Spectropolarimetric Inversions with Group Equivariant Convolutional Networks

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Introduction

The Stokes inversion refers to analyzing solar telescope data to infer the structure of the Sun's atmosphere. Current approaches use pixel-by-pixel inversion algorithms, but this is slow and ignores spatiotemporal patterns. We propose to use deep learning, which will be more efficient and potentially more accurate.

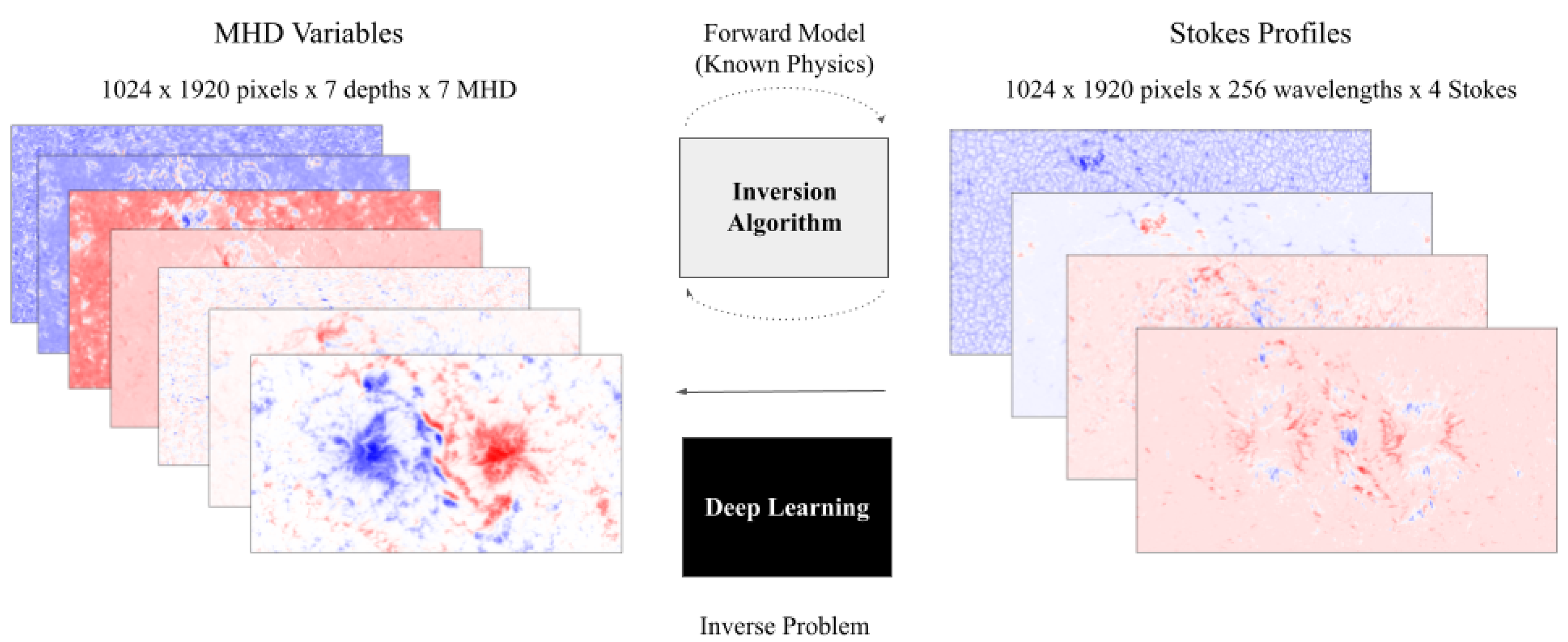

Figure 1: Inversion techniques make iterative updates to MHD guesses by simulating the forward physics and calculating the difference between the predicted and observed Stokes profiles. Instead, we use deep learning to invert Stokes profiles in a single step.

