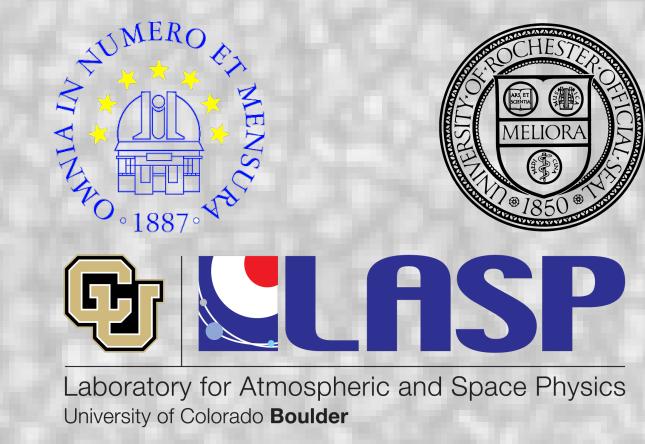
Sparse representation of HINODE SOT/SP Spectra using Autoencoders



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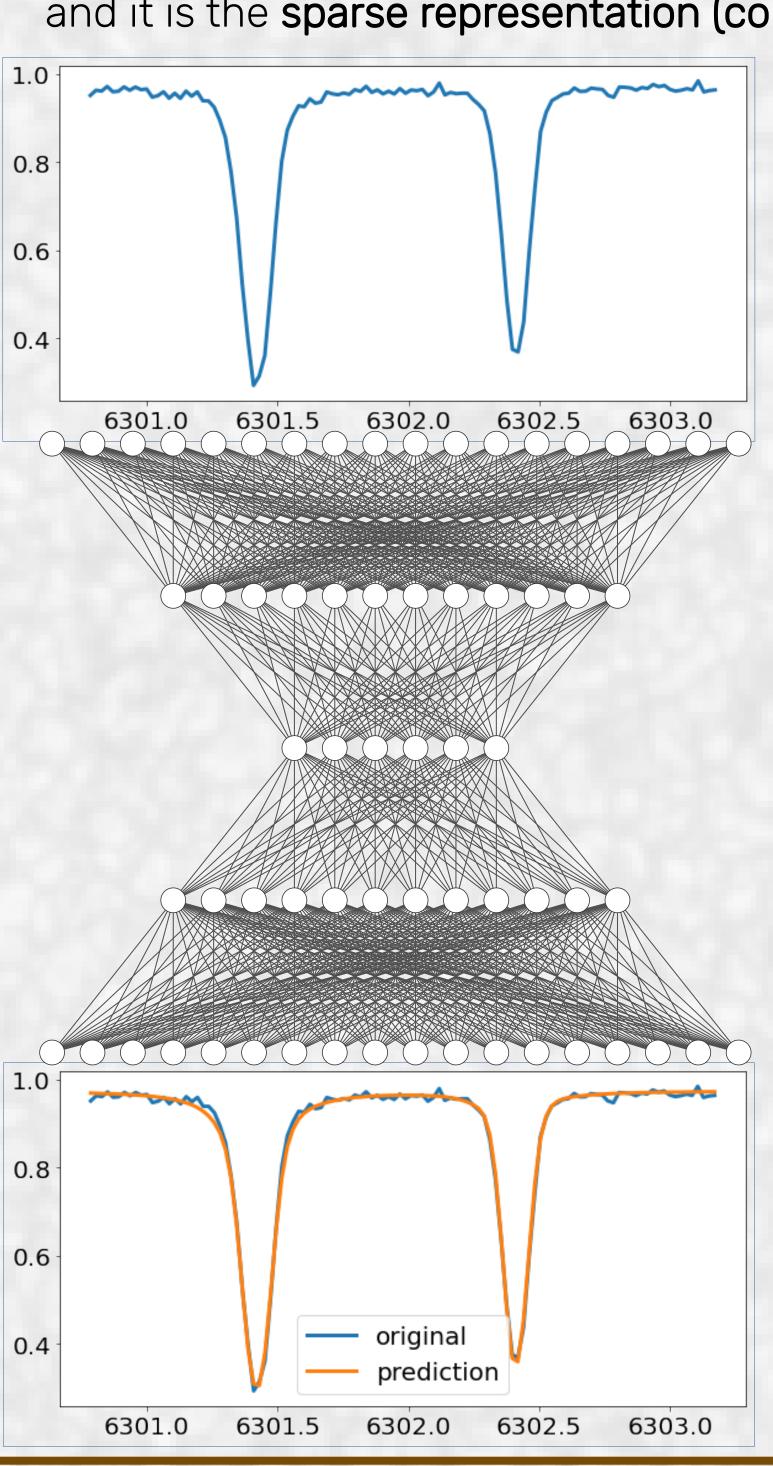
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Motivation

