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An Uncertainty Quantification Enabled Semi-Supervised Paired Neural Network for Few-Shot Classification

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SIAM UQ 4/15/22

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U.S. DEPARTMENT OF ENERGY

NNSA

Motivation

- Deep learning (DL) has become popular tool for finding trends in hyperspectral imagery (HSI)
- We don't always know what we're looking for
- We rarely have much **labeled** training data
- Traditional DL does not quantify uncertainty of predictions
  - This is problematic for **high consequence** problems

Model Requirements

1. Low-Shot Learning
2. Semi-Supervised Learning
3. Uncertainty Quantification

Megascene

Simulate **9** HSI scenes “Megascene” from DIRSIG

- **Three** MODTRAN-based atmospheres
  - Mid-latitude summer (MLS)
  - Sub-artic summer (SAS)
  - Tropical (TROP)
- **Three** times of day
  - 12:00
  - 14:30
  - 15:45

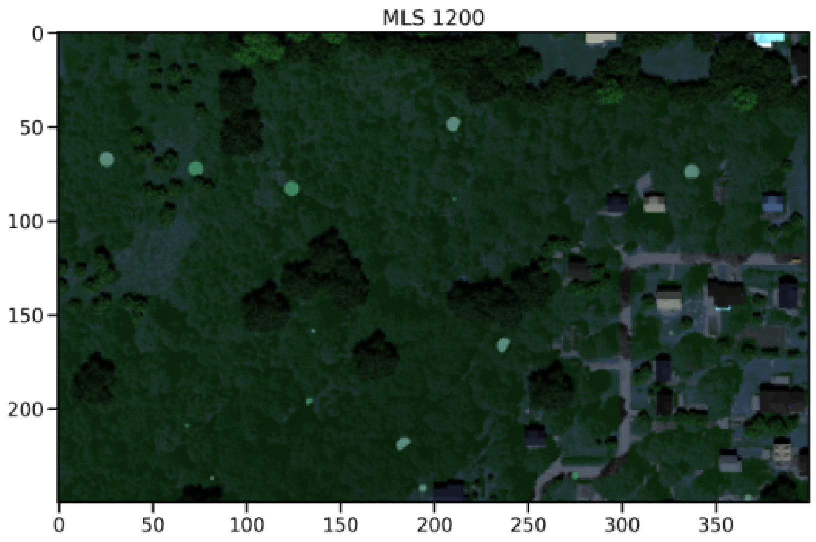
At every pixel, we have a full spectrum response across 211 spectral bands using AVIRIS-like sensor

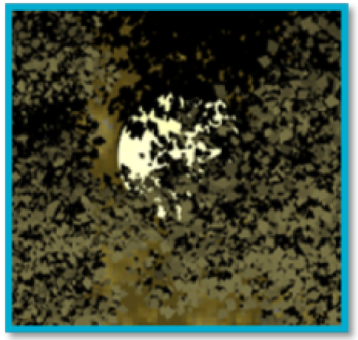
- 0.4 to 2.5 μm
- Elevation 4km
- Pixel size $1m^2$

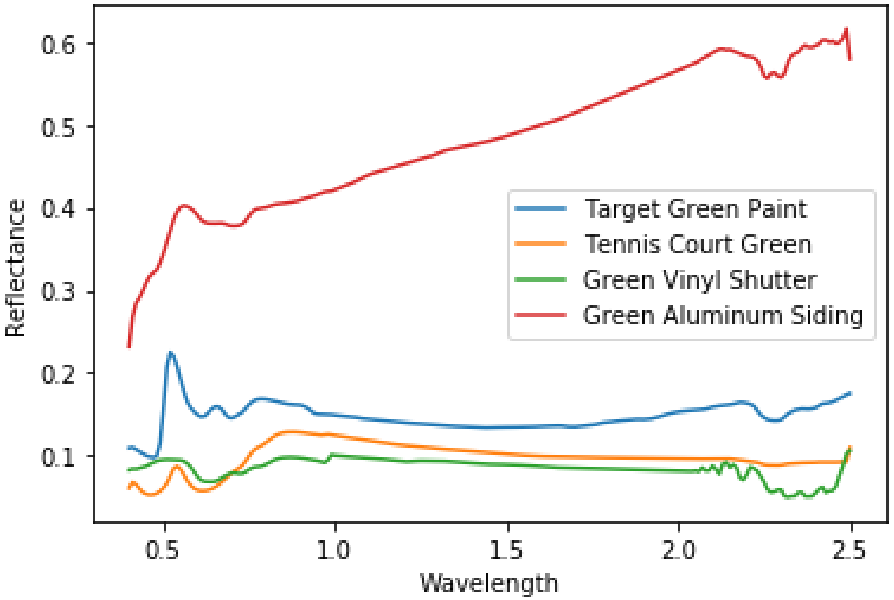
Megascene Targets

We manually add targets (green paint) to the scene

- 125 green discs in each of the **9** scenes, in different locations for each scene
- Radii of discs ranges from 0.1 to 4m
- Scene contains other green elements with similar spectral signatures