Datasets

- **MHD Variables**: Hidden variables of interest that fully describe the solar atmosphere. MHD variables are obtained via simulations of an active [1] and sunspot region [2]
- **Stokes Profiles**: Observable variables from solar telescopes. A forward model is used to obtain Stokes profiles from the simulated MHD variables [3]
- MHD and Stokes are initially sequences of 3d snapshots of the sun. Snapshots are split into non-overlapping 16×16 image patches, resulting in 76,800 different images for the active region and 9,200 images for the sunspot region.

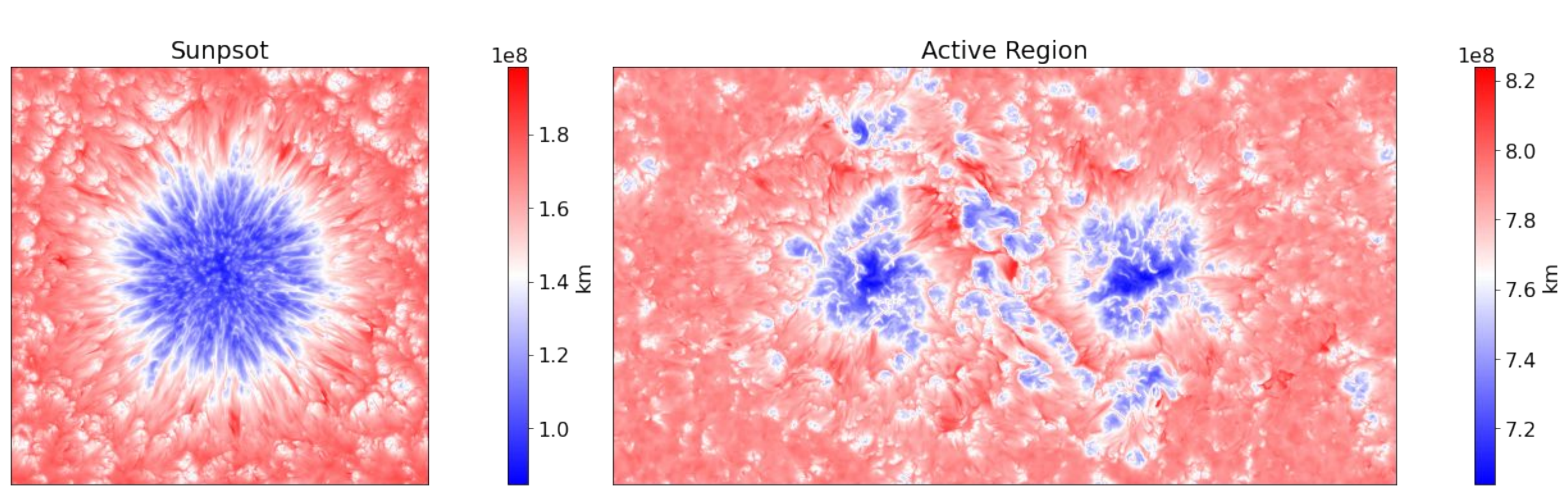

Figure 2: Single snapshot of surface height for sunspot and active region

Experiment 1: Multiple Line Observations

Multi-line observations should enable us to cover a wider range of physical heights. Traditional inversion algorithms invert lines independently, and here we investigate whether or not using multiple lines as inputs improves inversions.

