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Deep Transfer Learning for Pulse Shape Discrimination

Background & Objectives

- Pulse-shape discrimination (PSD) is a common procedure for making judgments on the identity of a particle that caused an observed event
- Differences — usually subtle — in detector waveforms resultant from particle interactions serve as basis for such discrimination
- PSD usually requires manual interpretation and threshold-setting dependent on individual detector & situation characteristics
- Transfer learning involves training a model on one dataset, then applying it to data obtained in separate circumstances

Objective: develop a robust, transferrable model for performing PSD

1. Datasets & Pre-processing

- Eleven datasets of silicone-based organic scintillator waveforms
- 256 time-samples per waveform
- Waveforms labeled using tuned function for each detector ID (*fig. 1*)
- Formulate as multiclass problem; three possible labels per waveform:
  - Neutron ('0')
  - Gamma ('1')
  - Noise ('2')

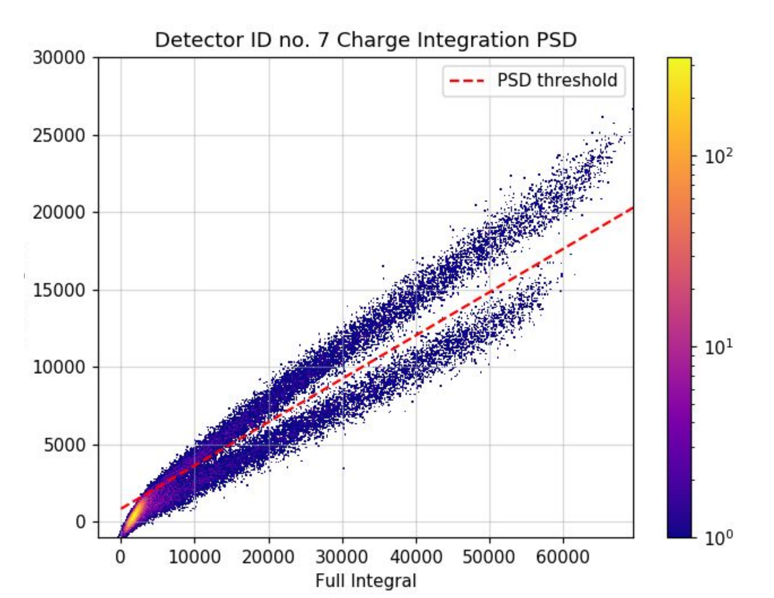


Fig. 1: Manual event labeling via charge integration PSD for detector ID no. 7 dataset

Silicone-Based Organic Scintillators

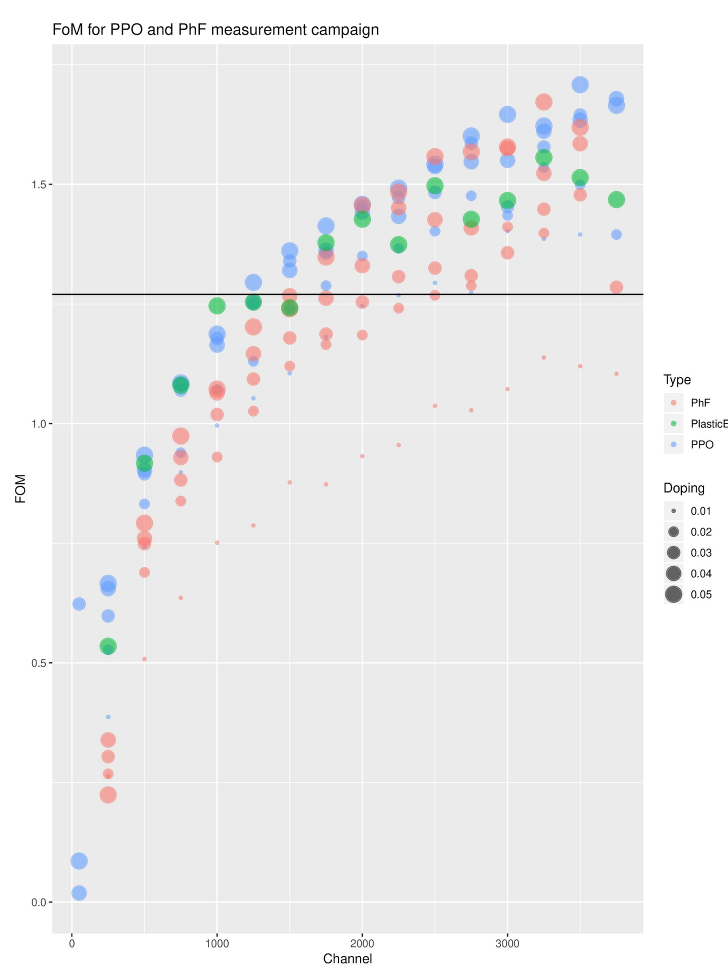


Fig. 3: Selection of organic scintillators used, sorted by energy-dependent PSD figure-of-merit (FOM)

