope identification is promising
  - ANNs can identify isotope mixtures in Nal γ-ray spectra using whole spectrum (Kamuda and Sullivan, 2017)
  - ANNs can perform uranium enrichment measurements in  $\gamma$ -ray spectra (Vigneron, 1996)
  - ANN applications to isotope identification usually involve dimension reduction techniques







## Experiment

- Simulated 2" x 2" Nal spectra dataset to represent HEU
  - 10,000 spectra in training set
- Taught three neural networks to quantify isotopes in enriched uranium spectra
  - Input is full spectrum
  - Input is principal component analysis (PCA) reduced spectrum
    - First 10 principal components used
      - Represents 90% of the variance in the data
  - Input is autoencoder (AE) reduced spectrum
    - Neural network based nonlinear dimension reduction method
    - Used 10 hidden layer nodes







# **GADRAS Simulated Training Details**

- Library includes main  $\gamma$ -ray producing isotopes in enriched uranium
  - U235, U238, U234, Th231, Th234, Pa234m, and background
- Spectrum parameters:
  - All isotopes in random combinations
  - Count rate on detector:
    - 10<sup>2</sup> 10<sup>4</sup> counts per second
  - Source is simulated to be behind uranium shield to teach the ANN self attenuation
    - 0.01 cm 0.25 cm
  - Collection time ranges from:
    - 10 seconds 10 minutes
  - Spectrum calibration:
    - Default: highest channel corresponds to 3 meV
    - Each spectrum rebinned to move the 186 keV peak within ±10 channels







# Training Results - Optimal network structures

- Optimal structure found using a random hyperparameter search (Bergstra and Bengio, 2012)
  - 60 ANNs searched
  - 1 4 hidden layers
  - 100 1000 nodes per layer
- Final ANN structure for:
  - Full spectrum input
    - 1024-449-205-9
  - Autoencoder
    - 10-16-316-9
  - PCA
    - 10-170-40-9







# **Training Results**

- Final validation set error was similar for each method
  - Autoencoder performed the worst
  - Full spectrum performed the best
- ANN trained using dimension reduction techniques stopped learning earlier than the full spectrum ANN



Mean squared error vs training iteration for a simulated validation dataset





# Mean Squared Error for Validation Set

- 1000 spectra simulated using the same method as the training set
- ANN performances
  - Both dimension reduction techniques performed the worst
  - Full spectrum performed the best
  - U235 had a very low error when using the full spectrum
  - Th231 and Th241 have very similar spectrums
    - easily confused

	Mean Square Error (10 <sup>-3</sup> )				
lsotope	Full Spectrum	РСА	Autoencoder		
U235	0.86	3.9	6.9		
Pa234m	3.5	4.1	6.6		
U238	4.8	5.2	7.37		
U234	4.4	6.1	7.1		
Th234	5.6	6.4	7.1		
Th231	6.0	6.7	7.4		
Average	4.2	5.4	7.1		





# **ANN Performance on HEU**

- Average ANN response to ten 30 second spectra of HEU
  - Rocky flats shells measured at the Nevada Test Site
- Each ANN performed poorly on these data



RIFICAN		Count Contribution Calculated by ANN [%]			
lsotope	Unattenuated γ-ray Intensities for HEU [%]	full spectrum	РСА	Autoencoder	
U234	44.0	13.2 ± 0.012	14.6 ± 0.003	12.2 ± 0.001	
U235	36.8	32.1 ± 0.022	18.4 ± 0.003	13.9 ± 0.001	
Th231	19.0	14.8 ± 0.007	14.2 ± 0.002	13.3 ± 0.001	
Others	<0.2	39.9	52.8	60.6	

Gamma-ray spectrum of HEU. Collected with 2" x 2" Nal in 30 seconds.





# Conclusion

- Three neural networks were trained to perform isotope quantification on enriched uranium spectra
- Evidence that using the full spectrum is superior to dimension reduction techniques
  - Full spectrum ANN kept learning where the dimension reduction techniques plateaued
- Identifications on HEU were inaccurate
  - Implies that either
    - ANN are a poor choice for the problem
    - The ANN was implemented was not optimal for the problem







# **Future Work**

- Collect spectra of various uranium enrichment for a validation set
- More accurately simulate volumes of uranium
- Explore other dimension reduction techniques
  - Autoencoders
    - Different architectures
    - Denoising autoencoders
  - feature extraction
    - Wavelet peak centroid and area extraction
- Directly output enrichment value instead of isotope contributions





## Questions







# Random Hyperparameter Search

- Number of hidden layers
  - Unif[1,4]
- Number of nodes in a layer
  - LogUnif[10<sup>2</sup>,10<sup>3</sup>]
- Mini-Batch size
  - LogUnif $[10^1, 10^{2.5}]$
- Learning rate
  - LogUnif[10<sup>-6</sup>,10<sup>1</sup>]
- L2 Regularization
  - LogUnif[10<sup>-1</sup>,10<sup>2</sup>]
- Dropout rate
  - Unif[0,1]







## Full spectrum final Hyperparameters

- layer\_1\_nodes = 258
- layer\_2\_nodes = 0
- layer\_3\_nodes = 0
- layer\_4\_nodes = 0
- L2\_scale\_factor = 0.179264479057
- learning\_rate = 0.000114459191534
- dropout\_rate = 0.621314297936
- batch\_size = 255





## **PCA Final Hyperparameters**

- layer\_1\_nodes = 170
- layer\_2\_nodes = 40
- layer\_3\_nodes = 0
- layer\_4\_nodes = 0
- L2\_scale\_factor = 0.637856144862
- learning\_rate = 0.00150010833203
- dropout\_rate = 0.781530068926
- batch\_size = 281







#### **Autoencoder Final Hyperparameters**

- layer\_1\_nodes = 16
- layer\_2\_nodes = 316
- layer\_3\_nodes = 0
- layer\_4\_nodes = 0
- L2\_scale\_factor = 0.163365910653
- learning\_rate = 0.000741537071015
- dropout\_rate = 0.662424609832
- batch\_size = 295







# Autoencoder







# Autoencoder and Neural Network





