An Interpretable Model of Climate Change Using Correlative Learning

Chuck Anderson and Jason Stock

Department of Computer Science

Colorado State University

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Current Approaches for Finding Indicators of Climate Change are Limited

Difficult to determine climate change signals from global temperature and precipitation data due to

- natural climate variability,
- differences in structural components in multiple climate models, and
- temperature and precipitation for a given year is a combination of internal climate variability and anthropogenic forcings, such as aerosol emissions and greenhouse gases.

Can these limitations be alleviated by learning a neural network model of climate data and extracting patterns from the network?

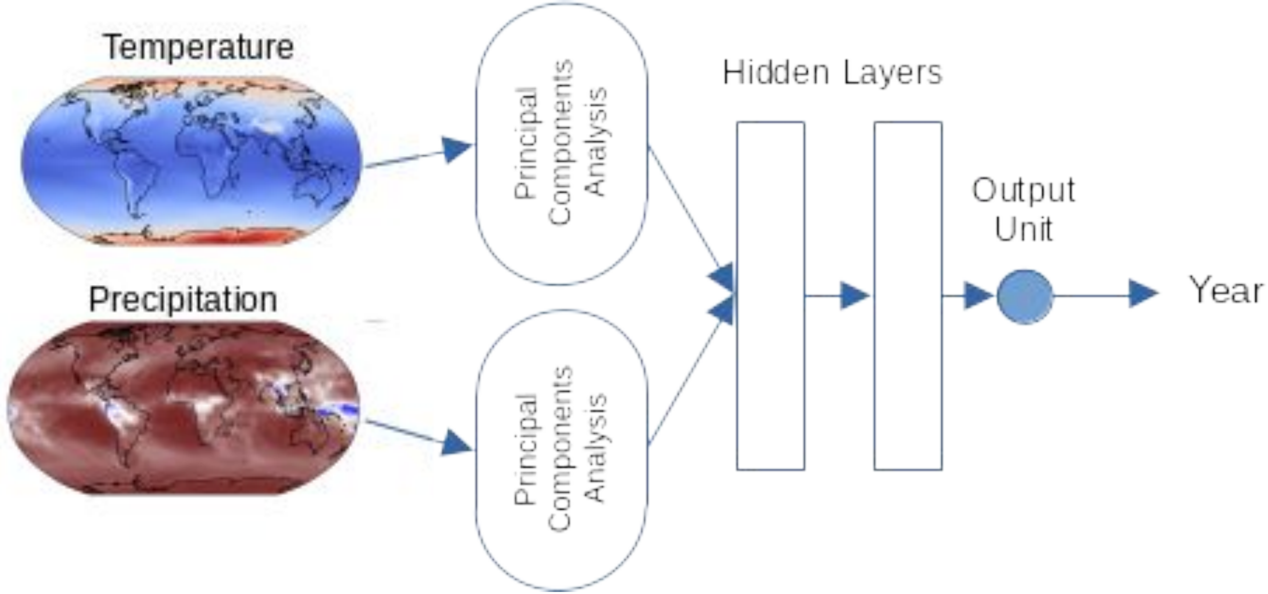
New Approach based on Neural Network Model to Predict Year from Annual Temperature and Precipitation

Trained on data from an ensemble of 35 models from the CMIP6 Coupled Model Intercomparison Project, 2016.

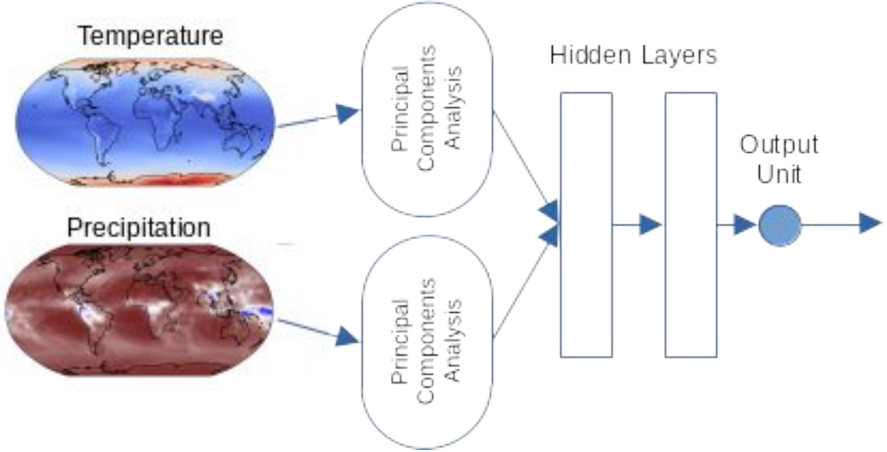
Annual temperature and precipitation maps for years 1850 - 2100, resolution of 120 latitudes and 240 longitudes.