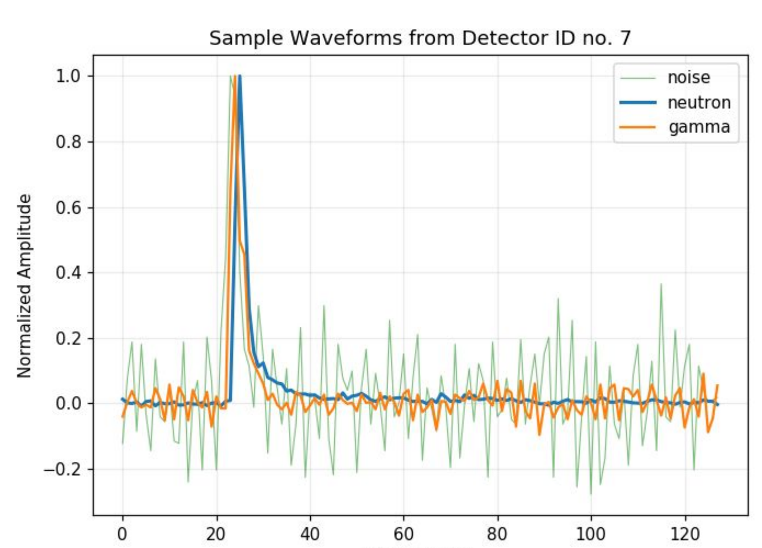


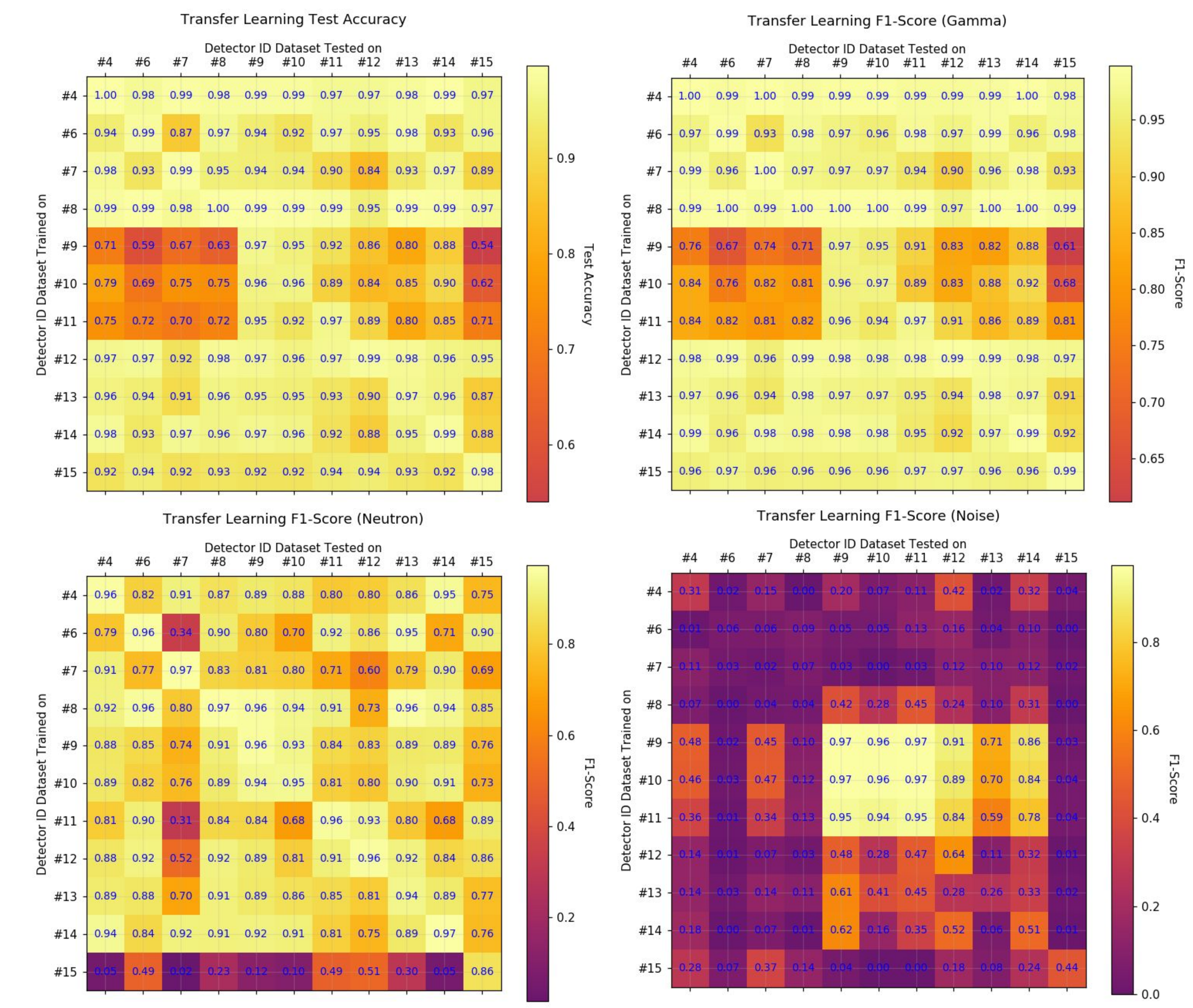
Fig. 2: Sample waveforms for each label for detector ID no. 7 dataset

