Discovering Spatial and Temporal Patterns in Climate Data Using Deep Learning

Charles Anderson[1], Imme Ebert-Uphoff[2], Yi Deng[2], Melinda Ryan[1]

[1]Dept. of Computer Science, Colorado State University
[2]Dept. of Electrical and Computer Engineering, Colorado State University
[3]School of Earth and Atmospheric Sciences, Georgia Institute of Technology

Abstract

Recent experiments involving the training of artificial neural networks with multiple layers, sometimes referred to as deep learning, have demonstrated the ability to automatically identify features that are critical to solving complex pattern classification tasks, such as speech recognition. Similar to speech, atmospheric data sets often consist of multiple time series with unknown, complex interrelationships. In this project we seek to explore what kind of interrelationships can be discovered in climate data by applying the framework of artificial neural networks. As a first application we look at establishing relationships between top of atmosphere radiative flux and air/surface temperatures. This is an important application, since a thorough understanding of those relationships is essential for understanding the effect of CO2-induced warming on the Earth's energy balance and future climate.

NASA CERES and MERRA Data

lw – long wave flux at TOA   st – skin temperature
sw – short wave flux at TOA   t1 – air temperature 500 hPa
si – solar insolation at TOA   t2 – air temperature 50 hPa
daily data from March 1, 2000 – December 31, 2013 (5,054 days)
low spatial resolution, 20 x 20 degrees, 7 latitudes, 18 longitudes
Each sample composed of 7 x 18 x 6 = 756 variables.

Objectives

1. Find low-dimensional (3) representation of each sample to study patterns among the 6 variables across spatial locations.
2. Compare linear PCA with nonlinear dimensionality reduction achieved with multilayer neural networks.
3. Compare standard way of training autoencoder network with new sequential approach using mutiple networks.

The key idea is to train neural networks from data and then study the network properties as function of location and field.

Principal Components Analysis

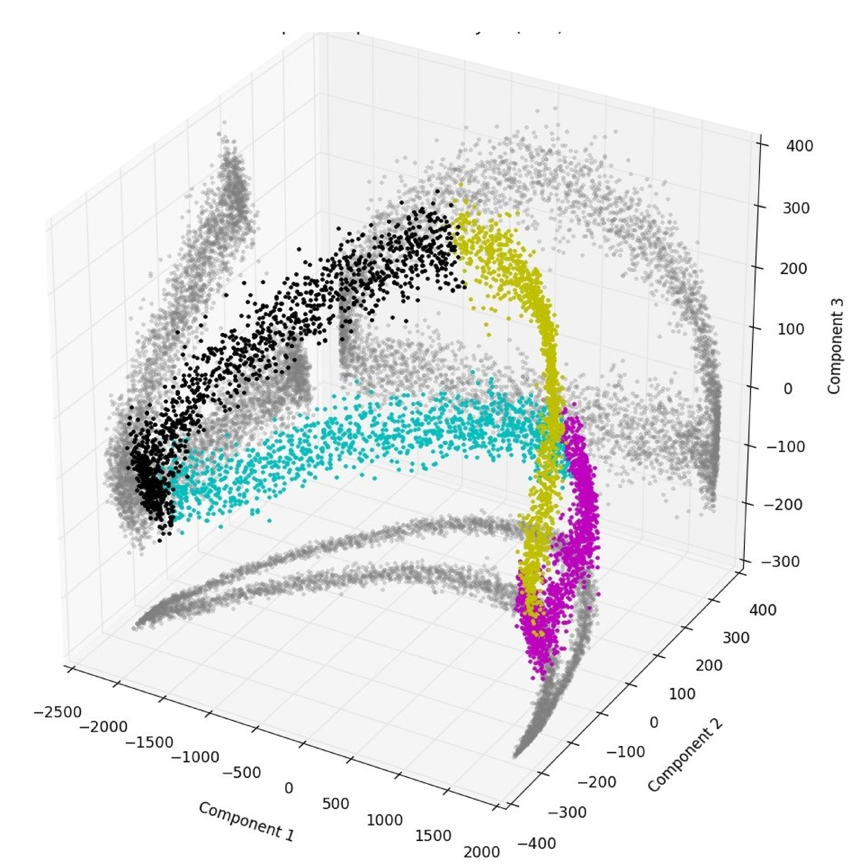
X is matrix of 5054 x 756 samples.

