Using Convolutional Neural Networks for Spectropolarimetric Inversions

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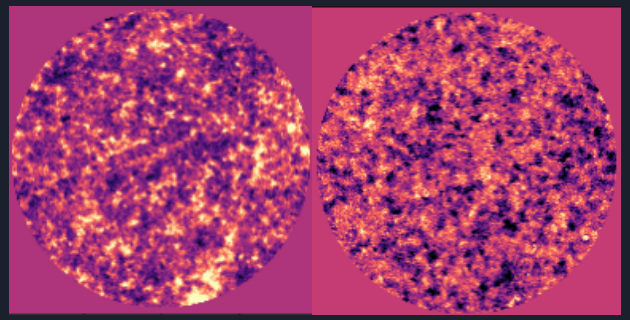
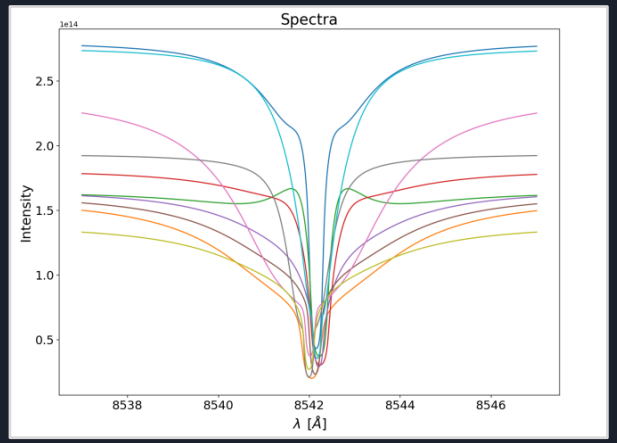
Background: Inversions

- We can't directly measure physical parameters of plasma in the solar atmosphere (temperature, velocities, magnetic fields, etc.)
- We *can* directly observe spectra lines
- Inversions take more time to compute than it does to receive new data [1]
- Machine learning hopes to bridge this gap



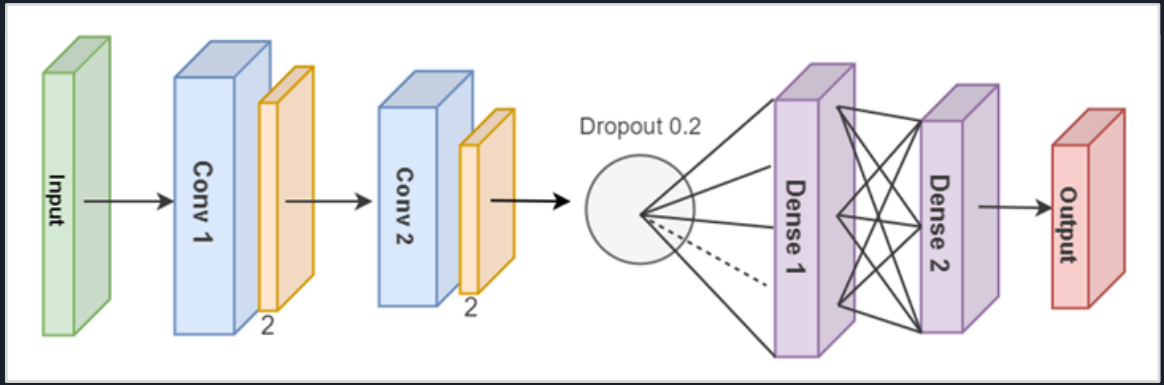


Background: Machine Learning & CNNs

- Convolutional Layers
  - Feature extraction
- Max Pooling
  - Reduces dimensions of data/down samples
- Dropout
  - Sets percentage of inputs to 0, which prevents overfitting data
- Densely Connected Layers/Dense Layers
  - Finds relationship between inputs and outputs

