Superresolution Techniques for Climate Simulation Output

GAN approach to climate upscaling with statistical constraints

Daniel Korytina†
Department of Computer Science
University of Colorado at Boulder
Boulder Colorado USA
korytina@colorado.edu

ABSTRACT

Existing *Super resolution generative adversarial network* models are deficient in dealing with *statistical properties* of *climate upscaling*. An enhanced *Super resolution generative adversarial network* is described, capable of providing more accurate predictions of *statistical properties* in *climate upscaling* designs. The model will be tested by comparing predictions against a baseline of *cv2.resize() nearest neighbor upscaling*. [4]

CCS CONCEPTS

• Computing methodologies • Artificial intelligence • Computer vision • Computer vision problems • Reconstruction

• Computing methodologies • Machine learning • Machine learning approaches • Learning latent representations

KEYWORDS

GANs, NetCDF, Climatology

ACM Reference format:

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1 INTRODUCTION

This project originally aimed to deploy a GAN model to upscale* coastlines from high resolution Daymet data (1kmx1km) into the lower resolution 50x50km or 25x25km CORDEX standard. This will make it compatible with the majority of existing simulations over North America. This is a non-trivial task. For example, simple naive averaging annihilates coast lines at the 50km x 50km resolution, see figure 1.

* Note that "downscaling" in the climatology domain means going to a higher resolution because you are focusing on a *smaller geographical region* in greater detail; hence, upscaling implies converting to low res. [5]

In order to visualize data in the NetCDF format, we use the NetCDF tool *ncview*. After opening a file in the NetCDF format in the ncview application, shortwave radiation, *srad*, was selected from the list of variables contained in the NetCDF file. To examine side effects of resolution reduction, I examined how coastlines change when decreasing spatial resolution. The parameters examined were coast lines and model outputs. Figure 1 shows the model output, srad, produced by extrapolating actual measured weather station data over all 1km points. [1]

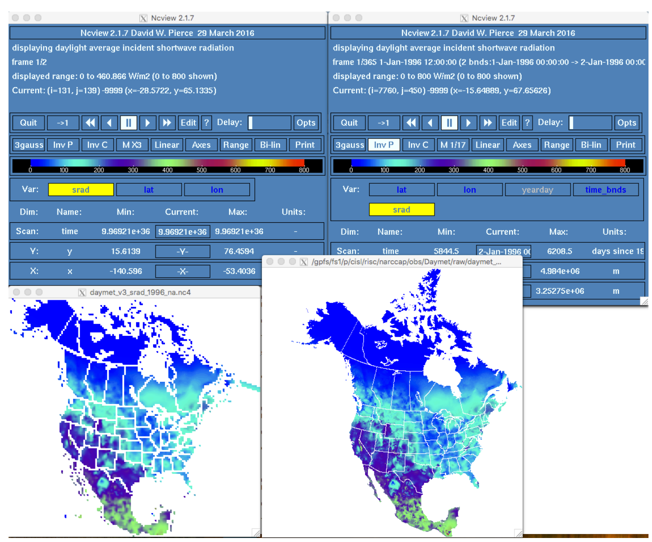

Figure 1: Shortwave radiation in units of Watts per m^2, over North America, on Jan 1, 1996, averaged over daylight hours. This is a screenshot of NetCDF tool, *ncview*. Left figure is at the standard 50x50km resolution, right figure is at the 1x1km Daymet resolution.

From Figure 1 (left and right panels), we can see that, overall, the left panel (50km map) has significant distortion of the coast lines (especially California), while the right map does not. The pixels-per-point on the left map decreased 2500-fold, while

the output variable *displayed range* decreased from [0,800] to [0,460.866].
Despite this, the low res values came to match the high-res originals well in non-coastal areas.

1.1 Overview

I'm a CS grad student, currently interning as a data wrangler at NCAR. This project provides an excellent opportunity to train deep nets, as well as mine climate simulation data.

My group simulates climate over North America, using the same software as local forecasters to simulate weather. We go bit further and let it run for 100 years or so, namely, 1950-2100, or sometimes shorter runs. These simulations output hourly temperatures, precipitation, wind and other variables for each 12km x 12km square over North America. There are other resolutions as well, including 25m and 50km.

