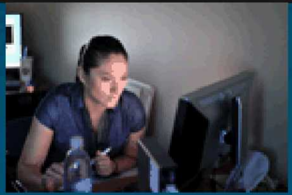
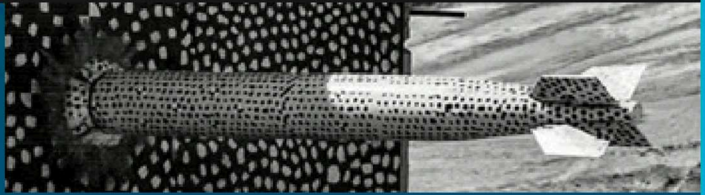
SAND2018-3139C

Machine Learning for Industrial Material Classification Applications with Color CT Datasets





PRESENTED BY
Srivathsan P. Koundinyan, April Suknot, Kyle R. Thompson, and Edward S. Jimenez

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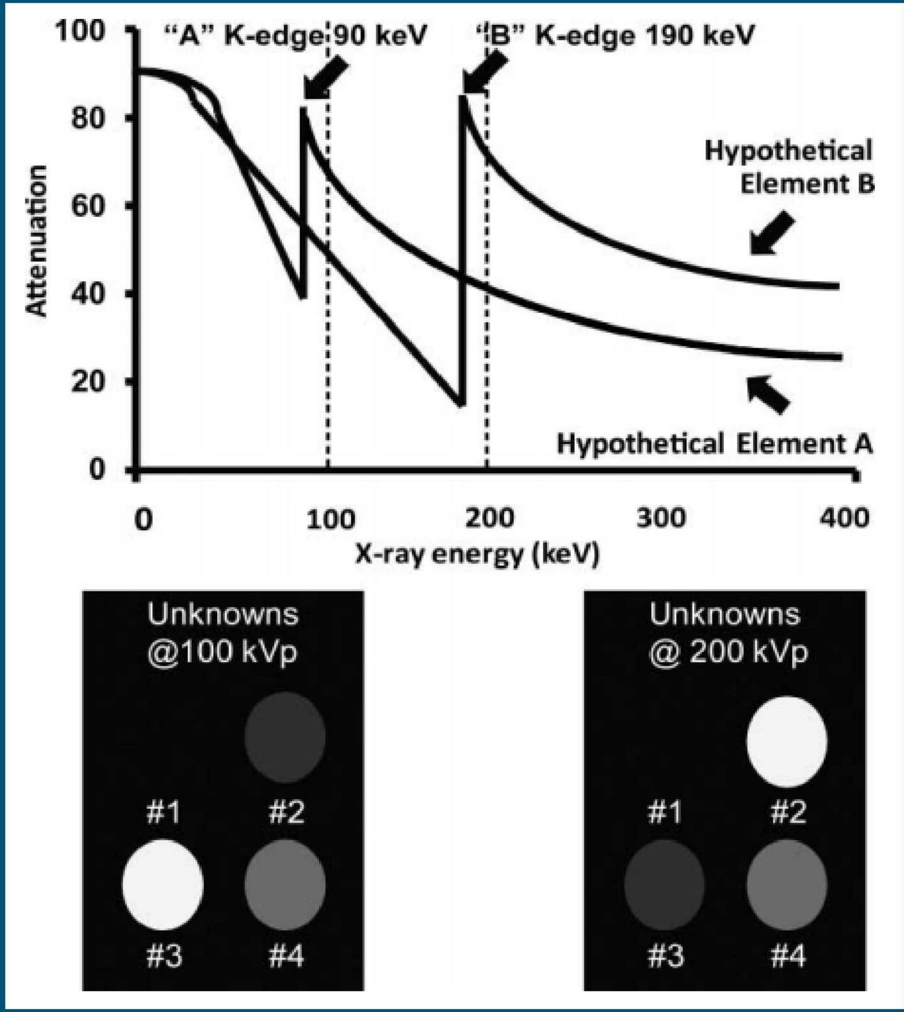
Introduction and Background

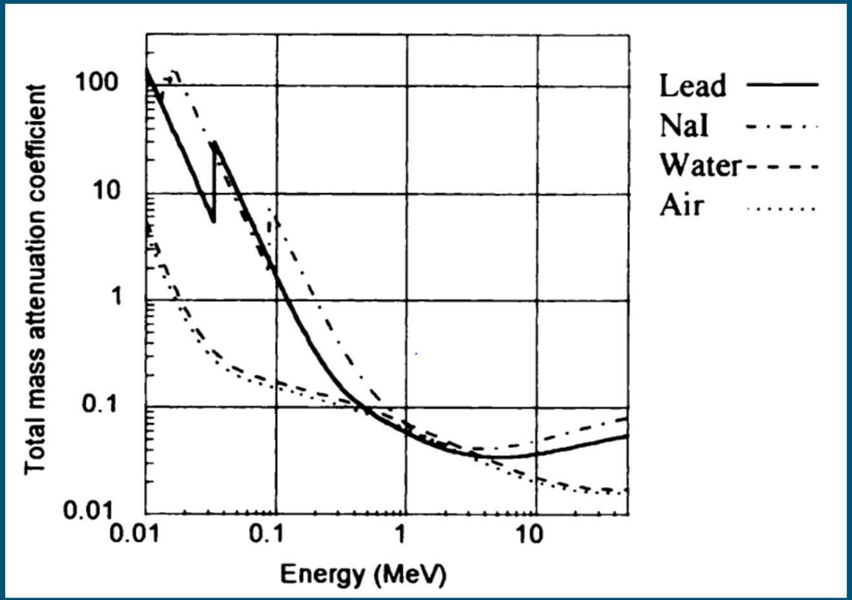
- Computed Tomography (CT) has a wide variety of applications:
  - Industrial
    - Verification and validation
    - Quality Assurance
    - Failure Analysis
  - Security
    - Checkpoint Screening
    - Materials Identification
    - Anomaly Detection
- Dual energy CT most commonly applied in these settings
  - Energy ranges from 100 keV to 160 keV
  - Typically requires two separate acquisitions



