Using Convolutional Neural Networks for Spectropolarimetric Inversions

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1. Introduction

The ability to perform spectropolarimetric inversions in heliophysics is invaluable to our understanding of the solar atmosphere. Although we cannot directly measure physical properties of the solar atmosphere, we can infer temperatures, velocities, and magnetic fields from the shapes of observed spectral lines. However, codes that perform these inversions remain computationally intensive and are orders of magnitude slower than the retrieval of the spectral scans.[1] Our project explores the use of convolutional neural networks (CNNs) to perform such inversions in a fraction of the time, while still remaining reliable and accurate.

2. Training & Architecture

We trained the CNN using an archive of 200,000 atmospheres created by introducing random perturbations to the semi-empirical FAL-C model of the solar atmosphere. Each atmosphere contained 58 points, 56 representing temperature, one for bulk line of sight velocity (V_{LOS}), and one for microturbulent velocity ($V_{\mu t}$). From this archive we calculated spectra of the Ca II 8542 line, frequently used for chromospheric diagnostics. We then trained the network to map an input spectrum to the appropriate atmosphere.

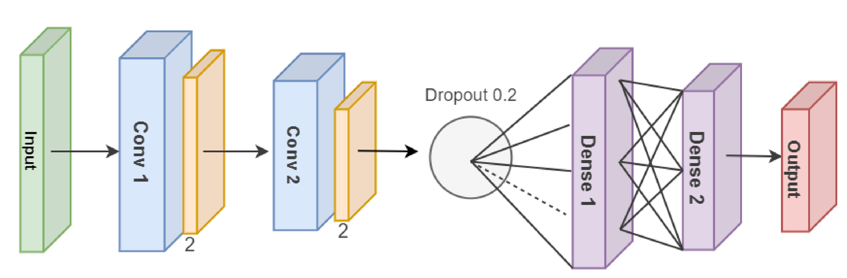


Fig. 1: The network architecture with which we found the best results. The blue layers represent convolutional layers, where each is followed by an orange max pooling layer of size 2. These layers were then followed by data regularization with a dropout of 0.2, then two densely connected layers colored purple.

3. Validation Results

- Comparisons between the predicted and validation values show that the network is able to accurately make these inferences, with the correlation between the two yielding >90% for all but the upper most atmosphere.
- The areas where the atmosphere does not correlate well demonstrate where our line, CA II 8542, is not sensitive to these parameters.