In this project I am interested in converting 1kmx1km dayment data into one of the standard resolutions (25km or 50km). The problem is that existing tools crash on anything finer than the 6kmx6km resolution.

Initial conditions for the climate simulations include a) physically measured weather data and b) atmospheric CO2 levels at either 4.5% or 8.5%. There are several regional and global "models" (HRHM5, WRF, REGCM4, ...), which produce different temp and precipitation outcomes. Current research compares which model produces more rain, droughts or ice (usually in Greenland), and what the different models might actually agree on. End users for the data include the military (where to build a base), prisons (will prisoners die in heat waves during TX summers if there's no air conditioning).

1.1.1 Climate vs Weather. Weather is a measurement of current atmospheric conditions, including temperature, rainfall, wind, and humidity, while climate represents the "general weather conditions." Climate is the statistics of weather over long periods of time. For example, comparing daily temperature with averaged climate data, one will see how weather is highly variable, but climate is not. [2]

1.2 Problem Statement

My objective is to take a 50km (low resolution) precipitation map over North America and produce an estimate of a corresponding 25km (high-resolution) map. This problem is underdetermined - multiple high-resolution images can be produced from the same low-resolution image. For instance, suppose we have a 2×2 pixel sub-image containing a small vertical or horizontal bar [Fig. 1]. Regardless of the orientation of the bar, these 4 pixels will correspond to just one pixel in a picture downscaled 4 times. With real life images, one needs to overcome an abundance of similar problems, making the task difficult to solve.

(https://deepsense.ai/using-deep-learning-for-single-image-super-resolution/)

1.3 Research Questions

- Is it enough to only consider neighboring pixels?
    - Can this prevent coastline fracturing?
- What extension mechanisms must be added to the core pipeline to allow climate-specific analysis?
- What capabilities can we provide with big data methods that you will not find in traditional scientific data analysis methods.

To evaluate my research, I could then add the following additional research questions:

- How easy is it for scientists to adapt this in their analysis tool chain?
- How much adoption was achieved?
- What limitations did the system have in this context?
- Was it able to handle all the analysis NCAR executes on a daily/weekly basis?
- How effectively does this regrid method improve the quality of research at NCAR?

1.4 Related Work (what has been done)

Clearly, there are established analysis methods for climate simulation data. These include:

1. Descriptive statistics.
2. Basic probability concepts.
3. Probability distributions.
4. Parameter estimation.
5. Statistical hypothesis testing
6. Basic linear regression
7. Multiple and nonlinear regression
8. Time series [3]
9. Non-blurry Super resolution. "MSE is the wrong objective for photo-realistic results" [6]

My unique contribution is to enact super resolution extrapolation from low res climate data, while attempting to keep aggregation monthly, annual and seasonal statistics consistent with the source.

2 DATA SET

My group simulates climate over North America, using the same software as local forecasters to simulate weather. We go bit further and let it run for 100 years or so, namely, 1950-2100, occasionally, shorter runs. These simulations output hourly temperatures, precipitation, wind, radiation and many other variables for each 12km x 12km square over North America. There are other resolutions as well, including 25m and 50km.

In this project I take 50km data, downscale it to 100km, then attempt to recreate the 50km via a GAN. These resolutions will make my experiments tractable on a modern MacPro with 16GB of RAM. Precipitation forms the most interesting and complex pattern, so I will start with this (whereas surface temps are more diffuse and don't benefit as much from high-resolution artifacts.

The 50km data is loaded into python on the ncar servers via the NetCDF4 Python library and saved as a Numpy array save file. This enables processing on my laptop without having to install the NetCDF4 suite.

Furthermore, instead of training on the map at once, I elect 20x20 subgrids, downsampled to 5x5, then again interpolated back up to 20x20. This produces areas of interest at scale to local precipitation events. Additionally, this creates a lot of data from a single frame. The downside is that upsampled precipitation events will not benefit from geographical context, e.g., over Rockies vs over Great Plains.

