Using Machine Learning to Improve Gamma-Neutron Discrimination in ^{6}Li Glass and P-terphenyl Detectors

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INTRODUCTION

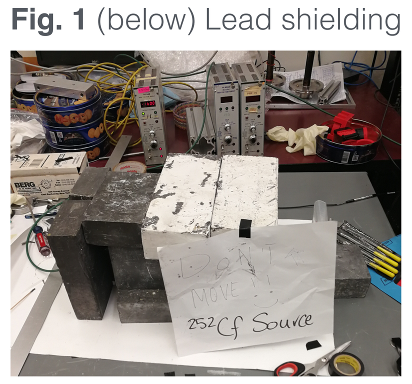
We present machine learning (ML) methods that improve current neutron-gamma discrimination. In particular, we sought to improve current areas of overlap for neutron-gamma discrimination. To create data with known classification, p-terphenyl crystal and ^{6}Li glass scintillators were used to detect gammas, fast neutrons (p-terphenyl), and thermal neutrons (^{6}Li glass). We use dimensionality reduction and neural networks for classification and evaluate the methods. Additionally we study autoencoding methods for generating datasets. We discuss their accuracy for neutron-gamma discrimination of both detectors, present dimensionality reduction methods that yield distinct neutron-gamma separation, and suggest the future of ML use in particle discrimination.

EXPERIMENTAL METHODS

^{6}Li Glass Detector

- ^{6}Li glass detector (3mm thick) + ^{252}Cf
- Polyethylene block reduces neutron energy to thermal levels
- Lead: shields detector from gammas
- No shielding: >99% pure gamma-induced scintillation

Fig. 1 (below) Lead shielding



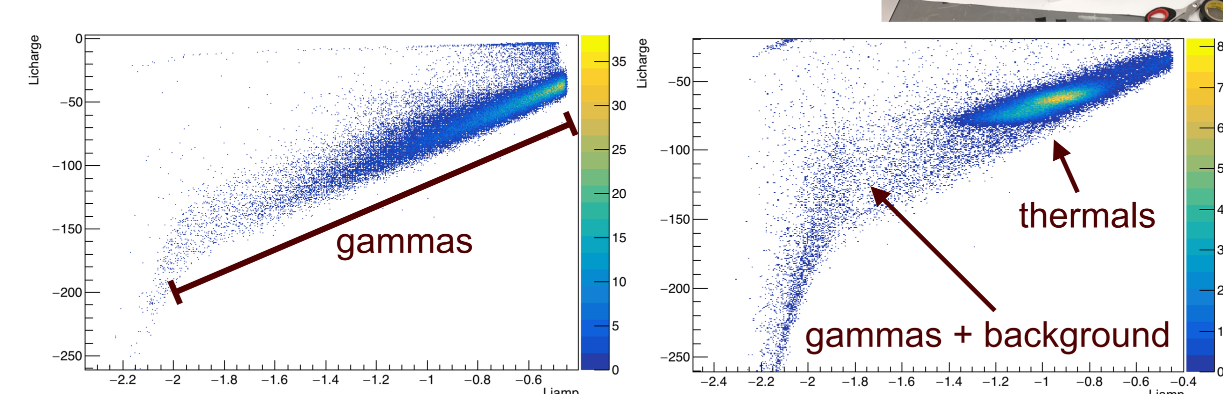
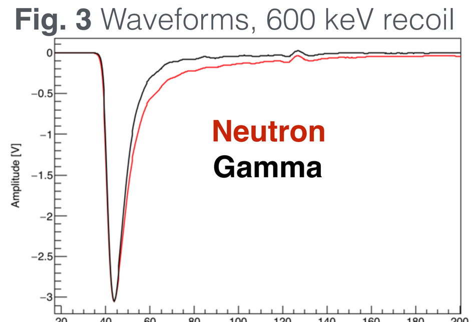


Fig. 2 Charge (nC) vs Amplitude (V) (left: no shielding; right: Pb shielding)

P-terphenyl Detector

- P-terphenyl crystal (5cm) coupled to 2 PMTs + ^{252}Cf
  - Detects fast neutrons and gammas; high scintillation (10^{4} photons/MeV)
  - Previous band separation only effective above 200 keV recoil

Fig. 3 Waveforms, 600 keV recoil



- Fission detection time of flight (TOF) experiment was performed for energy calibration and a priori identification

