The Consortium for Enabling Technologies and Innovation

Virtual Summer Meeting for Young Researchers

Gaseous Plume Detection: A Deep Learning Approach

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ETI

NNSA National Nuclear Security Administration

Introduction/Bio

- Just completed my fifth year of graduate studies at Duke University under Prof. Lawrence Carin
- Work with Chemistry – Physical Chemistry and Advanced Spectroscopy Group at Los Alamos National Laboratory
- Focus on applications of deep learning and machine learning – computer vision and natural language processing

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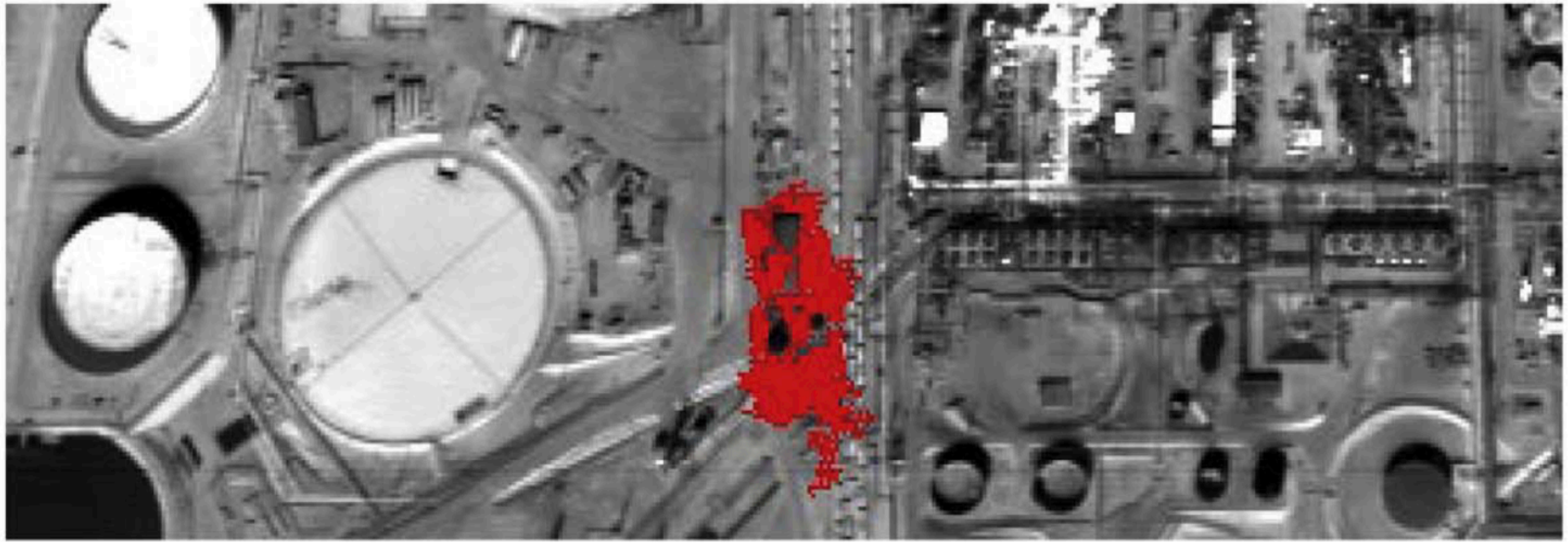
Gaseous Plume Detection