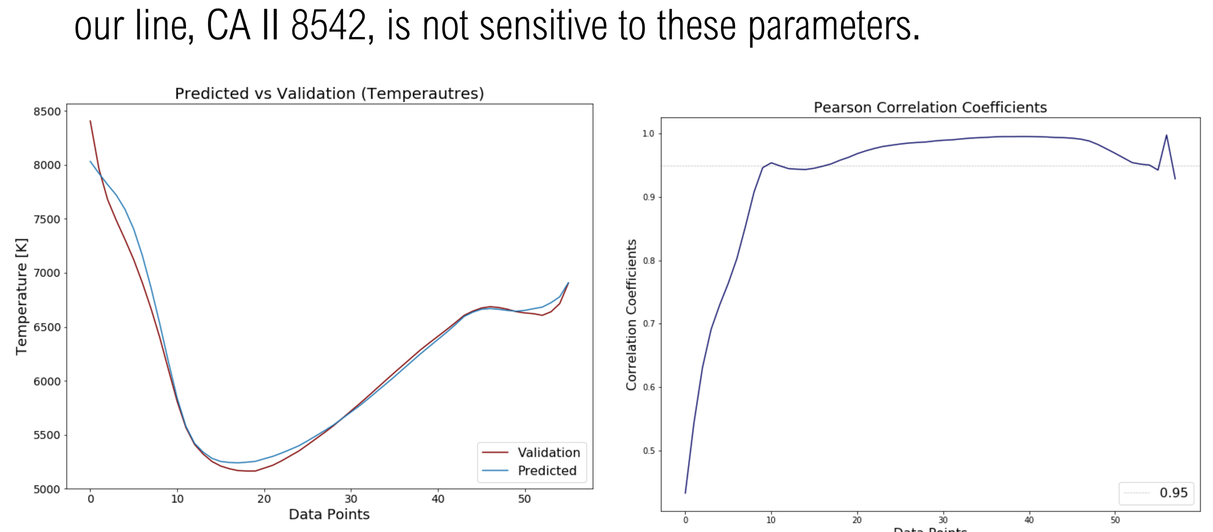
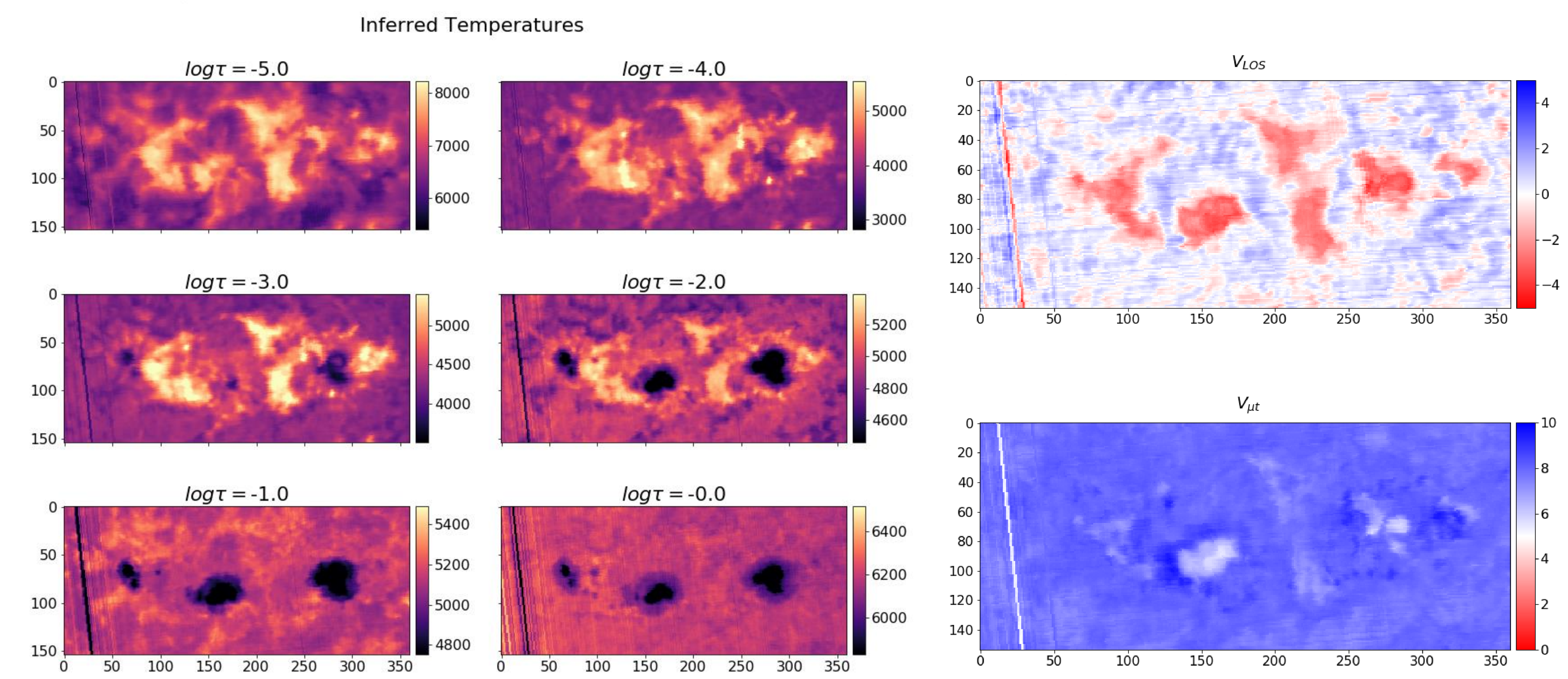


Fig. 2: Graphs of a comparison between normalized predicted and validation temperatures, and the Pearson correlation coefficients at each point of the validation data.