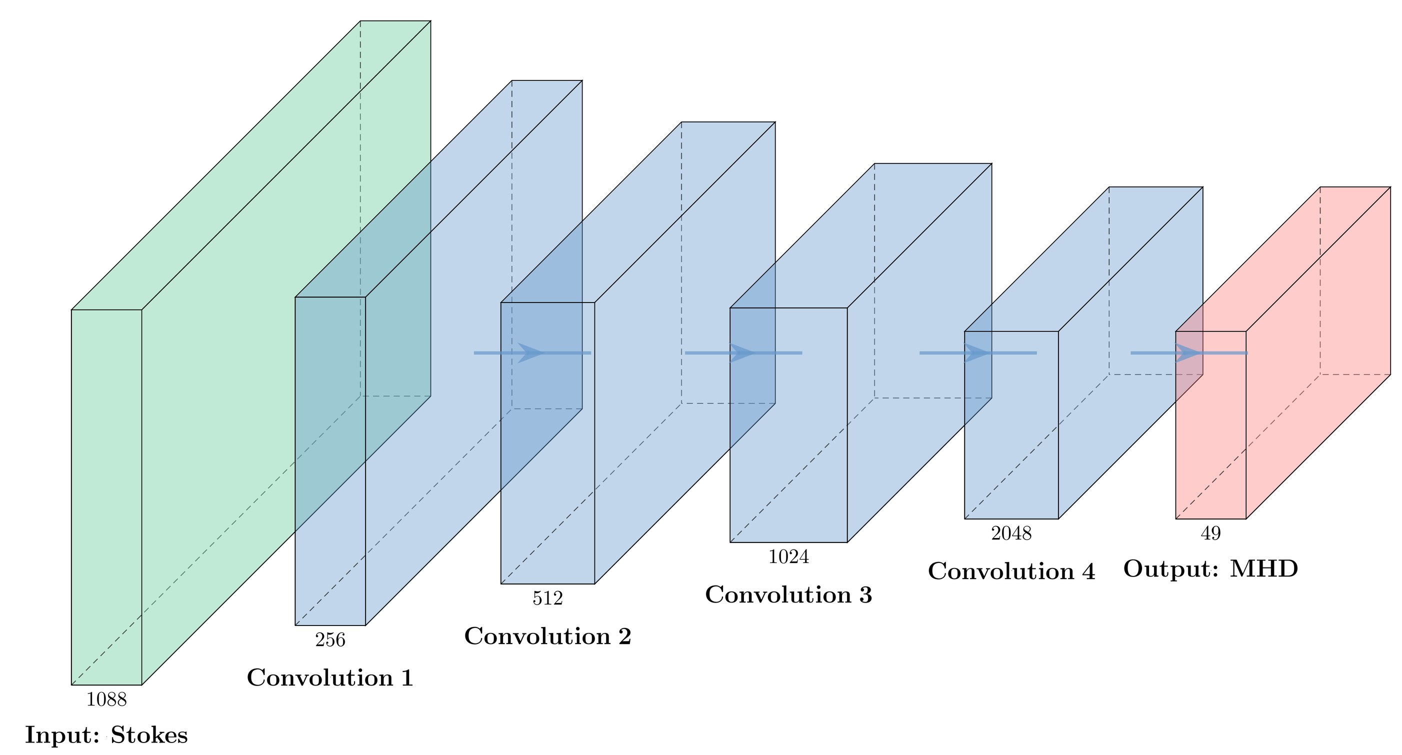

Figure 3: Two fully convolutional neural networks (CNNs) were trained with a different set of inputs: only single set of lines (112 wavelengths) and both sets of lines (272 wavelengths)

Experiment 2: Group Equivariance

- Motivation: G-CNNs [4] enforce *rotational* equivariance thereby, capturing the rotational symmetries found in the dataset.
- Intuition: Filters in G-convolution are rotated for each possible rotation and convolved with each feature map from the previous layer

