



Sandia
National
Laboratories

Analysis of Plumes through Neural Networks

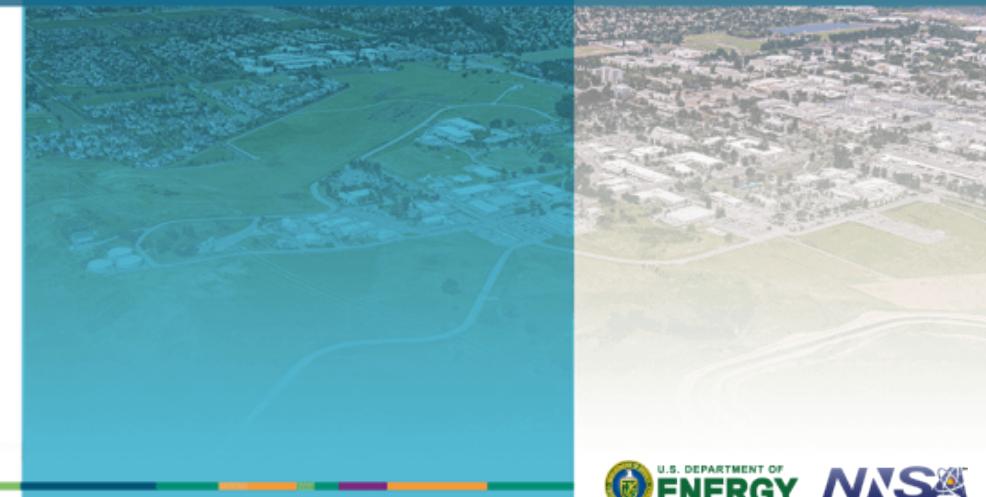
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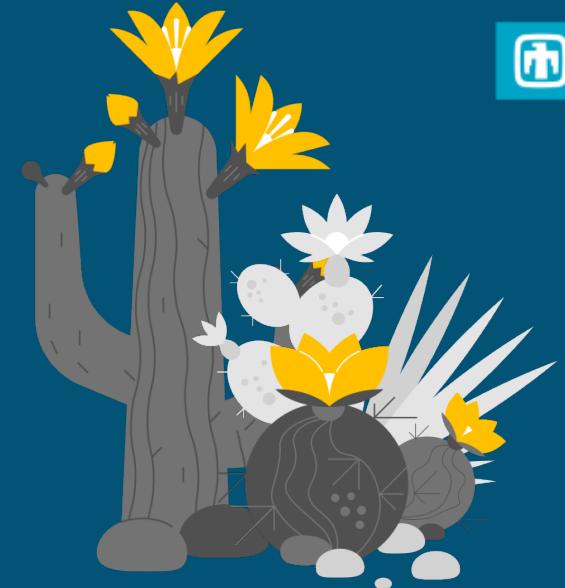
Virtual Intern Symposium



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Outline

- Role
- Core Concepts
- Projects
 - Inverse Solution
 - Vapor II
 - Watershed
- DIRSIG
- Summary/Goals





Main Role

- Insert models of plumes into DIRSIG as a way to **simulate** their interaction with the world
 - What **information** does DIRSIG need in order to put plumes in the scene (vector coordinates, concentration of plume, optical properties)?
 - Create data to train neural networks (Inverse Solution, Vapor II, Watershed).
- Work on trying to do so has been ongoing for the past 15 years between Sandia and DIRS
 - No automated way or existing tool

Secondary

- Develop a **data loading scheme** to extract a region surrounding a queried pixel for efficient loading to feed our deep learning models.
 - Models tend to detect pixels of interest better when spatial context is provided.

Core Concepts



Plumes

- One **fluid** vertically moving through another- a plume of smoke rises as a **column** through air
- The **release location** shown is the rocket. Other examples include wildfires, smoke stacks, and vents.
- Relevant to **national security** in terms of identifying chemical makeup, detection, and tracking of plumes.