4. Application to SOLIS Data

- To apply our network to SOLIS data[2], we first had to interpolate our training spectra to match the wavelength grid of SOLIS.
- Our training data contains 1001 wavelength points whereas SOLIS data contains only 100.
- Once trained, the inversion of the complete map (55,440 spectra) took between 2-4 seconds, or on the order of 10^{-5} seconds/spectrum.*

Fig. 3: Temperature, bulk line of sight velocity (V_{LOS}), and microturbulent velocity ($V_{\mu t}$) maps resulting from the inversion of 55,440 spectral lines. Temperatures are measured in Kelvin and velocities are measured in kilometers/second.

*Tested using an i7-8550U 4 core processor with 16GB of DDR4 memory.

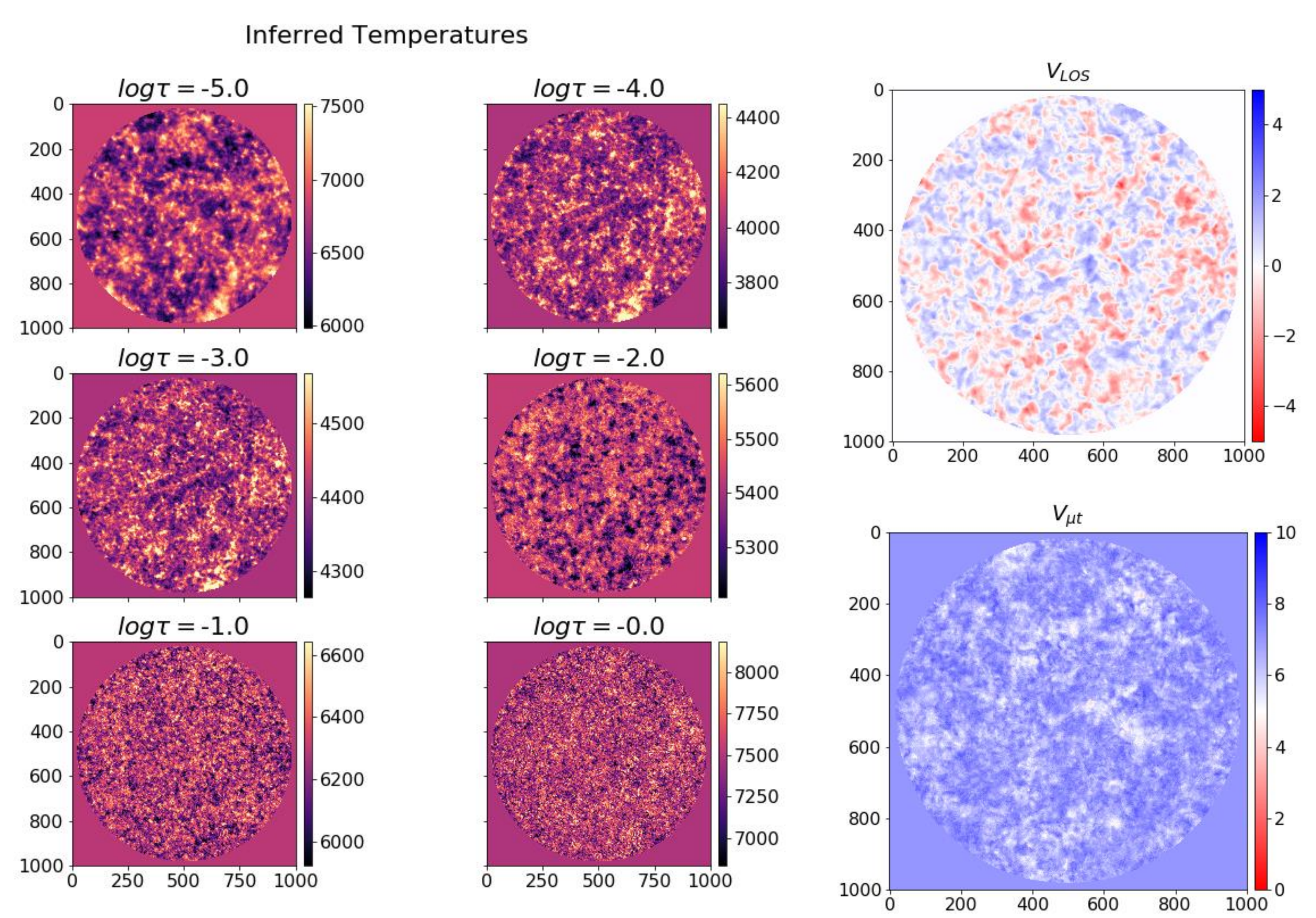


Fig. 5: Temperature, bulk line of sight velocity (V_{LOS}), and microturbulent velocity ($V_{\mu t}$) maps resulting from the inversion of 1,000,000 spectral lines. Temperatures are measured in Kelvin and velocities are measured in kilometers/second.

5. Application to IBIS Data

- Since IBIS data[1] (30 points) has even less wavelength points than SOLIS (100 points), it was necessary for us to simplify the architecture of our network.

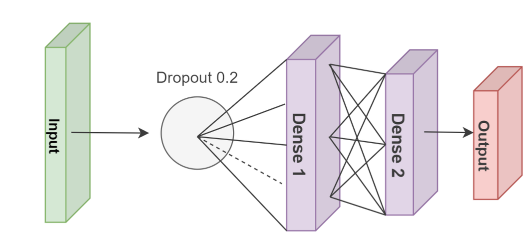
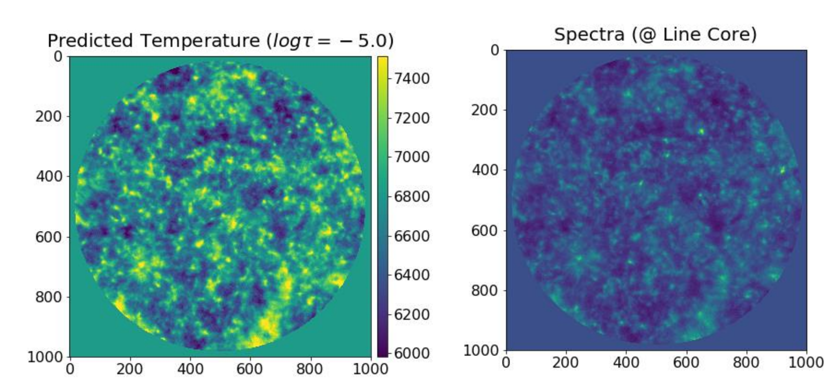


Fig.4: This network utilizes data regularization with dropout of 0.2, and maintains two densely connected layers, shown in purple in the diagram above.