Low-Shot Learning

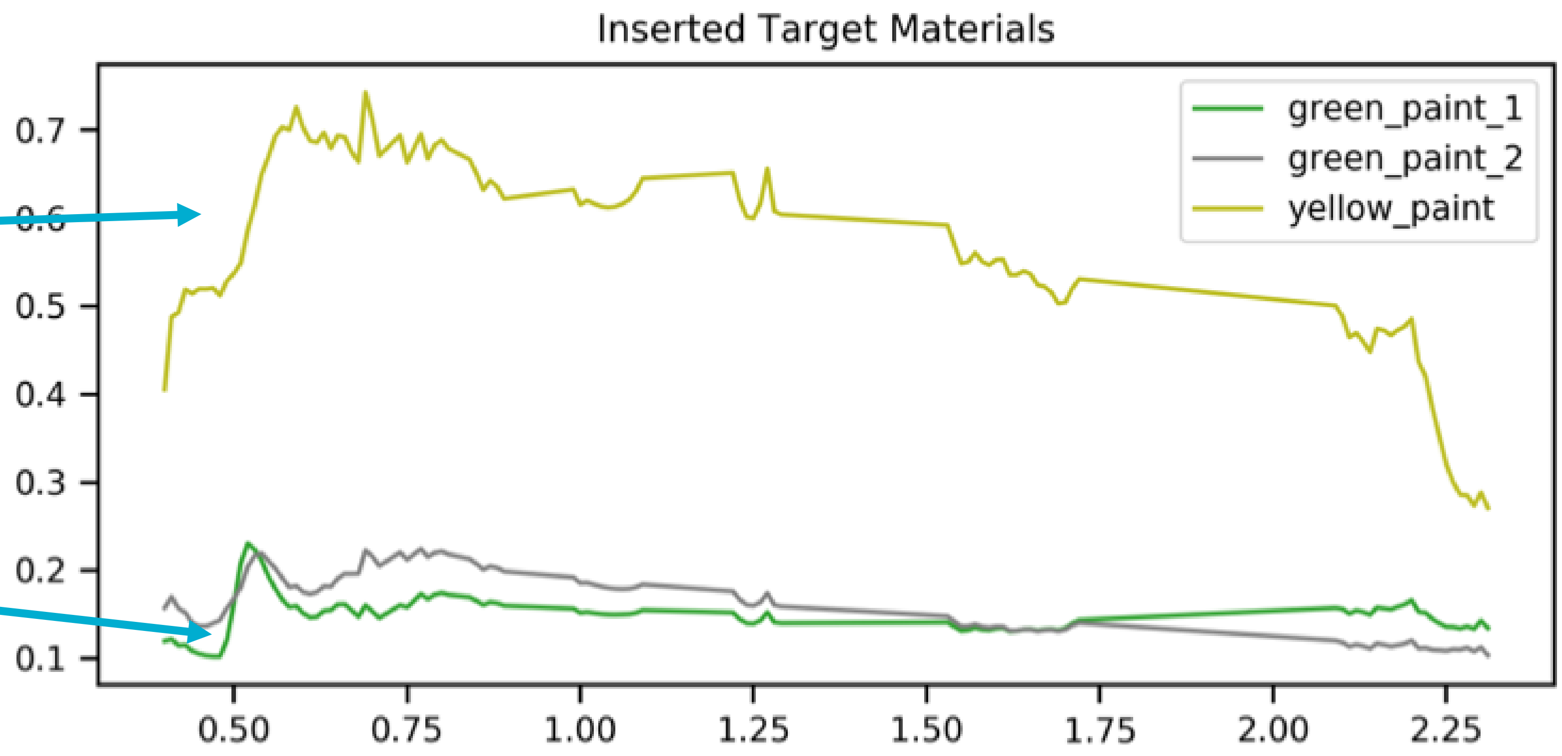
What is Low-Shot Learning?

We want to train on one material and extend to new ones

- Neural network by themselves need data from all classes to train
- We want to train on only one class and extend to others

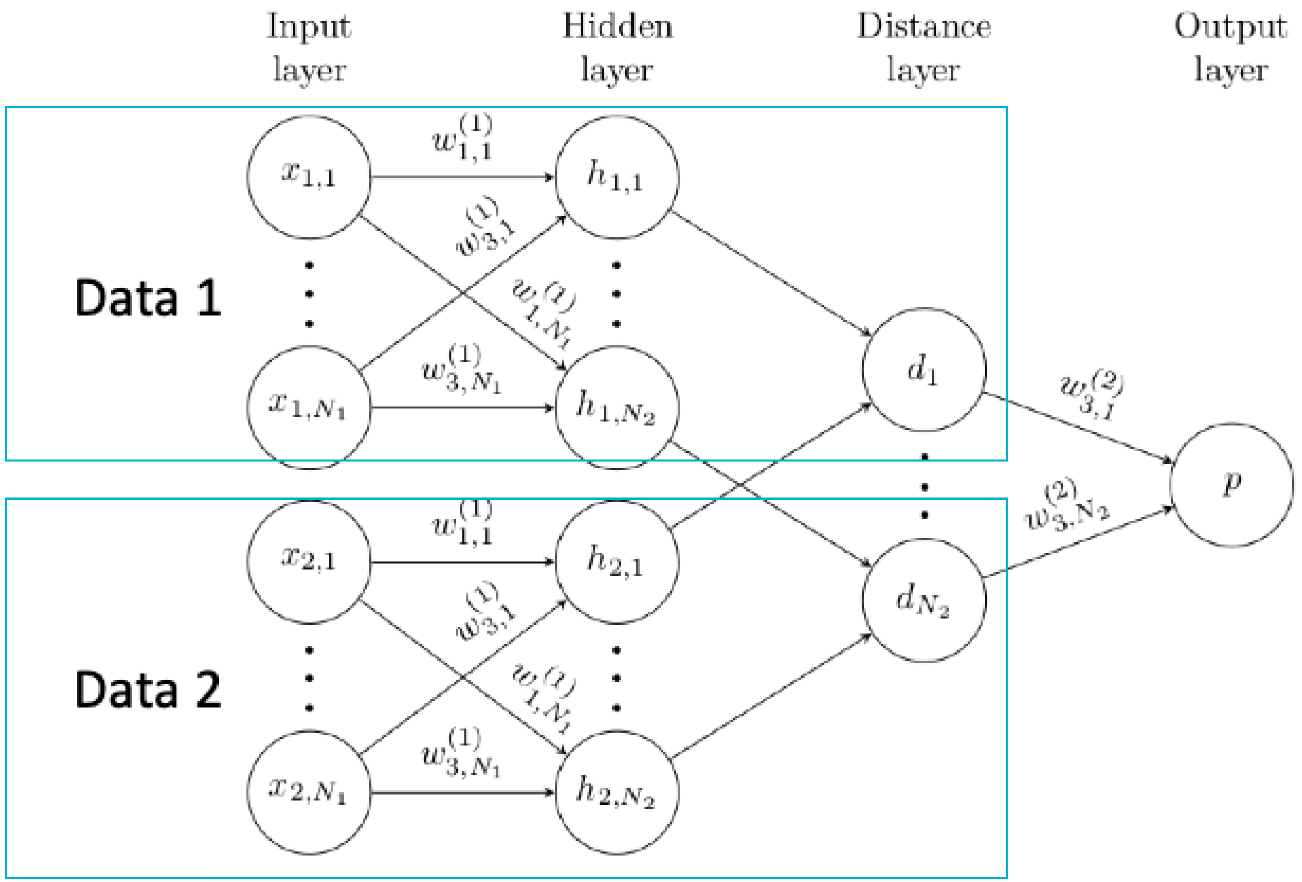
Expect model to find yellow paint in-scene even though not trained on it