GPS III-5 satellite being launched 6/17/2021



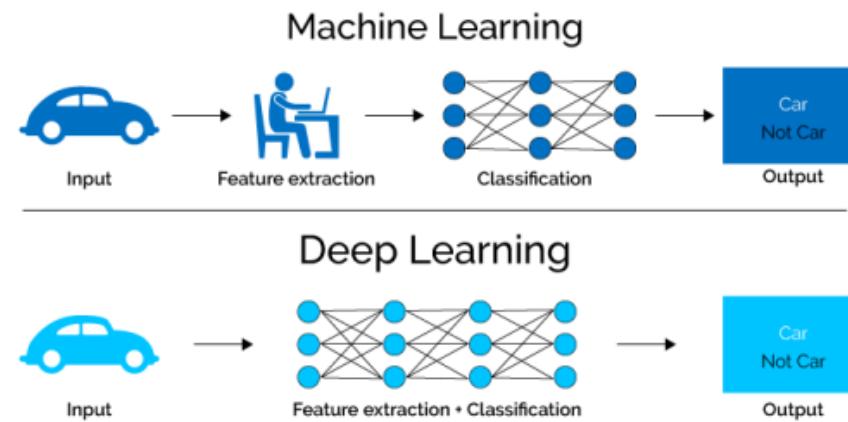
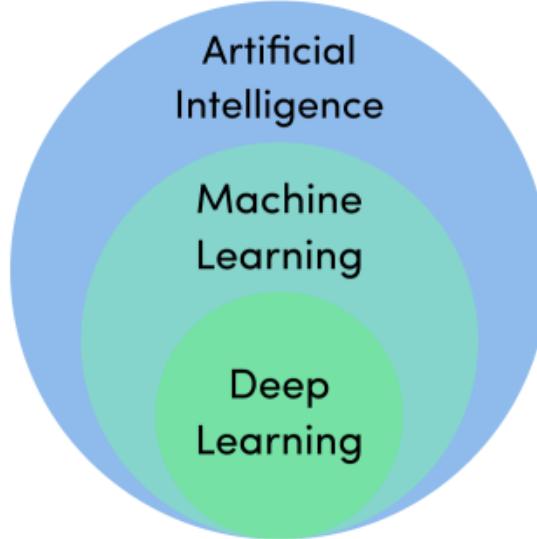
[<https://www.defense.gov/observe/photo-gallery/igphoto/2002744999/>]

Core Concepts

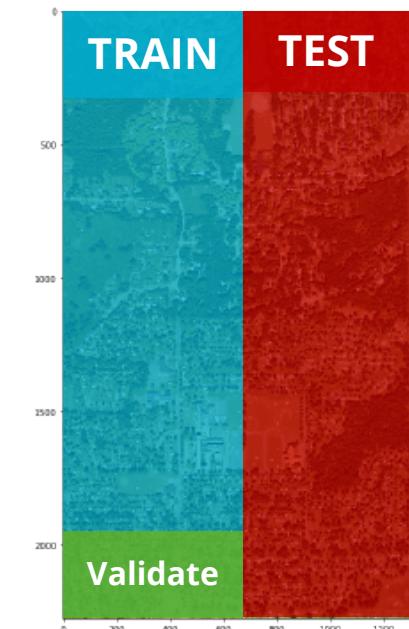


Neural Networks

- Algorithms that try to recognize **underlying relationships** in data through a process meant to mimic the human brain
- Each **pixel** in the data are run through the model
- Beneficial as a way of sorting through an exuberant amount of data (for identification purposes) relatively quickly **compared to humans**