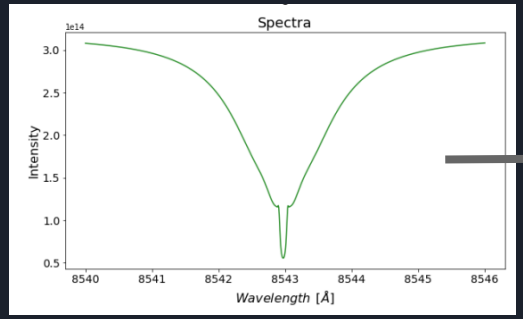
Main Architecture

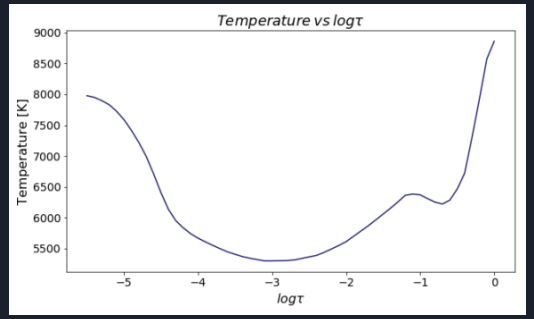
- Two convolutional layers, each with max pooling of size 2
- Dropout = 0.2
- Two densely connected layers

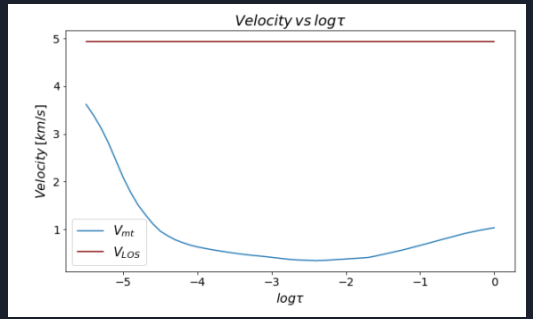


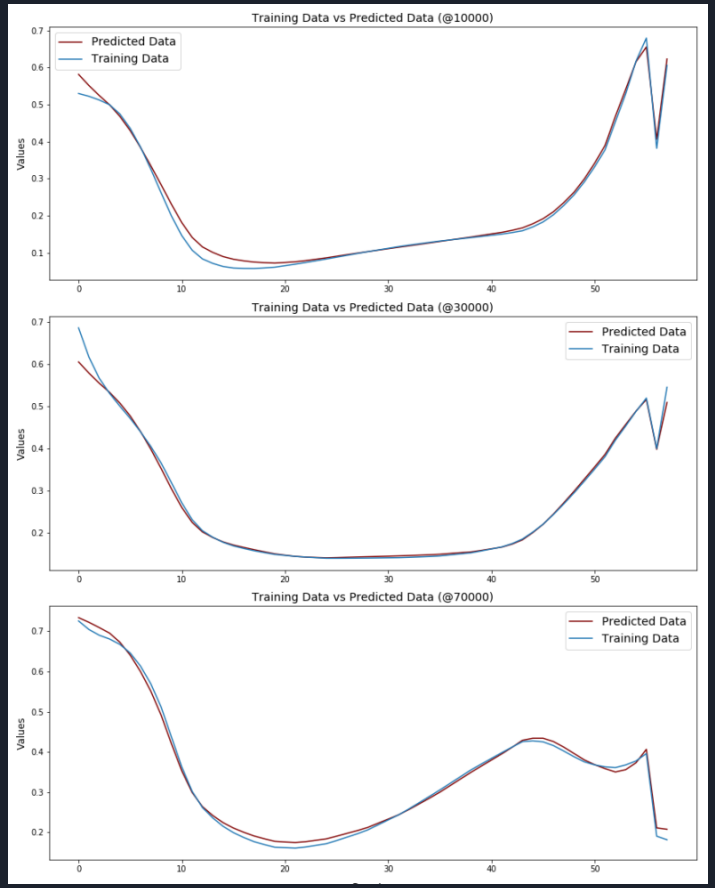
Training

- Training set of 200,000 atmospheres with reasonably randomized temperatures, line of sight velocities, and micro turbulent velocities
- Corresponding spectra for each atmosphere are then computed using a separate code
- 56 data points represent temperatures at different depths, one point for bulk line of sight velocity, and one point for micro turbulent velocity