Spectropolarimetric inversions aim to infer depth-stratified atmospheres. Theoretically, these atmospheres have high depth resolution but our input does not carry sufficient information to reconstruct them. We parameterize them using **nodes**, but there is no robust methodology yet. Constraining the complexity of the output (atmospheres) to match the one of the input (spectra) might help design a more robust inversion.

Autoencoder (AE)

A neural network (NN) that successively decreases the dimension of the input (encoder), followed by the series of layers that increase the dimension of the data (decoder). The aim is to reproduce the input (output = input). The smallest dimension of the AE is called bottleneck and it is the sparse representation (compression) of our spectrum.



We use a simple, densely connected autoencoder to compress the data down to the given bottleneck. Optimal bottleneck is the one that reproduces the input data up to the assumed noise level. The network is trained on the data synthesized from a quiet Sun MuRAM simulation, spectrally degraded according to Hinode SOT/SP instrument specifications. For this set (Stokes I only), we found optimal bottleneck width to be 6. NN is verified on the unseen synthetic data synthesized and tested on another simulation (right) and the quiet Sun observations (below).

Fig. 1: Sketch of the autoencoder, with the example input spectrum and the output reconstruction. Note that layer dimensions are illustrative.

Compressing the observations

We used the quiet Sun Hinode scan from 10th of March 2007 to test our network (the NN is trained exclusively on the simulated data). We compare the compression between a validation (unseen, simulated dataset) and this test set.

- Simulations capture the properties of the observed spectra very well!
- Hopefully this means we can use the atmosphere compression to construct an inversion code that works in this compressed space.