- Uniform transformations applied to each waveform (*fig. 2*):
  - "flipped", making peak positive
  - baseline corrected to zero based on average pre-peak amplitude
  - normalized to each waveform's maximum amplitude
  - uniformly block-reduced to 128 time-samples
- Identifying "Noise" events involved fast-fourier transform (FFT) analysis
  - Comparing regional FFT amplitude provides signal-to-noise ratio (SNR), which can be used as a threshold to select noisy events

2. Results & Analysis

Individually-Trained

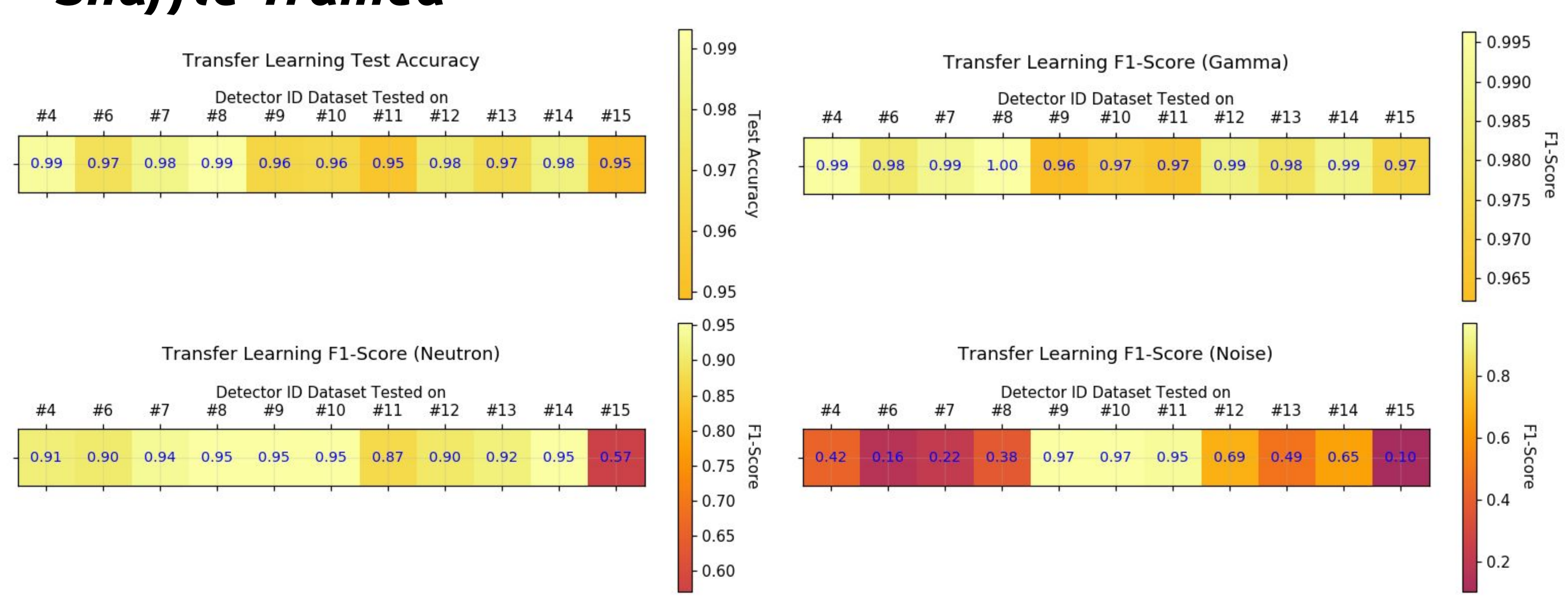
Fig. 4: Transfer learning evaluation matrices for models trained on individual datasets



