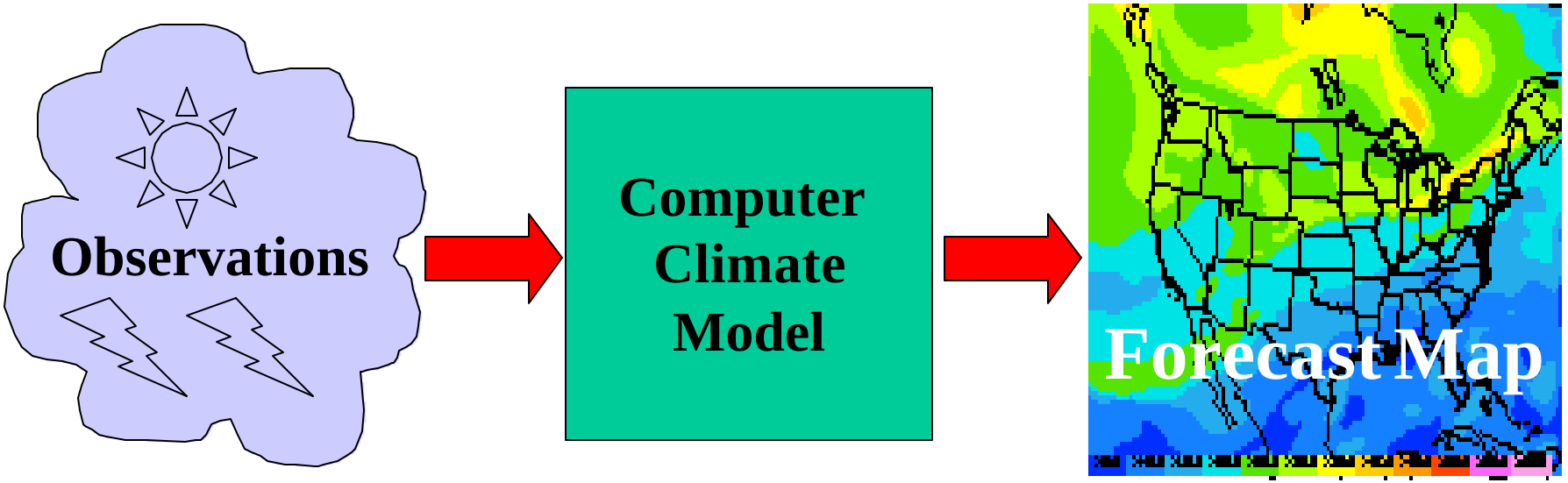
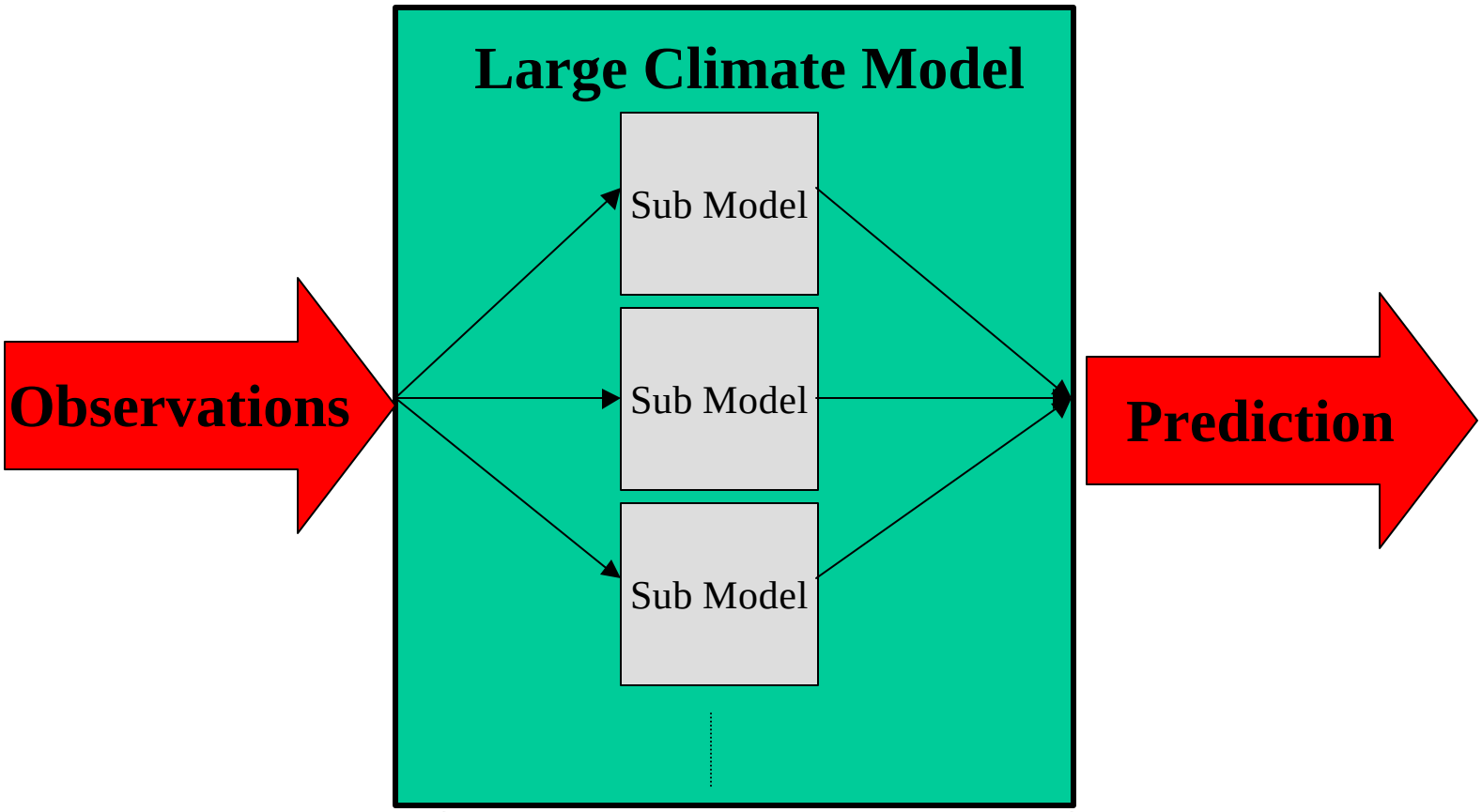
Where do Weather Forecasts and Climate Predictions Come From?