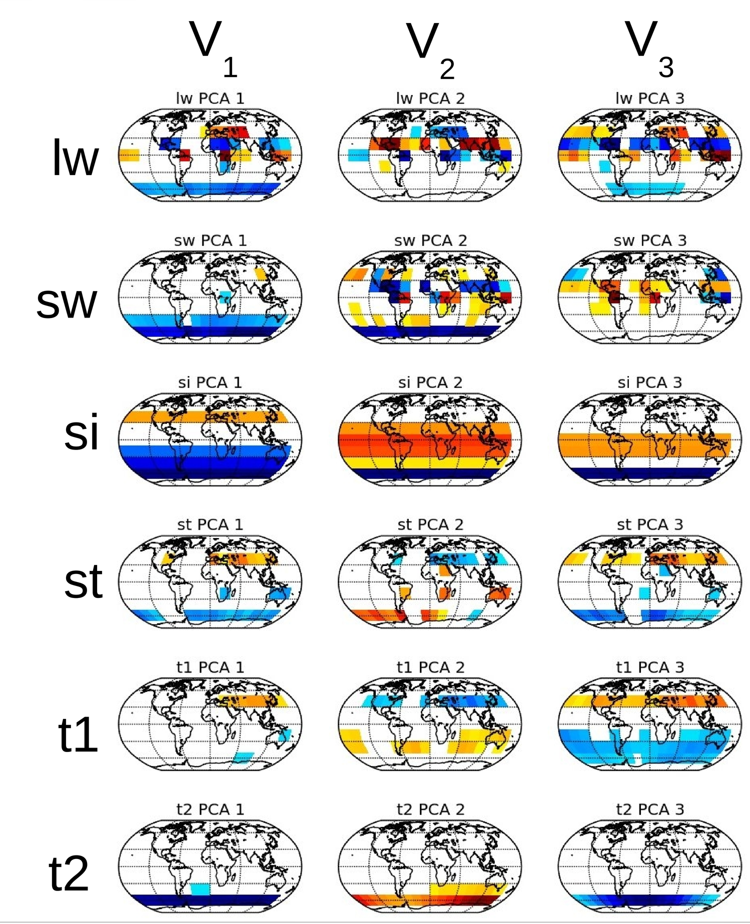
$$USV^T = svd(X - \overline{X})$$

Using first 3 components of V

Approximation error (RMS) is 77.9

Quarter 1
Quarter 2
Quarter 3
Quarter 4





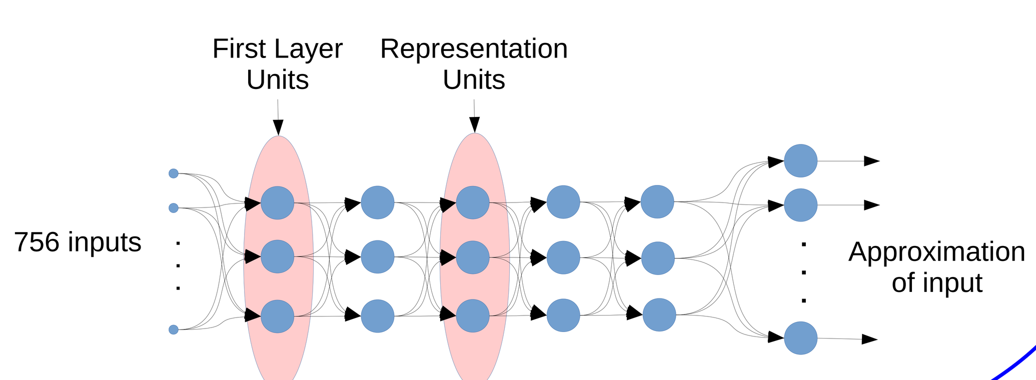
Components of eigenvectors as function of location and field. Small magnitude values are not shown.