[1] Anderson

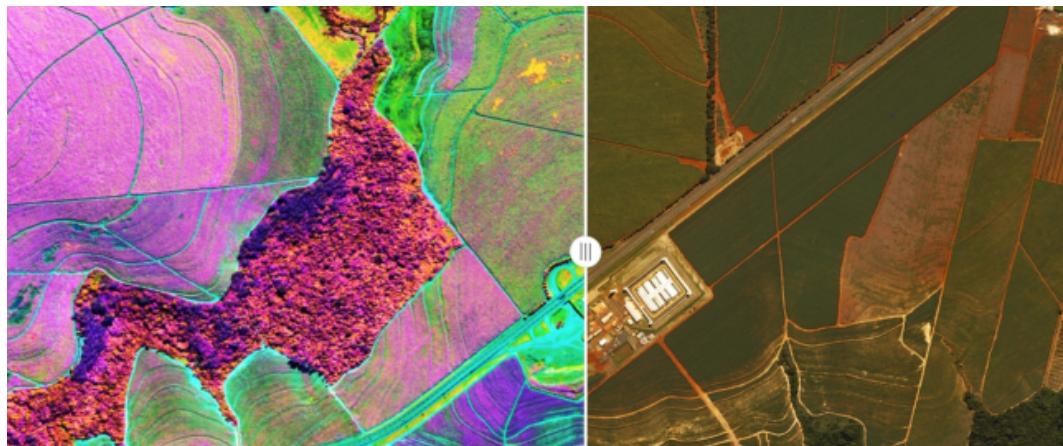


Core Concepts

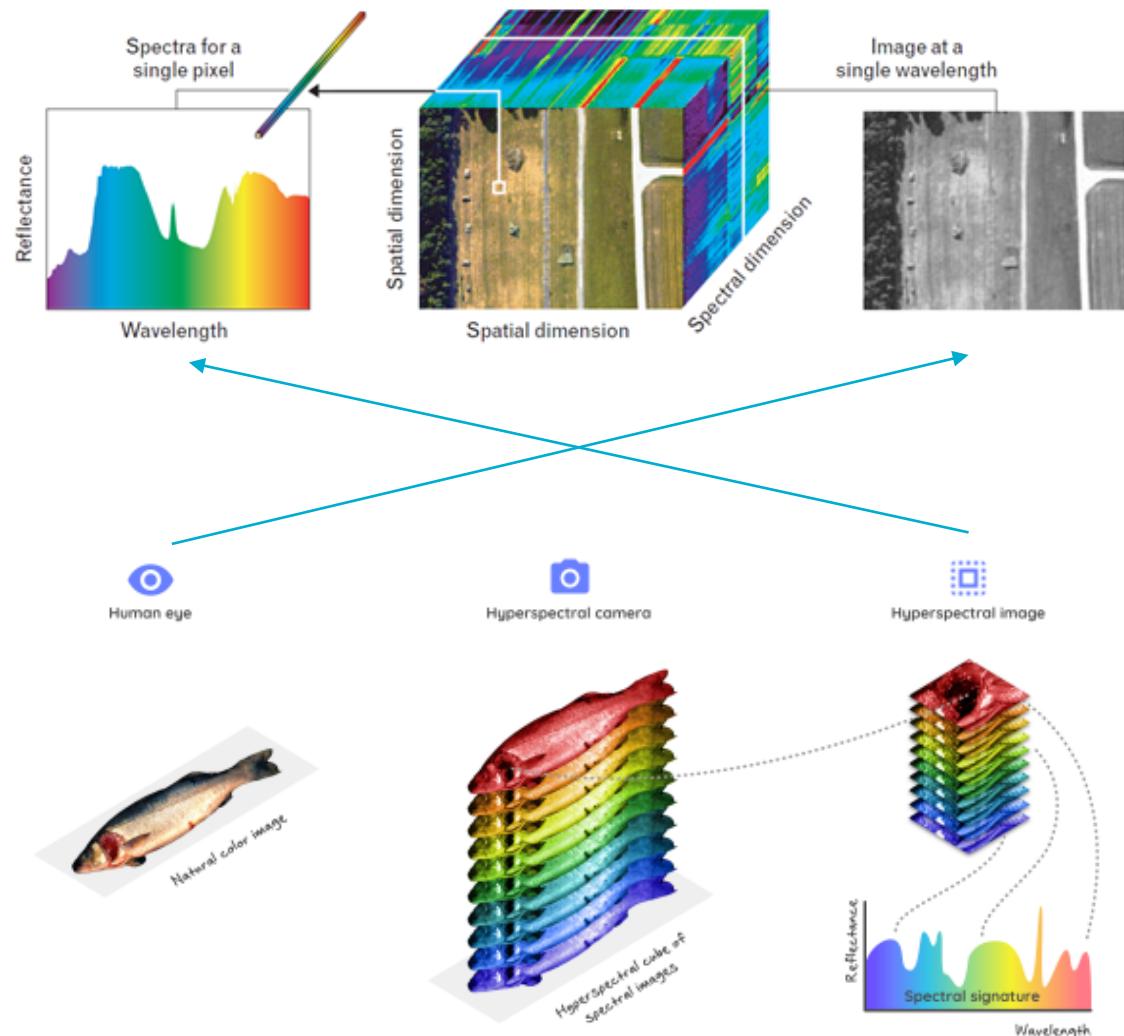


Hyperspectral Imagery

- Obtains spectra for each pixel that encompasses a scene
 - A spectra can consist of hundreds of thousands of bands 10-20 nm wide.
