Sparse Representation of HINODE/SOT/SP Spectra Using Convolutional Neural Networks

Serena Flint[1], Ivan Milic[2,3]
[1]University of Rochester, [2]LASP, [3]NSO
serena.flint (at) rochester.edu

Introduction

A fundamental problem in solar spectropolarimetry is relating observed spectra and their polarization to the physical parameters of the underlying atmosphere. One of the difficulties in this process is the fact that the spectra usually can be represented with a much smaller number of hyperparameters than what is suggested by the number of wavelength points used for sampling (e.g. [1]). Said differently, spectra can usually be compressed or described in a sparser basis. In this work, we use the neural networks to investigate the dimensionality of photospheric spectra**, and to compare the compressed spectra with the maps of physical parameters used to generate the said spectra.**

Spectra Compression and CNN training

We train our network on a set of 80000 atmospheres generated by applying random perturbations to a simulated 3D atmosphere. We calculated the spectra of neutral iron lines at 6300 angstrom. These are the lines observed by the HINODE spectropolarimeter and are commonly used to diagnose photospheric temperatures, velocities, and magnetic fields. We spectrally smeared the spectra and added Gaussian noise, to mimic instrumental effects. We then devised an **encoder-decoder** neural network to compress this data. The network takes spectra as the input and should, in principle, output the same spectra. The layer of smallest width (**dense 3 in Fig 1**) represents the “most sparse” or “most compressed” version of our spectra.

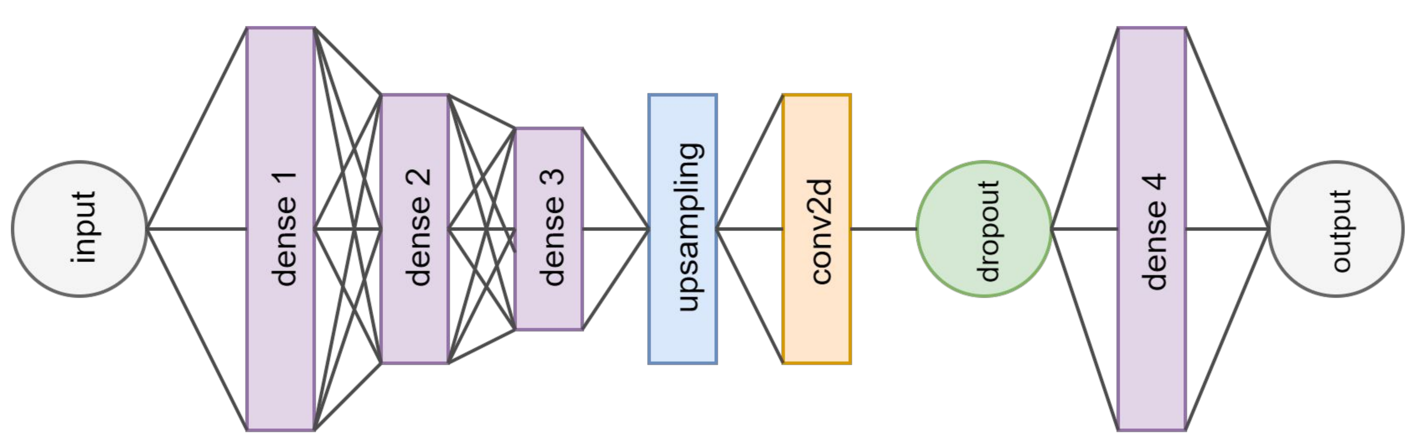
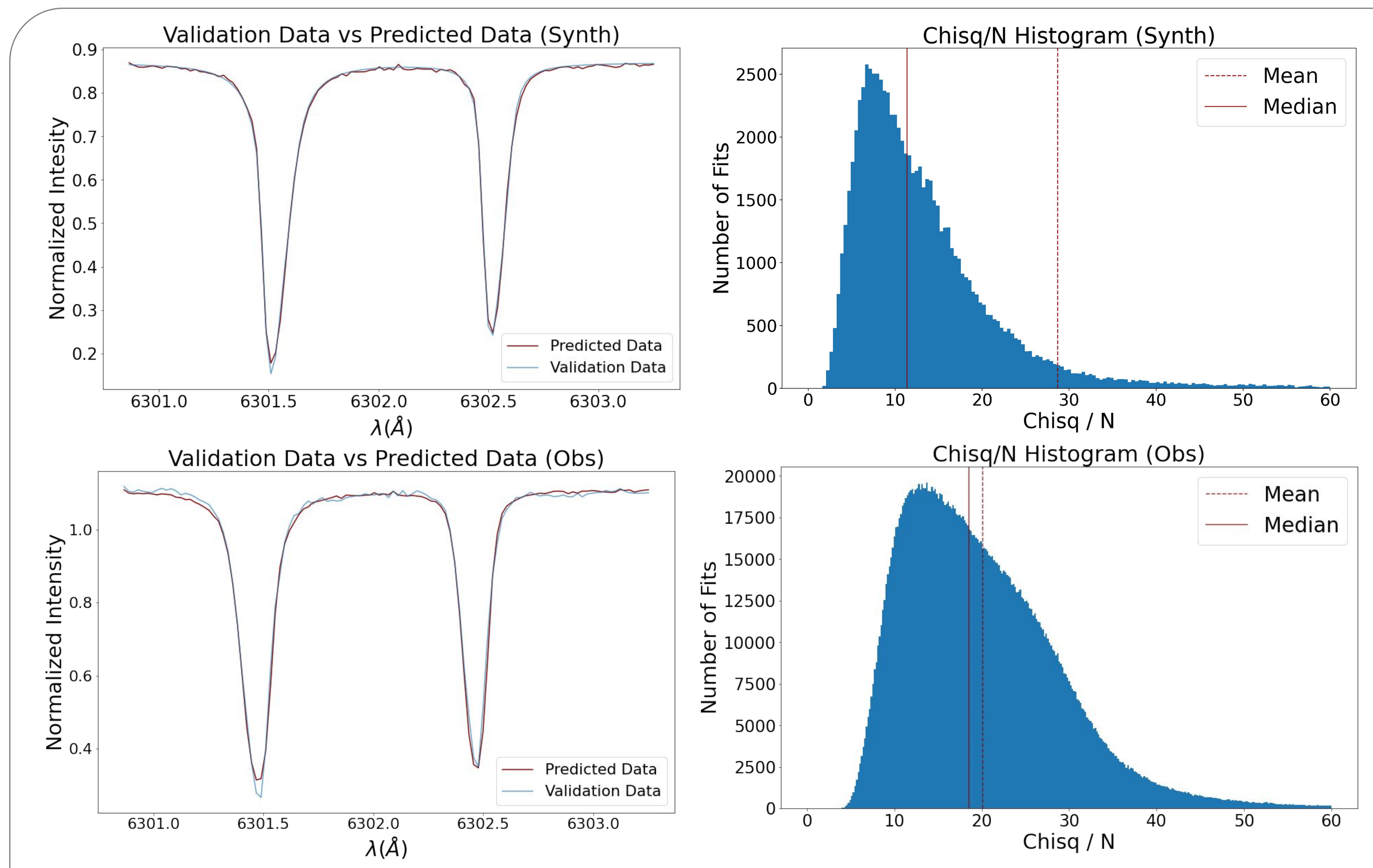


