Feature Learning for Multispectral Satellite Imagery Classification using Neural Architecture Search

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Overview

Automated classification of remote sensing data is an integral tool for earth scientists, and deep learning has proven very successful at solving such problems. However, building deep learning models to process the data requires expert knowledge of machine learning. We introduce DELTA, a software toolkit to bridge this technical gap and make deep learning easily accessible to earth scientists. Visual feature engineering is a critical part of the machine learning lifecycle, and hence is a key area that will be automated by DELTA.

Introduction

- Hand-engineered features can perform well but require a cross functional team with expertise in both machine learning and the specific problem domain, which is costly in both researcher time and labor.
- In order to automate the feature learning process, a neural architecture search samples the space of asymmetric and symmetric autoencoders using evolutionary algorithms. [1]
- Features generated by the best performing autoencoders evaluated on Landsat 8 flood mapping dataset with ground truth adapted from work by Coltin et al [2]. Dataset is split into 7 train images and 2 validation images.

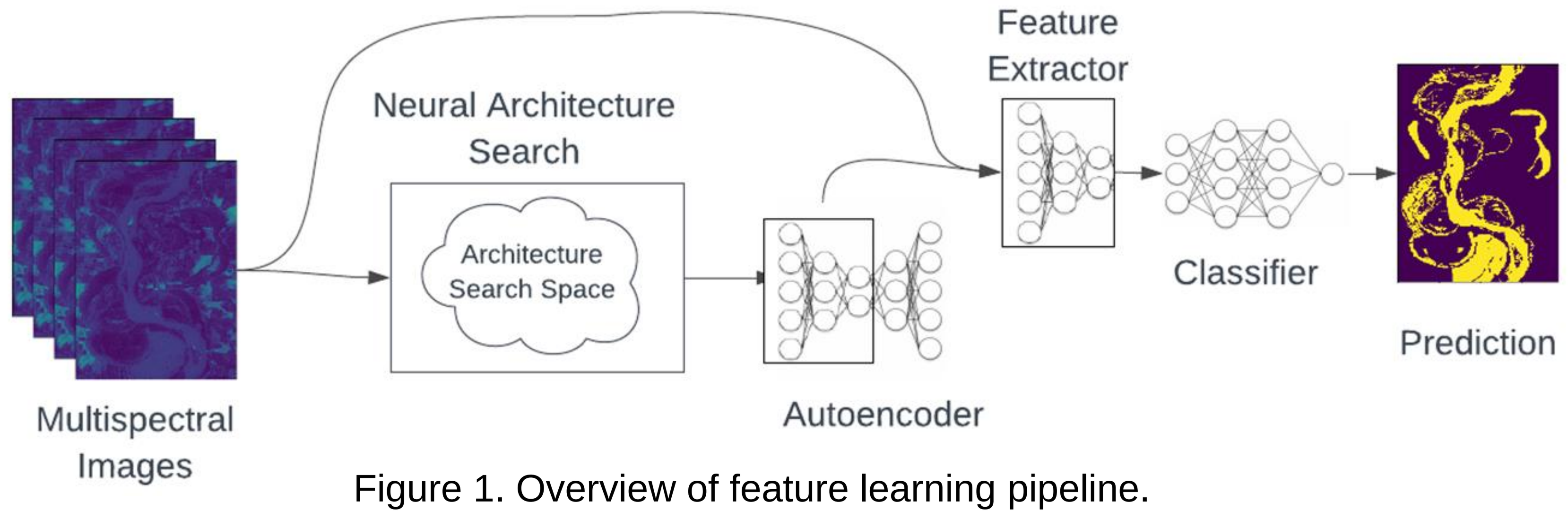

Figure 1. Overview of feature learning pipeline.

Feature Learning

- Autoencoders are a type of machine learning model that learn important features of the dataset by reproducing the input as the output (i.e. $f(x) = x$)
- Learning these features on a large data set for data types which are widely used by Earth scientists can amortize the cost of learning features so that scientists only need to learn the task-specific portion of the neural network
- Autoencoder search is performed for two architecture types: asymmetric and symmetric autoencoders and performance on classification tasks is compared.