Below is table of available variables:

Parameter	Abbr	Units	Description
Day length	dayl	s/day	Duration of the daylight period in seconds per day. This calculation is based on the period of the day during which the sun is above a hypothetical flat horizon
Precipitation	prcp	mm/day	Daily total precipitation in millimeters per day, sum of all forms converted to water-equivalent. Precipitation occurrence on any given day may be ascertained.
Shortwave radiation	srad	W/m2	Incident shortwave radiation flux density in watts per square meter, taken as an average over the daylight period of the day. NOTE: Daily total radiation (MJ/m2/day) can be calculated as follows: ((srad (W/m2) * dayl (s/day)) / l,000,000)
Snow water equivalent	swe	kg/m2	Snow water equivalent in kilograms per square meter. The amount of water contained within the snowpack.
Maximum air temperature	tmax	degrees C	Daily maximum 2-meter air temperature in degrees Celsius.
Minimum air temperature	tmin	degrees C	Daily minimum 2-meter air temperature in degrees Celsius.
Water vapor pressure	vp	Pa	Water vapor pressure in pascals. Daily average partial pressure of water vapor.

Table 1: List of available Daymet variables [1]

2 Methods

This project aims to apply Super resolution techniques, including a GAN modelm to upscale low resolution daily precipitation simulations over North America to a high resolution, specifically 4x resolution increase in both x and y dimensions.

Preserving statistical properties. Climatology is primarily concerned with long term averages of weather, referred to as climate. I propose adding a regularization term to SRGAN representing of 2-day average. Simplest example would be to:

- Simultaneously interpolate day(n) and day(n+1). Such that, Avg(I(day(n))+ Avg(I(day(n+1))==Avg(day(n), day(n+1))

This would preserve post-averaging statistics so they match in both the interpolated and interpolated data. I posit this will increase high frequency content of interpolated images. At the very least is will push the output images into a smaller manifold, constrained by statistical fidelity for adjacent image frames.

2.2 Feasibility

My intent is to keep the project computational feasible. An example would be to only focus on surrounding pixels, as priors (to restrict candidate interpolations). Below is a brief list of possible constrains to limit computational space.

- Interpolating 200km to 50km (instead of 1km)
  - Easier to spot low res artifacts, faster to train
- Break image into 20x20 patches
  - Native (166,138) is resized to (180,140) via cv2 then broken into 63 20x20 samples
  - Each nc4 file has 365 frames;
    - This then gives 63*365=22995 examples just for year 2014
- Data is extracted from NetCDF4 file on server and saved as a numpy .npy file to be Torched on my laptop

3 RESULTS

Baseline was achieved via the cv2 library, seen below.

```
us_shape = (166,138)
ds_shape = (us_shape[0]//4, us_shape[1]//4)
print(ds_shape)
ds_img = cv2.resize(d[0],ds_shape)
plt.imshow(ds_img)
plt.show()
```

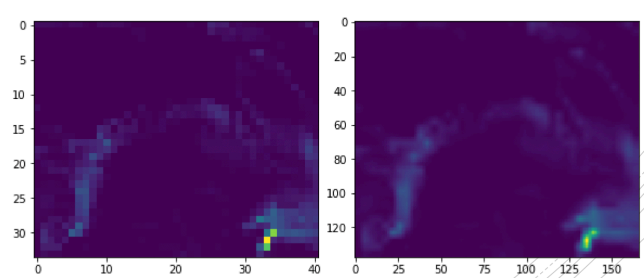

Figure 2: Daily average of precipitation over a 180-degree-rotated North America in units of Kg/m^2/second, on Jan 1, 2014. Center point is aprox 0.0004 Kg/m^2/s.

From Figure 2 (left and right panels), we can see that the left panel is resolution reduced by a factor of 4 in both x and y dimension. The right panel is the left panel upscaled by a factor of 4 via cv2.size nearest neighbor linear interpolation.

In order to examine GAN network training we examined now the generator, G, functioned for different training inputs.
The training inputs examined were MNIST and daily precipitation over North America.
Figure 3.top shows generator output when subjected to noise input when trained on MNIST, while Figure 3.bottom shows generator out when subjected to noise input when trained on daily precipitation over North America.