Positive
Negative

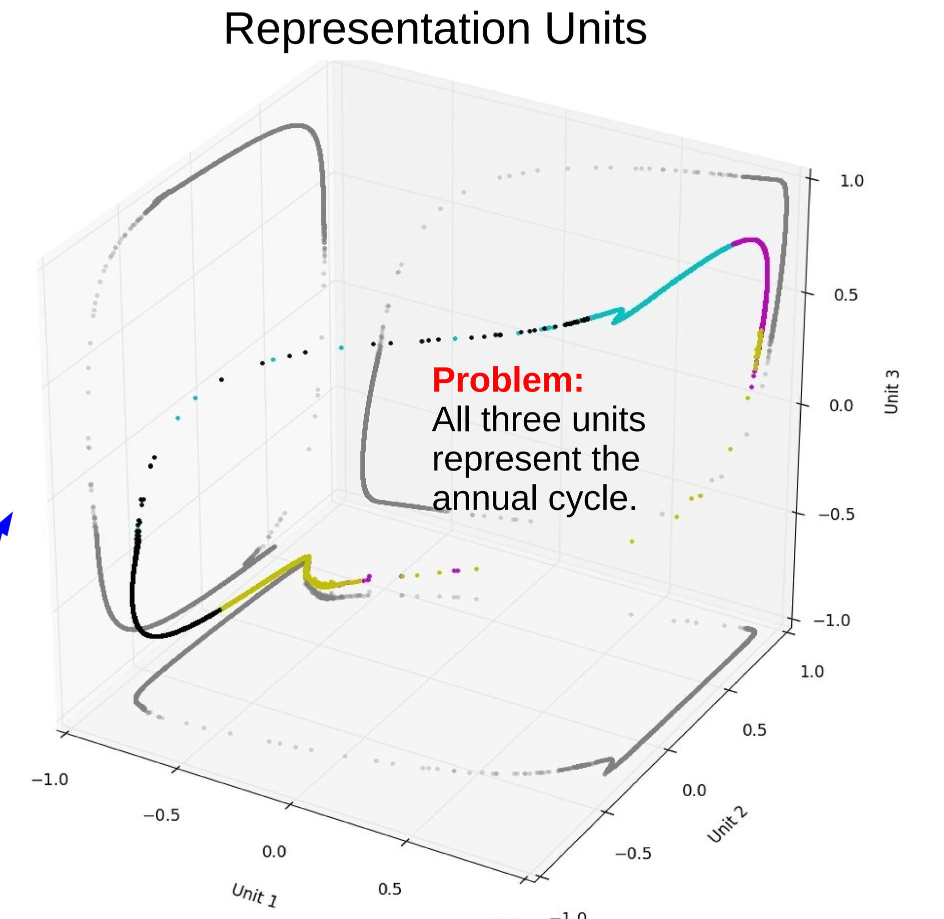
Neural Network as Autoencoder

Trained to minimize error in approximation (scaled conjugate gradient method)