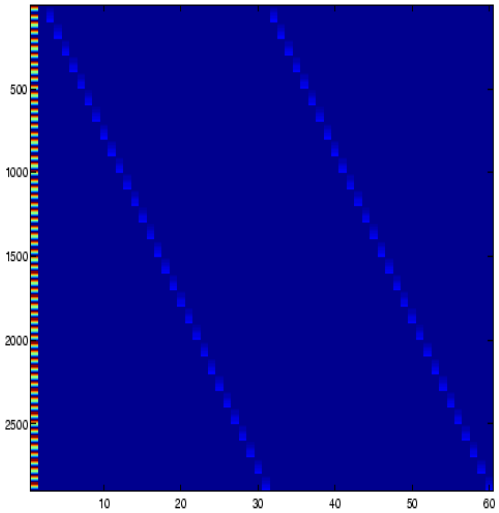
Observations are fed into a computer which predicts weather changes.

Computer models are made up of many smaller models



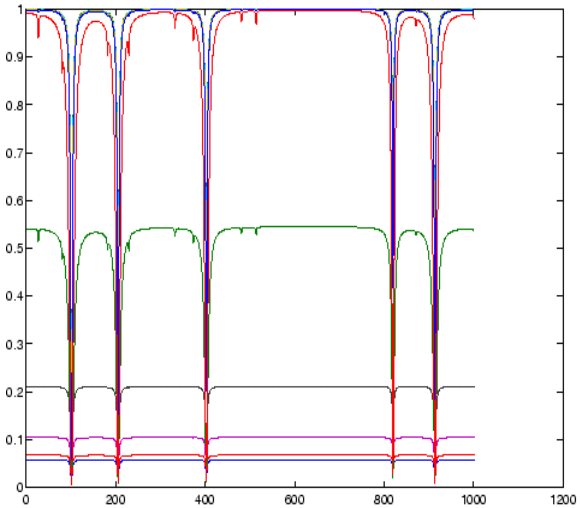
Each sub-model focuses on some aspect of the atmosphere. One sub-model is the solar flux model.

The Solar Flux Model



Cloud Observations

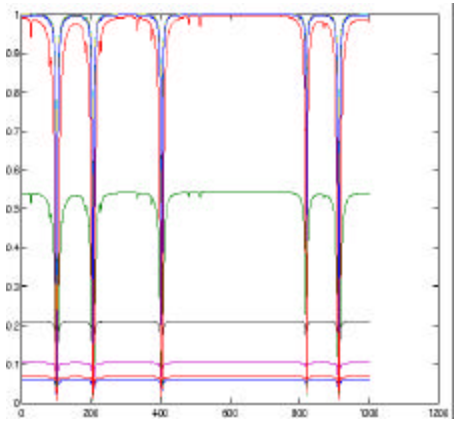
Public1.f Solar Flux Model

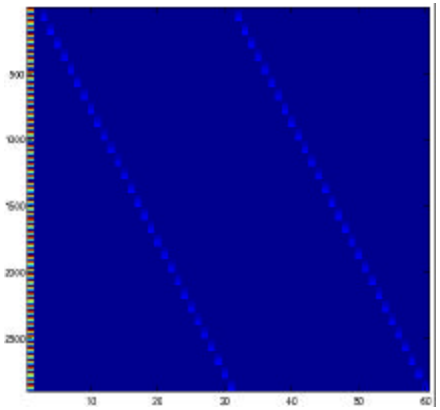


Expected Spectrum

The Public1.f Solar Flux Model is a Fortran program that takes cloud property observations and produces an expected light frequency spectrum.

Inverting the Model





Satellite **Observed Spectrum** **Cloud Observations**

- **Satellite gives an observed light spectrum**

BUT

How do we get cloud properties from the spectrum

Inverting the Solar Flux Model

Given an observed frequency spectrum, how do we predict cloud properties?

- **Compute a new model using the inverses of the functions in the original model**

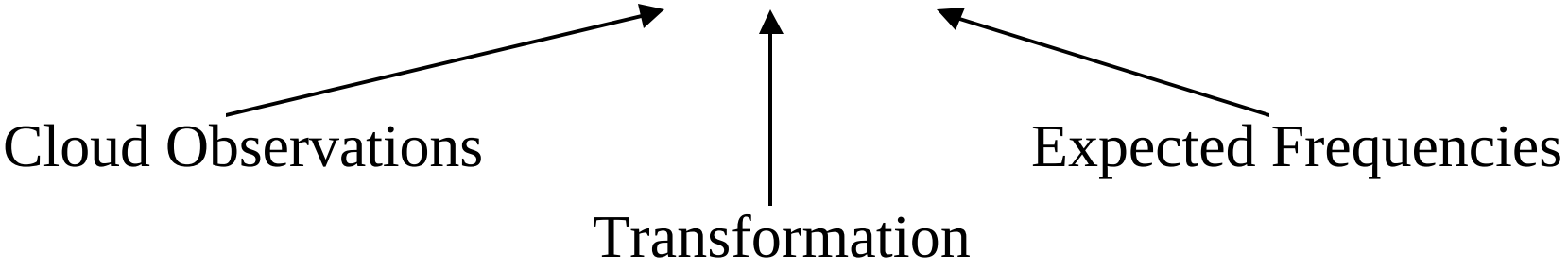
  BUT, the original functions may not be invertible, OR the time needed to run the new model may be prohibitive