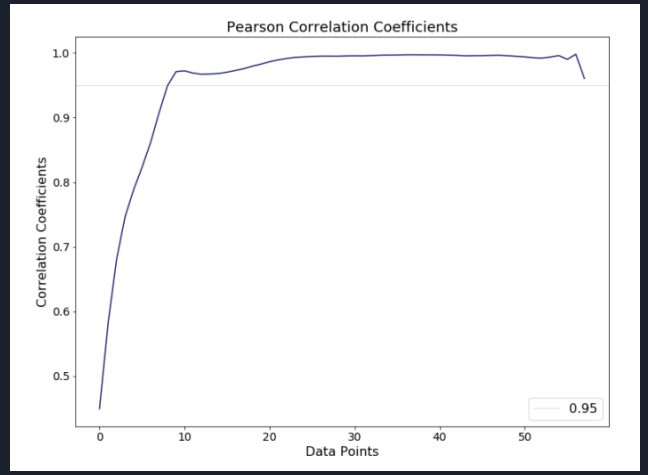




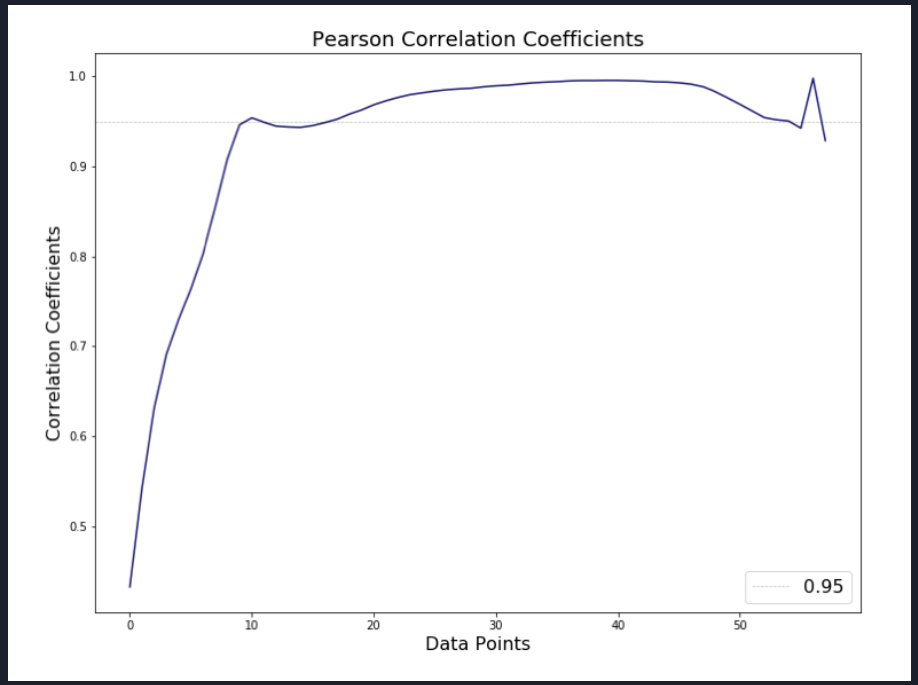


Training Results & Validation

- Trained for ~1 hour, validation errors on order of 10^{-4}
- Correlation coefficients above 0.95 for most of the data



Training Results & Validation

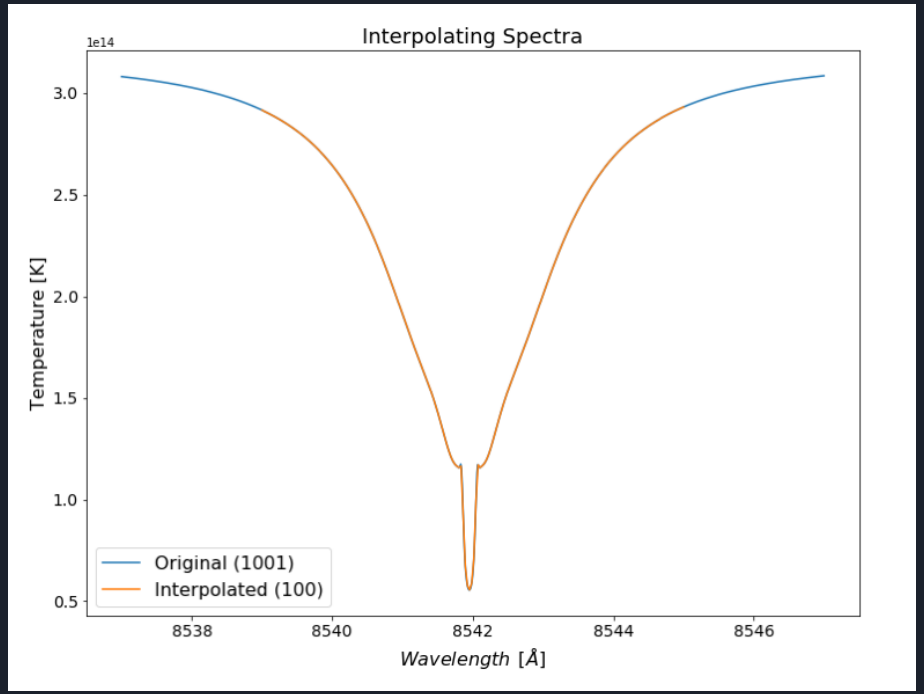


- Our algorithm has built in validation functions, however we created our own validation set
- 50,000 atmospheres and corresponding spectra created with the same methodology as the training data