- Relevant to **national security** in terms of identifying specifics chemicals within large areas (scenes)



[<https://agfundernews.com/growing-impact-hyperspectral-imagery-agrifood-tech.html>]

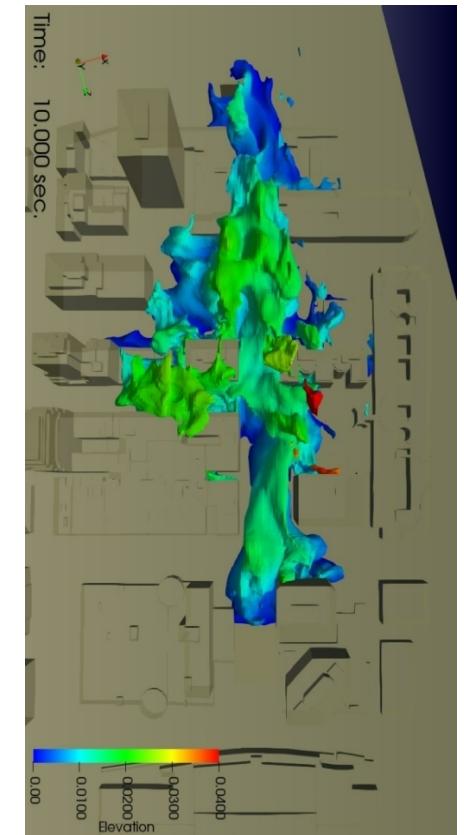
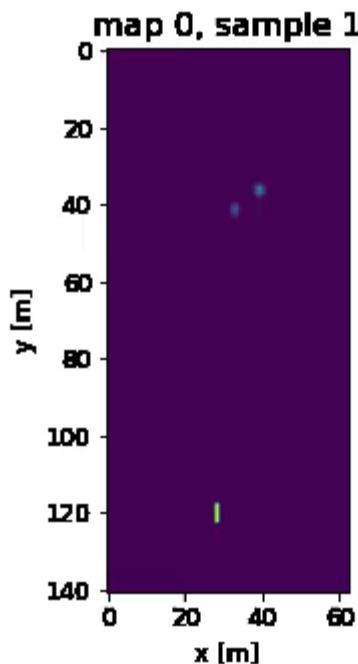
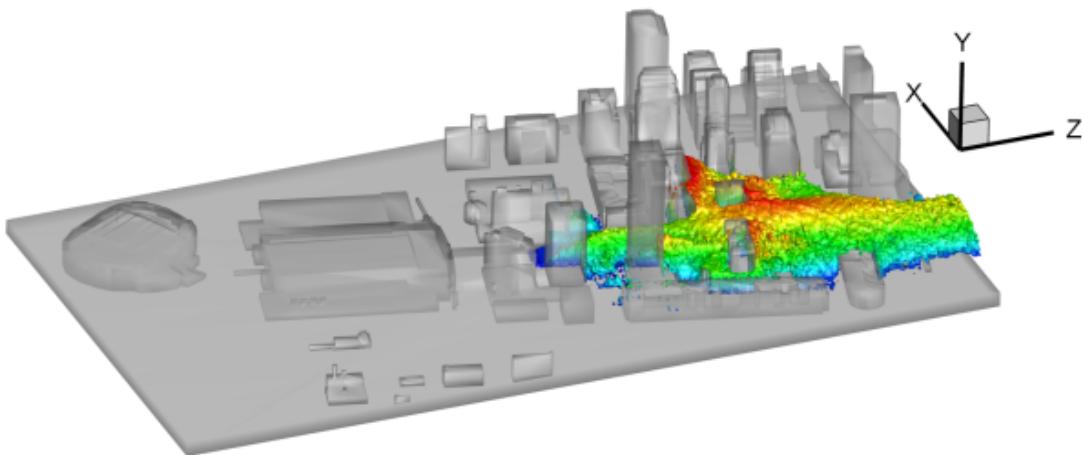