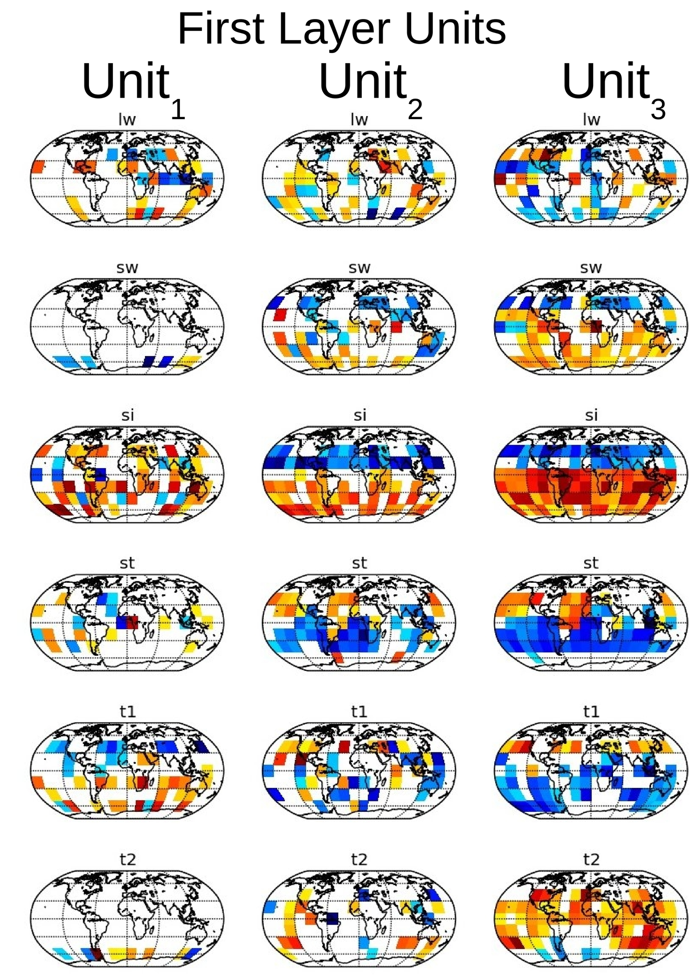
Approximation error (RMS) is 23.0



Representation Units



First Layer Units

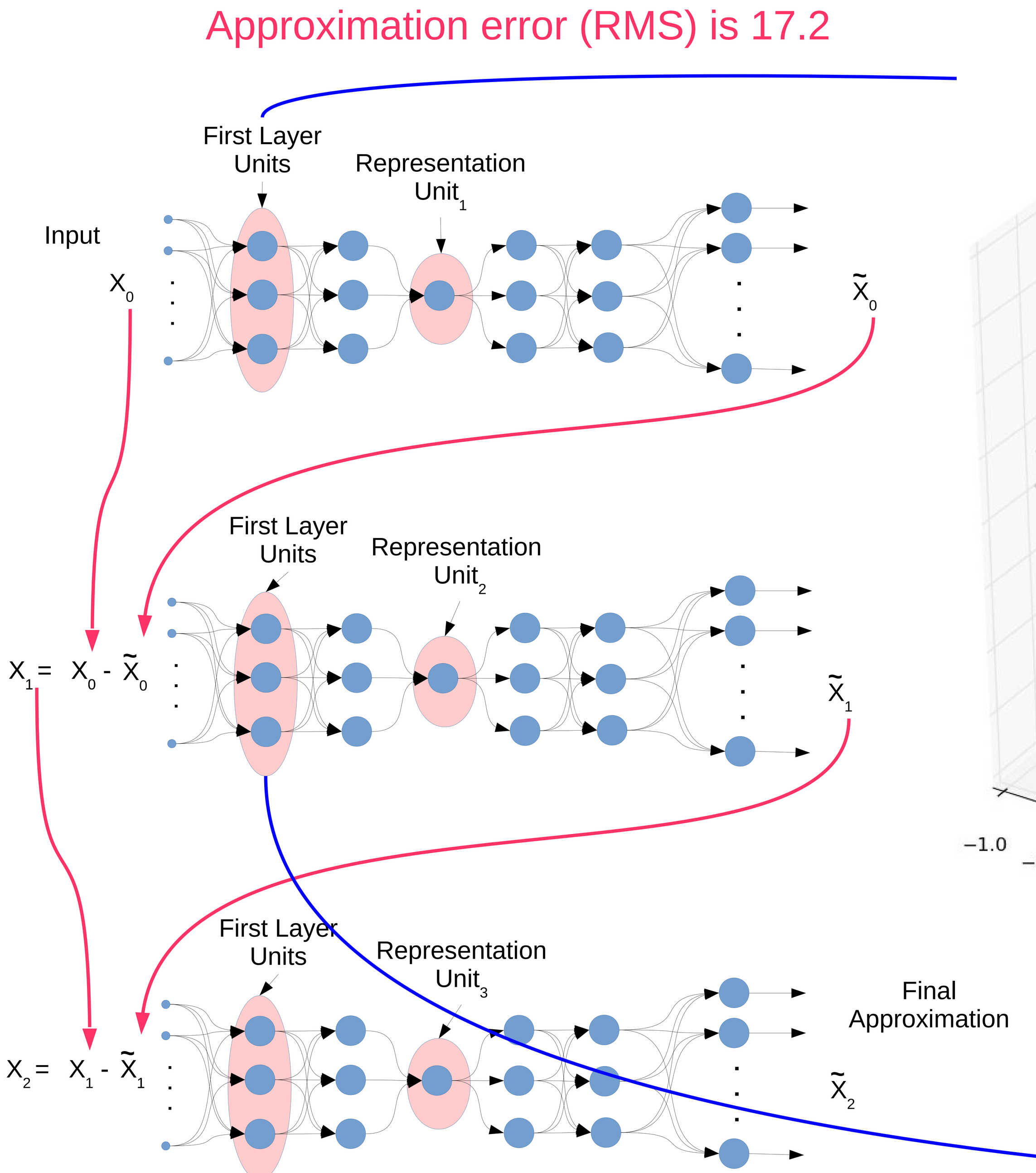


Weights of individual units in first layer as function of location and field. Small magnitude values are not shown.