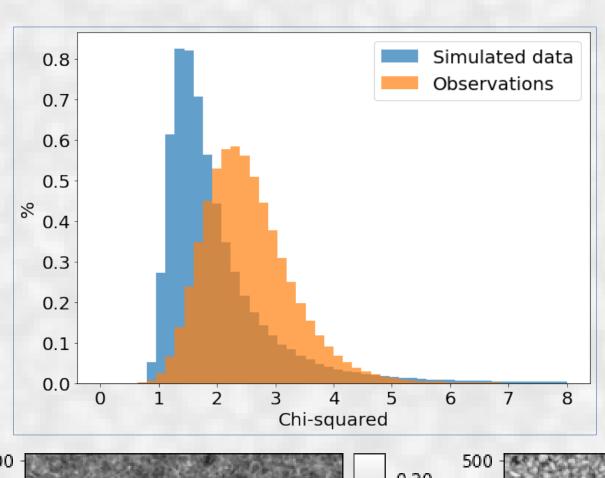
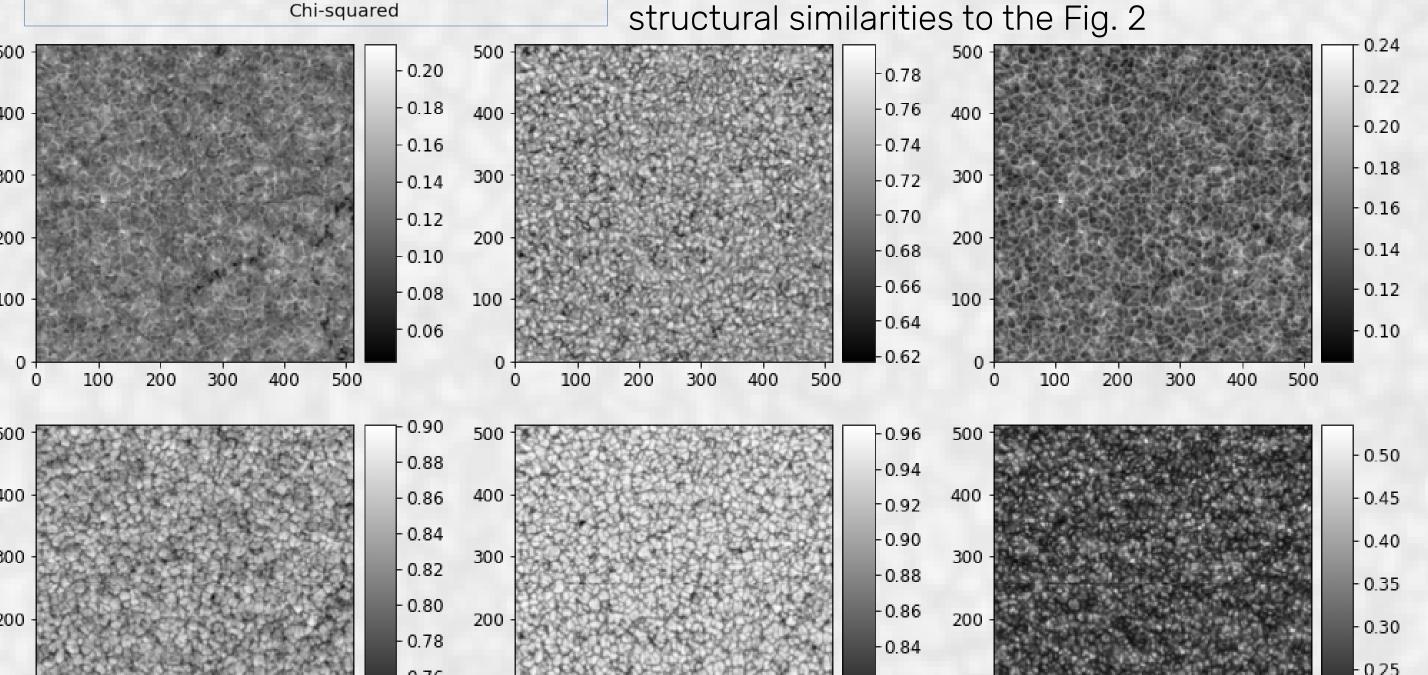


Fig. 3, Left: Distributions of the chi-squared values between the input and the output spectra, for the validation (simulated) and the test (observations) dataset.

Fig. 4, Below: maps of the compressed spectra for a sub-set of the observed QS map. Note the



Goals / questions

- Compress the spectra to latent (sparse) space. (AE)
- Do vectors in that space correspond to relevant physical parameters? (Yes, they seem to)
- Does this help us make NN more interpretable? (Hopefully!)
- Repeat for the atmospheres → Construct an inversion code (Soon!)

Structure of the latent space

We apply the AE to a set of synthetic observations (Fe I lines at 630 nm), to see if maps of compressed spectra have a meaningful structure.