- **View the model as linear transformation and compute the inverse transformation**
- **View the model as a function and learn an inverse using a neural network**

The Model as a Linear Transformation

We can view the model as a transformation of the form

$$\boldsymbol{I\ T = O}$$



We want the inverse of this transformation:

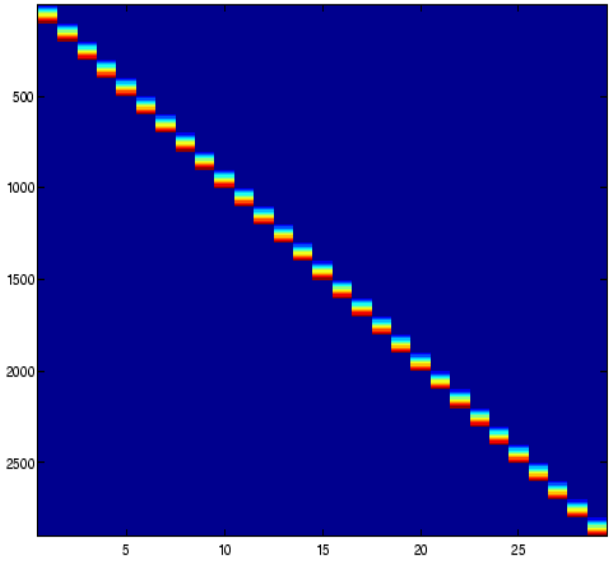
$$\boldsymbol{O\ T' = I}$$

$$O\,T' = I, \text{ so}$$
$$T' = I\,O'$$

If the model is linear, we expect $I = O\,T'$

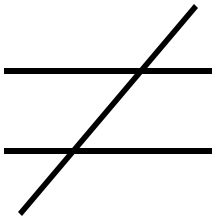
BUT

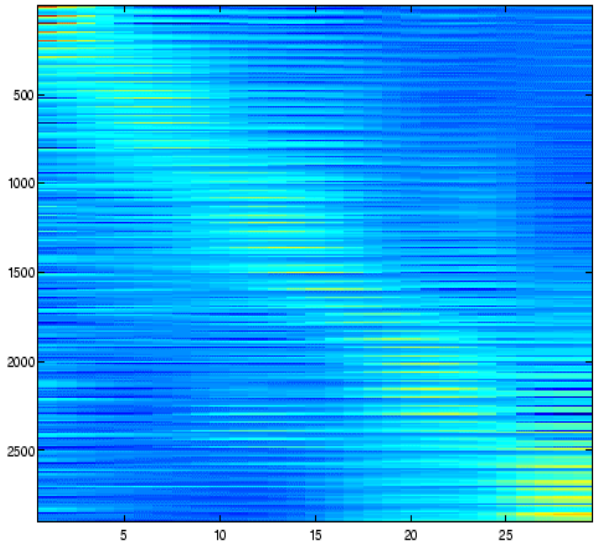
when we compute T', $I \neq O\,T'$



Matrix *I*

given cloud observations





O T'

computed from $T' = I\,O'$

Inverting the Model with a Neural Network

Why use a neural network?

- The function represented by the solar flux model is non-linear.

- Neural networks are capable of approximating non-linear functions

What is a Neural Network?

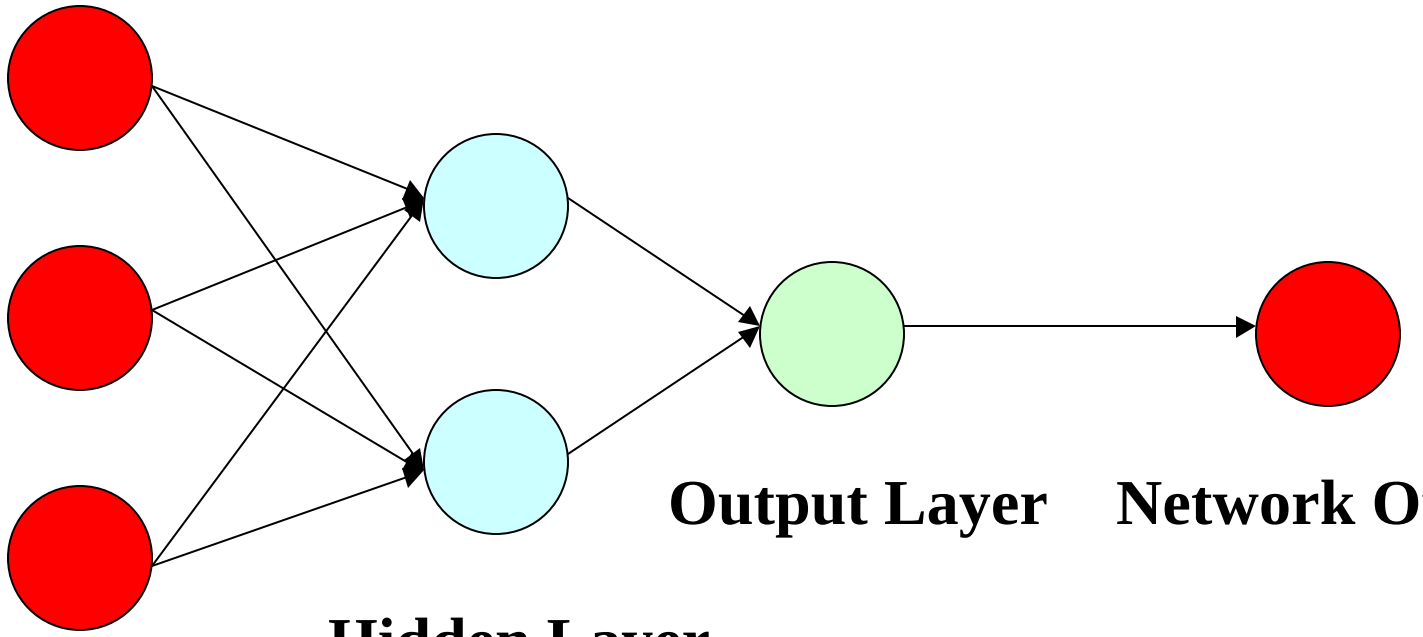
• Neural networks are inspired by biological systems, particularly the human brain.