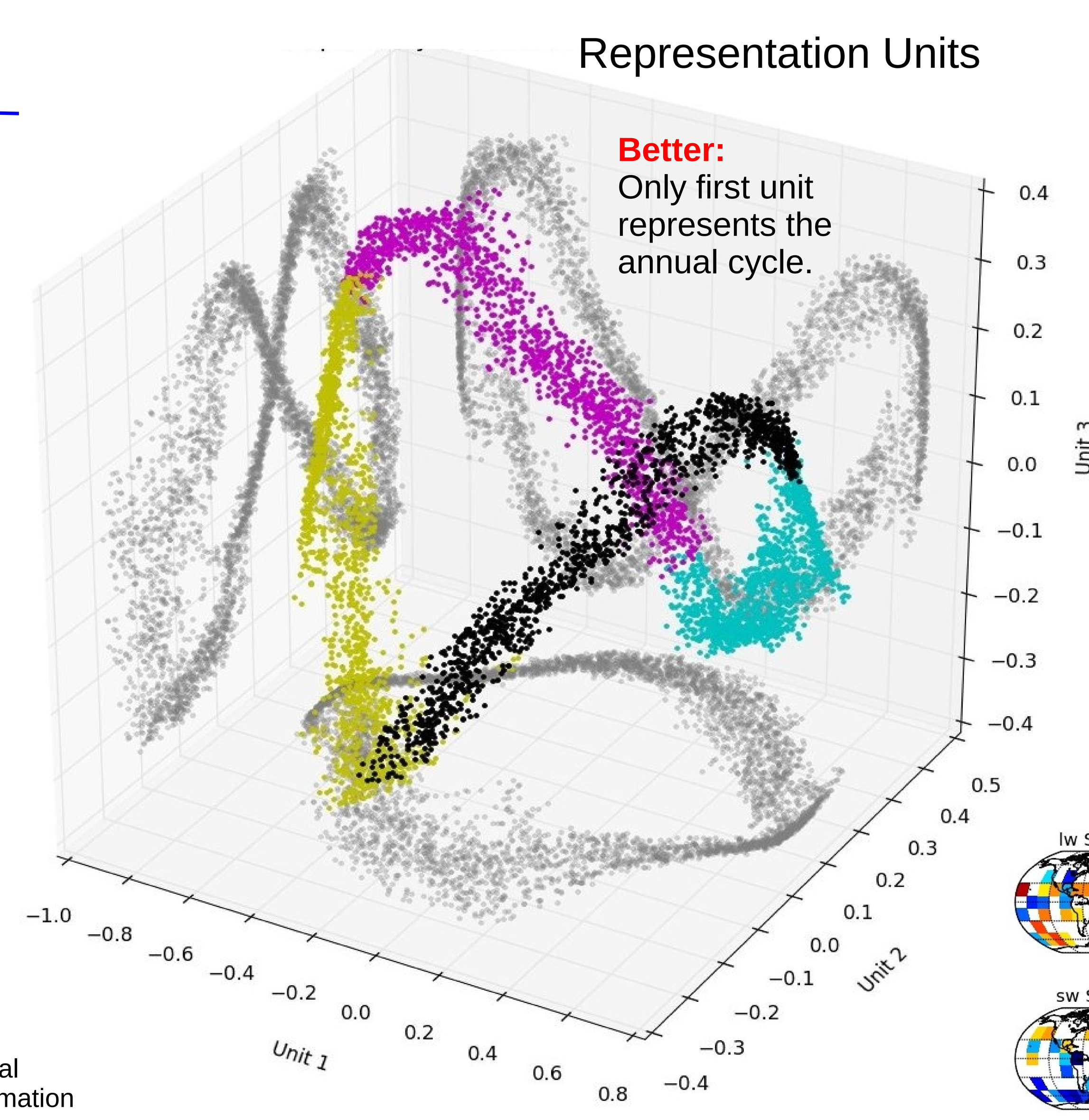
Multiple Neural Networks as Autoencoders