[<https://condifood.com/hyperspectral-imaging/>]

Inverse Solution



- “The aim of this project is to determine the **release location** and **concentration** of effluent releases with some level of confidence. Synthetic image data for algorithm development is based on **computational fluid dynamics** simulations of various scenarios and environments.”

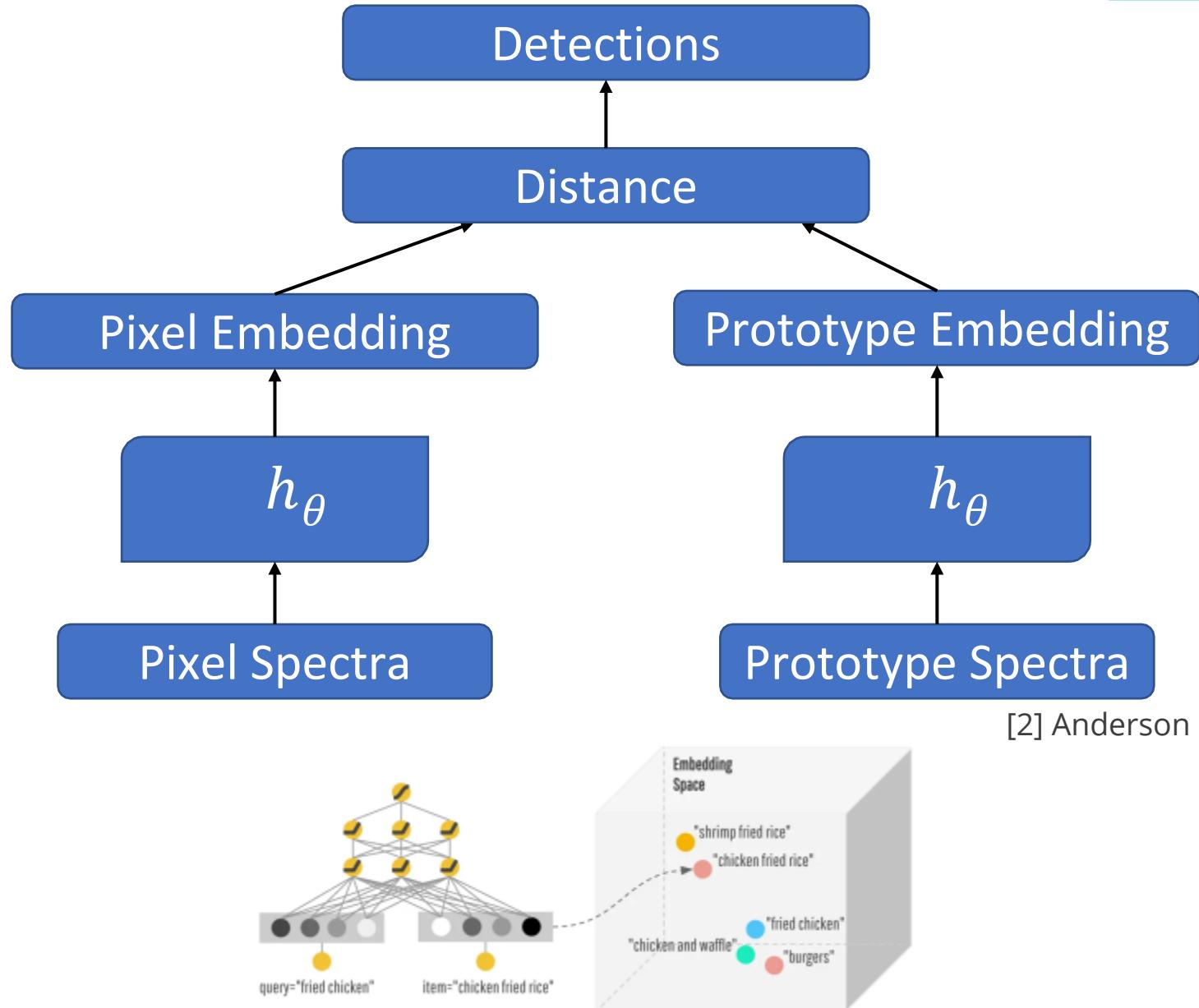


[1] Inverse Solutions Team

Vapor II



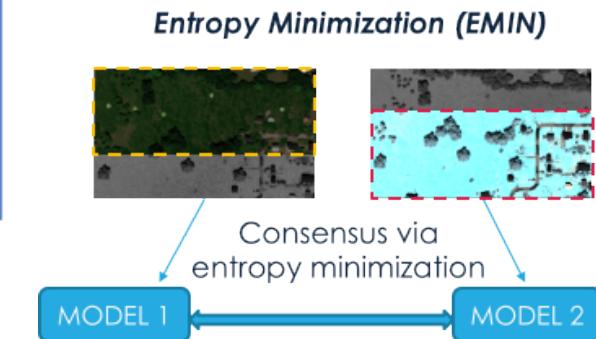