• Many small simple units, neurons, are connected together in complex webs which are capable of performing many difficult tasks.

• Neural networks are computer representations of neuron webs.

• Provide a general mechanism for machines to learn functions, or classifications, from a set of examples.

Basic Network Architecture



Neural networks are composed of layers of simple units.

The number of units in each layer can vary, but the number of inputs to and outputs from the network are determined by the problem.

Different architectures can represent different functions.

Basic Learning Mechanism

Neural Networks learn by example:

Inputs and a desired output are given to the network. The network tries to produce the desired output from the inputs.

- Each unit produces an output based upon a weighted sum of its inputs.

- The difference between the final network output and the desired output is calculated.

- Weights in each unit are updated based upon a gradient decent in the squared error.

- The process is repeated as long as desired for each example.

Steps for Inverting the Model with a Neural Network

1. Design and implement neural network software in JAVA

2. Generate the data examples used to train the network

3. Train different network architectures to see which most closely match the examples.

Design of Neural Network Software

Goals:

- Vary the number of inputs and outputs the network can handle
- Vary the number of units in each of the layers
- Vary the function the units use to determine output
- Vary the rate at which the units change their weights

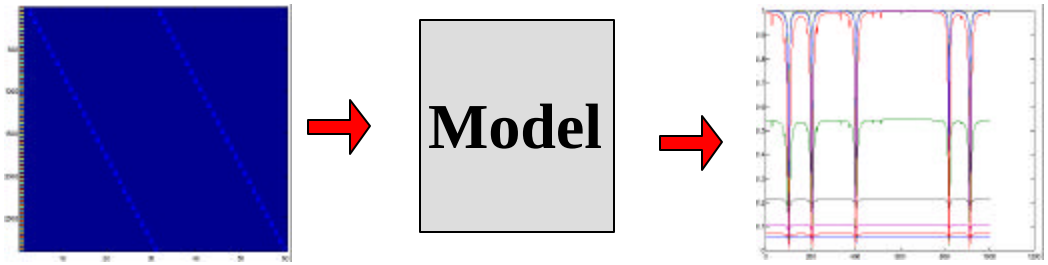
Limitations of my implementation:

- Network is constrained to two layers

Creating Training Data

1. Cloud observations are randomly created according to a set of rules.

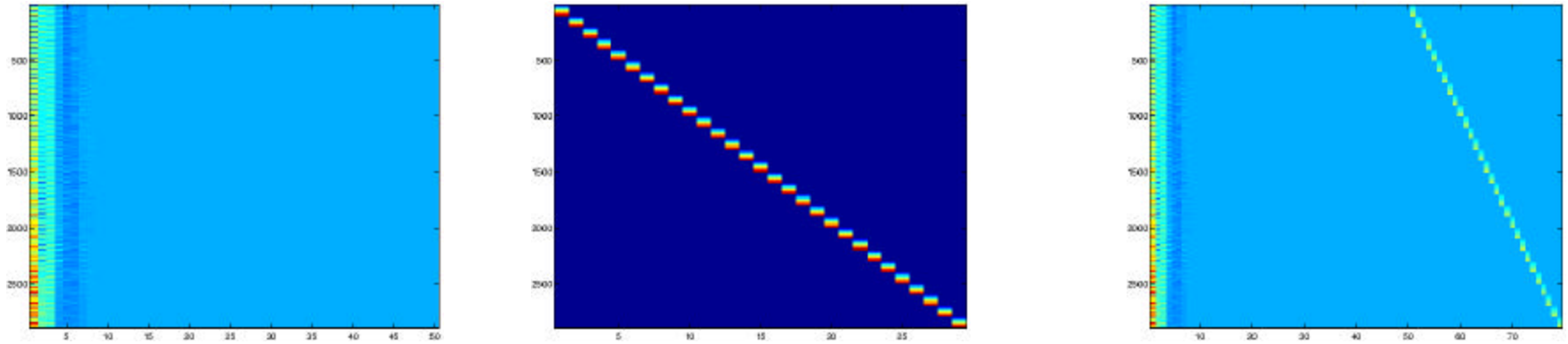
2. Observations are fed into the solar flux model to create frequency predictions.



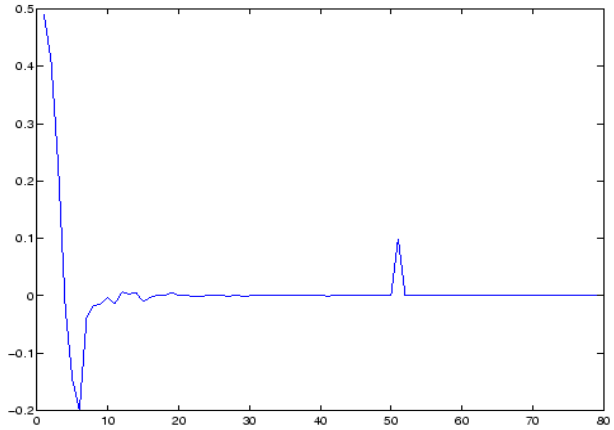
3. Observations are paired with frequencies to create a training example

We initially created 1000 training examples

A Training Example



Frequency Data and Cloud Observations make Training Examples



A single training example contains input to and expected output from the neural network

Constraining the Data

WHY:

- Networks trained on random data did not learn

HOW:

- Data was created so that each set of cloud observations contained measurements for one cloud layer
- 100 samples were created for each of 29 cloud layers
- Each sample was run through the model and paired with frequencies to create 2900 training examples
- The examples were randomly reordered to prevent the network from learning based on sample position

Reducing the Data

WHY:

- The constrained data contained 1003 inputs to the network.