Spectral Computed Tomography

- Industrial and security applications benefit tremendously from spectral CT data

Dual energy CT samples two points on these curves → two images

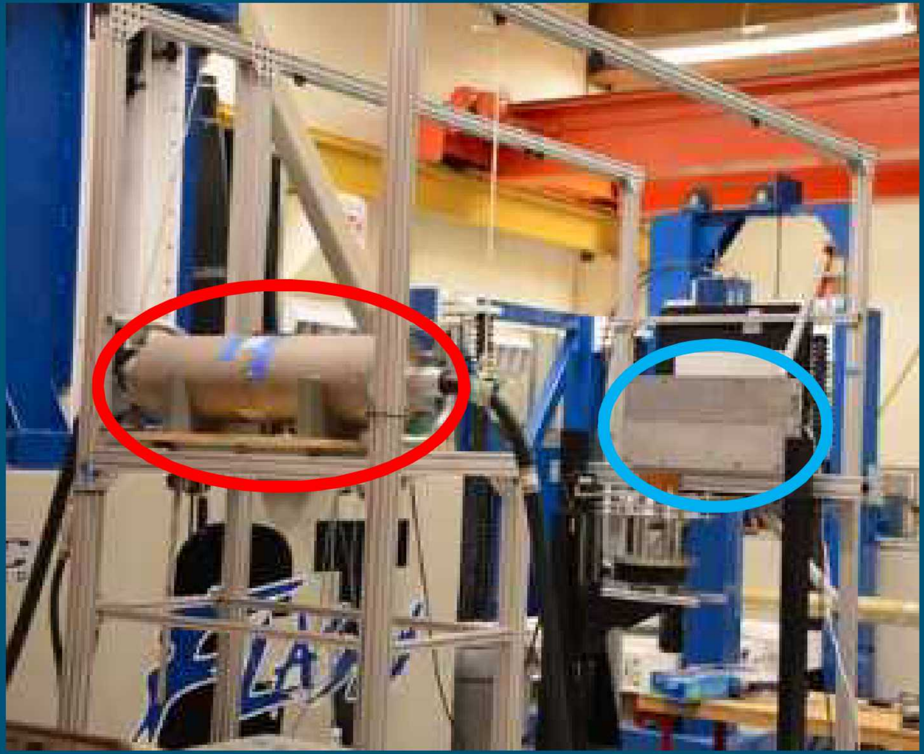


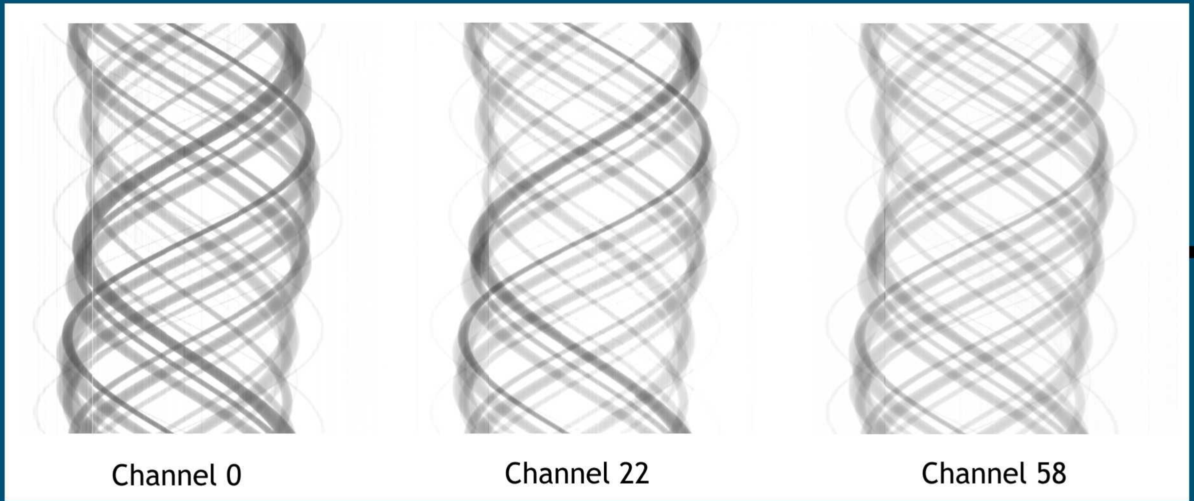
Spectral CT thoroughly samples these curves → images from several different energy bins

- Sandia National Laboratories is developing an advanced spectral CT system
  - Single acquisition system with energy-discriminating, photon-counting detector
  - Nearly twice the energy of systems in existence at 300 keV