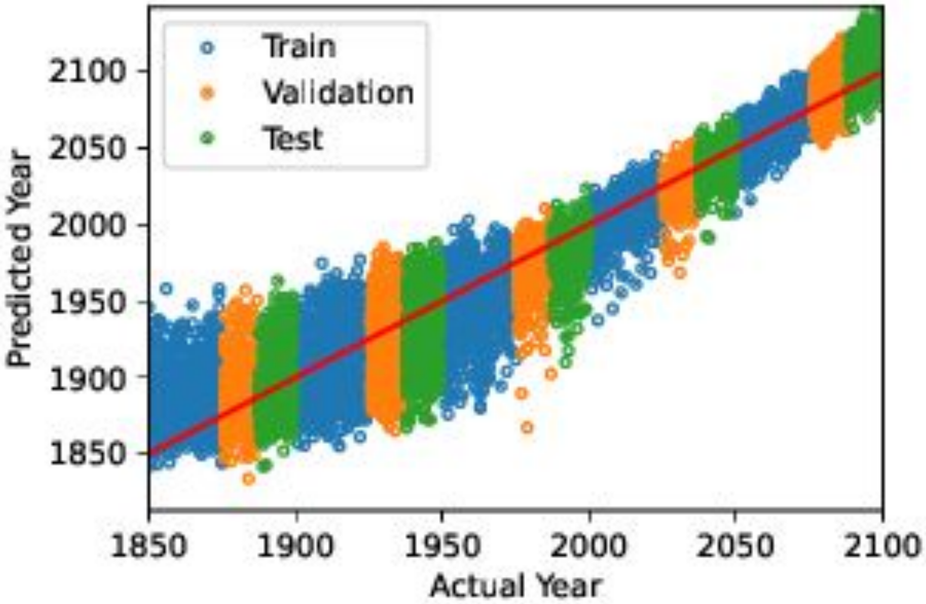
Global annual means subtracted from data for each year.

PCA used to reduce dimensionality using the first 250 singular vectors.



New approach based on neural network model to predict year from annual temperature and precipitation





Interpretation Methods of Trained Model

Gradient-based local methods

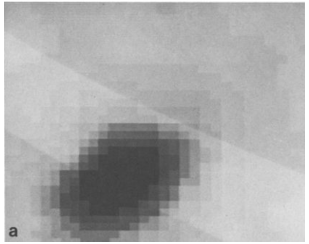
- For particular input, which components are most salient for accurate predictions
- Cumbersome for large data sets

Gradient-based global methods

- Not dependent on specific input
- Generates input patterns that maximize probability of correct classification or minimize squared error
- Results dependent on initial input

Here we test a global method that replaces the need for a gradient with a correlative learning approach.

Using Alopex to Find Optimal Input



Eric Harth, 1974, developed Alopex to determine receptive fields of visual neurons in frog brain.

Make small random changes to input components and keep changes with a probability that depends on their correlation with increases in accuracy of outputs from trained neural network model.

Average optimal inputs over 20 runs.

We first tested Alopex on the MNIST digits classification problem. Compared to gradient-based methods.

Then we applied it to our models of climate change.