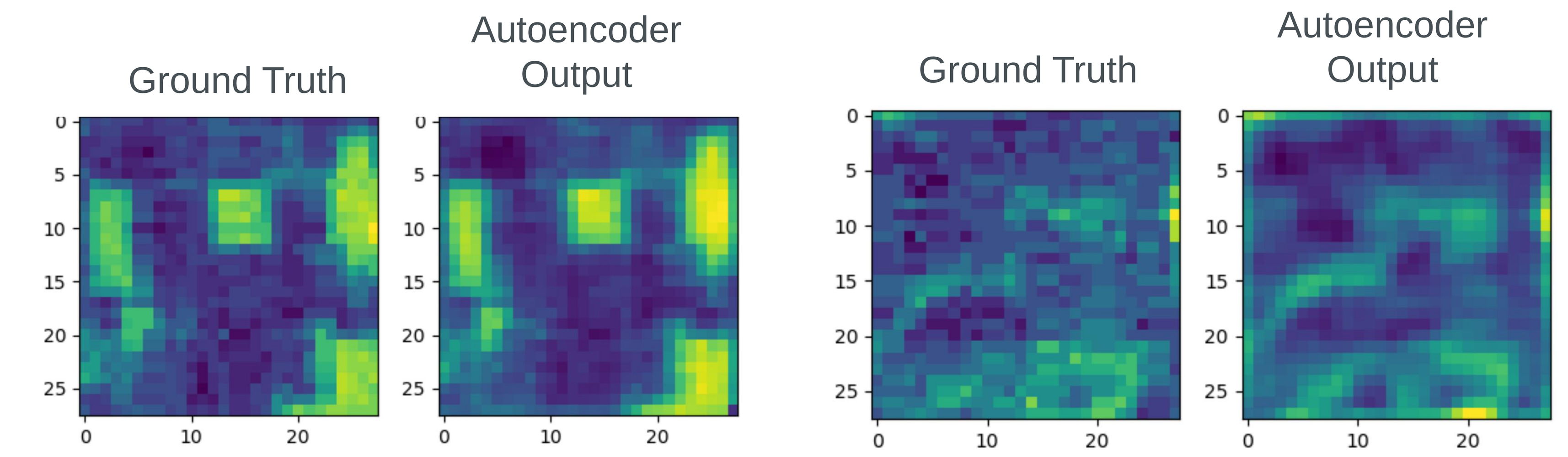

Figure 2. Output of autoencoder model discovered using neural architecture search. Discovered autoencoders reconstruct the input with high fidelity.

