Using Deep Learning to Predict Solar Far-Side Magnetic Flux From Far-Side EUV Flux

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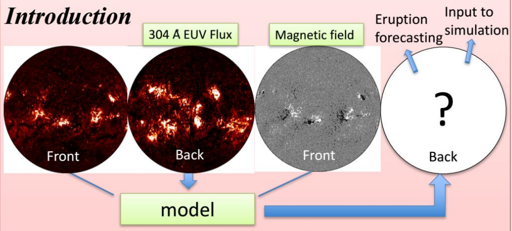
Abstract

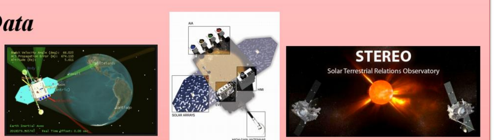
Solar magnetic field is the most fundamental observable in need for space weather forecasting. While the near-side magnetic field of the Sun is monitored, the solar far-side magnetic field is not available. However, the far-side extreme ultraviolet (EUV) flux is observed by NASA/STEREO mission, and can be used to produce proxies of far-side magnetic flux. Here we use deep learning to learn the relation between EUV flux and magnetic flux, using near-side observations where over 7 years of continuous data area available. Our model can reproduce the magnetic flux in great details and with a similarity of close to 0.9.

Introduction



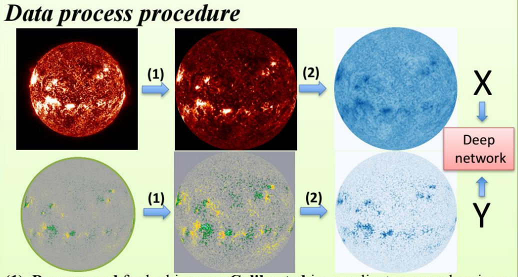
- Space weather influences human activities such as spacecraft and astronauts, satellite communication, commercial airlines, etc., making its forecasting in great need.
- Magnetic field is root of all solar activities, but far-side magnetic field is unknown. It is necessary for forecasting because:
- Sun is rotating. Whatever happens on far-side will be facing us in a few days.
- Whole-sun magnetic flux inputs are necessary for simulation and prediction of solar activities.

Data



- The near-side raw data fro training are from NASA/SDO mission, with 7-year data available from http://jsoc.stanford.edu/.
- I get 4 image pairs per day, giving a total of about **11,000** examples. About **600** examples each are set as dev and test set.

Data process procedure



(1) Prescreened for bad images. **Calibrated** in coordinates so each pair are of exactly same time and location. **Downsized** from $4096\times4096\times1$ to $\mathbf{512\times512\times1}$.

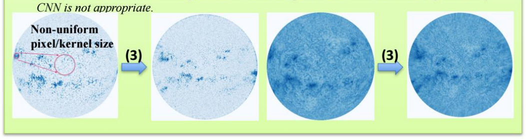
(2) Log scaled and normalized, to make the problem less non-linear.

$$\textbf{scaled data} = \textbf{log}(\ |\textbf{original data}| + \textbf{1})/\textbf{10}$$

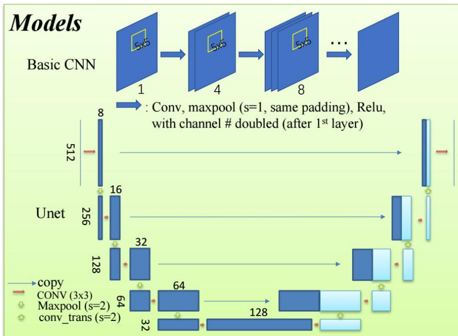
The original images are largely exponentially distributed, which would make the extreme bright points in images dominating the loss function, and also make the network relying on the non-linear part of activation function.

(3) Postel's transformation, stretching the image to near-uniform.

Pixel size could be 10 times larger near the limb compared to in the center, so weight share of CNN is not appropriate.



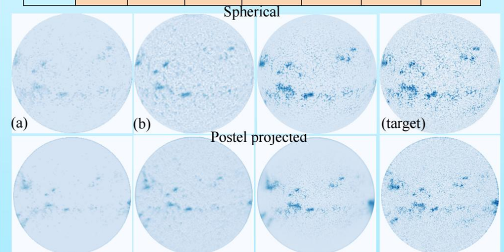
Models



Results

- Loss: mean distance between iamges
- Metrics: cosine similarity (progress)
- Adam optimizer, BatchNorm, Flipping images for augmentation.

Model	Layer	Loss (train)	Loss (dev)	Similarity progress (train)	Similarity progress (dev)	Similarity (train)	Similarity (dev)
Basic CNN	2-layer	0.005446	0.005457	-0.002265	-0.003675	0.854364	0.853590
	3-layer	0.004908	0.004845	0.010299	0.011169	0.866880	0.867097
	4-layer	0.004839	0.004775	0.010599	0.011731	0.867097	0.868996
Unet	4-Layer	0.003722	0.003758	0.039024	0.039983	0.896574	0.897562
	5-Layer	**0.003476**	**0.003510**	**0.046574**	**0.046686**	**0.903930**	**0.904201**



- Unets works better, because it captures both large-scale and small-scale features and balance them well.
- Postel's projection only helps when network struture is very simple. When the model is complex enough, Postel's projection is not necessary as the model can learn the geometry.

Summary

Our model using Unet works well to learn the transform between solar near-side AIA EUV (304 A) flux to the near-side HMI magnetic flux, with a similarity close to 0.9 and mean distance around 0.004 (out of 1). This is a promising result to produce proxies of the solar far-side magnetic flux using STEREO EUV flux, which is valuable for space weather forecasting.

Reference

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