Figure 1: Architecture of the encoder-decoder neural network used in this work.

All training was done in Keras [2] using default MSQE loss, and the built-in ADAM optimizer. The network was trained through 1000 epochs for all trials, and each took on average 30-45 minutes. Training was done on a machine with enthusiast hardware, including an i7-10700k CPU at 4.7Ghz, 32GB DDR4 RAM, and an SSD. Since the code was set up to utilize only a CPU, it’s reasonable to assume that training speeds could be improved by reconfiguring it to utilize a recent-generation GPU instead.



Application to simulated and real data

We test the performance of our network by applying it to the spectra calculated from a state-of-the-art MHD photospheric simulation as well as to a spectropolarimetric map of the quiet Sun observed by HINODE/SP. **We find the optimal compression for network with “bottleneck” of 7. This means that the spectra is compressed to 7 numbers, down from 112 wavelength points.** We assess the quality of the compression by calculating the chi-squared metric between the original spectra and the one obtained from the sparse representation. **Average agreement between the original and compressed spectra is of the order of 1%.**

Figure 2: Example comparison of the original and compressed spectra (left) and histograms of chi-squared values between the original and compressed spectra (right). Up: simulated data; Down: observed HINODE data.

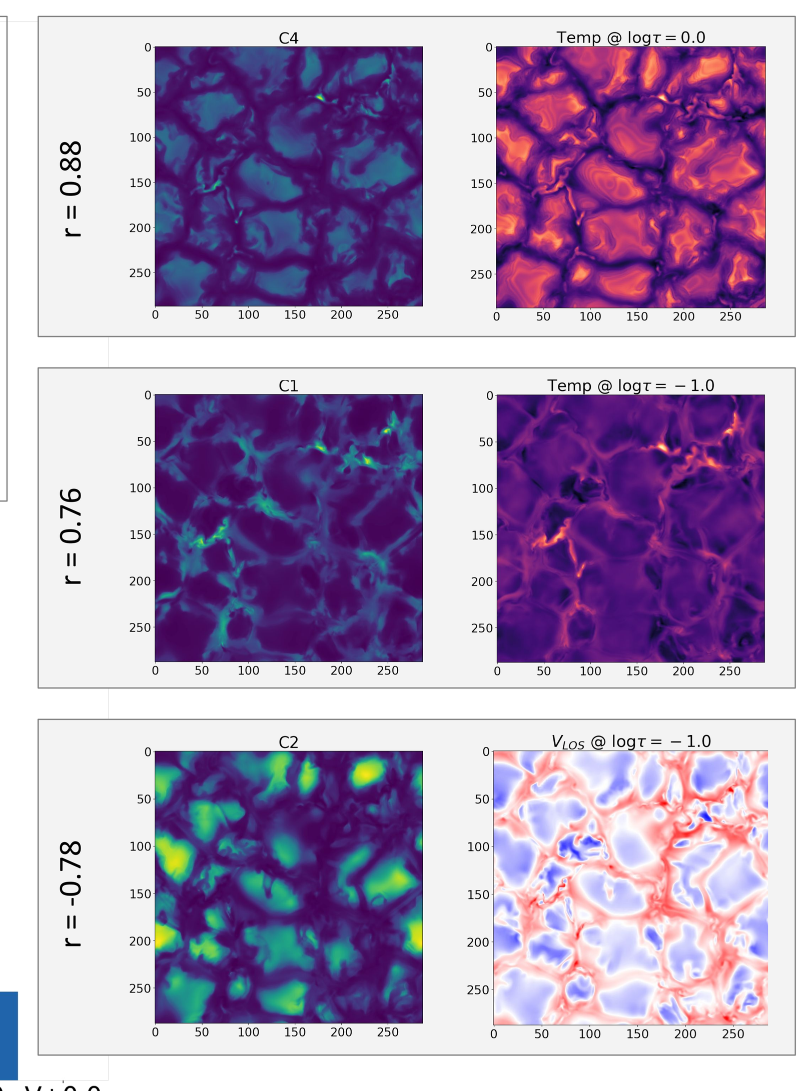
Correlations between compressed spectra and physical parameters

After applying the encoder part of the network to the data, we end up with the spectra compressed down to 7 hyperparameters. The maps of the hyperparameters from the synthetic spectra can be compared to the maps of the physical parameters at depths relevant to the line formation. We calculated correlation coefficients between the maps of sparse parameters and the maps of temperature and velocity at log optical depths -2, -1, and 0.

Figure 3: Left: Correlation between the maps of hyperparameters (C0-C6), the maps of temperature (T-2.0, T-1.0,T+0.0), and the line-of-sight velocity (V-2.0, V-1.0, V+0.0). Right: Examples of some highly correlated maps.

	C0	C1	C2	C4	C5	C6	T-2.0	T-1.0	T+0.0	V-2.0	V-1.0	V+0.0
C0												
C1	0.17											
C2	-0.56	-0.58										
C4	-0.77	-0.39	0.71									
C5	0.32	0.3	-0.47	-0.37								
C6	0.31	0.55	-0.42	-0.6	-0.022							
T-2.0	0.062	0.77	-0.54	-0.31	0.13	0.57						
T-1.0	-0.15	0.76	-0.28	-0.0034	0.27	0.29	0.63					
T+0.0	-0.78	-0.5	0.77	0.88	-0.36	-0.59	-0.41	-0.17				
V-2.0	0.21	0.45	-0.62	-0.31	0.18	0.17	0.55	0.33	-0.38			
V-1.0	0.46	0.62	-0.78	-0.56	0.52	0.33	0.55	0.53	-0.7	0.65		
V+0.0	0.57	0.59	-0.65	-0.67	0.49	0.47	0.41	0.37	-0.78	0.37	0.72	

It seems that the compressed spectra correspond very well to specific physical parameters. Perhaps the network can extract the physical parameters through compression?



Conclusions and future work

The logical next step in our research is to create a simple, but robust neural network that will match compressed spectra to atmospheric parameters and thus enable CNN-based inversion. We expect the main advantage of this inversion to be the capability to reproduce input spectra well (this is something CNN inversions are struggling with). Namely, the relationship between compressed spectra and the parameters should be very simple, and can be inverted.
Stay tuned!

References & Acknowledgements

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[1] Asensio Ramos, A.; Socas-Navarro, H.; López Ariste, A.; Martínez González, M. J.,; 2007, The Astrophysical Journal, Volume 660, Issue 2, pp. 1690-1699
[2] Chollet et al.; 2015, https://github.com/fchollet/keras