Spectral Computed Tomography

- MultiX Detector:
  - 5 modules
  - 0.8 mm pixel pitch
  - 128 channels
  - 300 keV maximum energy detection
- 4 axis motion control to allow for maximum flexibility
- FOV: images objects up to half meter wide and 9 meters tall
- System has been acquiring data as of May 2017
- 128 images reconstructed from each of the channels using Recon



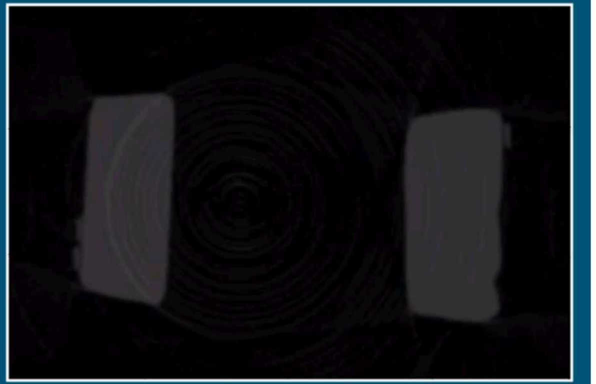


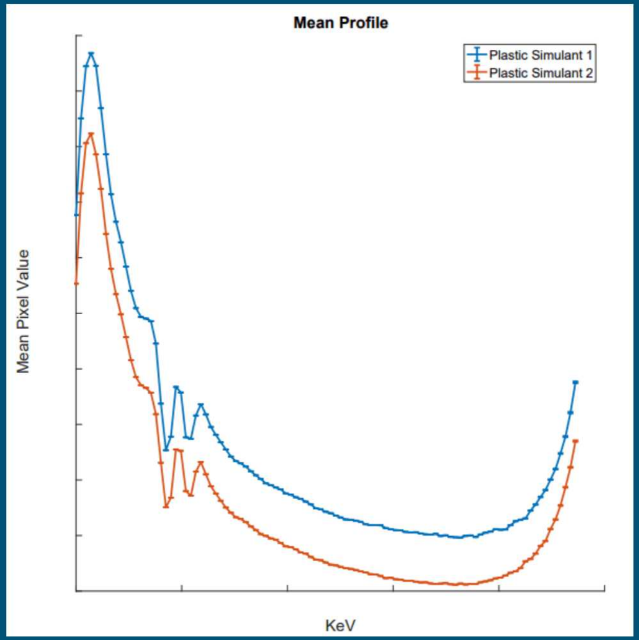
Preliminary Experiments

- Two 1 pound block of explosive simulant
  - Very similar composition

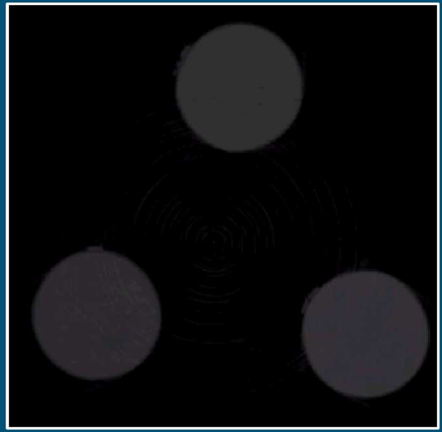
- Three 1-inch diameter cylinders of powder explosive simulants
  - Very similar composition