Train model using only Green paint as a **labeled** target



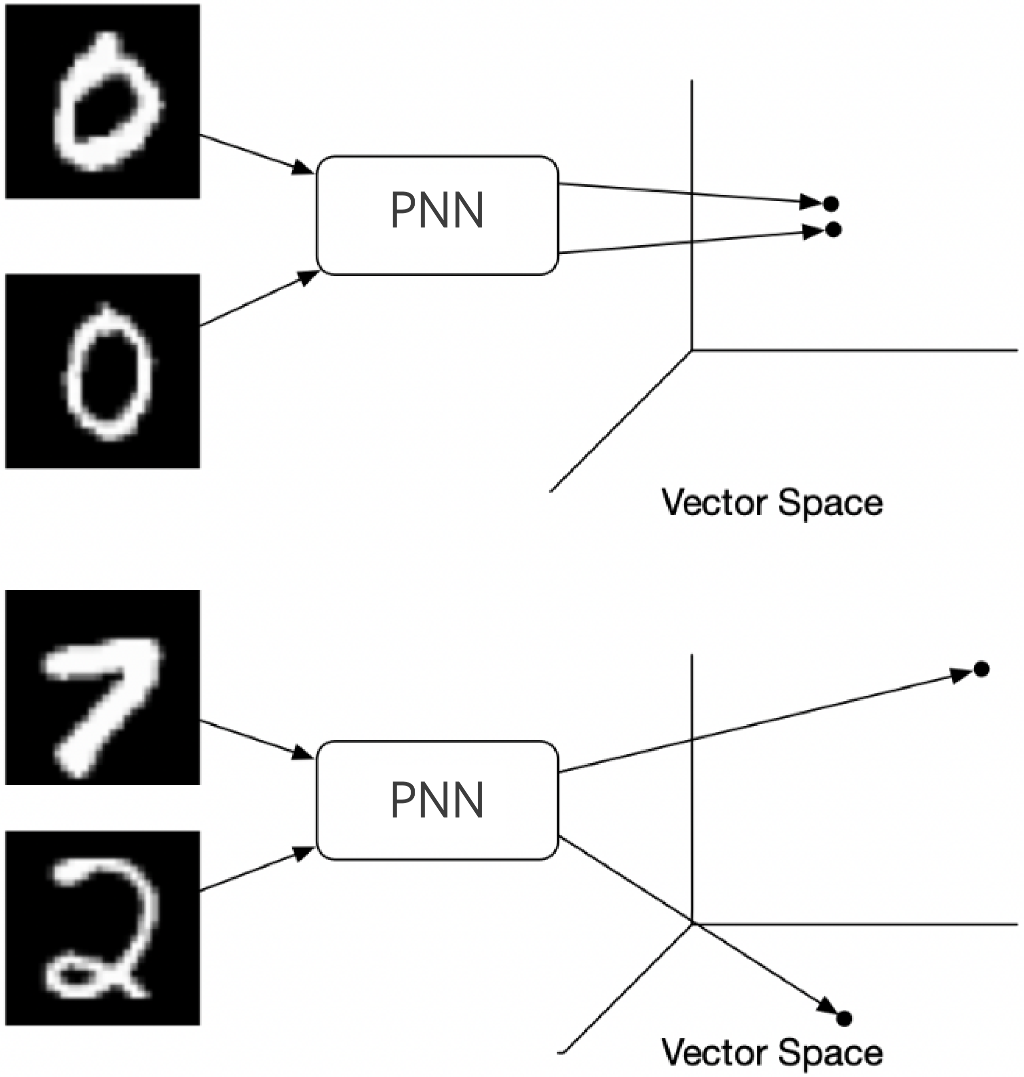
Paired Networks

- Learn **embedding** space
- Want:
  - Small distances between similar datapoints
  - Large distances from dissimilar



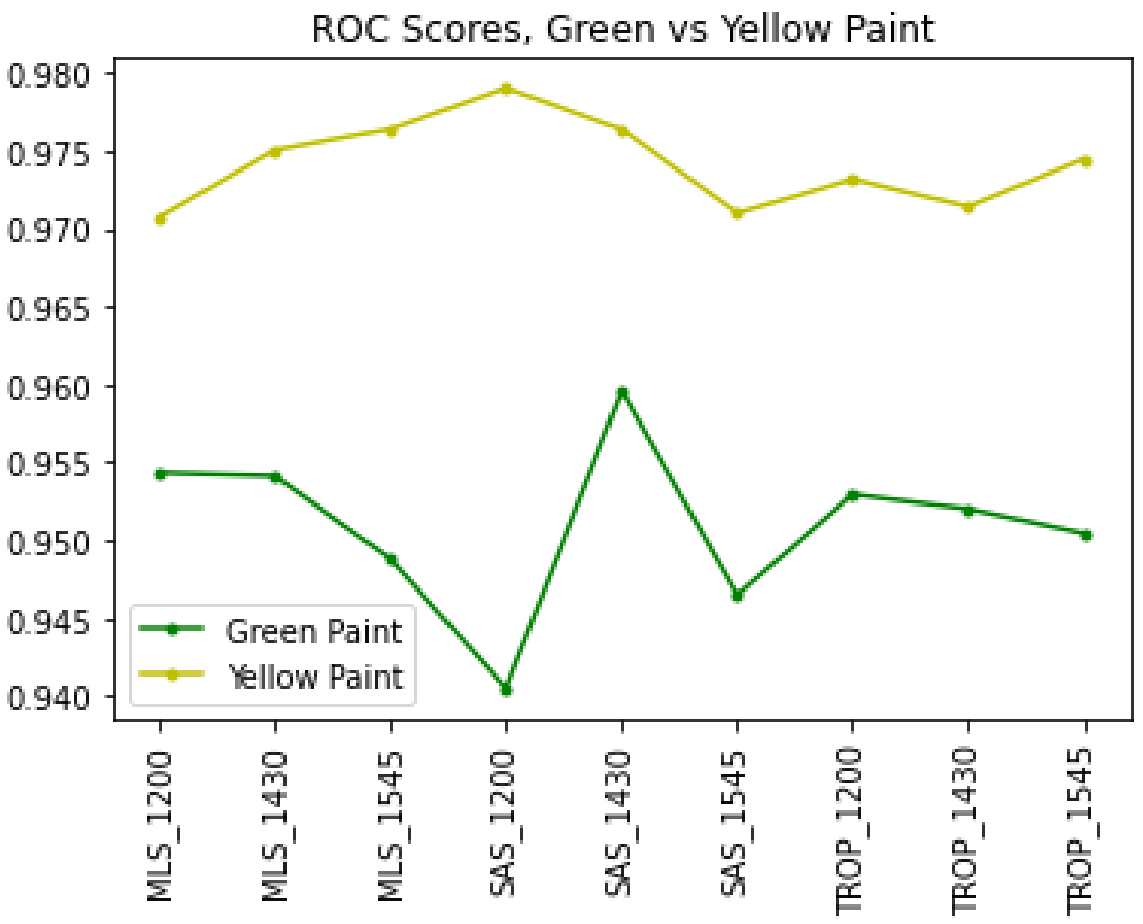
Paired Networks - Idea

- End up with an embedding space
- Hopefully, we will get any similar datapoints to a similar location in embedding space