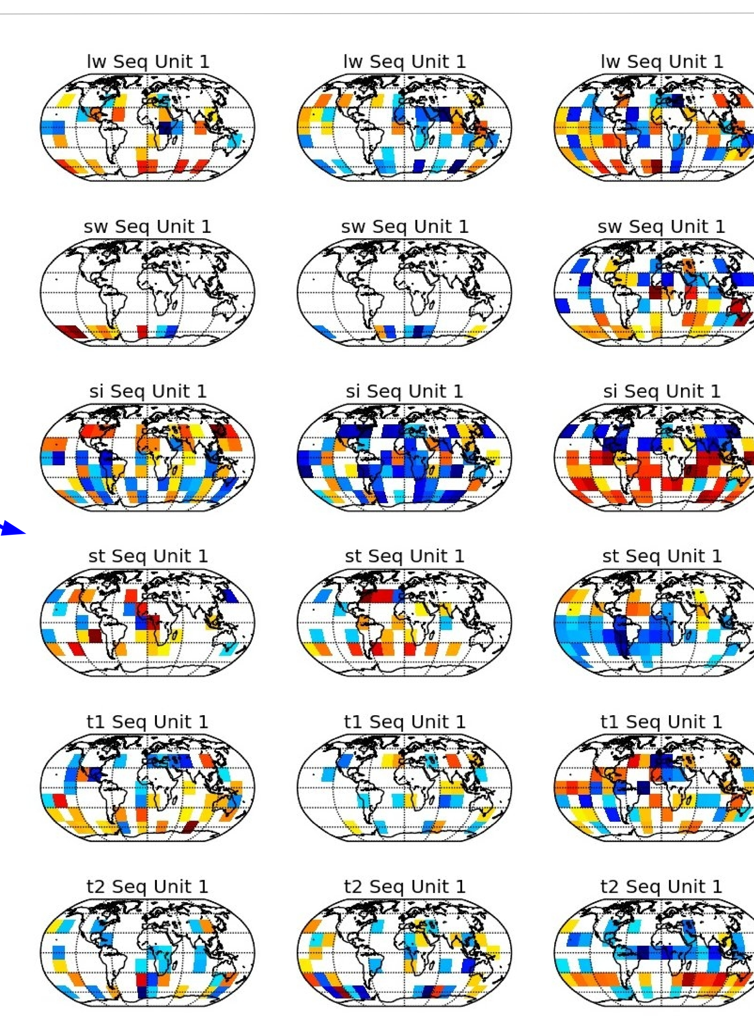
Networks with single representation unit trained with approach akin to Gram-Schmidt.