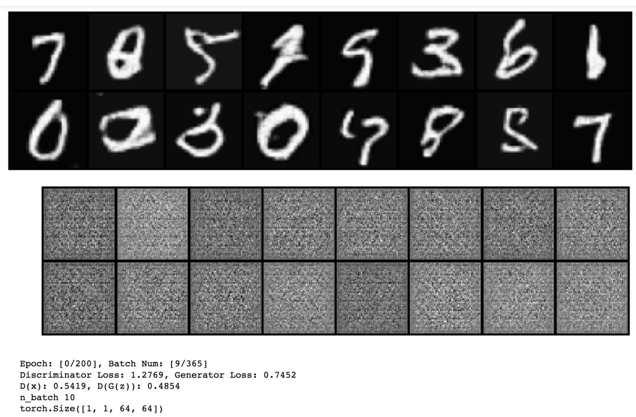

Figure 3: Generator response to random noise in a GAN model. Above, the same GAN network is trained on the MNIST dataset, and in the lower pane, trained on precipitation over North America.

From Figure 3 (upper and lower panels), we can see that the upper panel is resolution reduces by a factor of 4 in both x and y dimension, which the right panel is then upscaled

From Figure 3 top and bottom, we can see that, overall, MNIST-trained data was the most successful, while the precipitation data (bottom) did not converge. This is due to the above pane running overnight and probably grater stability and regularity of digits, vs. rather dynamic fluid behavior of precipitation, while at the same time lacking enough epochs for conversion.

Finally, in Figure 4, we examine the difference between two interpolations side-by-side. The interpolations examined were linear nearest neighbor and sklern's LinearRegression regressor.
Patch 0 is the 20x20 area starting at coordinate (0,0), while Patch 63 is the last 20x20 pixel are in the bottom right corner. The first column represents the 5x5 input to be interpolated, the 2nd column represents nearest neighbor interpolation, 3rd column is the output of LinearRegressor, and 4th column is the original 20x20 patch trying to be approximated by the previous 3.

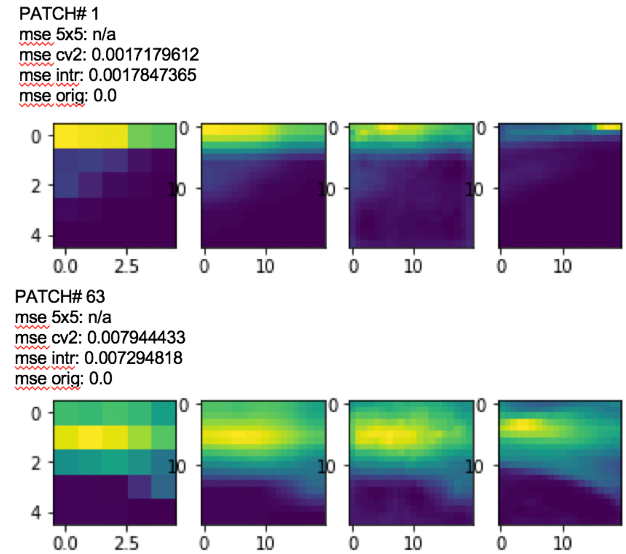

Figure 4: 5x5 input vs. cv2 upscale, sklearn's LinearRegression regressor, original patch.

From Figure 4, columns 2 and 3, we can see that nn interpolation is produces very similar output is LinearRegressor. While nn acts only on nearest neighbors as context, LinearRegressor was trained on almost 30,000 examples. Though not see here, nn had lower MSE on more of the examples. The last column is the original, which the previous are attempting to approximate.

3 CONCLUSSION

This project aims to deploy super resolution techniques to both upscale and downscale historically-measured daily weather variables over North America. [1] While some variables like shortwave radiation are smooth and continuous, precipitation is interesting. In particular, Maximum a Posteriori (MAP) Inference will be attempted in order to obtain sharp features in the interpolated data, preferring solutions that have high probability, give certain context cues. [6]

3 FUTURE WORK

I suspect adding additional features could lower loss and increase high frequency characteristics, namely, temporal cues and related variables like humidity, wind and surface temps.

Temporal cues might aid in predicting translation of precipitation in time. Same goes for wind and surface temperature.

Preserving statistical properties via 2-day average – the average of 2 days should be the same before and after the interpolation. These additional constrains help specify an underspecified solution (there are 16 high res interpolations for every low res pixel)

Simultaneously interpolate

day(n) and day(n+1)

Such that,

Avg(I(day(n))+ Avg(I(day(n+1)) = Avg(day(n), day(n+1))

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