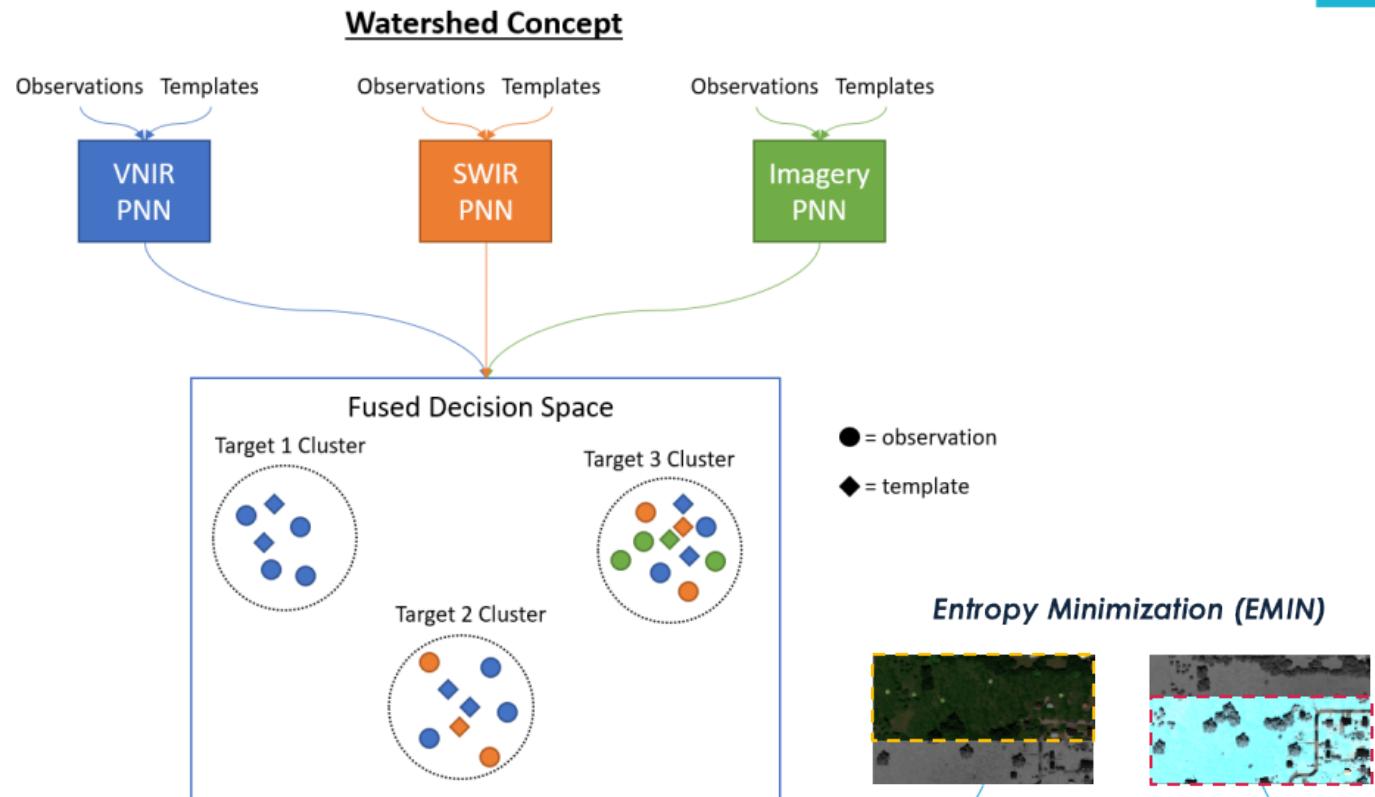
- “Deep-learning approaches such as **paired neural networks** are being studied and developed for detecting plumes in **hyperspectral imagery**.”
- Work originated with Vapor I for using PNN’s on hyperspectral imagery to try and solve the **Expanding Library Problem**.
 - Collect a library of target spectra under as many different conditions as possible.
 - This construction must be performed for each new target material. [1] Anderson