- Once trained, the inversion of the complete map (1,000,000 spectra) took between 25-35 seconds, or on the order of 10^{-5} seconds/spectrum.*
- The maps of the deeper layers become dominated by noise in the data, with no visible structures from the upper layers present.

Fig. 6: The map of the predicted temperatures and the map of the spectral lines at the line core show similar structures. This serves as a rudimentary test to show that our network is performing as expected.[3]



*Tested using an i7-8550U 4 core processor with 16GB of DDR4 memory.

6. Conclusions & Future Work

Using CNNs, we were able to significantly reduce the amount of time and computational power required to invert a full spectral scan. Inversions of individual spectra through these networks take on the order of 10^{-5} seconds/spectrum while only using modest hardware.

Moving forward, we are looking to extend this network to perform magnetic field diagnostics from full Stokes observations. We would also like to explore the possibility of using a Boltzmann machine network to eliminate the need for interpolation to different wavelength grids.

7. References & Acknowledgements

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[1] Beck, C., Gosain, S., & Kiessner, C. (2019). Fast Inversion of Solar Ca ii Spectra in Non-local Thermodynamic Equilibrium. The Astrophysical Journal, 878(1), 60. doi:10.3847/1538-4357/ab1d4c

[2] Data were acquired by SOLIS instruments operated by NISP/NSO/AURA/NSF.

[3] Beck, C. (2019, July 24). Personal interview.