Convolutional Neural Nets in Climate Model Ensembling

Increasing Spatial Fidelity for Near-Term, Local Predictions

Brian Reed | CS 230 Course Project Spring 2018

Introduction

Motivation: Climate models tend to be less accurate over small spatial and temporal scales, even when considered in ensembles.

Approach: Use convolutional architecture to combine predictions of global circulation models & better predict spatial distribution of daily max temperature.

Results: Overall error dramatically drops with CNN, though patterns carry over from individual ensembles.

Data & Features

Gridded Daily Hindcasts & Max Daily Temp., 1900-2005

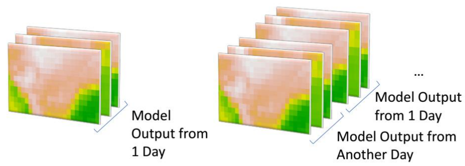
→ Hindcasts: Coupled Model Intercomparison Project 5

→ Observations: Berkeley Earth Surface Temp.

→ Normalized per day to focus on spatial distribution

Approaches to Combining Data

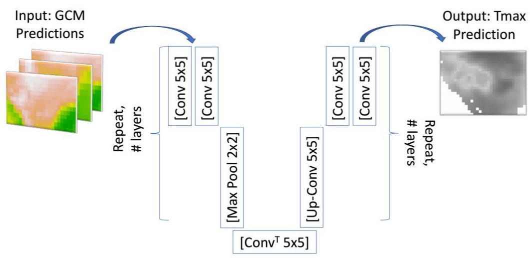
Take 1: 1 Day Stack **Take 2**: 5 Day Stack



Data Split

Model

General Structure: Based on u-net (Ronneberger 2015)



Full Architecture: Layers above repeated 2x. Learning Rate 0.001. L2 regularization, penalty 0.01. Batch 128.

Loss: $\mathcal{L} = \frac{1}{mp}\sum_p \sum_m \left(\hat{y}_{mp} - y_{mp}\right)^2$, pixels p, samples m

Results

Training Set: 32,400 images | **Test Set**: 2,190 images

Model	Training MSE	Test MSE
Ensemble, 1 Day	1.85	1.72
CNN, 1 Day	0.434	0.402
Ensemble, 5 Days	1.78	1.65
CNN, 5 Days	0.495	0.418

Visualizing Results (Top Right):

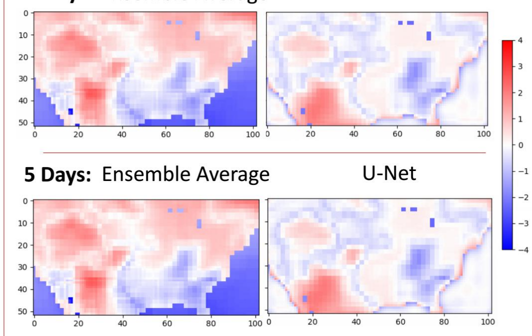
→ Pixelwise sum of errors. Insight into regional patterns.

$$Above\ Right: \sum_{01/01/2000}^{12/31/2005} \hat{y}^{model} - y$$

Pixelwise Error, Test Set

1 Day: Ensemble Average U-Net

5 Days: Ensemble Average U-Net



Discussion & Future

Overall Takeaway: We can learn from pixel-level data within models and better predict actual conditions.

Multi-Day Inputs: Benefit ensembles more than CNN.

Areas with Largest Error: Texas, High Plains, Southeast.

Errors Track with Ecological Zones: Arid zones around TX, forests around Southeast.

With 6 more months: Include data from additional models. Predict temperatures directly. Test different timescales: models typically run for several years.

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