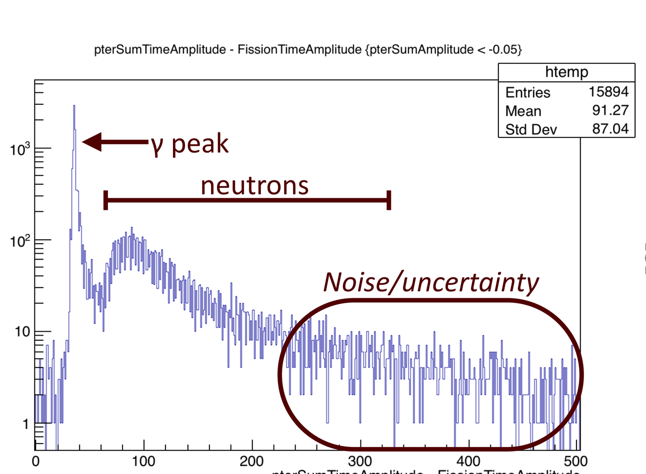


Fig. 4 TOF histogram

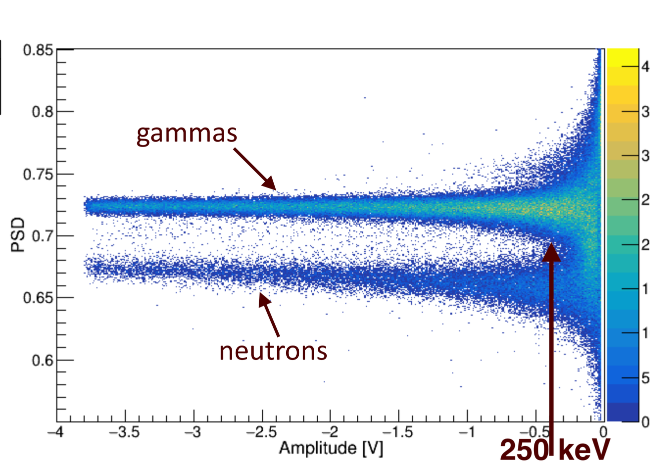


Fig. 5 Previous wavelet transform [2] band separation

MACHINE LEARNING METHODS

1. Artificial Neural Networks (ANNs)

Basic Principles:

- Layers of "neurons" weighted by effectiveness in classification
- Training epochs maximize accuracy, reduce loss by varying weights

Pros: Model can be tested easily; flexible training; controllable parameters

Cons: Supervised; requires known classification; may over-fit to training data

Input:

Sequential-1: Waveforms

Seq.-2: Wavelet transform values [2], charge, amplitude

Layers:

Seq.-1: Convolutional layers (feature-mapping)

Seq.-2: Dense training (combinations of previous layer neurons)

Output:

Binary (0,1)

Network Optimization

- Validation set: avoids overfitting
- Metrics: accuracy and loss functions
- Hyper-parameters: manually optimized user inputs
  - Learning rate (.0005), dropout (0.2), batch size (64), epochs (50-70)
- Result of ANN: Metrics of unseen data test; trained ANN weights

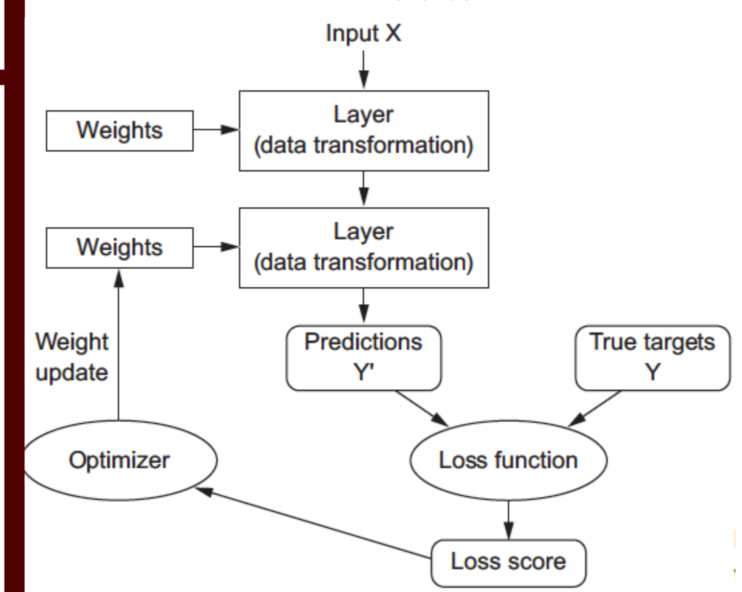


Fig. 6 ANN supervised learning via *back-propagation*[1]