Approximation error (RMS) is 17.2



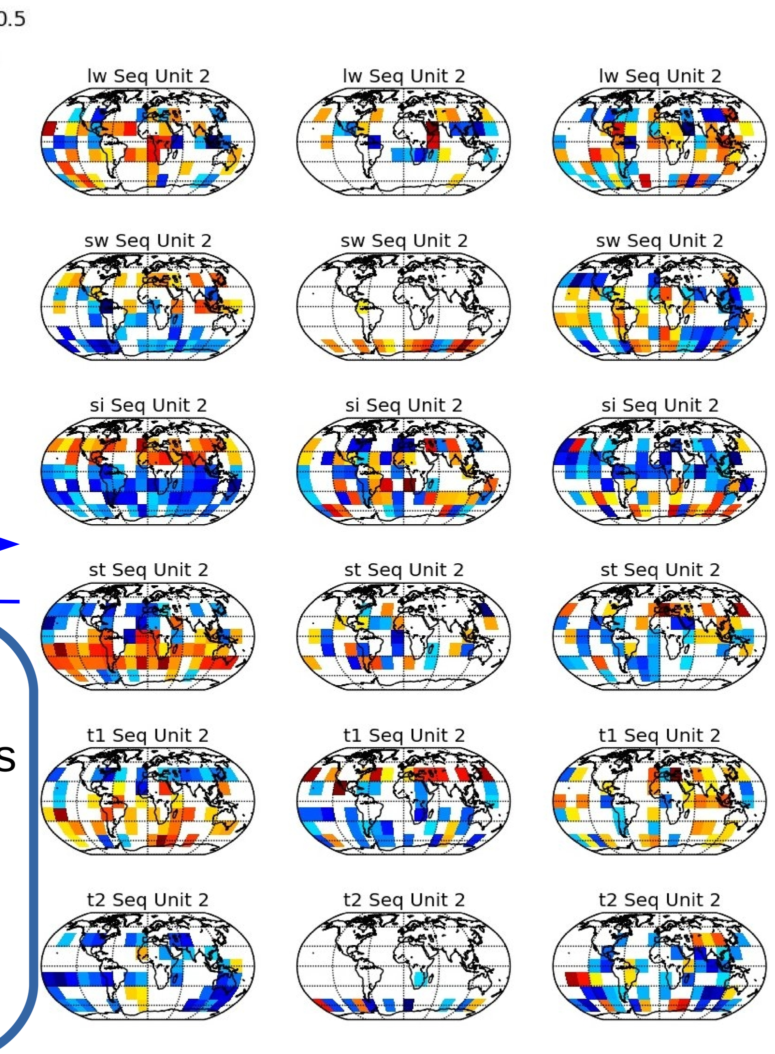
Representation Units

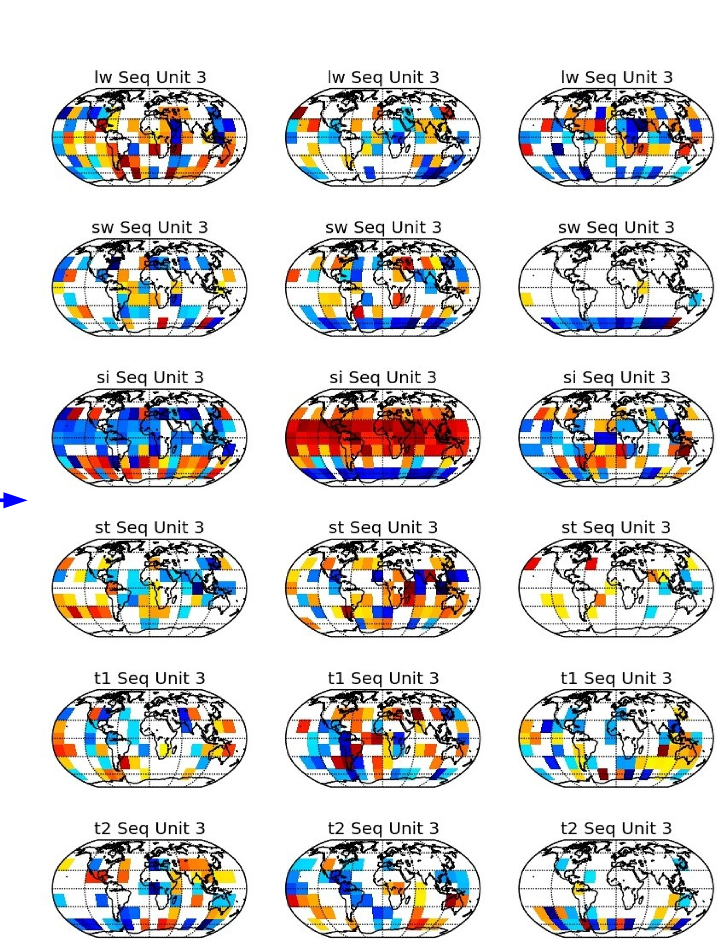




Weights of individual units in first layer of first network as function of location and field. Small magnitude values are not shown.

Below figures show weights of individual units in first layer of second and third networks.





Discussion and Future Work

The example and initial results provided here illustrate the basic approach we plan to take, namely to train neural networks from data and to then *study the network properties* to discover interesting patterns in the data. The displays of weight magnitudes reveal subsets of locations and fields that are positively or negatively correlated in the set of data samples. We expect that further analysis of the network properties will reveal nonlinear combinations of key locations and fields that will facilitate an understanding of spatial and temporal variations in the data. We have only just started to implement these ideas, so the initial results presented here serve as an illustration of the general process.