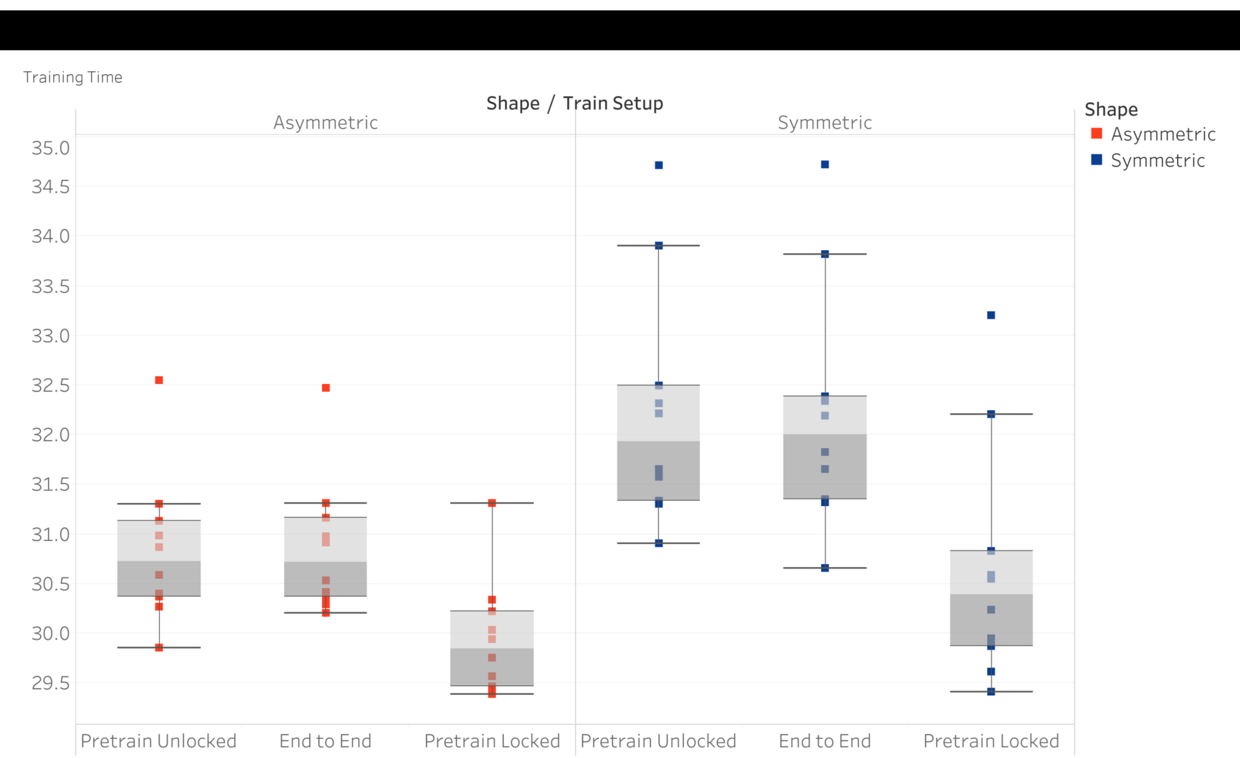

Figure 3. Time to train across training paradigms and feature extractor architectures. *Pretrain locked* shows a significant train time advantage.

Training Paradigms

- Training identical model without pretrained features (*End to End*)
- Training pretrained model with feature extractor, allowing feature extractor to train as well. (*Pretrain Unlocked*)
- Training pretrained model with feature extractor locked. (*Pretrain Locked*)