Low-Shot Learning Results

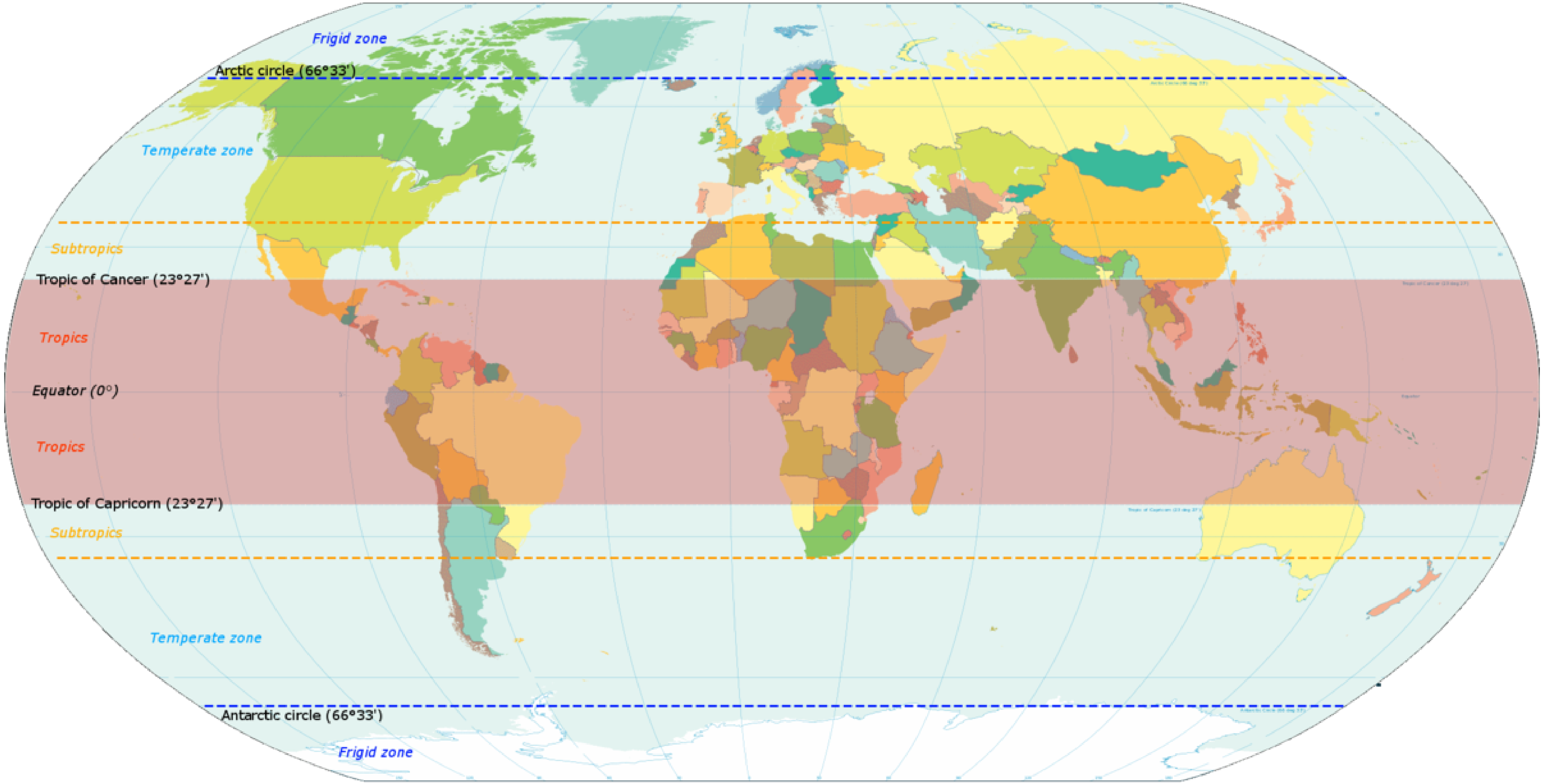
- Model was trained using only green paint targets
- PNN is easily able to detect yellow paint due to the learned embedding space