Application to Observations

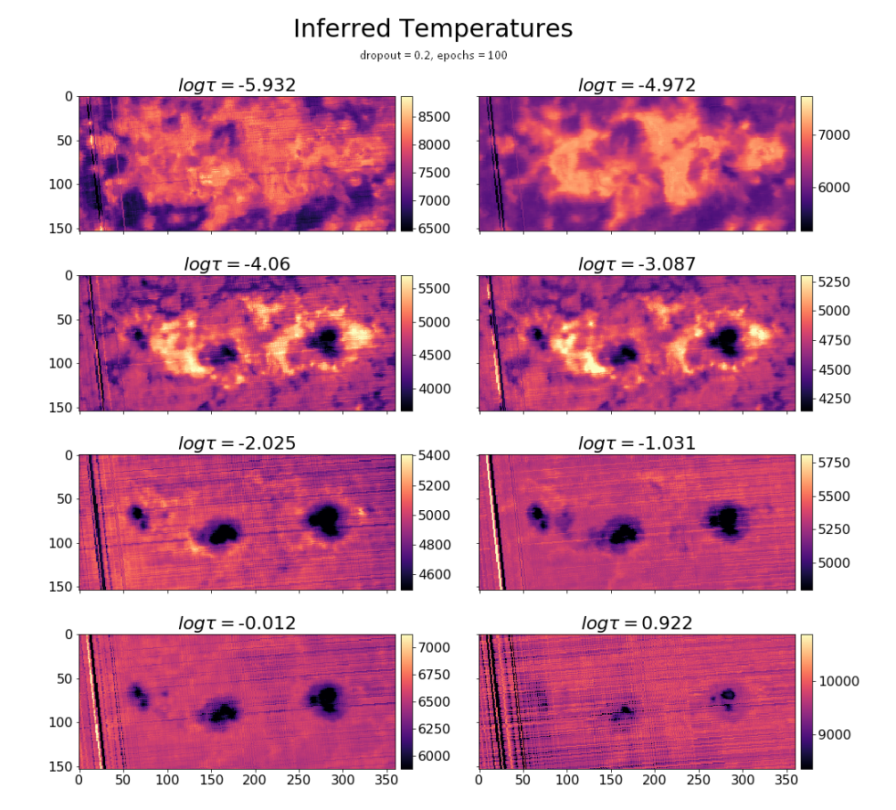
- Have to interpolate wavelength grid so training and observation data match

- Need to modify the training set to be more representative of conditions we observe on the Sun



SOLIS Data

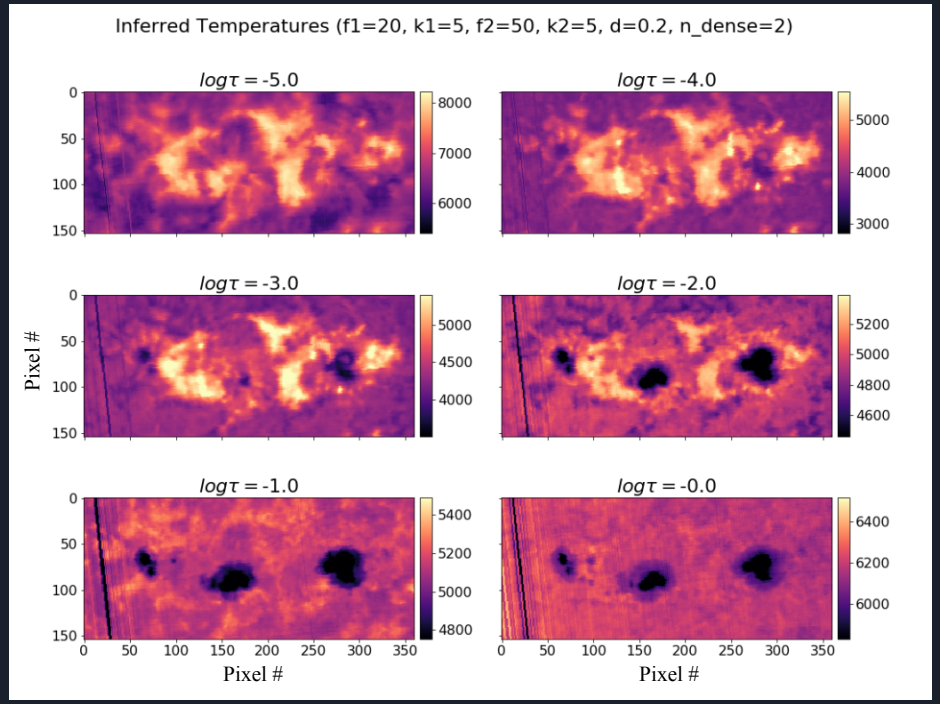
- Smaller wavelength grid than training (100 vs 1001)
- 2-4 seconds to invert 55,440 spectra
- We notice some horizontal artifacts in the deeper layers