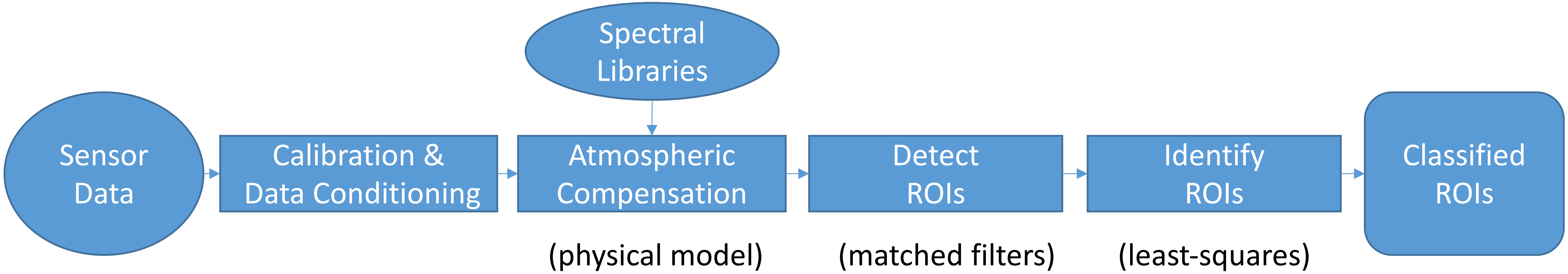
- Airborne hyperspectral LWIR imaging yields wealth of information about terrain and environment
- Goal: use such data to *detect* and *identify* areas with fugitive gases



Example detected Butane plume from Chevron El Segundo Oil Refinery. Image from Buckland et al (2017)

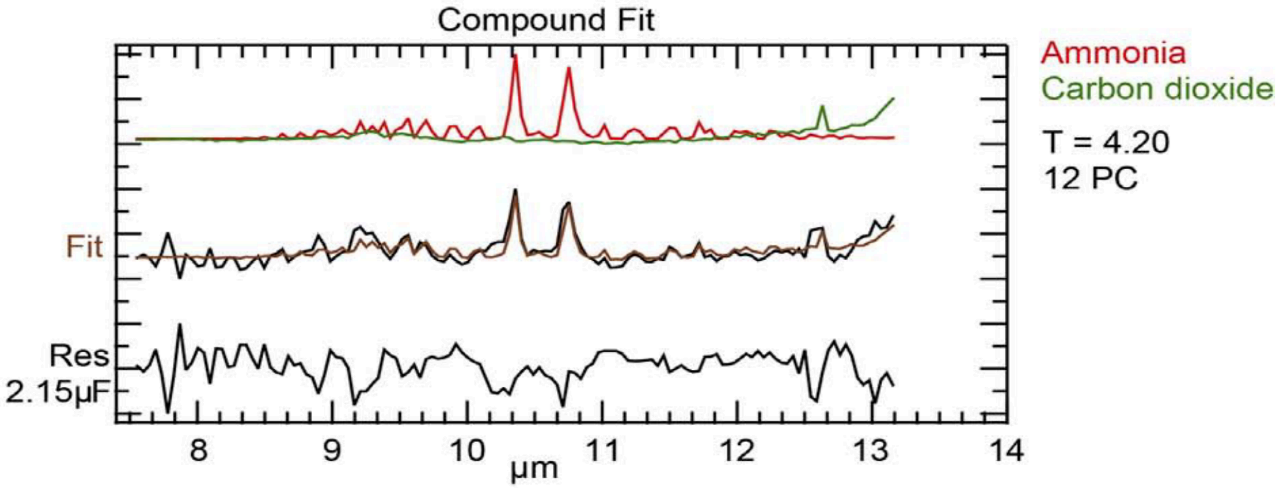
HSI Data-Processing Pipeline

- Sensor collects *radiance* data which is calibrated and preprocessed before detection/identification
  - Bad pixel replacement, Atmospheric compensation, data whitening
- Spectral signatures of chemical species are collected via laboratory characterizations
  - These *spectral libraries* are used to construct the *filters* from which detection/identification occurs



Spectral Signature Matching

- Comparison to library spectra underpins current detection + identification techniques
- Currently: these libraries are used to create spectral matched filters for detection and for fitting stepwise least-squares (SWLQ) identification models
- Deep Learning: convolutional filters are trained to activate on features in spectral responses



Example fit of a detected plume for two gaseous species. The key takeaway is from the top series, which shows the library spectra for Ammonia/CO_2 and demonstrates what we are comparing against.
Image from Buckland et al (2017)