Semi-Supervised Learning

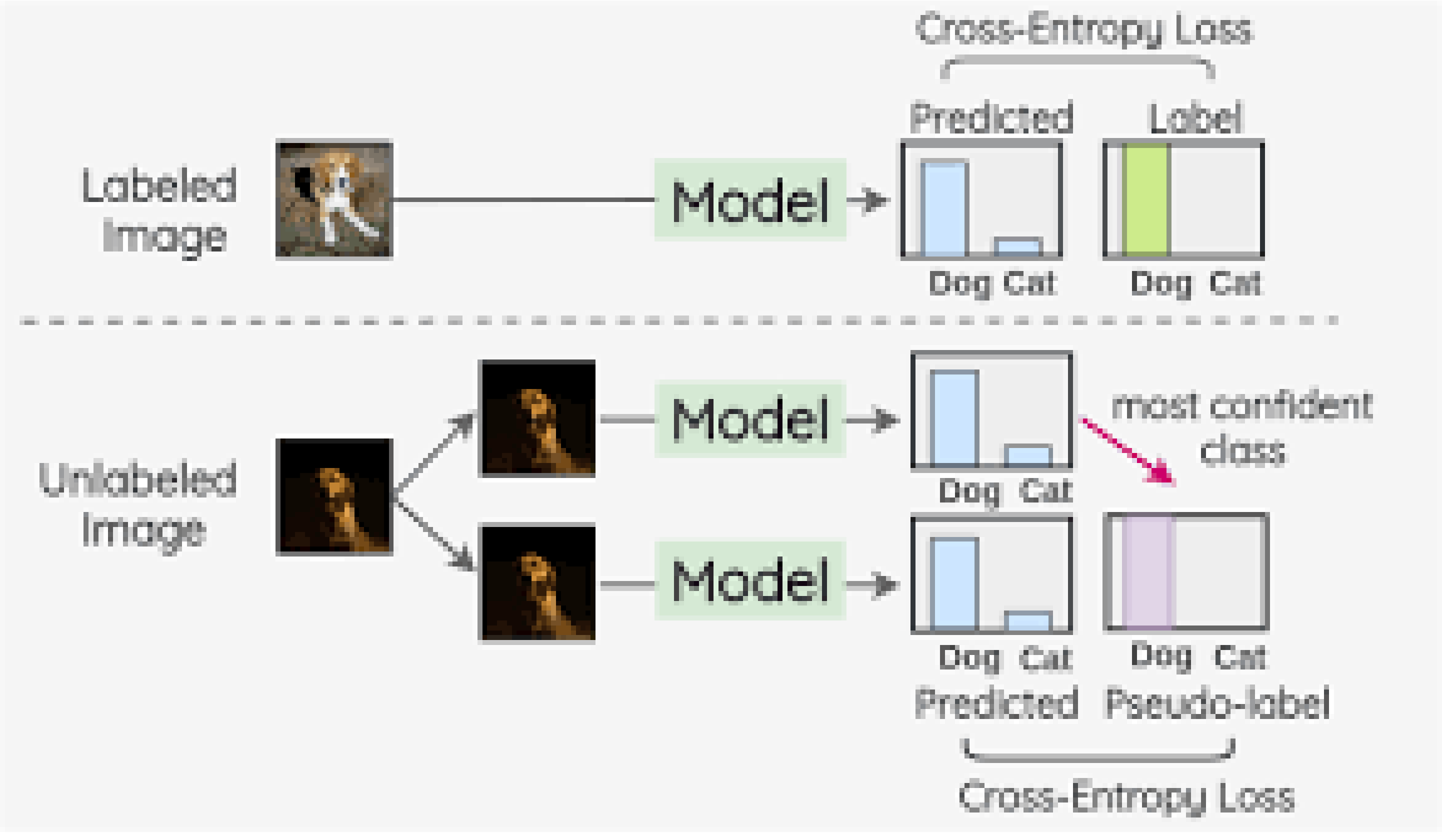
What is Semi-Supervised Learning?

We have several datasets, not all of them are labeled. We want to be able to use this data.



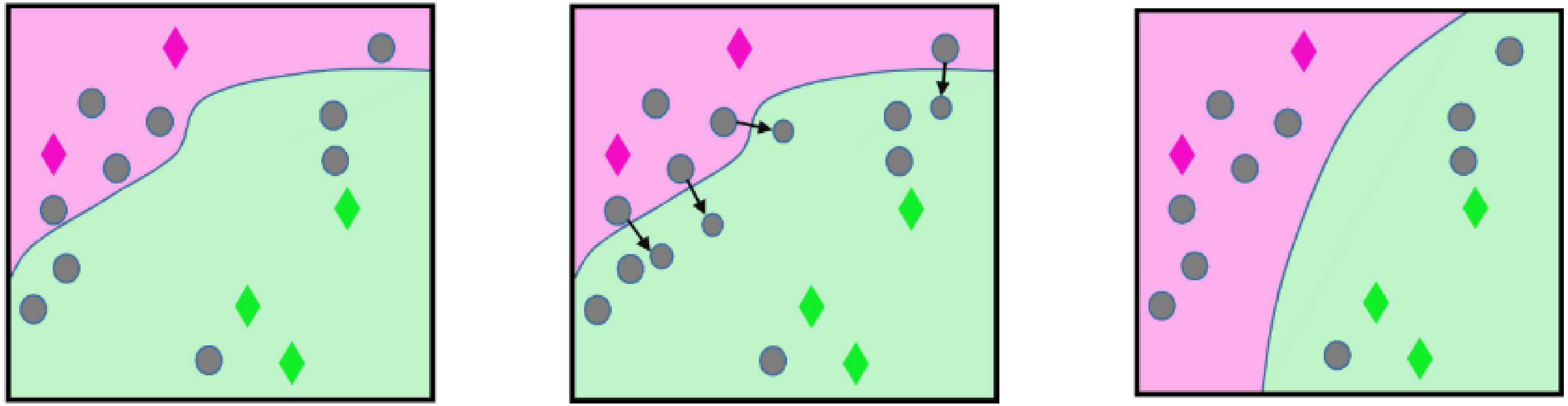
Mean Teacher (MT)

- Student and Teacher models
- Teacher updates each round as mean of students



Virtual Adversarial Training (VAT)

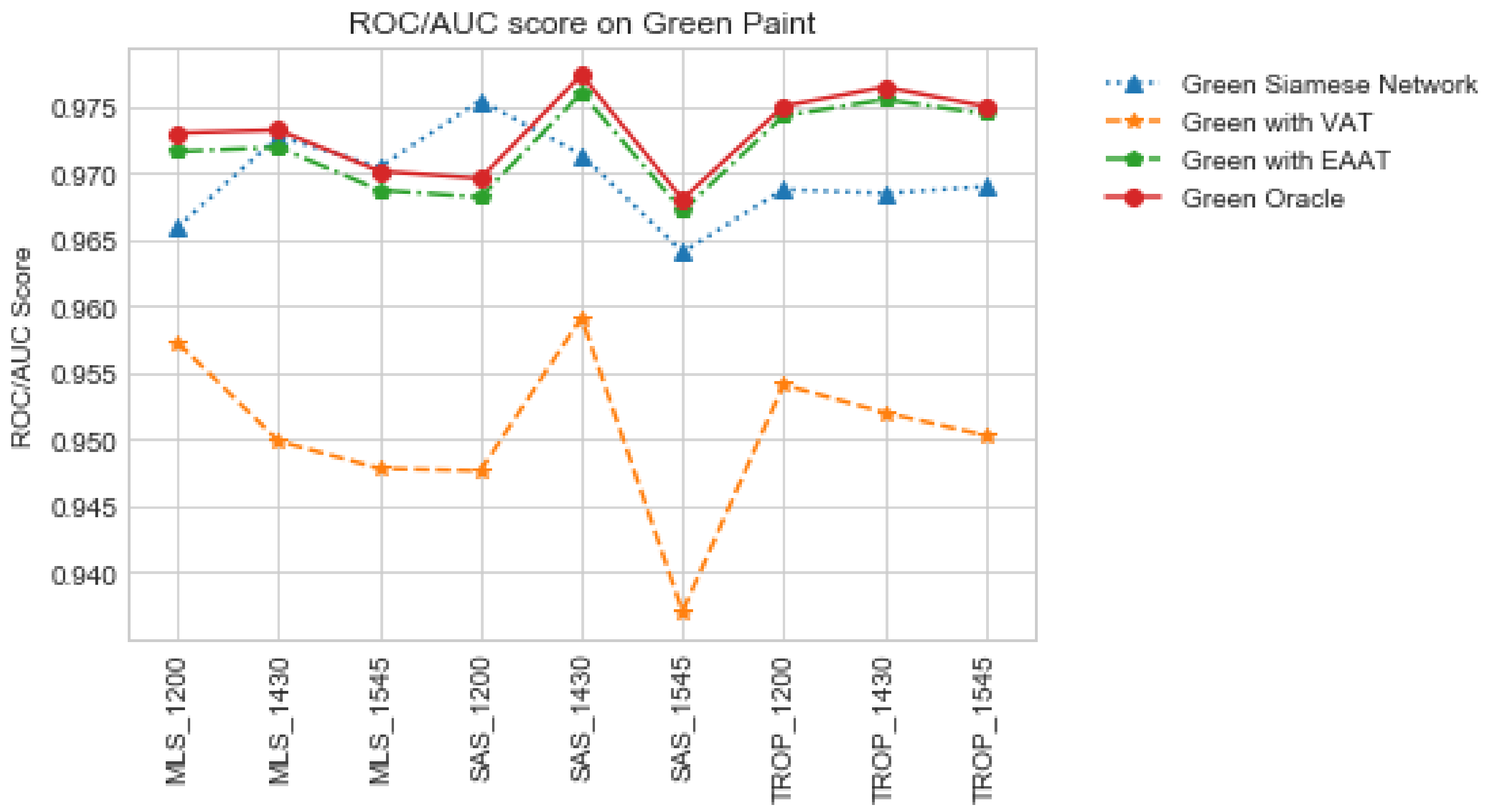
Perturb all datapoints towards the boundary and penalize if this changes the prediction