SOLIS Data: Artifacts?

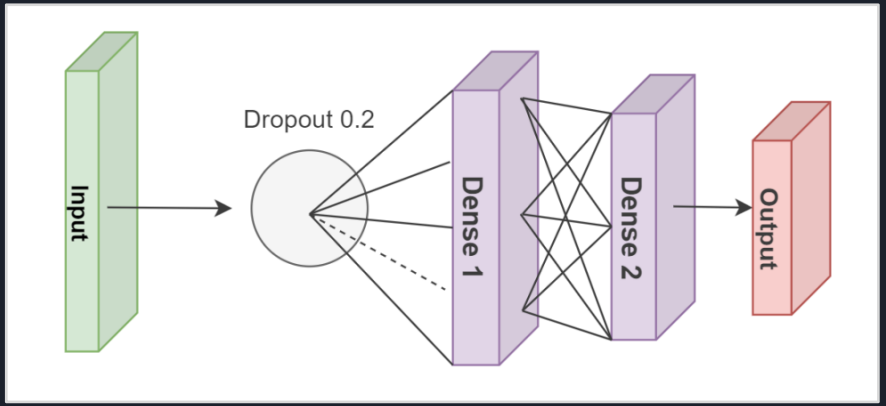
- Reduced the number of filters, convolutional layers, and dense layers

- Removed the top most and bottom most layers



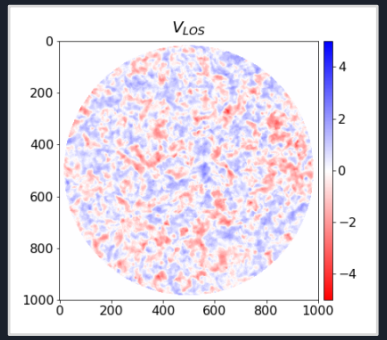
IBIS Data: Slight Change in Architecture

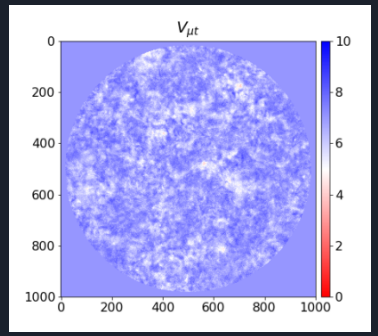
- Higher resolution than SOLIS
- IBIS spectra only have 30 wavelength points
- As a consequence, our network must be simplified