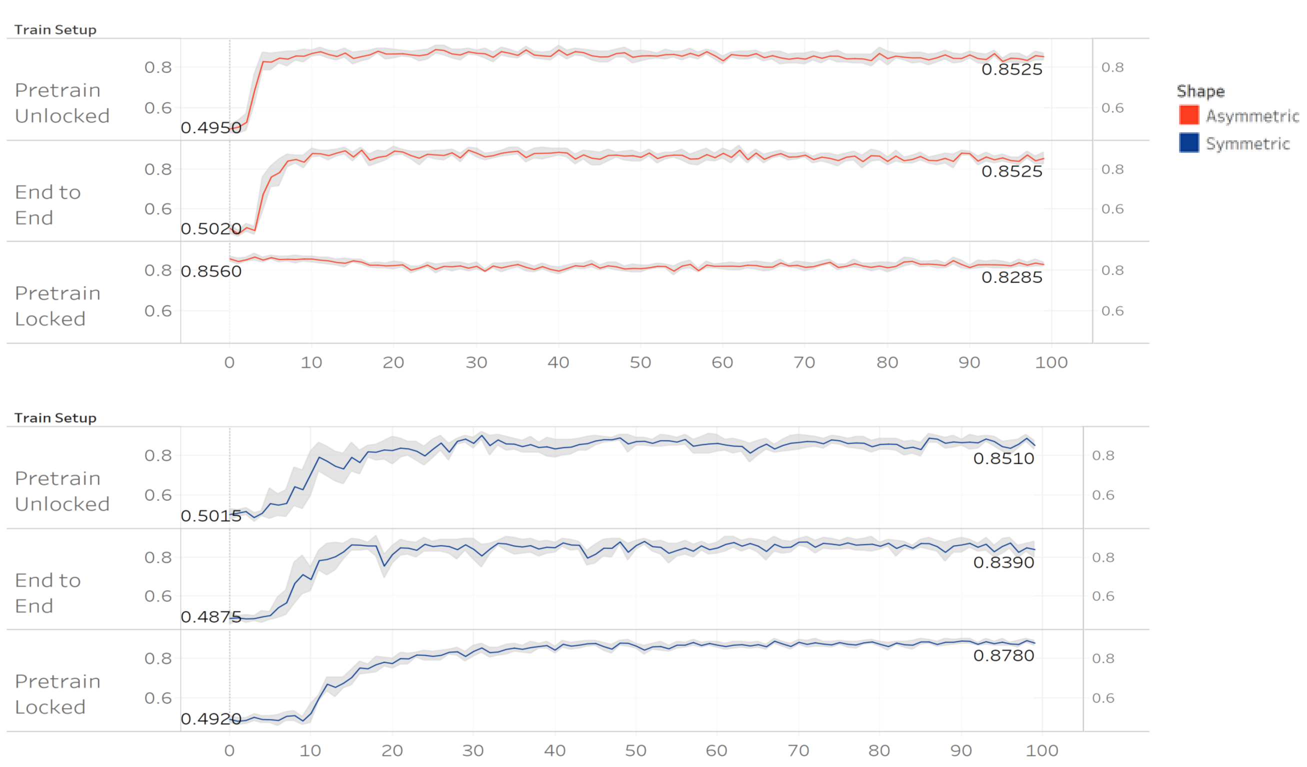

Figure 4. Validation accuracy over training for 100 epochs

Flood Mapping

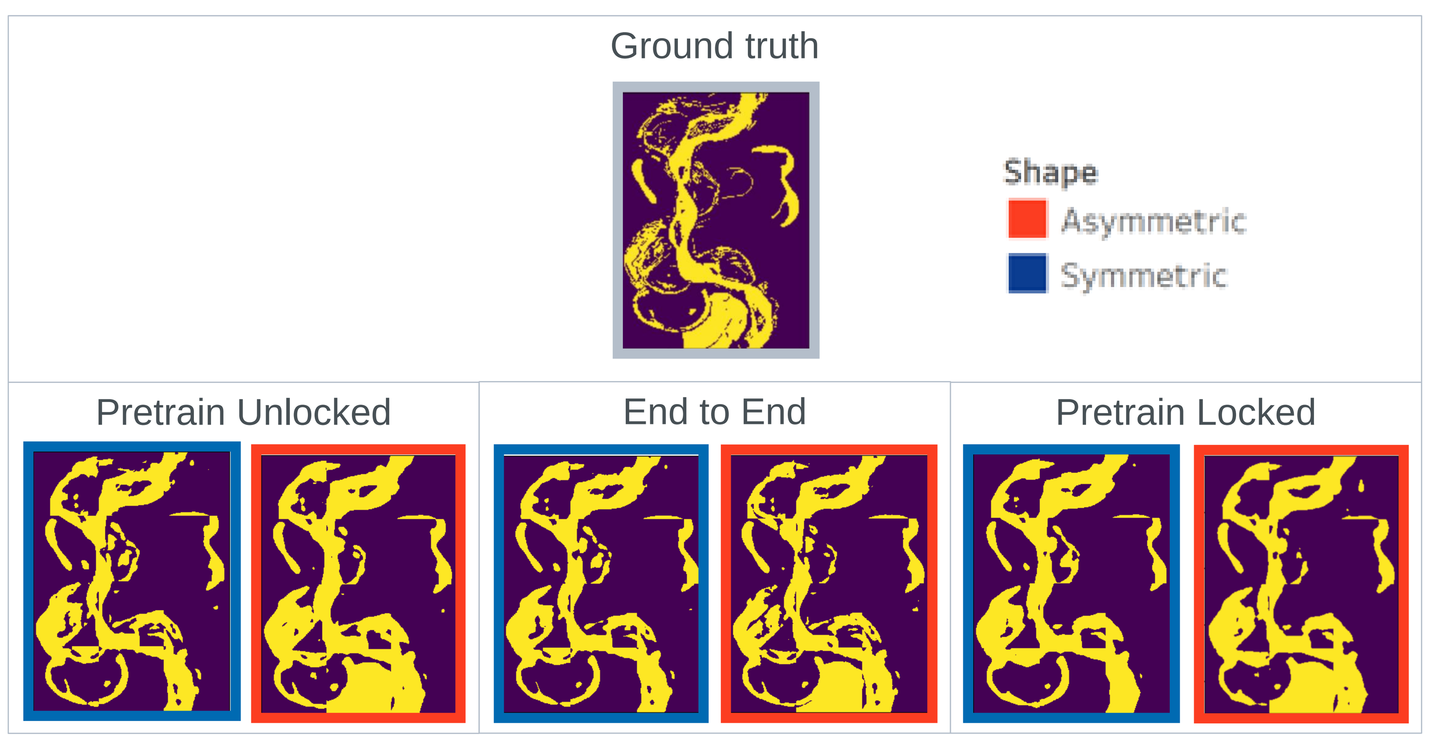

Figure 5. Classifier output of all training paradigms on validation data

Conclusion*:* *Pretrain locked* significantly reduces training time while maintaining algorithm performance, compared to *end-to-end* and *pretrain unlocked.*

References and Acknowledgements

- [1] M. Suganuma, M. Ozay, and T. Okatani, "Exploiting the potential of standard convolutional autoencoders for image restoration by evolutionary search,"ArXiv e-prints, Mar. 2018.
- [2] Coltin, Brian, et al. "Automatic Boosted Flood Mapping from Satellite Data." International Journal of Remote Sensing, vol. 37, no. 5, Mar. 2016, pp. 993–1015., doi:10.1080/01431161.2016.1145366.
- Majumdar, Angshul, and Aditay Tripathi. "Asymmetric Stacked Autoencoder." *2017 International Joint Conference on Neural Networks (IJCNN)*, 2017, doi:10.1109/ijcnn.2017.7965949.

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