Exponential Averaging Adversarial Training (EAAT)

- Combination of MT and VAT
- Students are trained with VAT
- Teacher remains the same

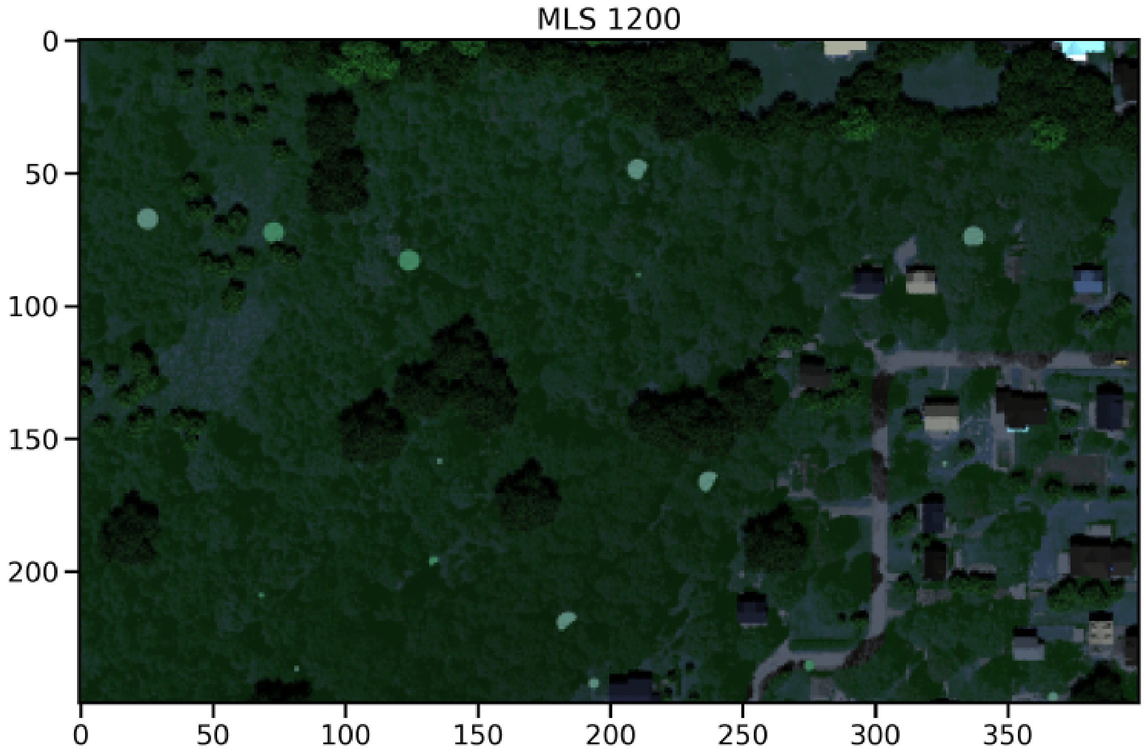
Results

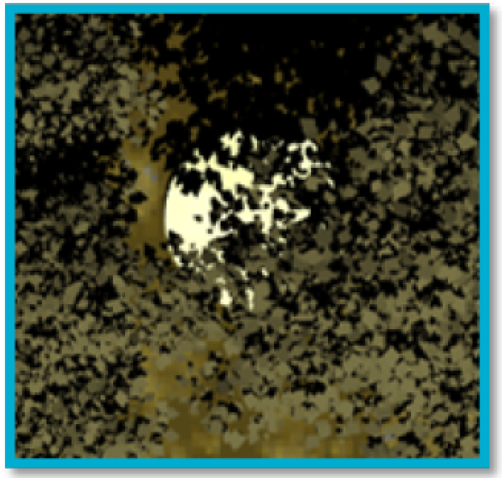

ROC/AUC score on Green Paint
ROC/AUC Score
0.975
0.970
0.965
0.960
0.955
0.950
0.945
0.940
MLS_1200
MLS_1430
MLS_1545
SAS_1200
SAS_1430
SAS_1545
TROP_1200
TROP_1430
TROP_1545
Green Siamese Network
Green with VAT
Green with EAAT
Green Oracle