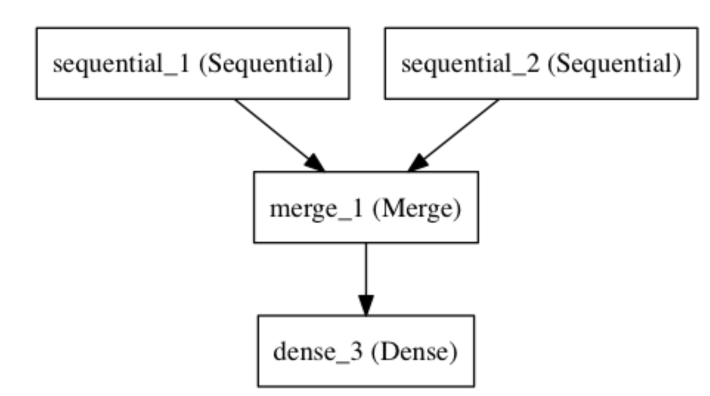


Fig. 7 NSNN structure

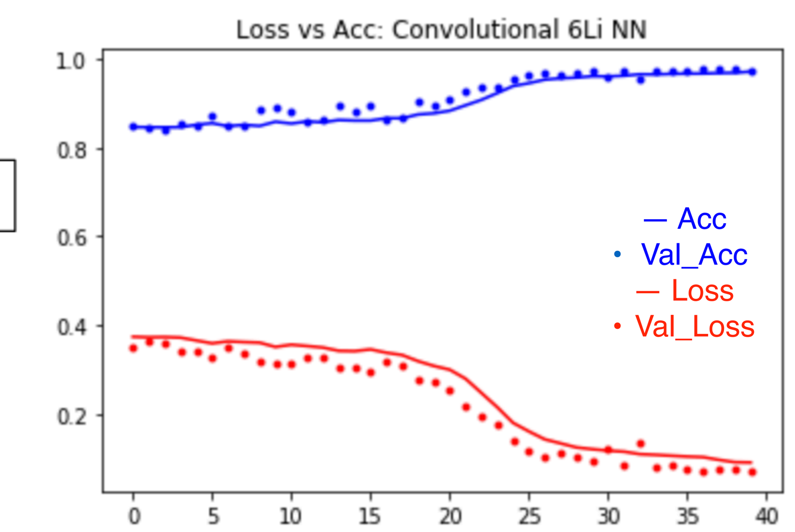


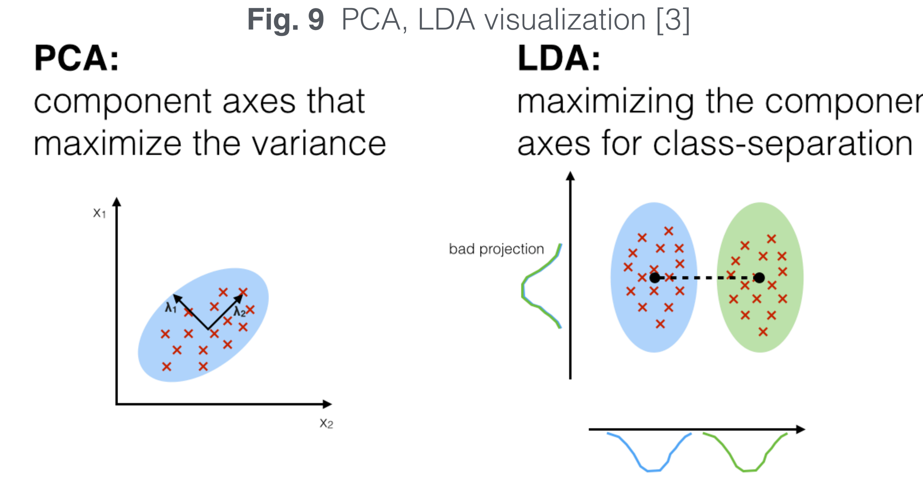
Fig. 8 Metric value vs. epoch

2. Dimensionality Reduction

Waveforms transformed to eigenvalue via between-class and within-class covariance matrices using Linear Discriminant Analysis (LDA)