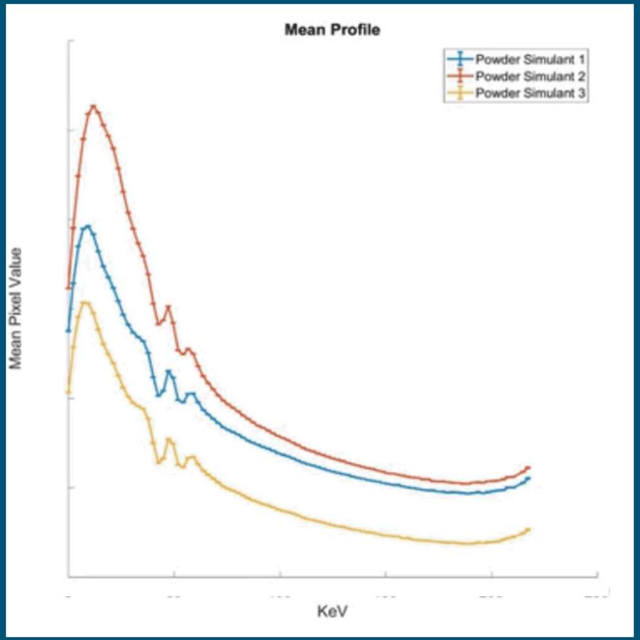
116 keV energy bin





116 keV energy bin



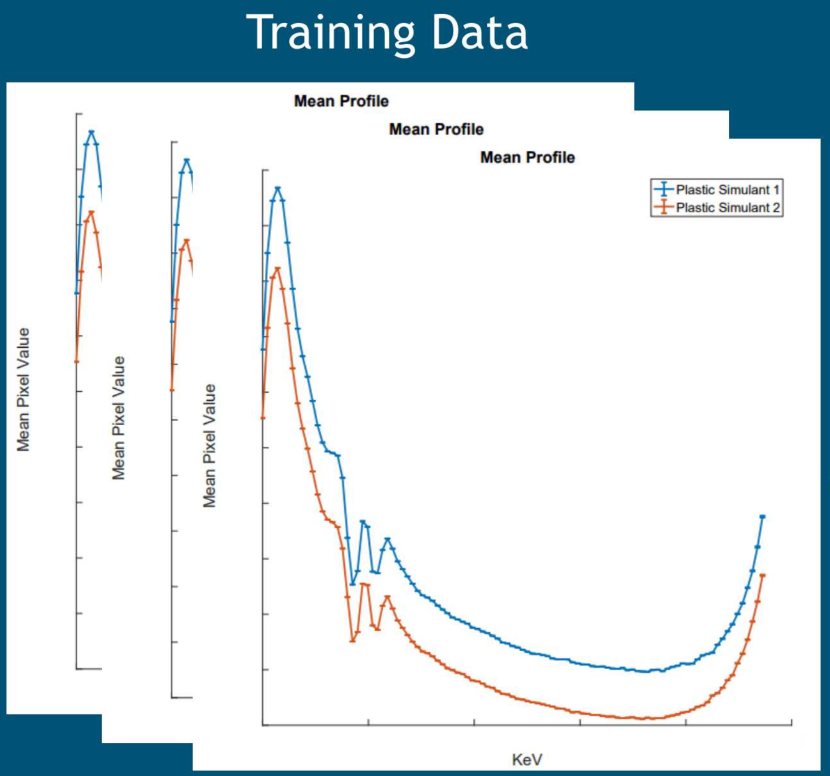


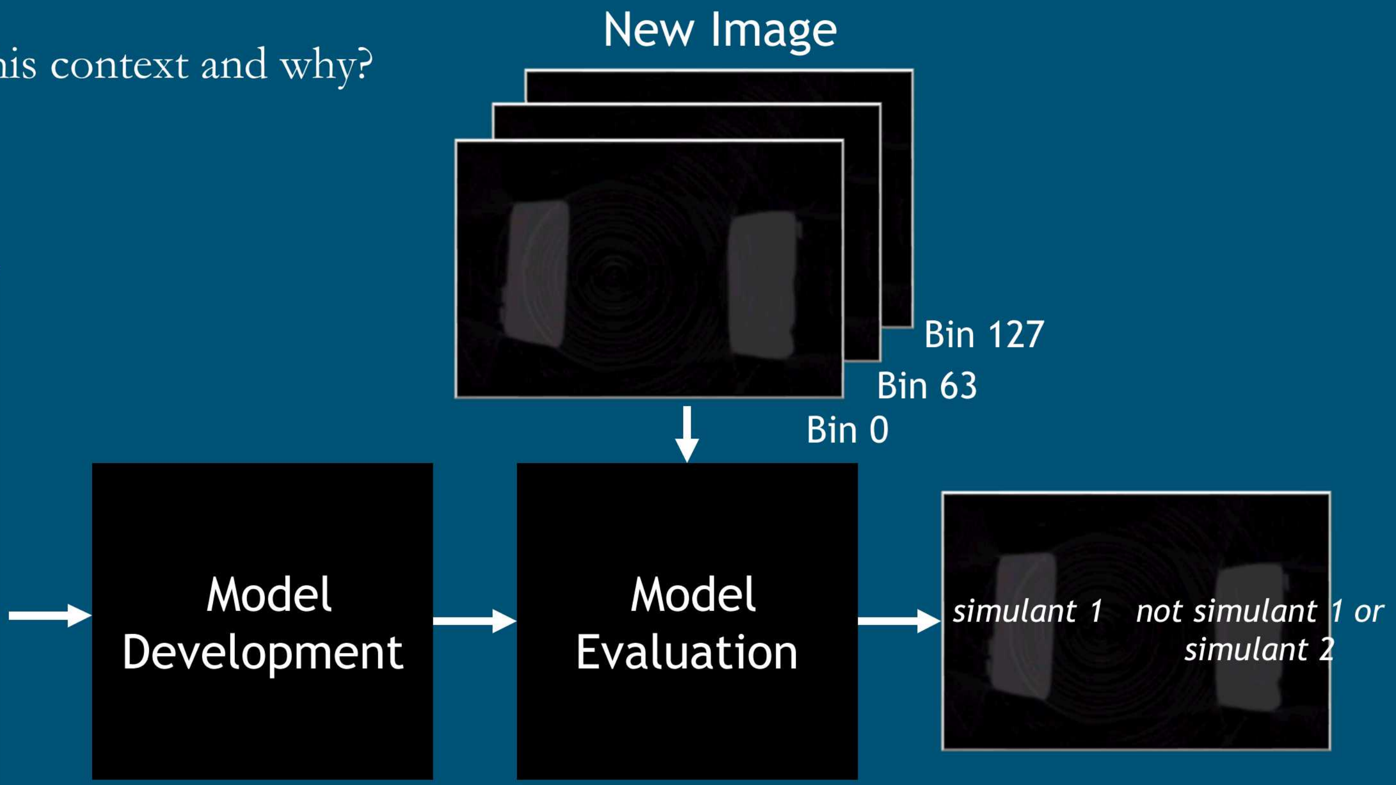
Materials with similar composition can be quantitatively separated using energy-dependent attenuation waveforms from spectral CT system[1]

1. Jimenez, Edward S., et al. "Leveraging multi-channel x-ray detector technology to improve quality metrics for industrial and security applications." *Radiation Detectors in Medicine, Industry, and National Security XVIII*. Vol. 10393. International Society for Optics and Photonics, 2017.