Uncertainty Quantification

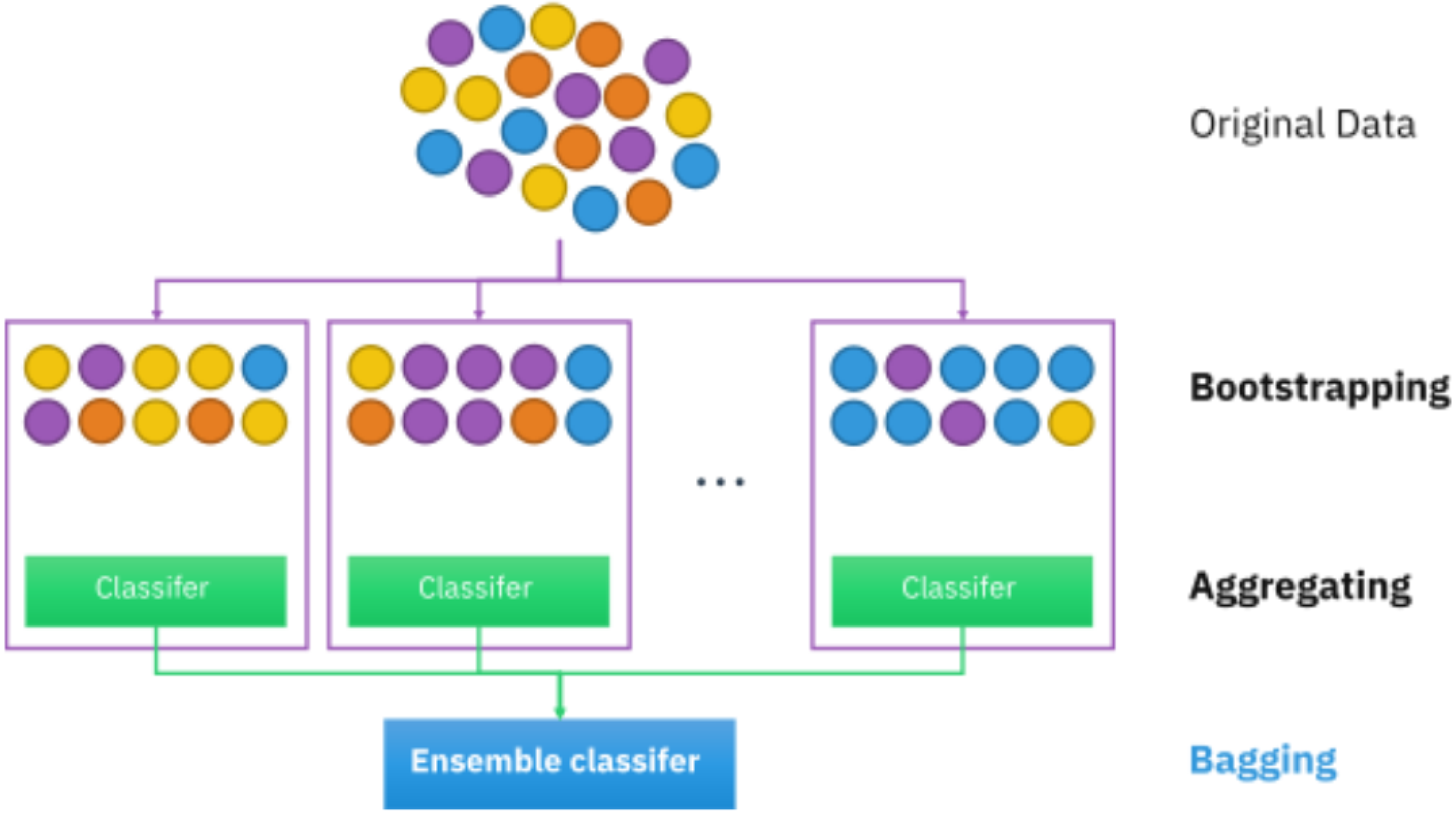
Uncertainty Quantification

We have targets of different sizes and visibility and with different mixing backgrounds. We want a way to categorize how certain the model is the target exists





Bootstrapping

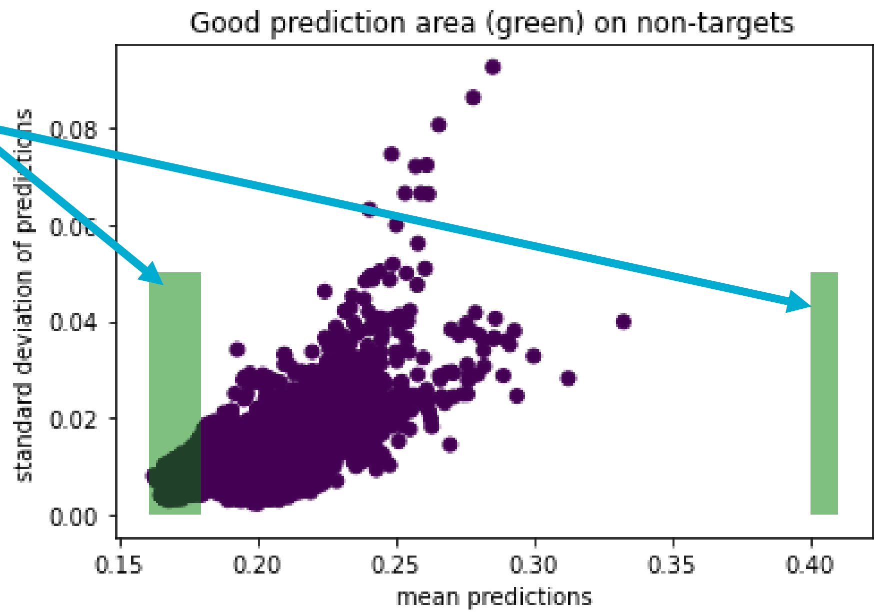


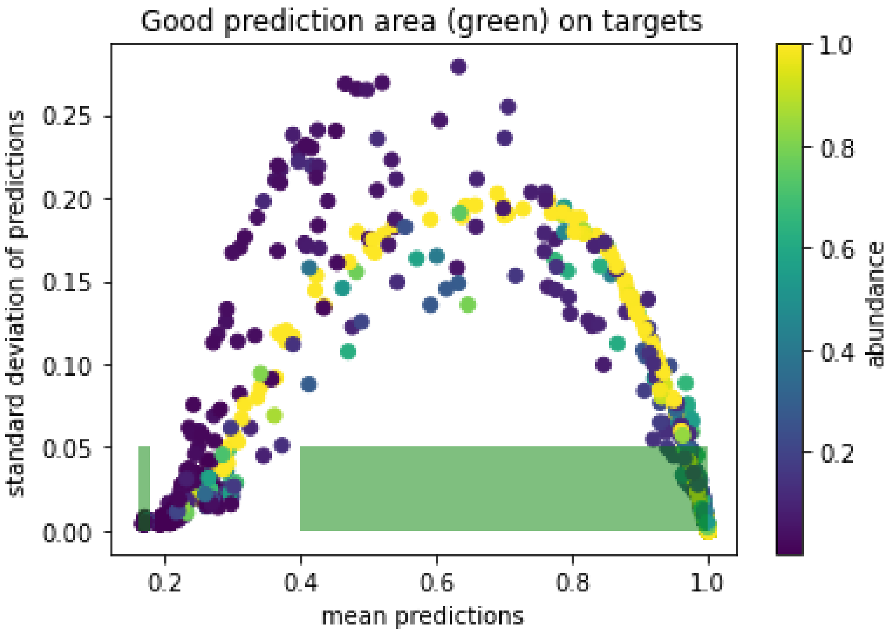
Creating a High Confidence Set

How do we define which values are classified with high confidence?

