Supervised Deep Learning Land Surface Classification of Airborne Hyperspectral AVIRIS Reflectances.

CS 637 - Team 7 - Josh Chapman, Mitchell Dodson

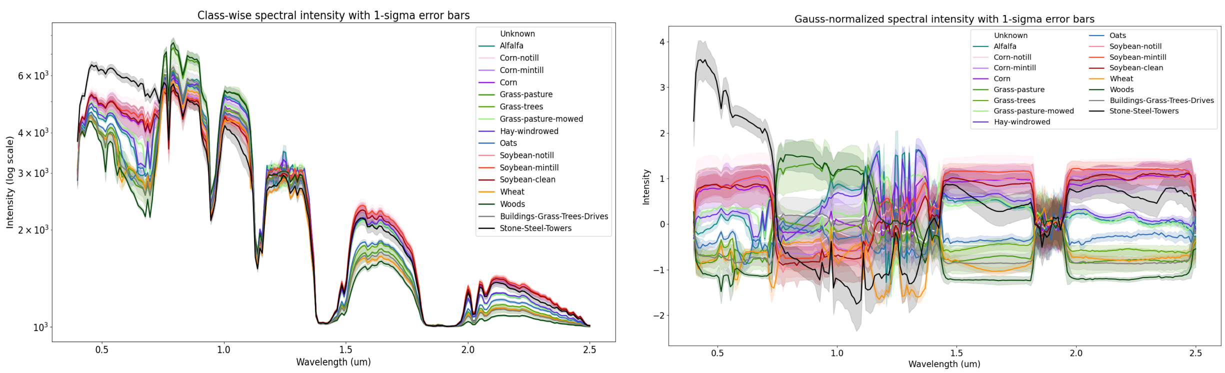

Fig 1. Regular and gauss-normed spectral distributions of surface classes.

Objective:

The goal of this project is to explore deep learning approaches for resolving the surface category of hyperspectral radiance values at 220 channels in the .4-2.5um range. In doing so, we will seek to develop a parsimonious neural network architecture for independently predicting the category of each class.

Dataset and Preprocessing:

We selected Purdue University's Indian Pines dataset [1], which consists of a single granule depicting several crop fields, and was captured by the airborne NASA AVIRIS instrument in June 1992. In addition to the 21,025 hyperspectral pixels on the 145x145 grid, the dataset includes an integer array identifying each grid cell as a member of one of 17 surface classes. The left image in Figure 1 shows the spectral distribution of each surface class with 1σ error bars.

Preprocessing of the data includes normalization, shuffling, and separation into training, validation, and testing datasets. We will normalize the pixel values by linearly-scaling each feature to align with a gaussian having a mean value of 0 and standard deviation of 1. The importance of doing this independently for each feature is demonstrated by the second image in Figure 1, which shows the class-wise distribution of normalized intensities. Since each band is enabled to vary over a similar scale, the signals that distinguish each class are much more apparent. Datasets will be shuffled and different network architectures will be trained and compared using a commonly-seeded random number generator. The split between training, validation, and testing data is a hyperparameter we will evaluate. Finally, class labels will be cast to 16-element one-hot vectors in order to evaluate the cross-entropy loss function.

Network Architecture:

We will evaluate several variations on a multi-layer perceptron (MLP) architecture for the classification task. Each model will take all 220 bands of a pixel as input, and will use Adam to minimize the categorical cross-entropy loss of predictions with respect to the 16 class labels. Other hyperparameters including the hidden layer count, layerwise node count, activation function, training and validation split ratio, and dropout rates are chosen manually.

We will select the models that are best at making accurate predictions, generalizing to validation data, and which have minimal complexity. If time allows, we will visualize the pixel-wise hidden layer activations in order to determine if they are interpretable.

References:

[1]: Baumgardner, M. F.; Biehl, L. L.; Landgrebe, D. A. (2015). **220 Band AVIRIS Hyperspectral Image Data Set: June 12, 1992 Indian Pine Test Site 3**. Purdue University Research Repository. doi:10.4231/R7RX991C