- Pro: Distinct class separation; used in conjunction with Principal Component Analysis (PCA) for downsampling 1024-dimension waveforms
- Con: Supervised method (requires classification a priori)

Fig. 9 PCA, LDA visualization [3]



3. Autoencoding

- Generation of waveforms from random noise, using training data passed through convolutional neural network
- Purpose: combats experimental drawbacks, including noise, time of experiment, and uncertainty in a priori neutron-gamma discrimination
- Current limitations: amplitude and noise matching

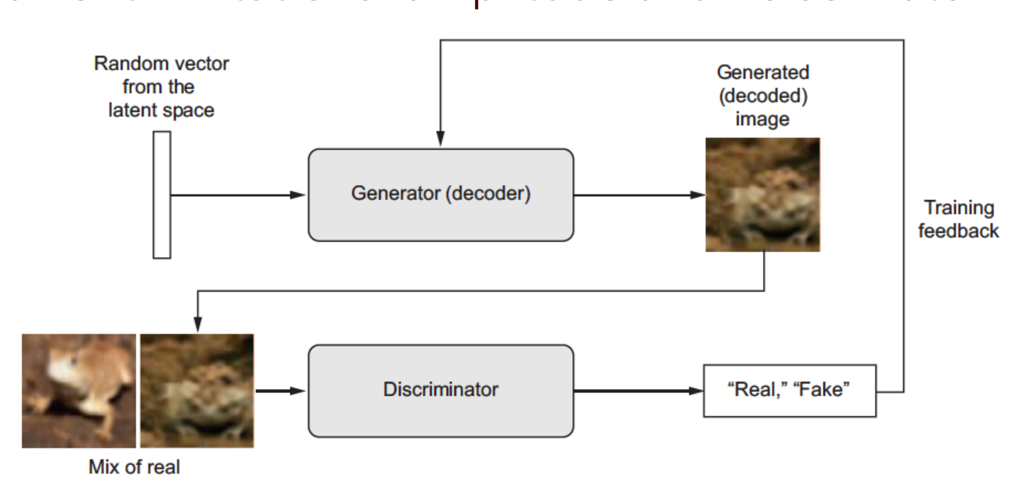
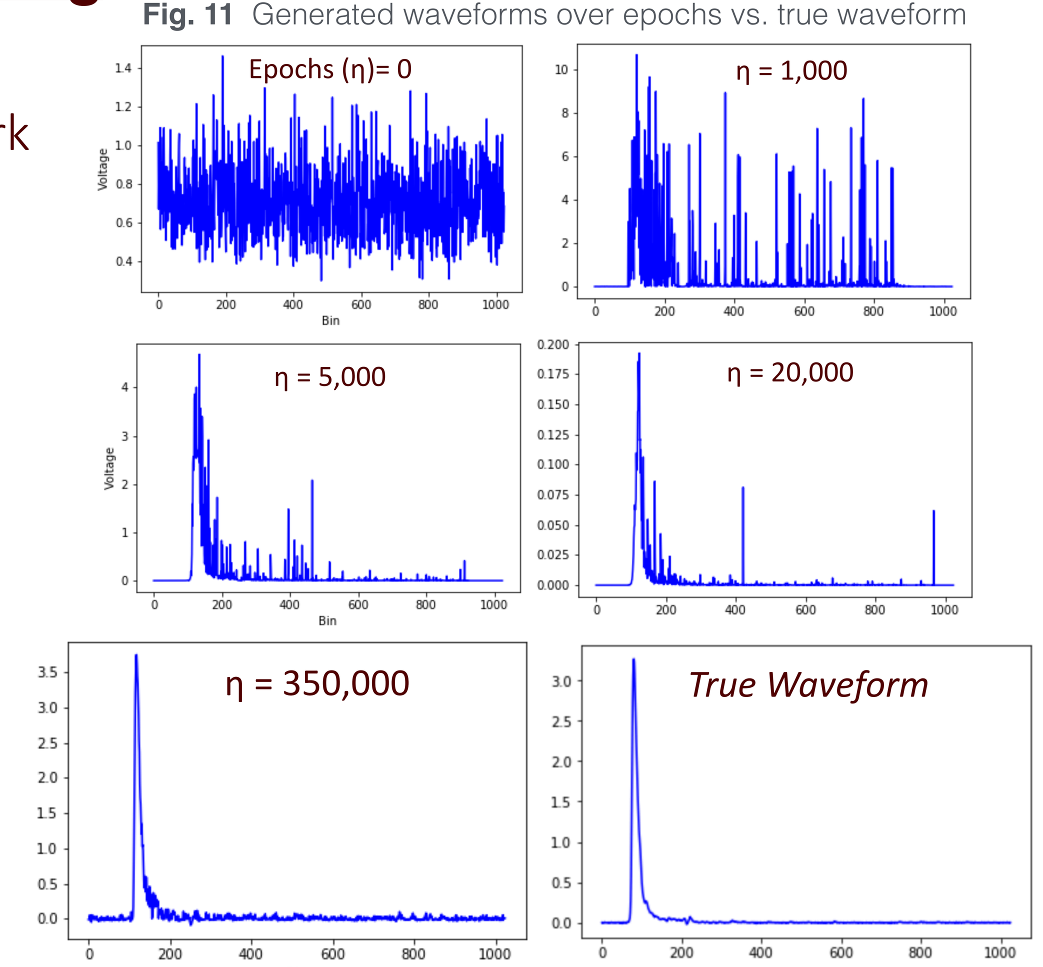