Watershed



- “This project investigates multi-modal techniques to solve **hyperspectral imagery problems**, including studying the effects of a **missing data** stream. The data fusion process uses pixel-to-pixel **paired neural networks**.”
- Using similar concepts to Vapor I (**embedding spaces**) while trying to fuse data from different sensors
- Entropy (randomness) minimization with PNNs encourages modality specific models to learn a shared embedding space.



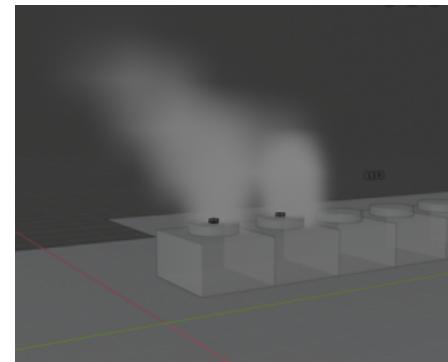
Predictions **benefit** from full data coverage and **benefit** from context using disparate data sources.

Example: PNN learning a shared embedding space for VNIR and SWIR

Digital Imaging and Remote Sensing Image Generation



- Produced and expanded on by professors and scientists out of Rochester Institute of Technology for over 20 years
 - Used by Laboratories and Universities across the country
- A model designed to produce **imagery**, **test** image systems, and **produce data** for training.
- Projects use **Hyperspectral** data made in DIRSIG as a way to test and build up models