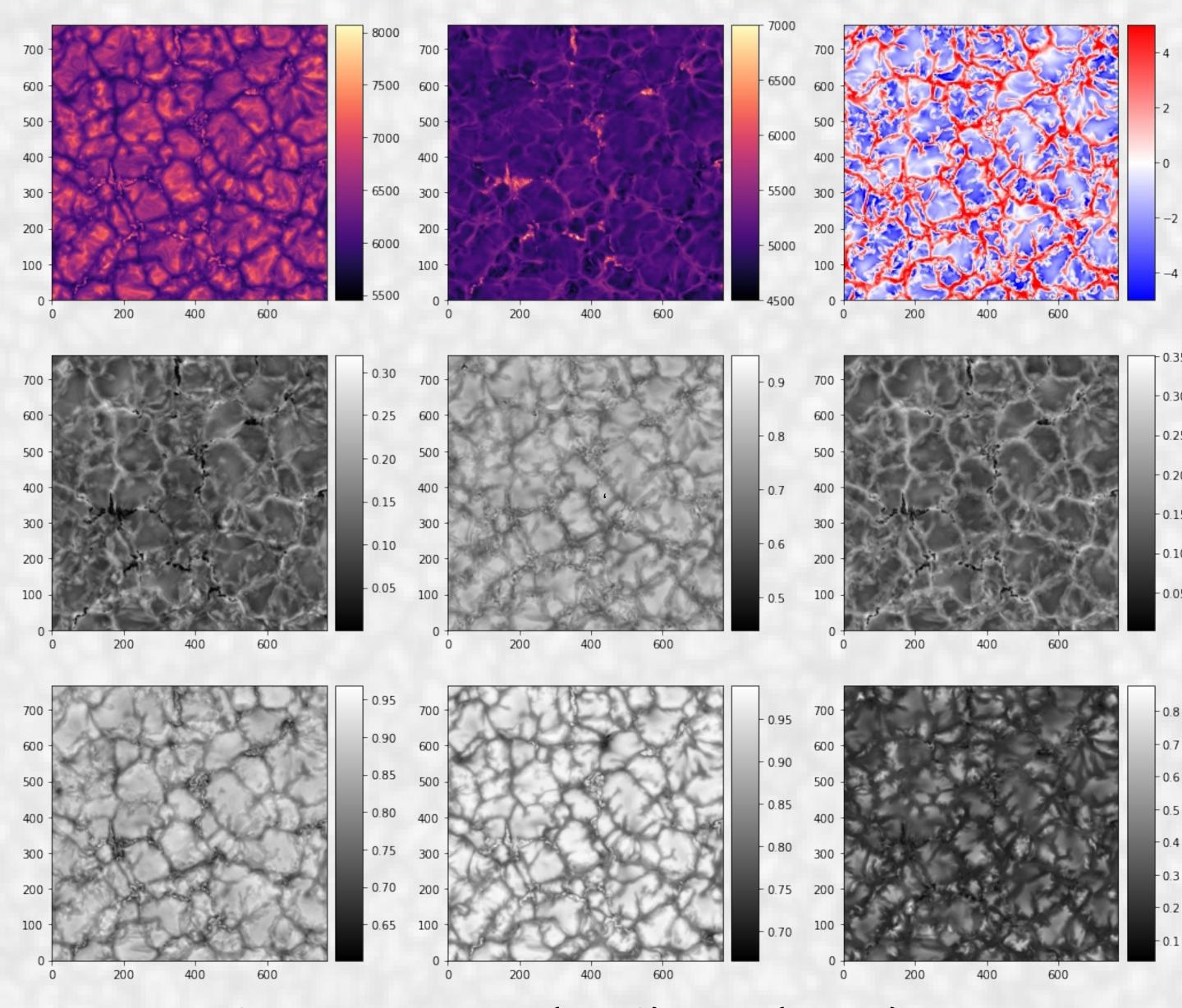
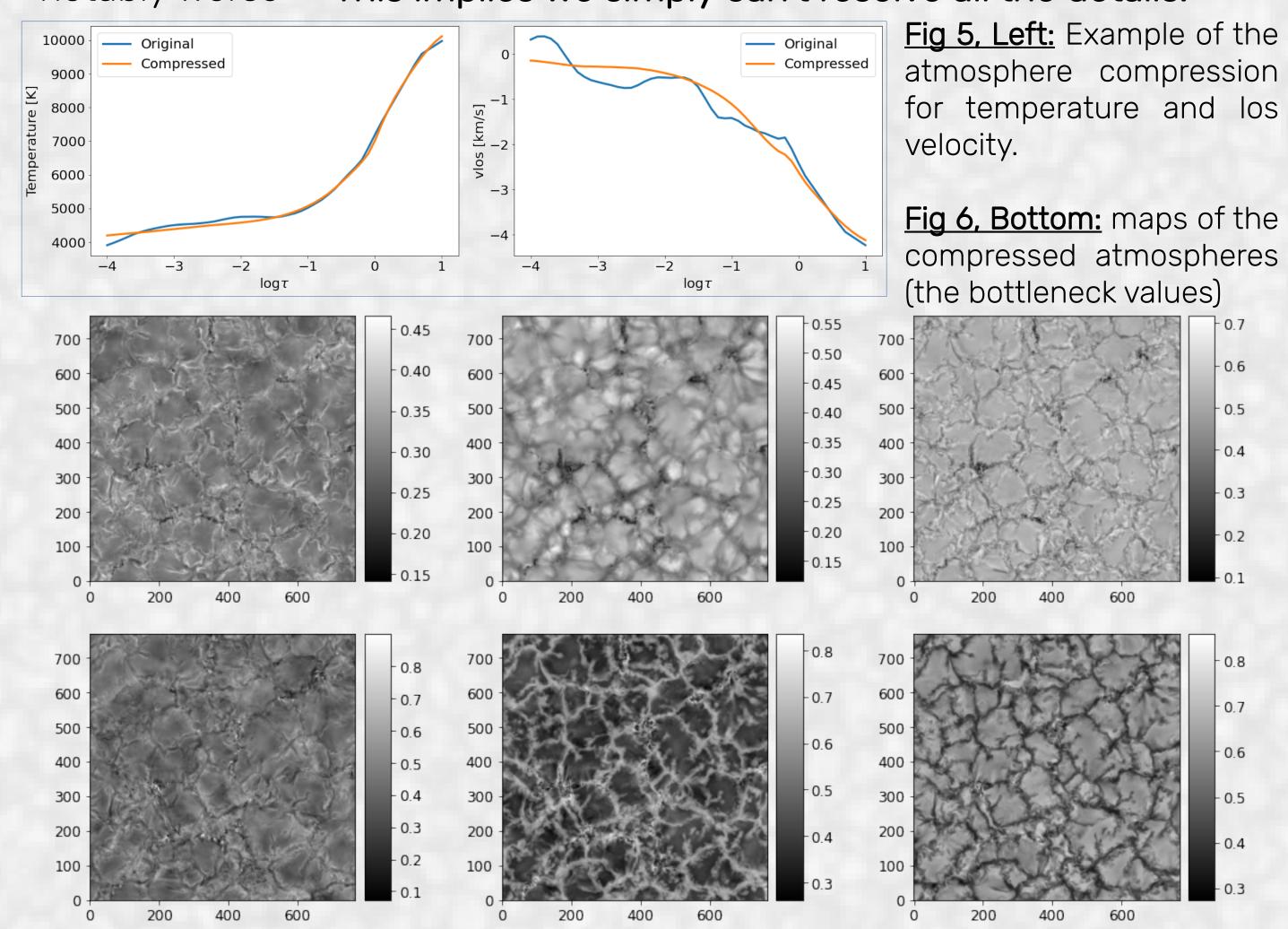


Fig. 2: Maps of temperature at log τ =0 (top left), log τ =-1(top mid), velocity at log τ =0 (top right), and the maps of compressed spectra (i.e. the six bottleneck values)

Compressing the atmospheres

Dimension estimated by the spectra compression implies the complexity of the atmospheres. We compress the simulated atmospheres using the same network architecture (but retrain the network). Compression is notably worse → This implies we simply can't resolve all the details!



Next steps

- Map compressed intensities to compressed atmospheres via simple invertible relationship
- Extend to full Stokes + Magnetic field
- Get a robust inversion code!
- All the codes, plots, and digital poster: github.com/ivanzmilic/spectrum_ae

Reach out with questions and suggestions!