HOW:

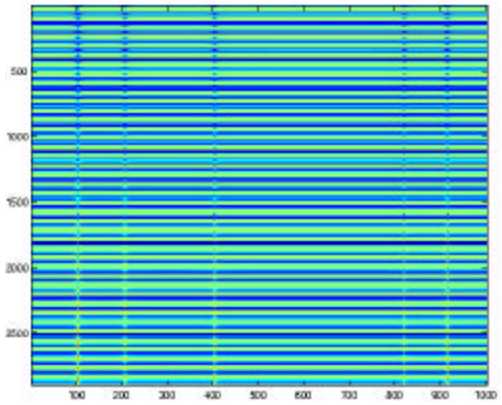
- The inputs were reduced from 1003 to 50 using an eigenvector projection

• View the inputs to the network as a matrix.

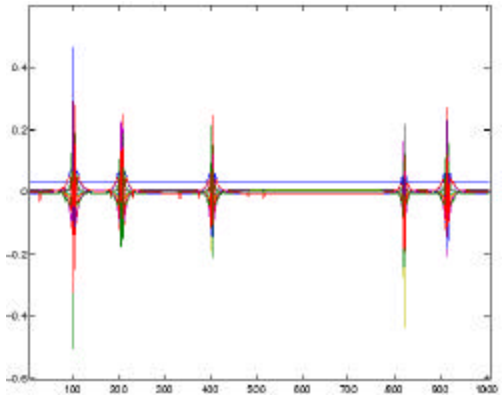
• We picked the eigenvectors associated with the 50 largest eigenvalues of the covariance matrix of the input. These vectors contribute the most to the function that describes the input matrix.

The new network input matrix is:

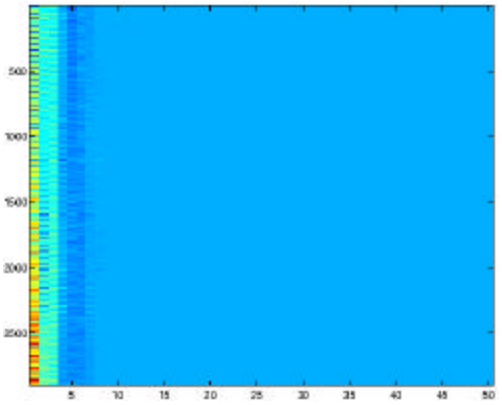
$$I\,E = N$$



Original Input



Eigenvectors

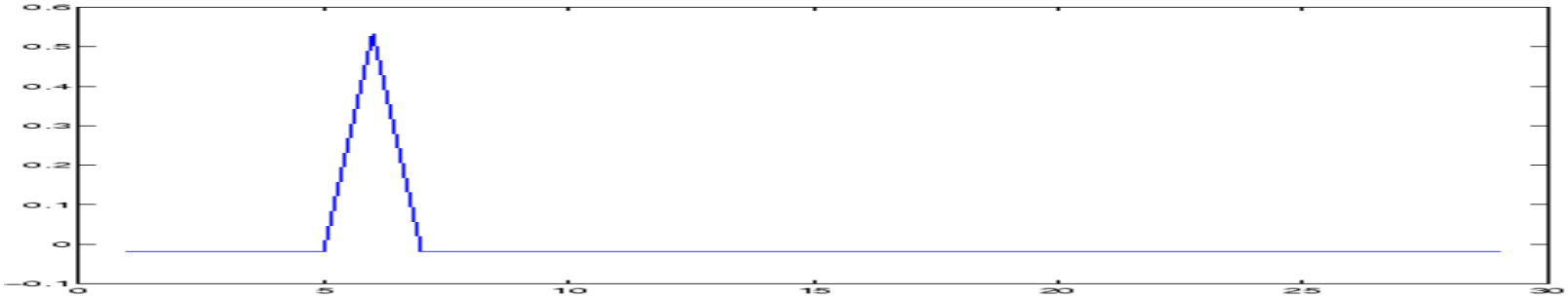


New Input

Training Different Networks

Hypothesis:

A neural network can successfully invert the public1.f solar flux model.



Desired network output, the cloud layer occurs at the spike

Success is measured by the number of correctly identified cloud layers in a group of unseen examples

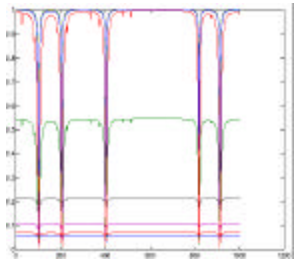
Trained a number of different networks

- Used the constrained, reduced data

- Varied the number of units in the hidden layer between 10 and 100

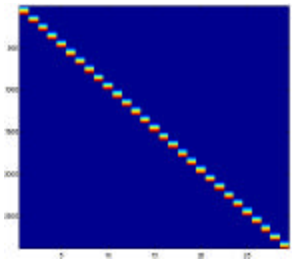
- Varied the rates at which the weights are updated between 0.01 and 0.0001

- Used both hyperbolic tangent and logistic functions to determine a unit's output



Frequencies

Neural Net



Observations

The Best Network

Architecture:

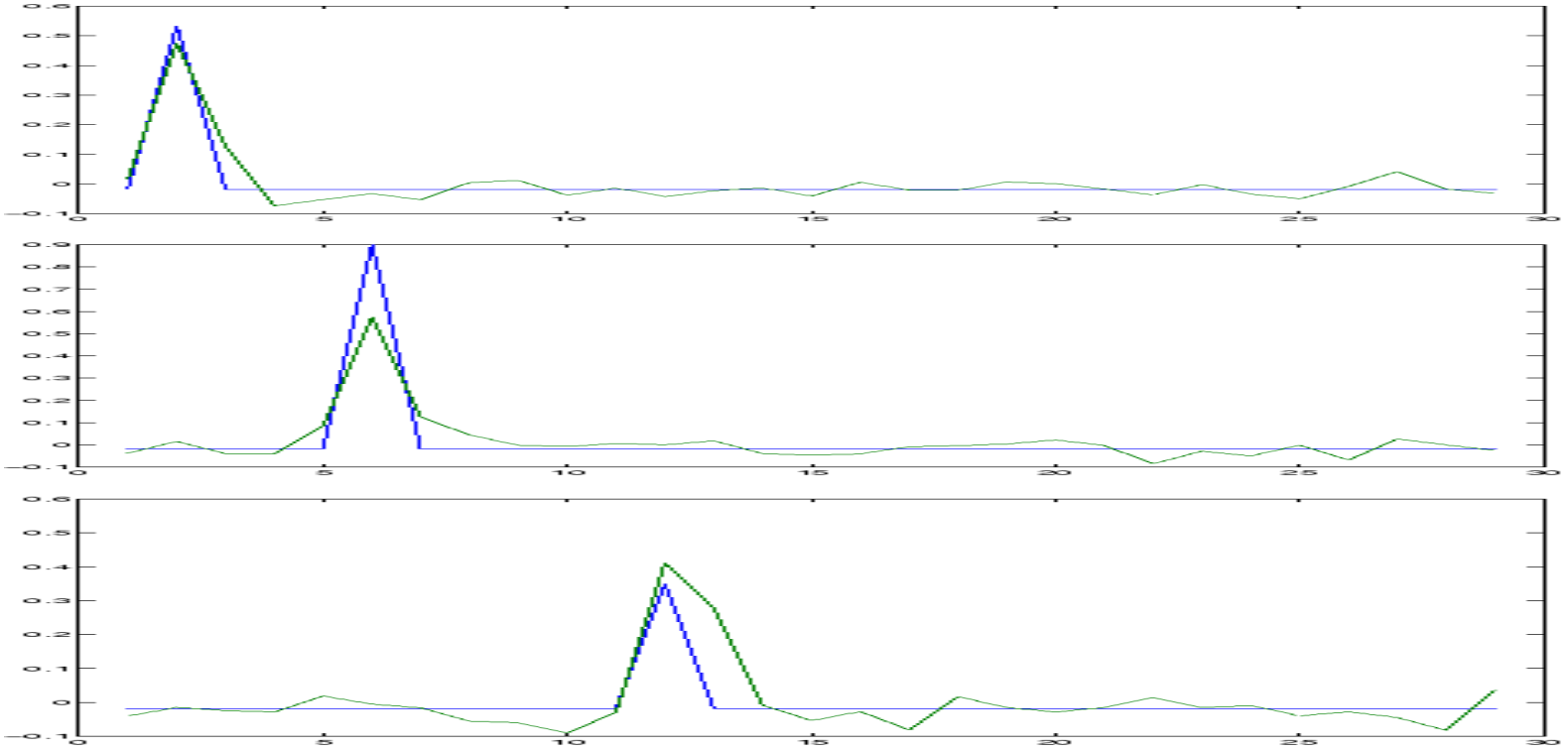
- 80 units in the hidden layer
- Hidden units used a learning rate of 0.01
- Output units used a learning rate of 0.001
- Unit's output determined by a hyperbolic tangent

Results:

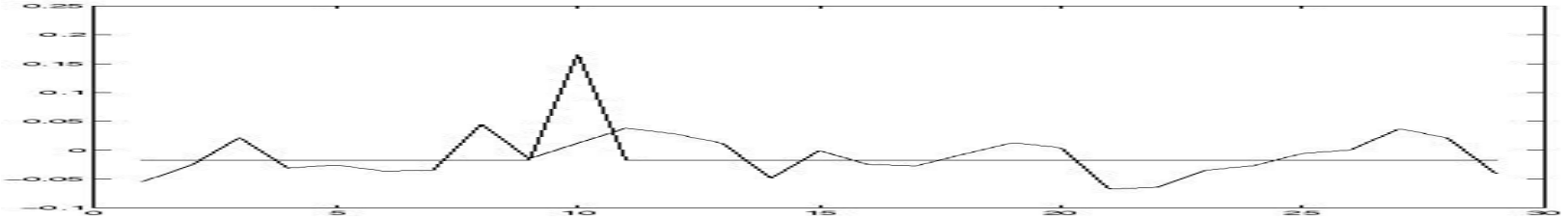
- Each unit had a root mean error of 0.067
- The network correctly identified 167 out of 290 unseen examples