Objective

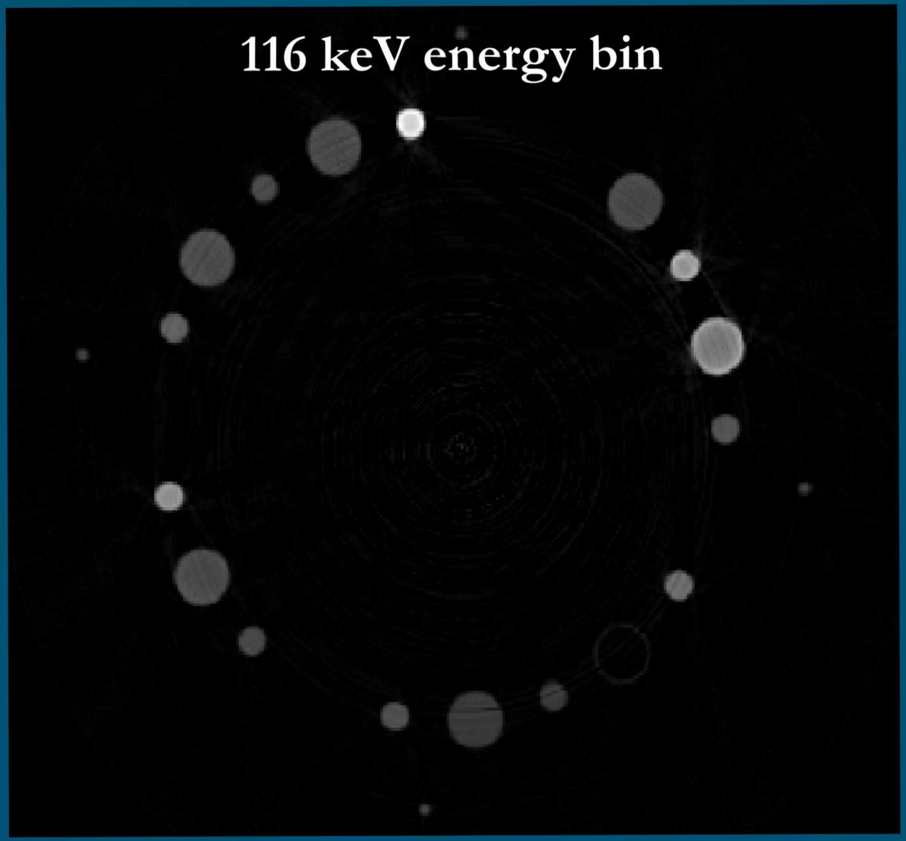
- To investigate the utility of machine and deep learning techniques for understanding quantitative spectral CT information
  - Given training/reference data for various materials, can algorithms be developed for automated material classification?
  - Which algorithms perform optimally in this context and why?





Dataset

- 17 cylindrical samples in circular orientation
  - 128 images reconstructed for energy bins uniformly spaced up to 250 keV
  - Variety of materials: empty polyethylene bottle, Nylatron, Delrin, SAE 30 motor oil, acrylic, nylon, two samples of water, teflon, polyethylene, soft-drink Pepsi, lexan, diet soft-drink Coke, aluminum, magnesium, salt, and phenolic
- Small dataset
  - Voxel-by-voxel attenuation profiles extracted for each material
- Split into training (70%) and testing (30%) subsets
- Task: develop model to correctly label each object



Models & Classification Techniques

Logistic regression

- Binary regression model with *linear* decision boundary

$$\sum_{i=1}^{m} y^{(i)} \log(h_\theta(x^{(i)})) + (1 - y^{(i)}) \log(1 - h_\theta(x^{(i)}))$$

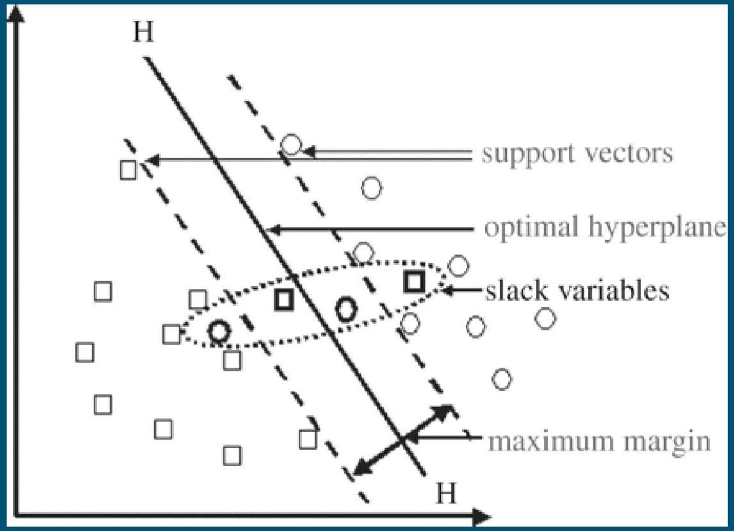
- Model extended to multi-class setting with error-correcting output codes (ECOC)
  - 17 objects → 136 binary classifiers (= 17(17-1)/2) → majority voting scheme