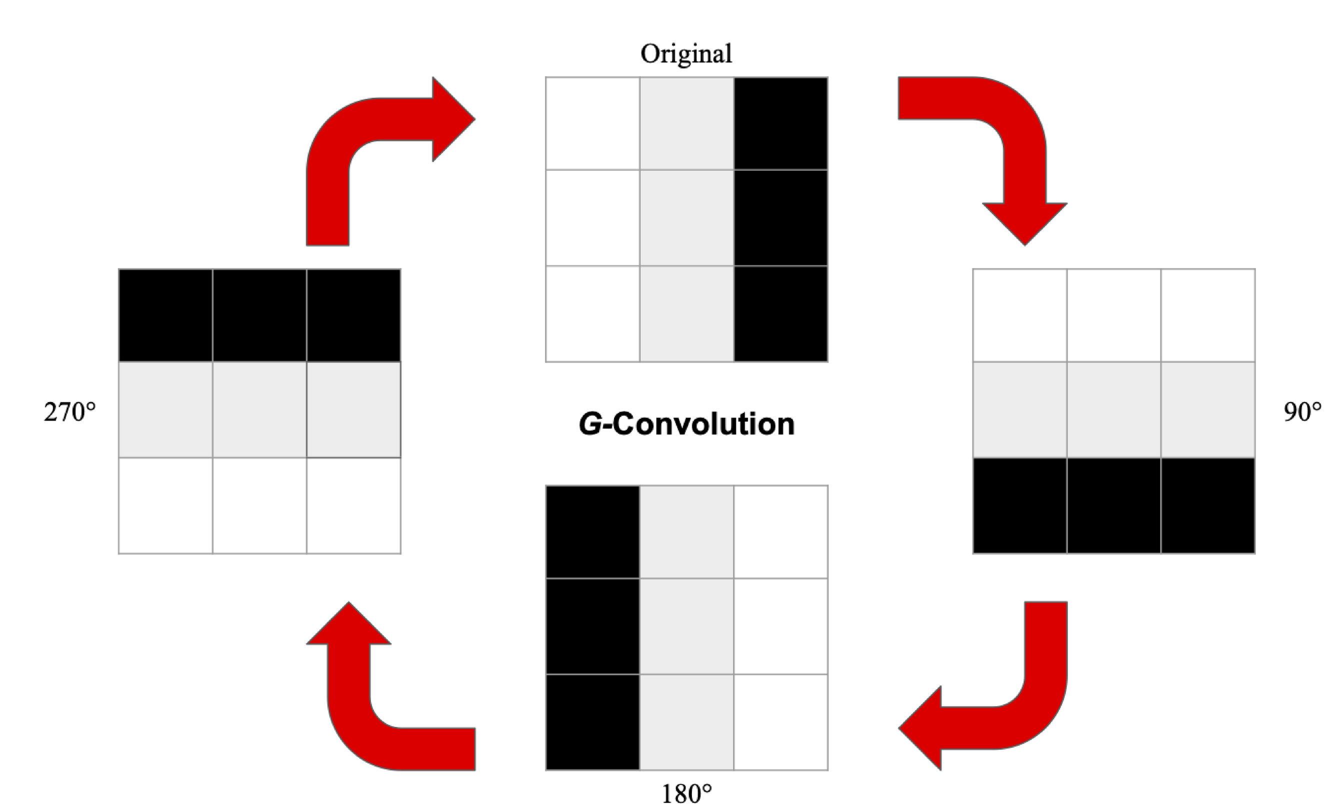

Figure 4: An example 3×3 kernel at the initial layer and its rotation in G-convolution.

Results

Property		Active Region Single	Active Region Multiple	Active Region G-CNN	Sunspot Region Single	Sunspot Region Multiple	Sunspot Region G-CNN
Height	km	0.19%	0.17%	0.14%	1.28%	1.23%	1.14%
Temperature	K	1.27%	0.87%	0.70%	1.46%	1.16%	1.00%
Pressure	Pa	4.43%	3.77%	3.20%	6.78%	6.36%	6.15%
Velocity	m/s	27.38%	20.93%	17.97%	49.18%	41.66%	38.31%
Mag. field Q	$gauss$	31.56%	24.27%	21.35%	32.95%	26.23%	23.61%
Mag. field U	$gauss$	32.53%	24.66%	22.03%	33.07%	25.00%	22.06%
Mag. field V	$gauss$	33.08%	26.03%	22.16%	30.19%	25.31%	22.74%

Table 1: Relative error on the test set for a CNN trained on single line inputs, a CNN trained on multi-line inputs, and a G-CNN trained on multi-line inputs.