Optimal Inputs for MNIST Data

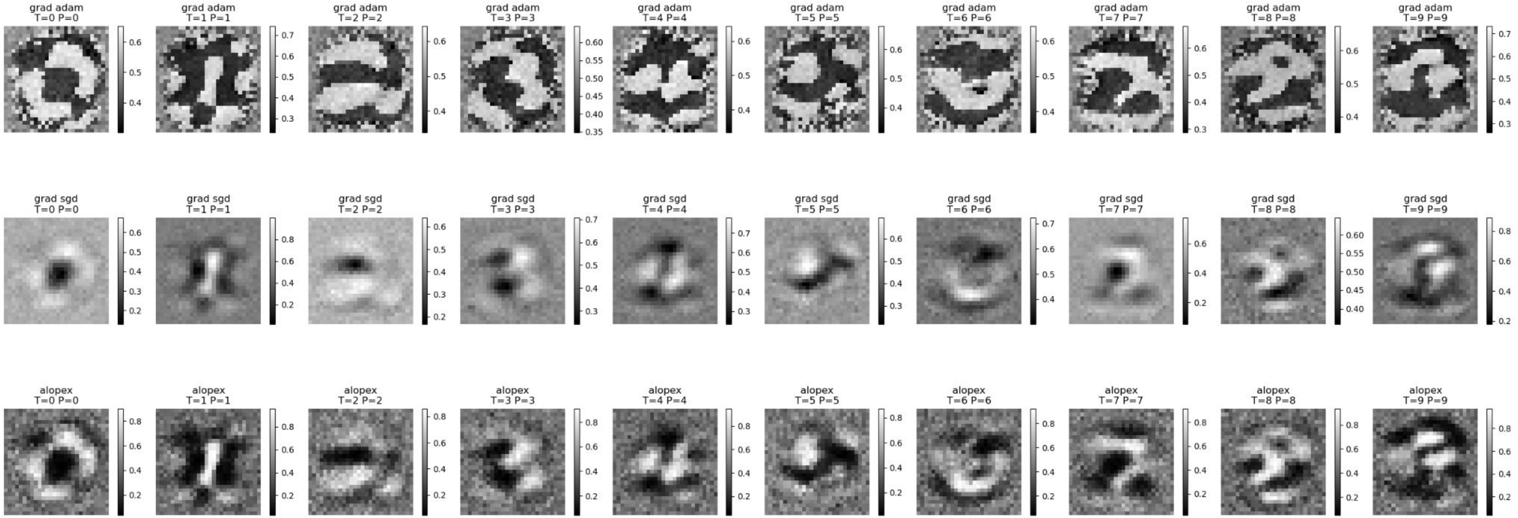
Gradient methods

Adam

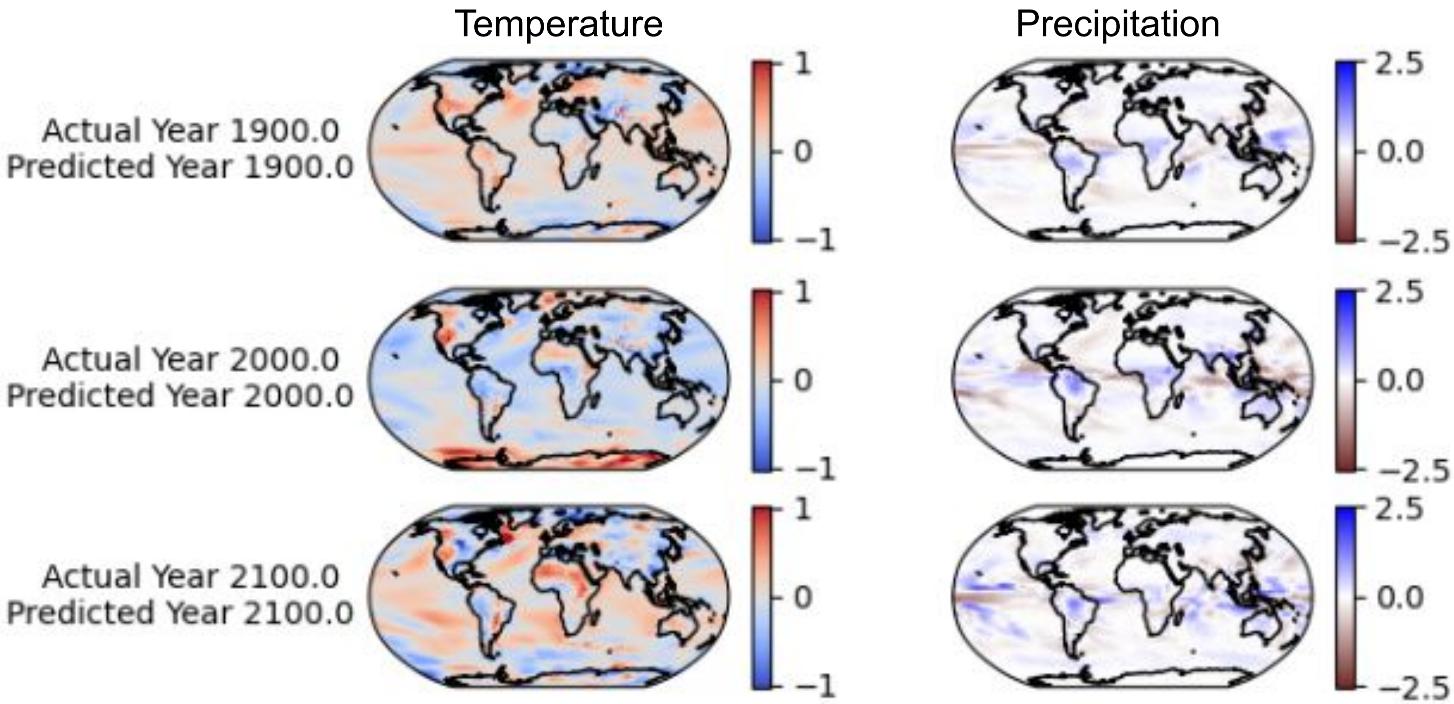
SGD

Nongradient method

Alopex



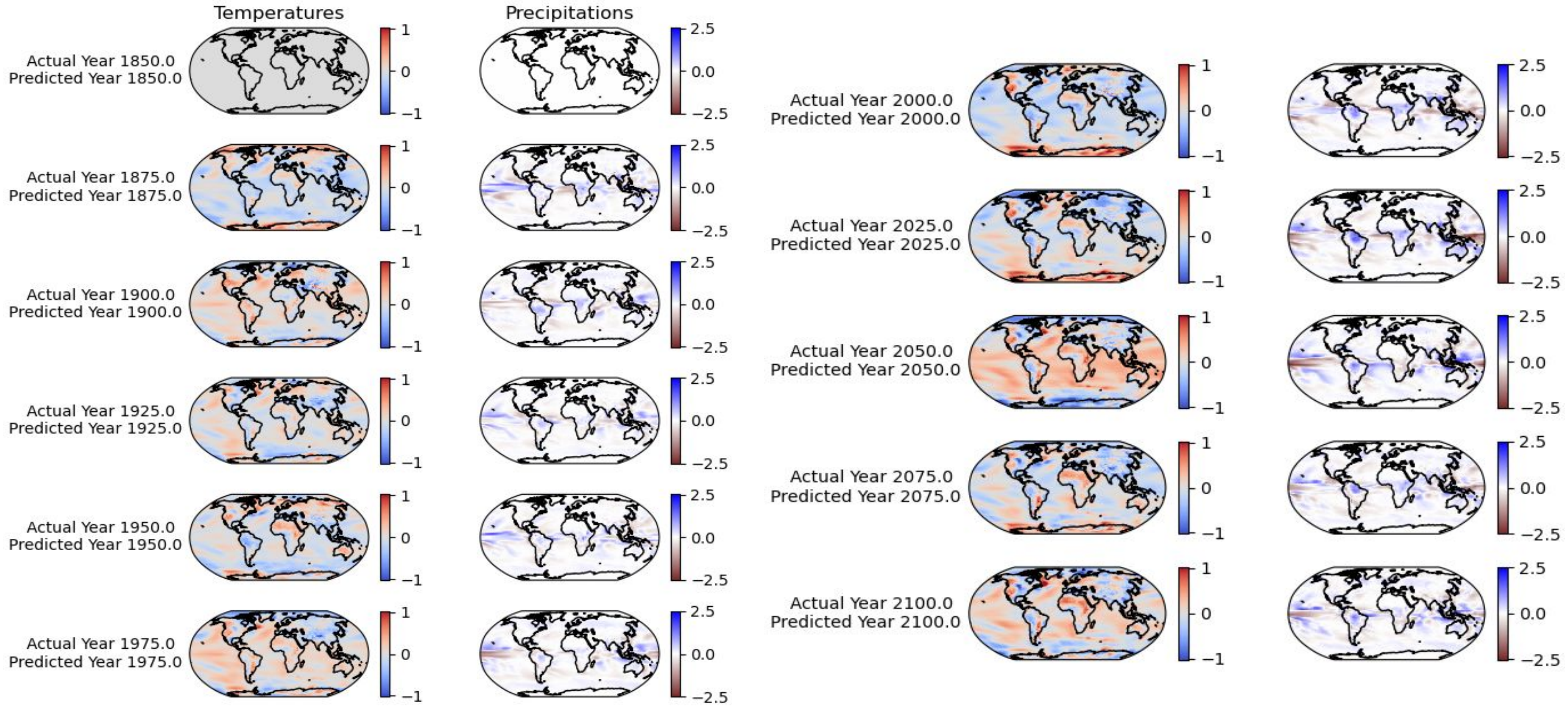
Optimal Inputs for Climate Data found by Alopex



Maps shown are differences from map for 1850.

Arctic warming not apparent because it is not a reliable year-to-year signal.
Antarctic warming is reliable signal for years near 2000 due to ozone hole.

Optimal Inputs for Climate Data every 25 years Found by Alopex



Thank You.

https://www.cs.colostate.edu/~anderson

chuck.anderson@colostate.edu