Soft-margin support vector machine (SVM)

- Binary regression model with consideration of non-linearly separable data

$$\min_{\gamma, w, b} \frac{1}{2}\|w\|_2^2 + C\sum_{i=1}^{m} \xi_i$$
$$s.t.\ y^{(i)}(w^T x^{(i)} + b) \geq 1 - \xi_i,\ i = 1, \ldots, m;\ \xi_i \geq 0, i = 1, \ldots, m$$

- Performs well in the presence of small training sets
- Augmented with ECOC



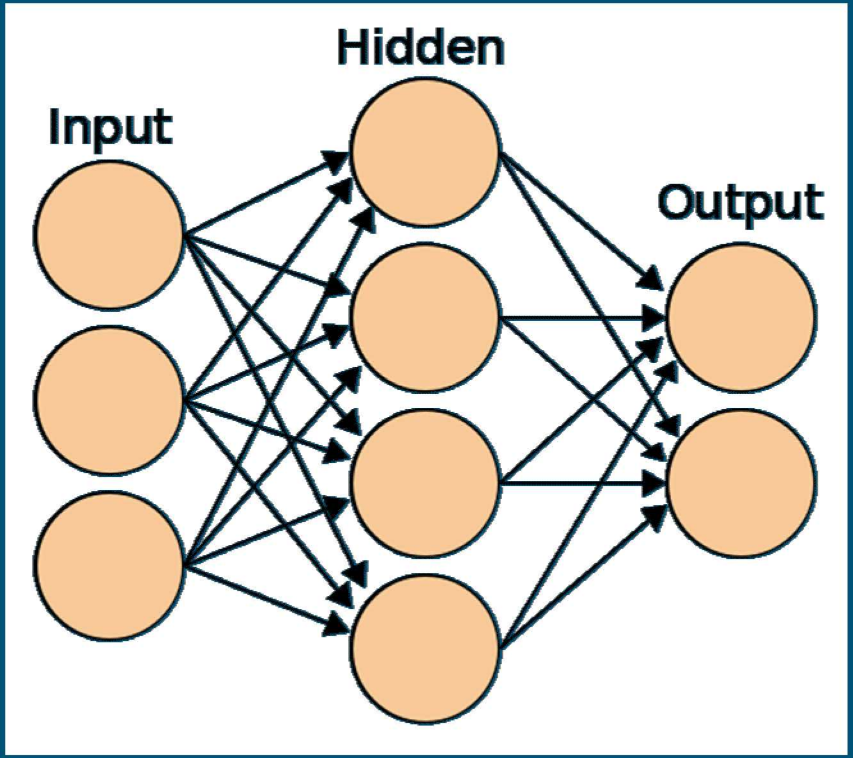
Models & Classification Techniques

Kernelized soft-margin support vector machine

- Maps input features to higher-dimensional space prior to model calibration
  - Utilizes gaussian (exponential) kernel
- Augmented with ECOC