Sample Output

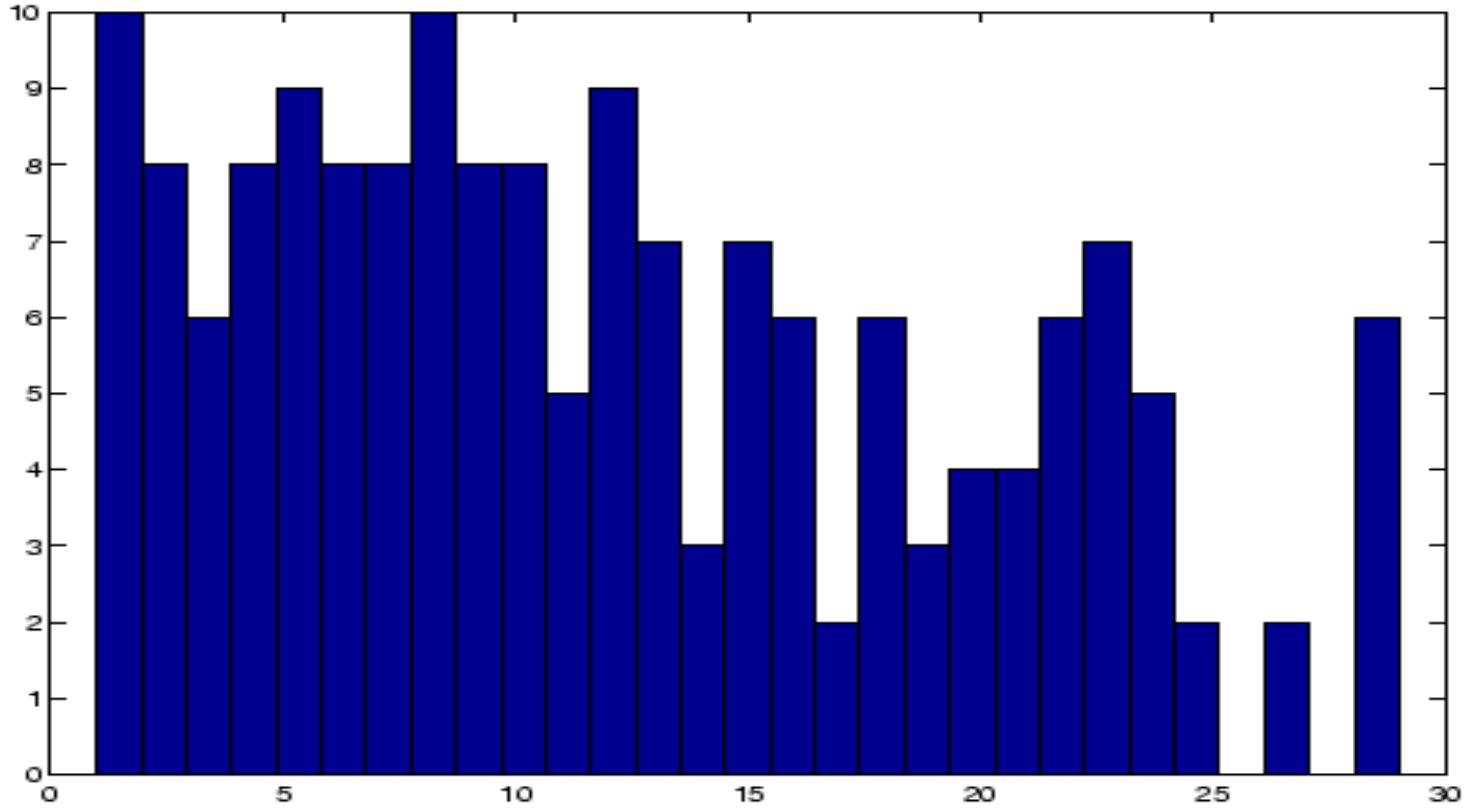
Correct Classifications:



Incorrect Classification:

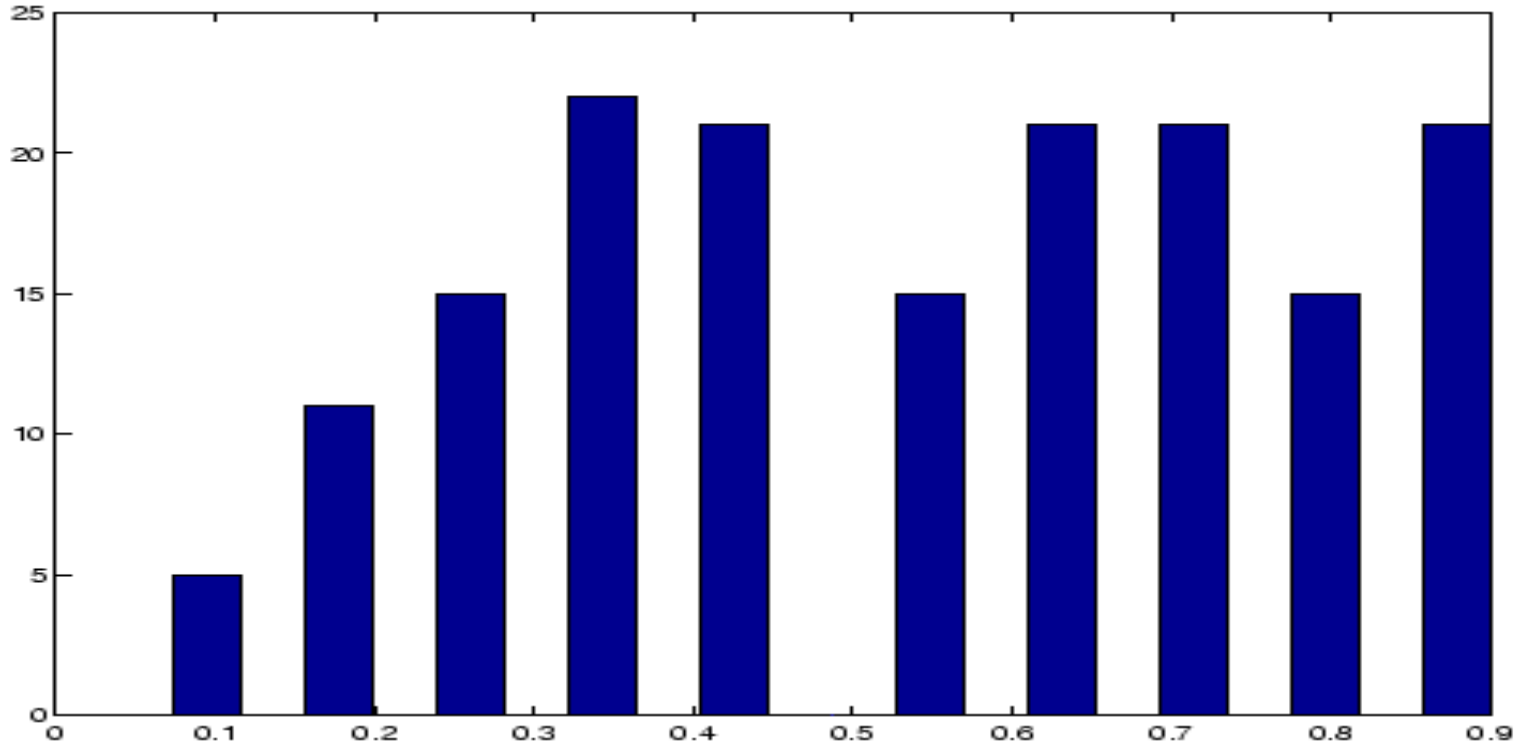


Result Summary



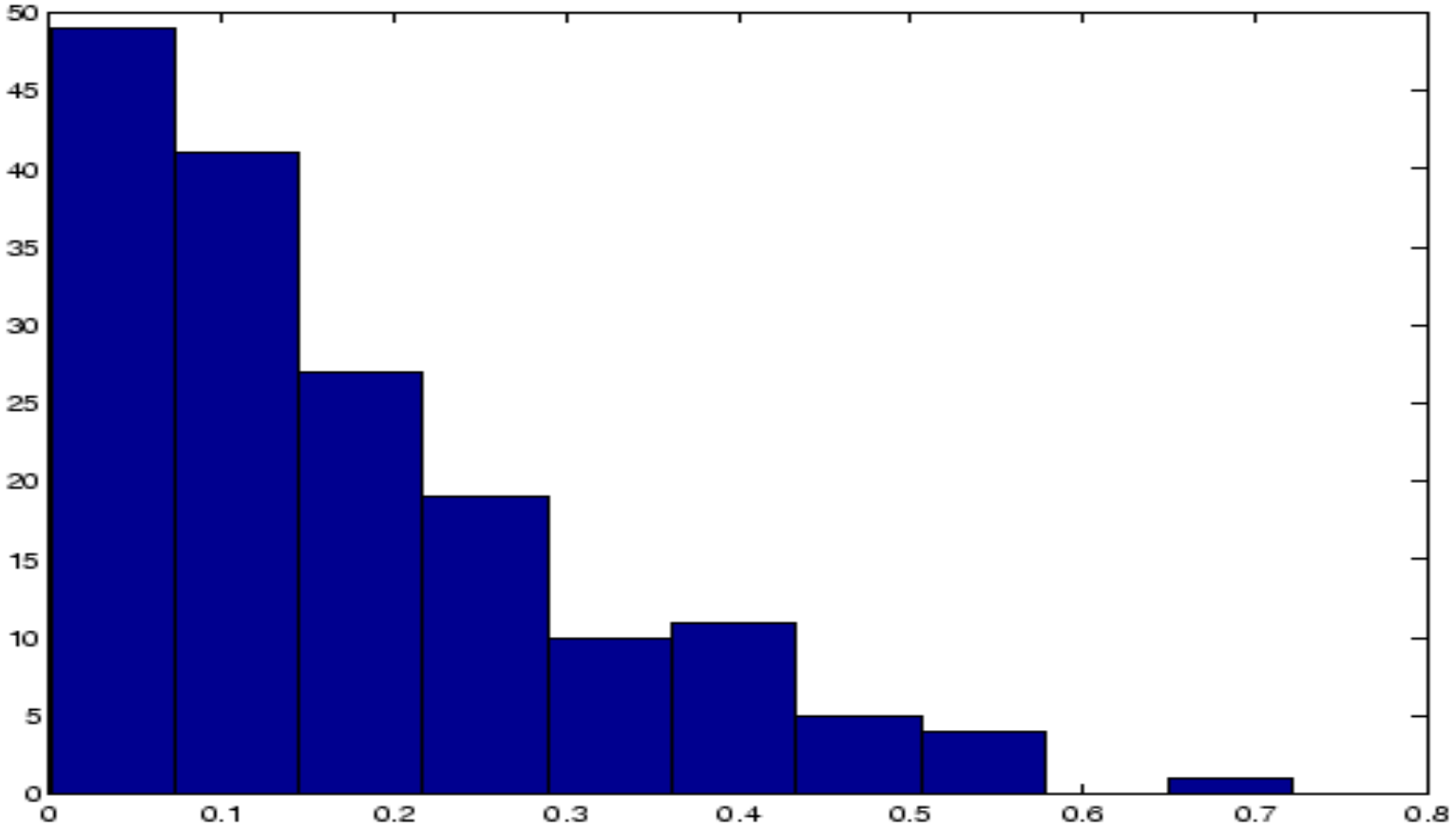
Number of correctly identified examples by cloud layer

There are 10 examples for each of the 29 different cloud layers



Correct by Maximum Value

Cloud layers are identified by 10 different values ranging from 0.07 to 0.9. The unseen examples are evenly distributed among these values.



Error in Correctly Identified Examples

The difference between the desired network output and the actual network output ranged from 0.0002 to 0.7.

Conclusions

- Neural Networks are able to successfully invert the solar flux model on a limited range of data
- Once a network has been trained a sample can be inverted VERY quickly.

The Next Step:

- Work on identifying cloud layers with low maximum values.
- Train networks using less constrained data.