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


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