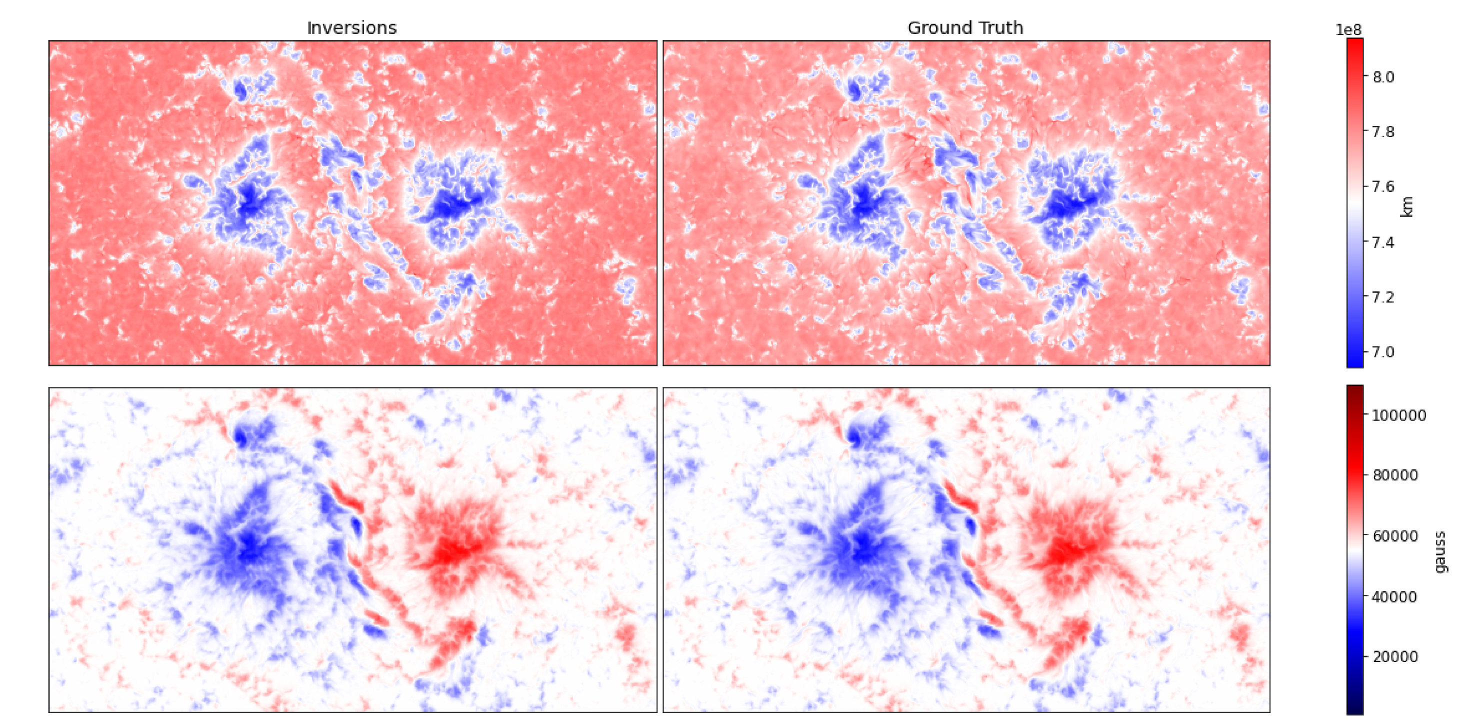

Figure 5: Stokes inversions for the active region using a G-CNN (left) vs. ground truth (right) on the test set. Here, we show surface height and magnetic field V.

Contributions

- Once training is complete, deep learning inference is orders of magnitude faster than traditional inversion algorithms
- Multi-line inputs improve performance by 7%, and the use of G-CNNs further improves performance by 13%
- These insights will be leveraged in future works using large-scale MHD simulations currently being run at NCAR

References

[1] Cheung, M. C. M., M. Rempel, and M. Schüssler. 'Simulation of the formation of a solar active region.' The Astrophysical Journal 720.1 (2010): 233.

[2] Rempel, Matthias. 'Numerical sunspot models: robustness of photospheric velocity and magnetic field structure.' The Astrophysical Journal 750.1 (2012): 62.

[3] Ramos, A. Asensio, and CJ Díaz Baso. 'Stokes inversion based on convolutional neural networks.' Astronomy & Astrophysics 626 (2019): A102.

[4] Cohen, Taco, and Max Welling. 'Group equivariant convolutional networks.' International conference on machine learning. PMLR, 2016.