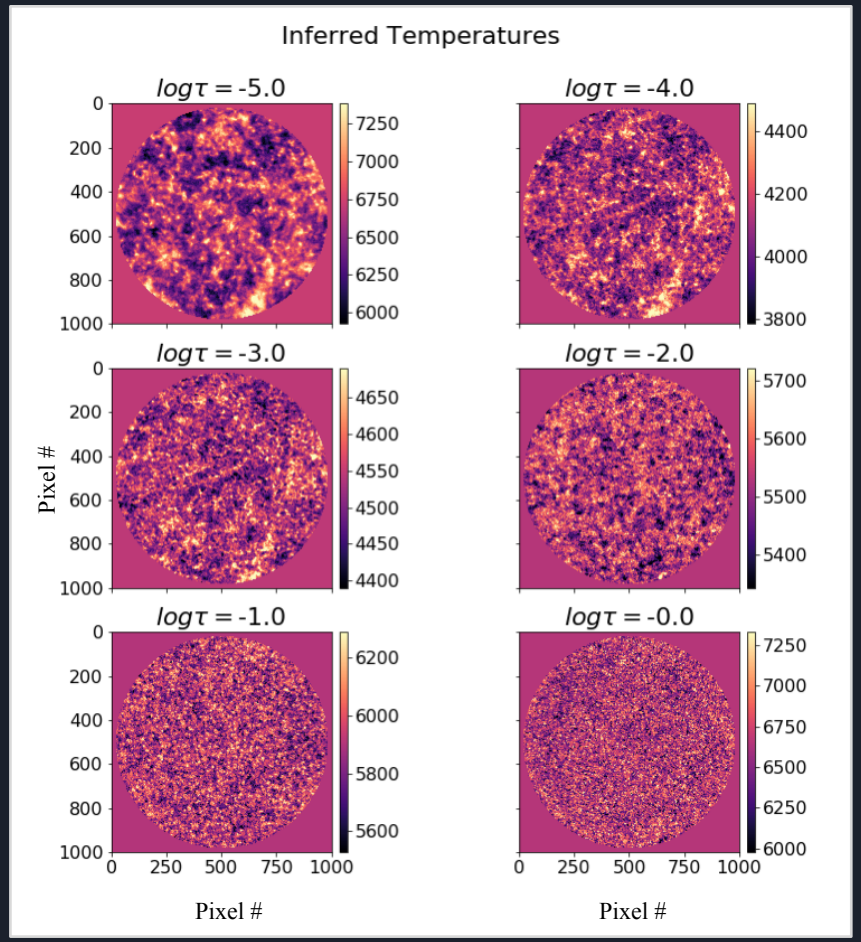


IBIS Data

- 25-30 seconds to invert 1,000,000 spectra
- Noise becomes dominant in the deeper layers

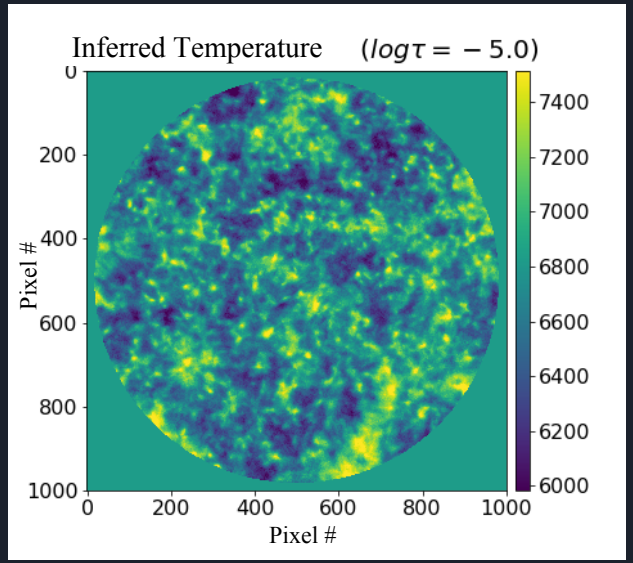


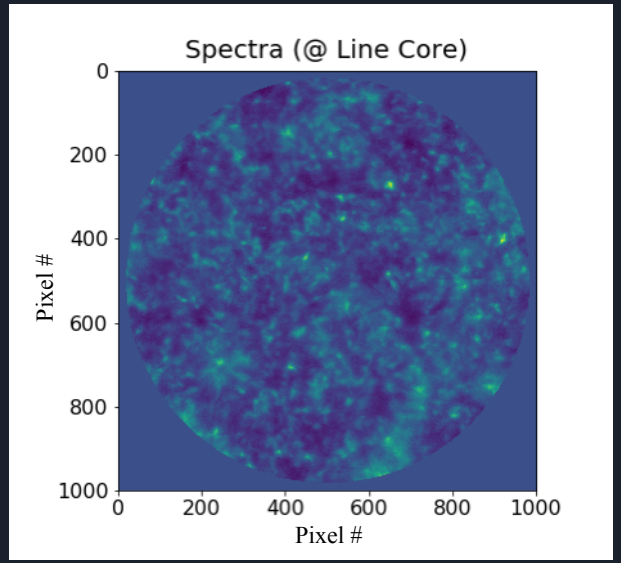




IBIS Data

- We can compare the structures found in the temperature maps to the spectra map as a quick test that our neural network is on the right track [2]





Moving Forward

- Expand which parameters we look at
  - Magnetic fields, full Stokes profiles
- Further optimize the network
  - No cut and dry way to figure this out, trial and error
- Encoder-Decoder Networks
  - Minimizes number of parameters

References and Acknowledgments

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

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