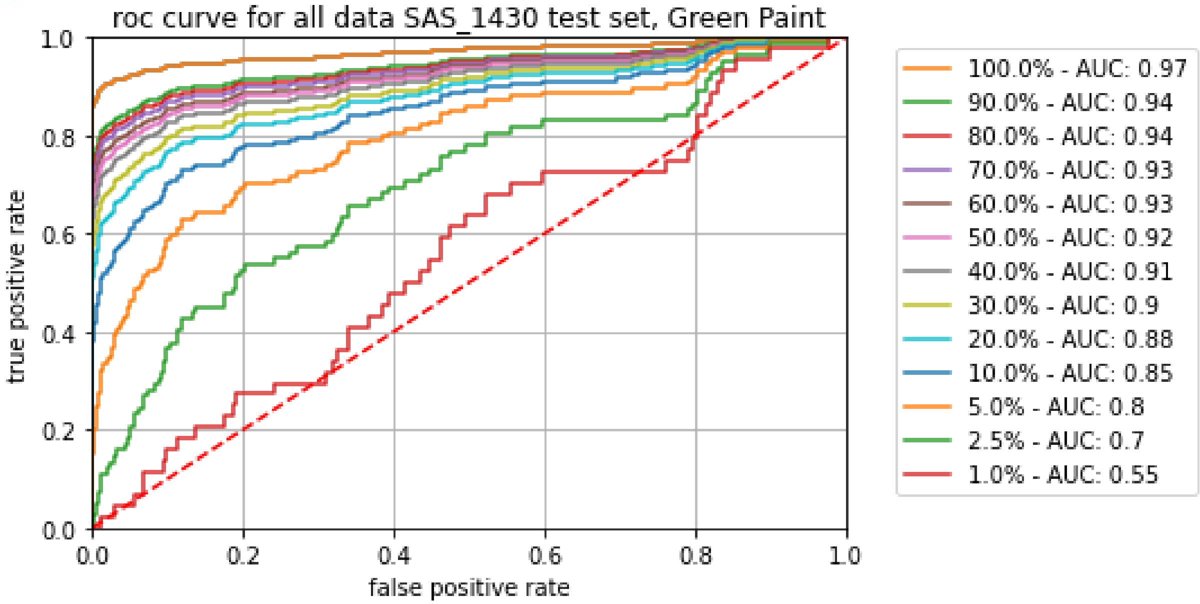
- We construct a **high confidence set** by defining:
  - Upper threshold for *predicted* target probabilities close to 0
  - Lower threshold for *predicted* target probabilities close to 1
  - Maximum standard deviation of bootstrap prediction distribution for a given pixel

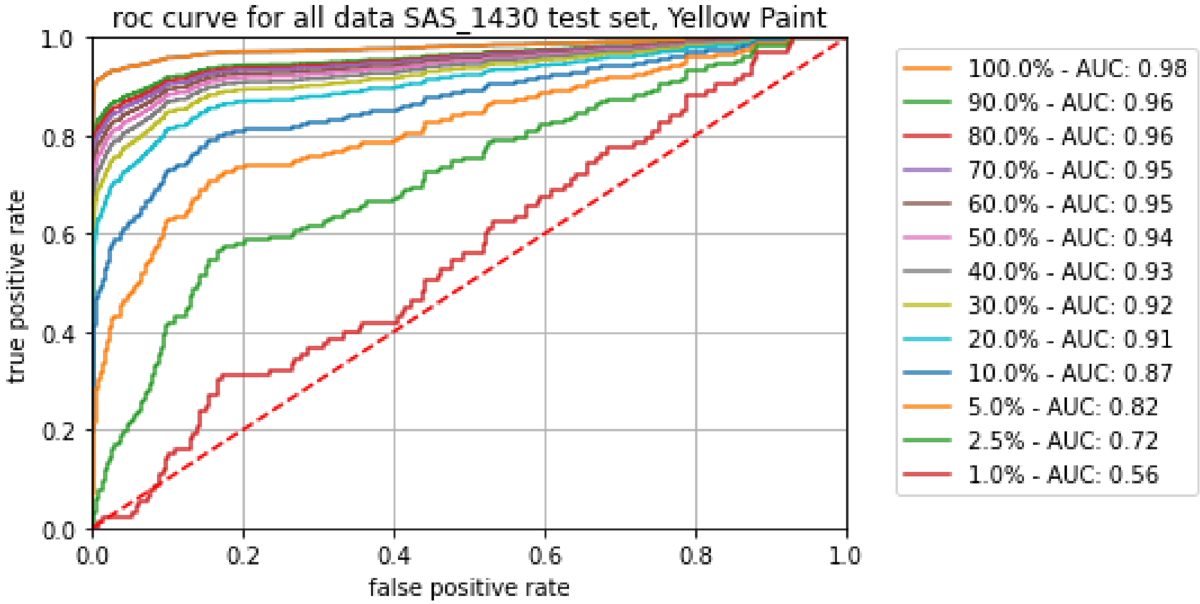
High confidence set





Results





CFAR Score (green paint)	0-0.25	0.25-0.75	0.75-1
Total	0.717	0.991	0.998
High Confidence	0.774	0.995	1
Low Confidence	0.660	0.952	0.941

Summary

We required a model that had:

1. Low-Shot Learning
2. Semi-Supervised Learning
3. Uncertainty Quantification

Questions?

Email: dries@sandia.gov

Training/Test Splits

In order to understand the generalizability of the models across atmospheres, time, and space:

- <u>Train</u> on left hand side of **only** MLS1200
- <u>Test</u> on right hand side of all **9** scenes

Train on pixels in shaded region

MLS 1200

Test on pixels in shaded region