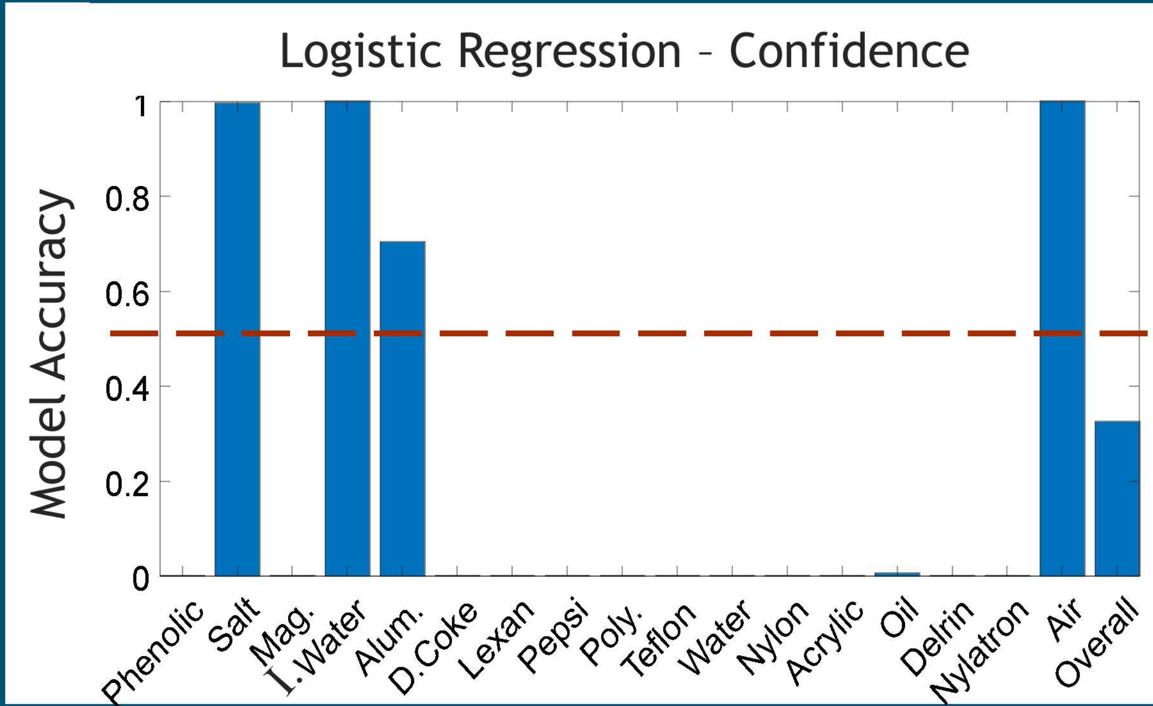
Multilayer perceptron

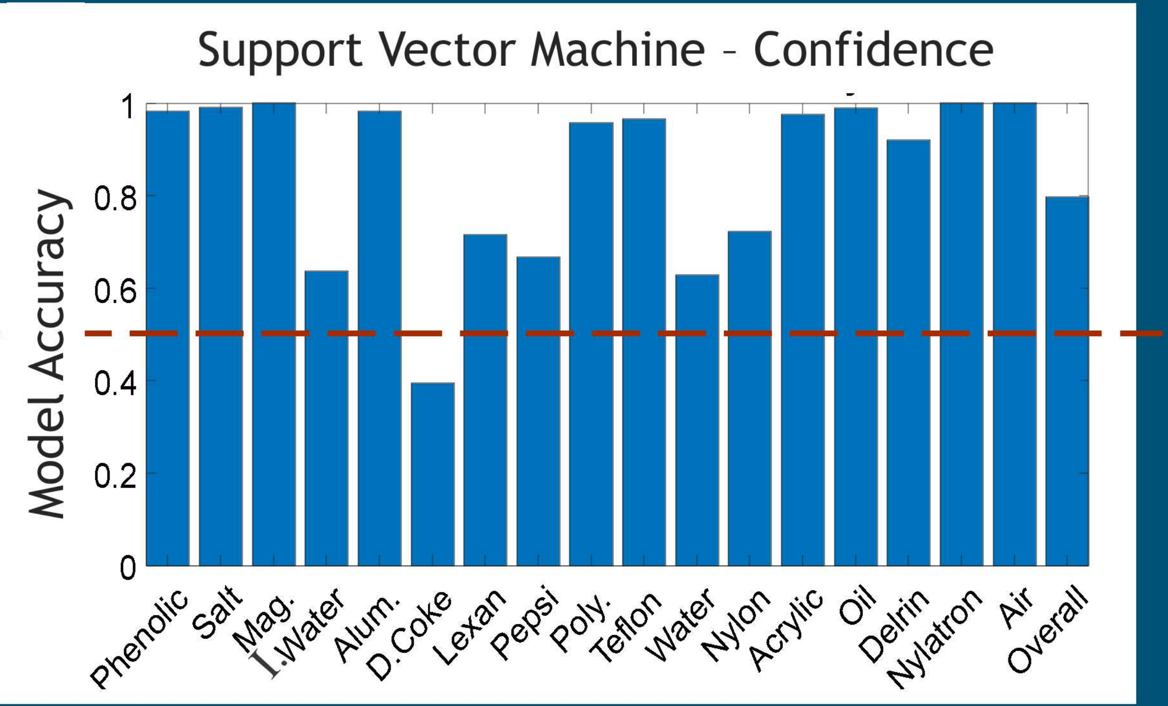
- Single hidden layer with 300 neurons
- Softmax output layer
- Cross entropy loss



Intra-dataset classification accuracy

- Voxel-by-voxel attenuation waveforms split in a 70 : 30 fashion (training : validation)
  - Accuracy above 50% (dashed red line) designates successful classification





Intra-dataset classification accuracy

Intra-dataset classification/training accuracy

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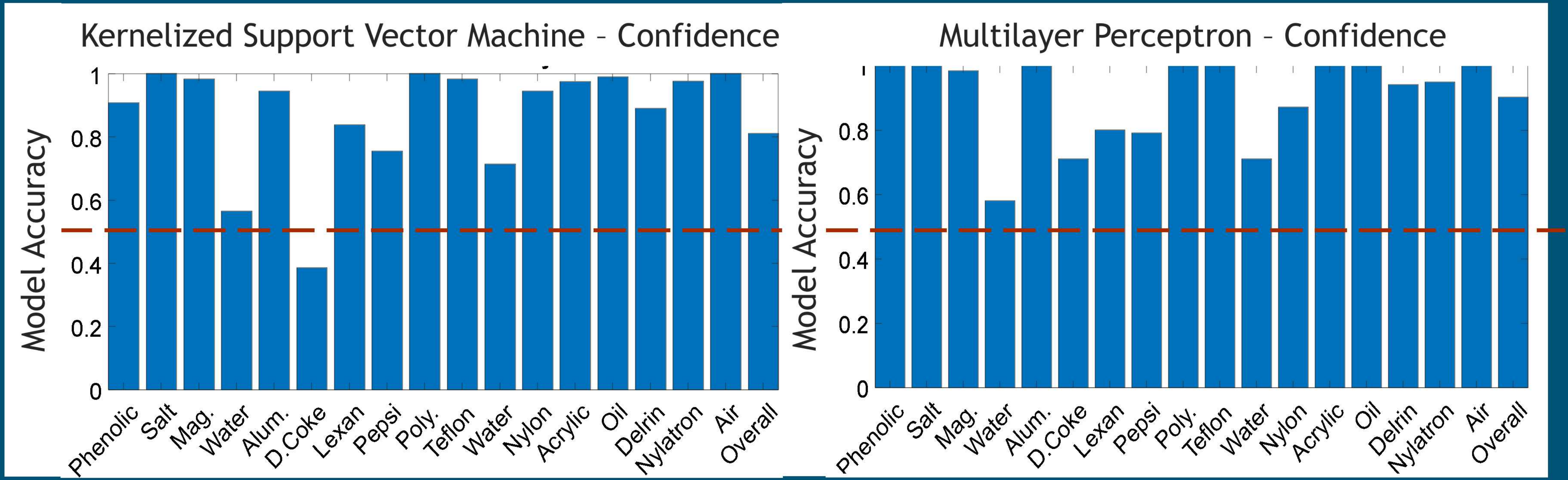