Fig. 10. Autoencoding process, useful in image generation [1]

Fig. 11 Generated waveforms over epochs vs. true waveform



RESULTS

^{6}Li Glass Experiment

Fig. 12 ANN results

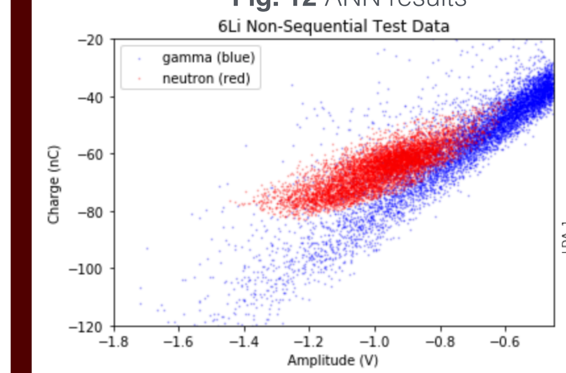
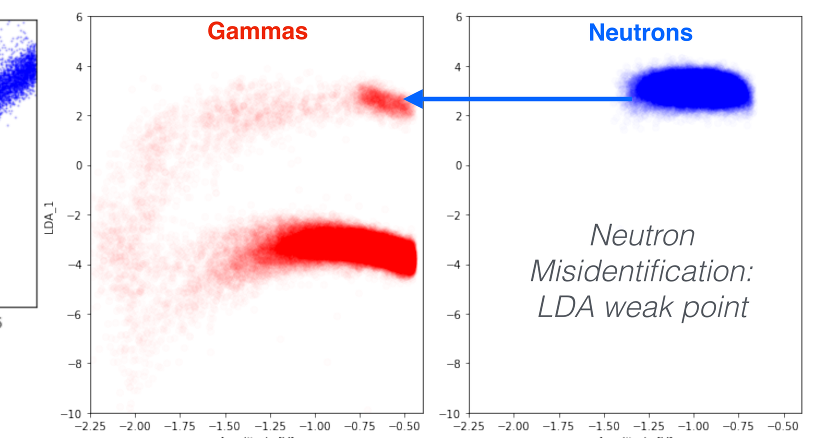


Fig. 13 LDA of waveforms



*The confusion matrices list the accuracy of each method in characterizing gammas and neutrons.

ANN Confusion Matrix:

Actual Class \ Predicted Class	thermal	γ
thermal	99.70%	0.30%
γ	0.32%	99.68%

LDA Confusion Matrix:

Actual Class \ Predicted Class	thermal	γ
thermal	94.97%	5.03%
γ	0.02%	99.98%

The data contained trace amounts of misidentified particles due to background, so <100% accuracy was expected. Fig. 13 shows that LDA misidentifies neutrons in the thermal range, as LDA confusion matrix confirms. LDA was noticeably weaker for thermal identification, but provided better visualization.