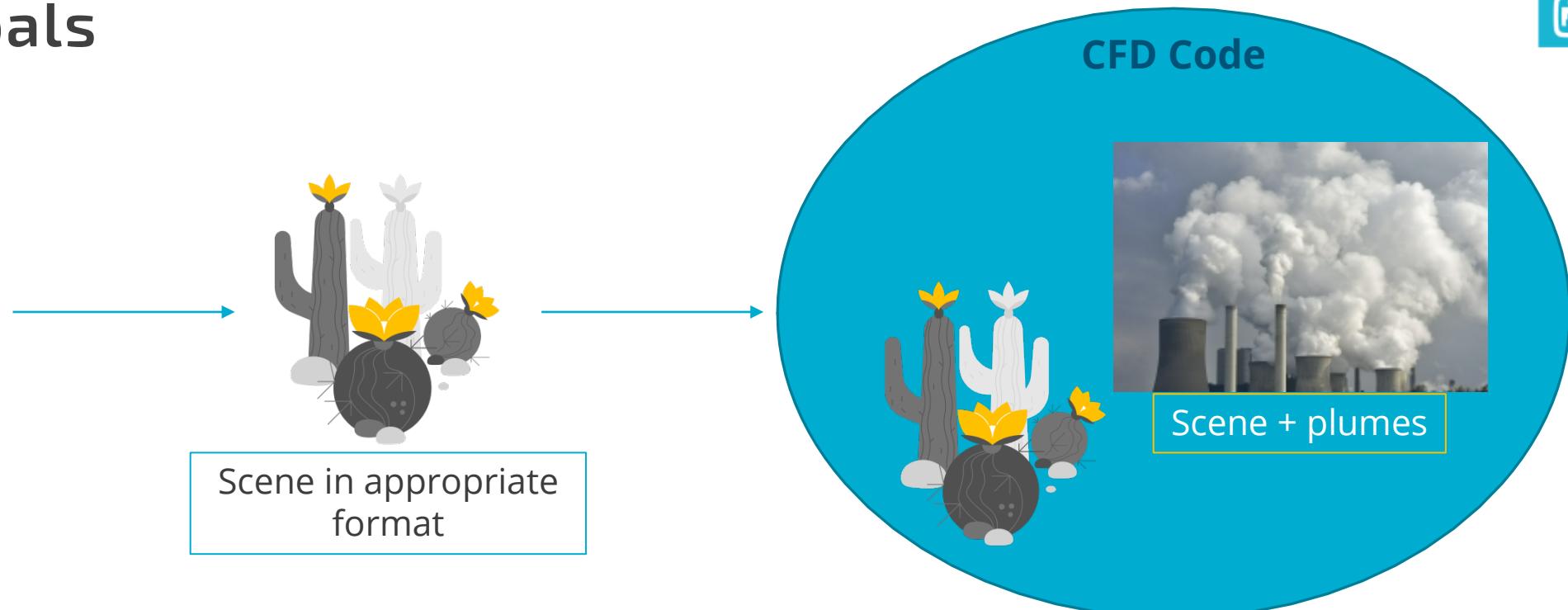
[4] DIRS



Current Goals



Work Goal



Professional Goals

- Convert Summer Internship into Year-Round Internship
- Finish Undergraduate degree and earn a MS/PhD in Imaging Science at RIT



[4] DIRS

References



- [1] Inverse Solution Team, "Inverse Solution Overview," [PowerPoint slides]. Available: <https://wiki.sandia.gov>. [Accessed: July 1, 2021]
- [2] Dylan Z. Anderson, Joshua D. Zollweg, Braden J. Smith, "Paired neural networks for hyperspectral target detection," Proc. SPIE 11139, Applications of Machine Learning, 111390J; 2019. [Online]. Available: <https://doi.org/10.1117/12.2531310>. [Accessed: June 29, 2021]
- [3] Watershed Team, "Watershed Kickoff," [PowerPoint slides]. Available: <https://wiki.sandia.gov>. [Accessed: June 30, 2021]
- [4] Digital Imaging and Remote Sensing Lab, "Digital Imaging and Remote Sensing Image Generation(DIRSIG)," Chester F. Carlson Center for Imaging Science, Rochester Institute of Technology, 2021. [Online]. Available: <https://dirsig.cis.rit.edu>. [Accessed: June 28, 2021]