Deep Learning Mitigation

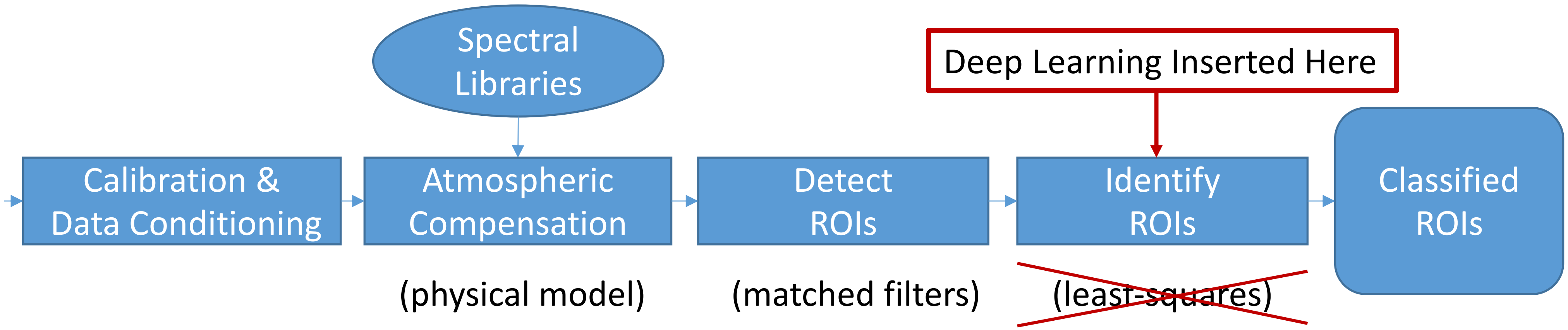
- Deep Learning algorithms approximate complex data mappings from input to output
- Supervised methods: use labeled data to learn model parameters for feature extraction and prediction
  - Complication: we do not have exact labels. Instead, we have spectral libraries to match to
- We can use the spectral libraries to *generate* data from which to train a neural network for chemical species classification (identification)

Training Data Generation

- We synthesize training data by whitening the spectral libraries
  - The whitening transform comes from the atmospherically compensated and whitened HSI datacubes (i.e., from the preprocessing of the data)
  - Essentially, inner product of the spectral libraries with the whitening matrix for each datacube
- Doing this essentially "applies" the atmosphere of the real data to each characterized gas in the library

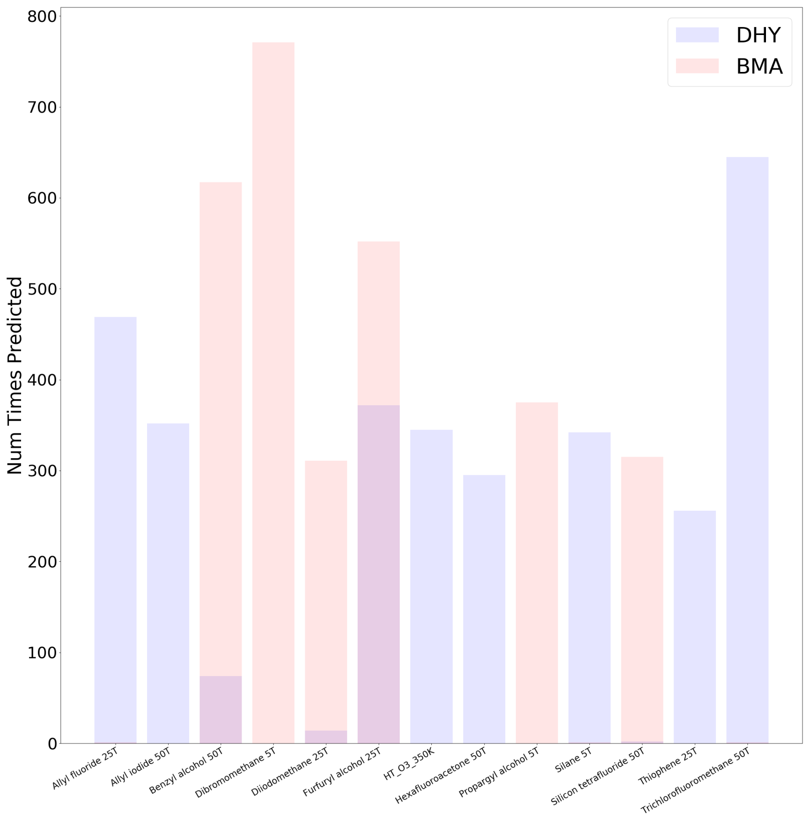
Deep Learning Classification of Gas Species