- Individually-trained models showed remarkable transferability for neutron & gamma events
- Transfer learning allows us to easily draw conclusions about similarities between detectors
  - Difference between ID #9, #10, & #11 and rest of detectors very apparent
  - Detector ID #15 seems to have poorest PSD characteristics, whereas we might guess #7 produces more unique neutron waveforms

Shuffle-Trained

Fig. 5: Transfer learning evaluation matrices for models trained on shuffled datasets



- Models trained on a combined, shuffled dataset show great generalization for all categories except noise, possibly simply due to not enough "Noise" samples in the shuffled datasets
- F1-scores for neutrons are very good except for detector ID #15, which we noted had issues with neutron waveforms in the individually-trained model analysis

3. Methods

- Two kinds of datasets used for training models:
  - **Individual Datasets**: datasets from one specific detector
  - **Shuffled Datasets**: shuffled datasets generated using waveforms from all eleven detectors
- Metrics used to gauge performance were overall accuracy on test sets & F1-score for each class label
- 20% of every dataset held back for testing, while the other 80% was used to train & validate using the k-fold method

Training Method	Individually Trained	Shuffle Trained
Training Chunk	**100k waveforms**	**110k waveforms** (10k from each Wacker dataset)
Chunks Trained	**5** chunks trained	**20** chunks trained
Training Method	K-Fold training/ validation (**5 folds**)	K-Fold training/ validation (**5 folds**)

Table 1: Selected details of training methods

- Keras (with Tensorflow backend) in Python used for neural networks
- Primary model used was feed-forward neural network (FFNN)
- FFNN compiled with Adam optimizer and sparse categorical cross-entropy as loss metric

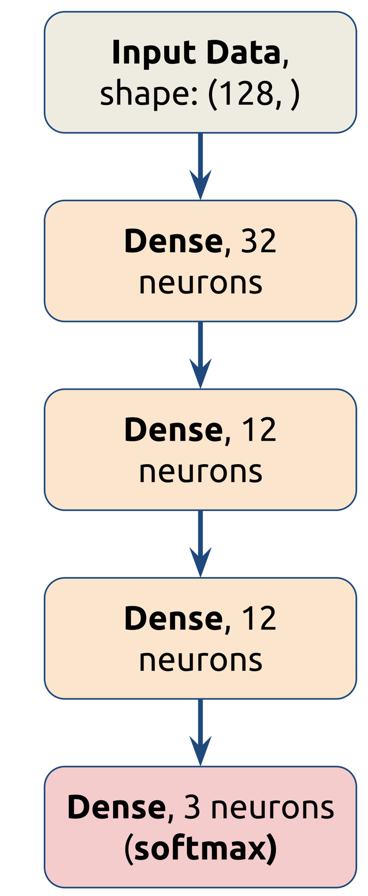


Fig. 6: Feed-forward neural network architecture used for this work

4. Conclusions & Future Work

- We have proven transferability across different silicone-based organic scintillators of deep learning models for pulse shape discrimination in neutron and gamma waveforms
- It has been demonstrated that training PSD deep networks with waveform datasets from a range of detectors can allow them to generalize to data from a specific detector
- Follow-up work should attempt similar procedures across wider ranges of detector material (for example, testing whether models transfer to the well-characterized organic scintillators anthracene and stilbene as well as to inorganics)

References & Acknowledgements

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3. Stéfan van der Walt, S. Chris Colbert and Gaël Varoquaux. "The NumPy Array: A Structure for Efficient Numerical Computation." *Computing in Science & Engineering*, 13, 22-30 (2011), DOI:10.1109/MCSE.2011.37 (publisher link).
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