- For intra-dataset classification, a multilayer perceptron model provides the best performance

Discussion & Conclusion

Model development

- Logistic regression not applicable for classification task
  - Other linear classifiers (i.e. Naïve Bayes) may perform poorly as well
- Support vector machines yield high training/intra-dataset classification accuracies
- Kernelization of input features does not appear to facilitate classification
- Neural networks yield the best intra-dataset classification performance
  - Potential overfitting issues may be present

Material classification

- Dissimilar materials (i.e. plastics and soft-drinks) consistently distinguished from one another
- Performance within different types of plastics (e.g. polyethylene and acrylic) or elements (e.g. magnesium and aluminum) unclear

→ Materials potentially mislabeled in dataset likely matched with highly similar materials

Future Work

(1) Expand training set size

(2) Quantitatively evaluate models on different set

(3) Explore performance metrics (i.e. precision, recall, f-score) beyond accuracy

(4) Investigate convolutional neural networks for classification tasks

(5) Comparison with duel-energy CT or traditional, energy-integrating detectors for material classification

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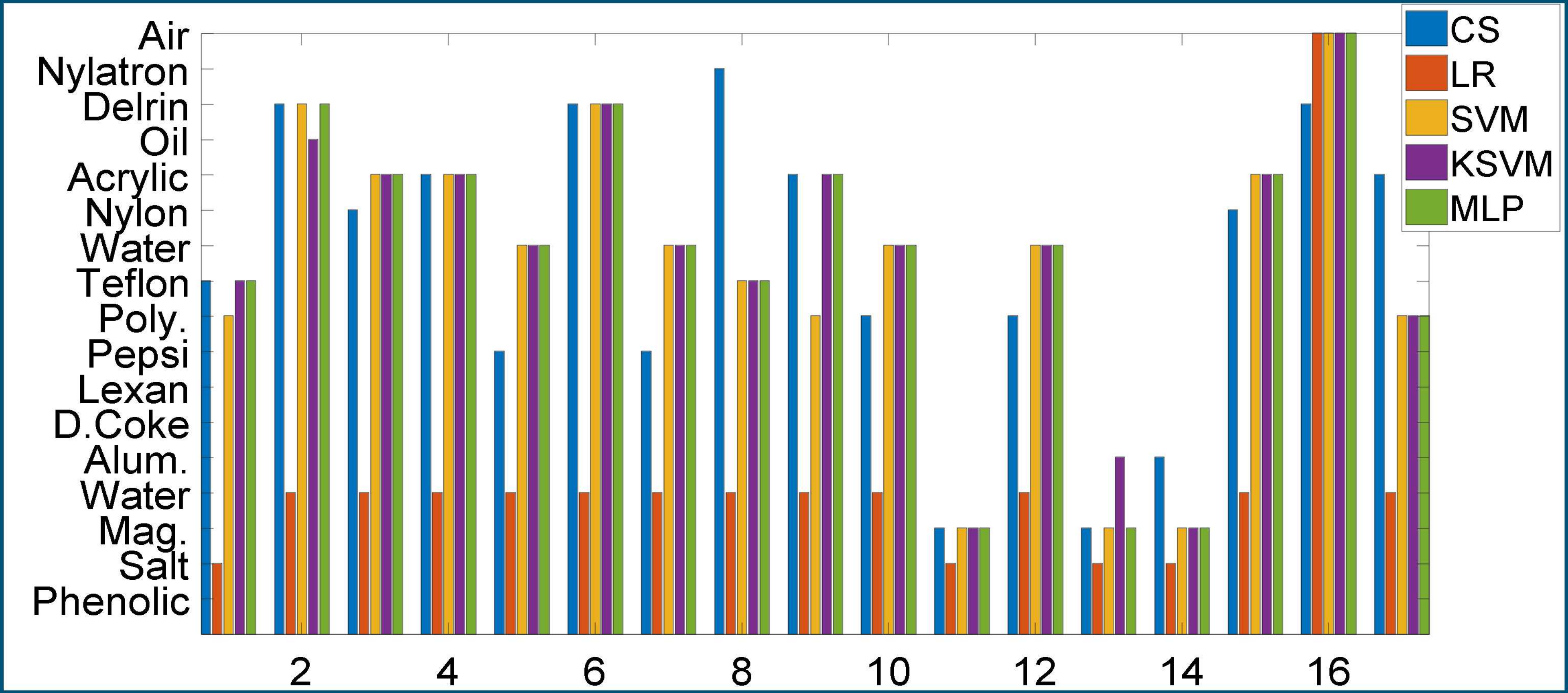

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THANK YOU!