- We employ a cascade of *convolutional* layers to extract features from the preprocessed/whitened data of a *region-of-interest (ROI)*
  - Convolutions occur over the *spectral* dimension of the ROI (standard deep learning for images operates over *spatial* dimensions)
  - Input is an average of whitened radiance for pixels in ROI (e.g., we do classification pixelwise, over ROI *superpixels*)
- A fully-connected network and softmax layer are used to classify features

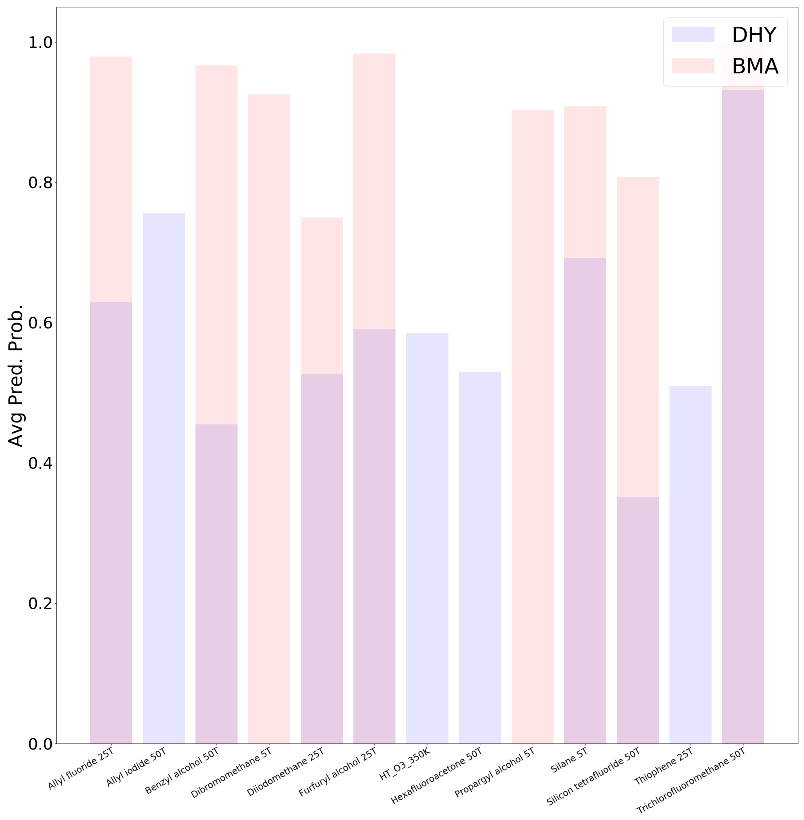


Classification Results/Comparison

Number of Times Model Predicted
(For Species Predicted Over 200 Times)



Model Predicted Probabilities
(For Species Predicted Over 200 Times)



Results Commentary

- BMA – Bayesian Model Averaging (currently used for classification)
- DHY - Deep Hyperspectral Model (proposed model)
- We expect that species predicted frequently are *false-alarms*
    - We wish to predict these less frequently
    - Notice that DHY model predicts these species with a lower probability
    - Indicates that DHY model is "less sure" of these predictions, which is good if we don't want to alarm on them – we can use *thresholding*

Acknowledgement

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