P-terphenyl Experiment

Fig. 14 NSNN class accuracy

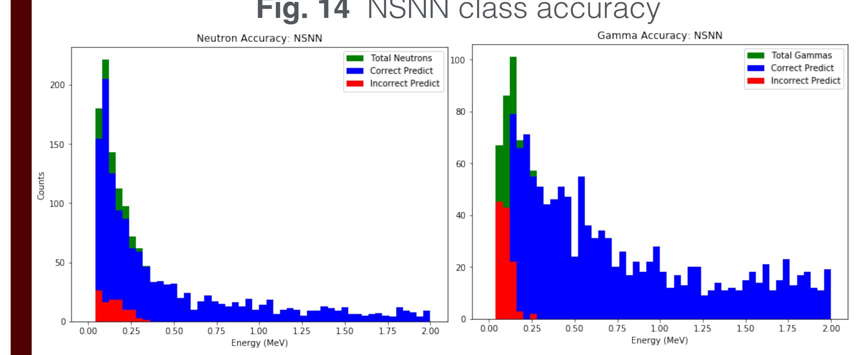


Fig. 16 PCA separation

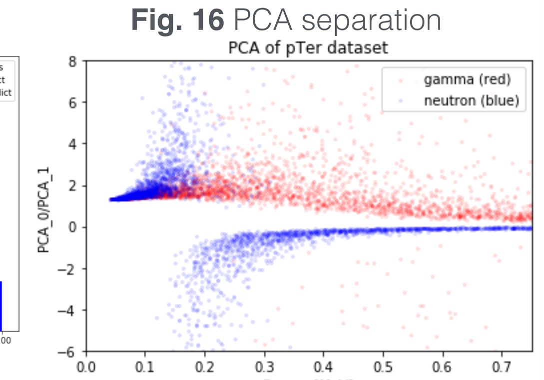


Fig. 15 LDA class accuracy

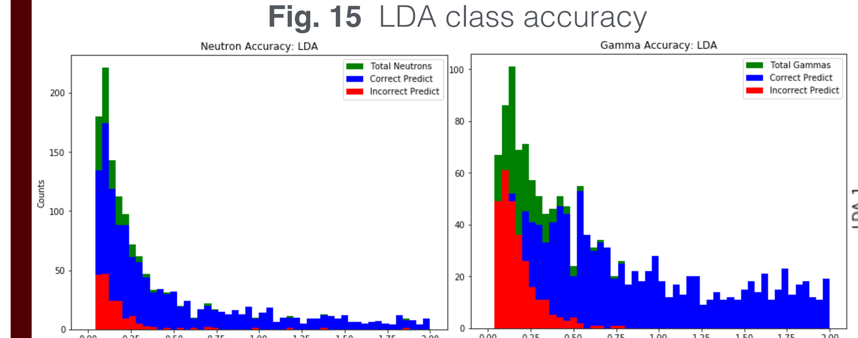
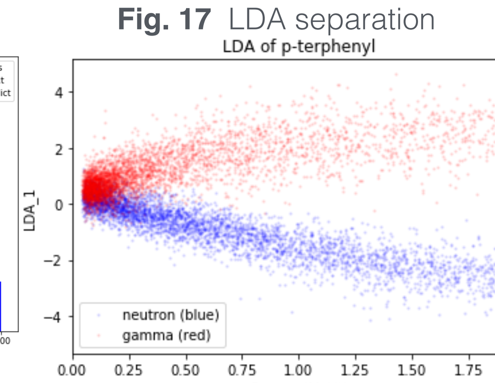


Fig. 17 LDA separation



ML is successful above 250 keV. Gamma inaccuracy significantly greater than 50% below 250 keV suggests that the source was too weak to overcome background (Fig 4). Hence, TOF discrimination misidentified background and fission products. Improving a priori identification and reducing background using stronger sources or autoencoding will improve these methods beyond current limitations.

CONCLUSION

While ML improved discrimination in both detectors, low-energy limitations persist using p-terphenyl. Improving this requires a stronger fission source and better shielding. Alternatively, autoencoding can be used to generate pure datasets. ANNs and DR are both ideal for thermal neutron-gamma discrimination. With future study, ML will likely improve fast neutron-gamma discrimination as well.

REFERENCES

[1] F. Chollet, "Deep Learning with Python" (2018)
[2] S. Yousefi et al, NIM A 598 551-555 (2009)
[3] S. Rashka, Linear Discriminant Analysis Blog (2014)
[4] V. Lavrenko, PCA Lecture (YouTube) (2014)

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