# Recovering Spectral Information with Deep Learning Techniques

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## The Problem: The Spectral PSF of our instruments alter the scientific conclusions drawn from our data

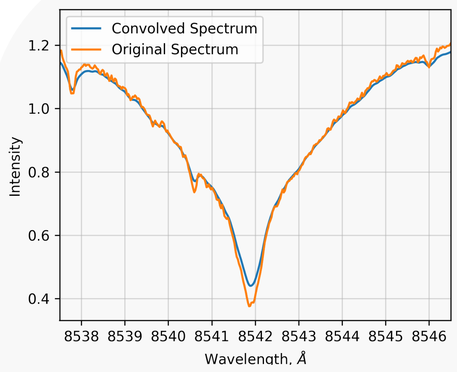
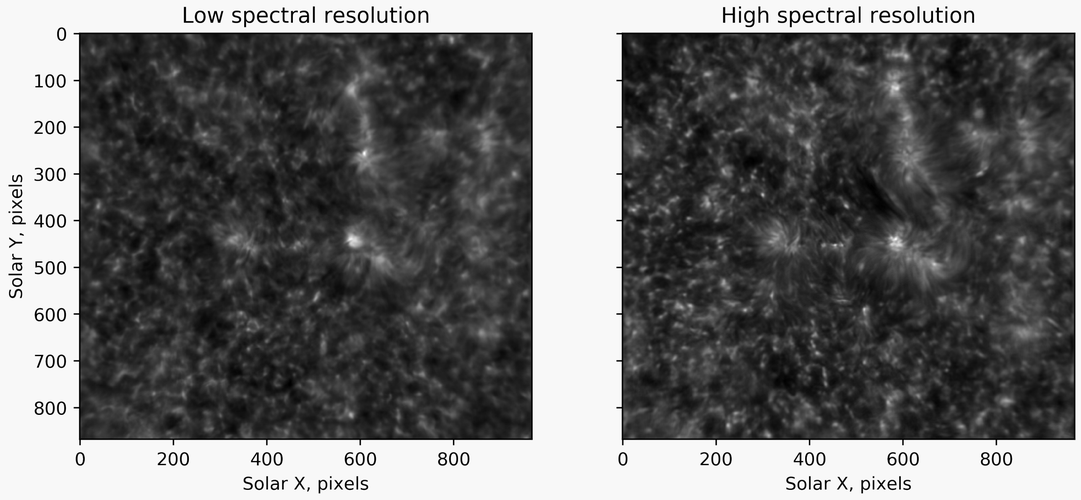



**Fig. 1** Convolving a spectral line with a wide SPSF makes it broader and makes the line core intensity higher.

The finite spectral resolution of real instruments affects the inferred signal by blending the intensity at different wavelengths. This phenomenon is particularly problematic for spectral lines, since the shapes of spectral lines encode essential information about the solar atmosphere. However, some instrument designers also seek to use lower spectral resolution to increase instrument throughput and reduce the sampling time. Since the use of a broad spectral PSF (SPSF) typically results in a multiplexed sampling of the line profile, it should be possible to recover much of the underlying spectral information. In this work, we seek to evaluate machine-learning techniques to retrieve high-resolution spectral profiles from instrumentally broadened spectral profiles.

The effect of spectral smearing is shown in Figure 1 with an example spectrum of Ca II 8542 Å from the FISS/BBSO[4] spectrograph. The blue line is the spectrum as observed with a spectral resolution of R ~ 150,000*, whereas the orange line shows the spectrum convolved with a spectral PSF with R ~ (30,000). The convolution with a broad SPFS increases the intensity of the line core and broadens the wings of the profile. This smearing tends to increase the similarity of all the spectral profiles, reducing the spatial contrast and the ability to identify small-scale structures at particular heights in the solar atmosphere. An example of this is presented below in Figure 2 with an observation from the IBIS[1] instrument at the DST in the core of the Ca II 8542 Å line.

*Spectral resolution (R) ≈ **λ** / FWHM(SPSF)



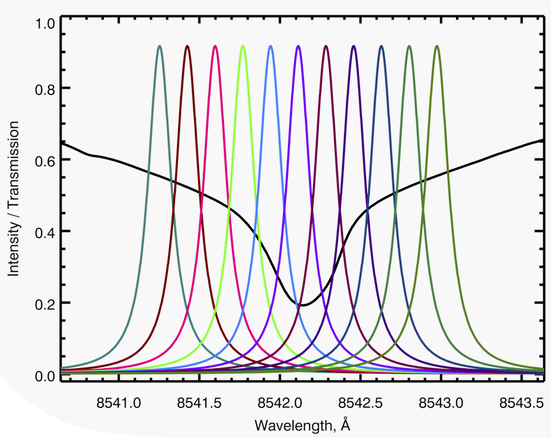




**Fig. 2** — Comparison of two images taken from IBIS with low (R~30,000) and high (R~200,000) spectral resolution in the core of the Ca II 8542 line. The different spectral resolutions were achieved with removing one of the Fabry-Perot etalons from the optical path.

**Fig. 3** — Transmission profile of first Fabry-Pérot etalon (FP 2) of the Interferometric BIdimensional Spectrograph (IBIS) at the Dunn Solar Telescope overlaid over the average spectrum of the Ca II 8542 Å line. The multiple peaks show different samplings of the line, which result in a smeared measured profile. In Results (1) we present a technique to remove this spectral smearing robustly using deep learning.. This is a similar SPSF to the one of the initial VTF[6] setup with a single FP etalon.

## The Solution: A Deep Learning Approach

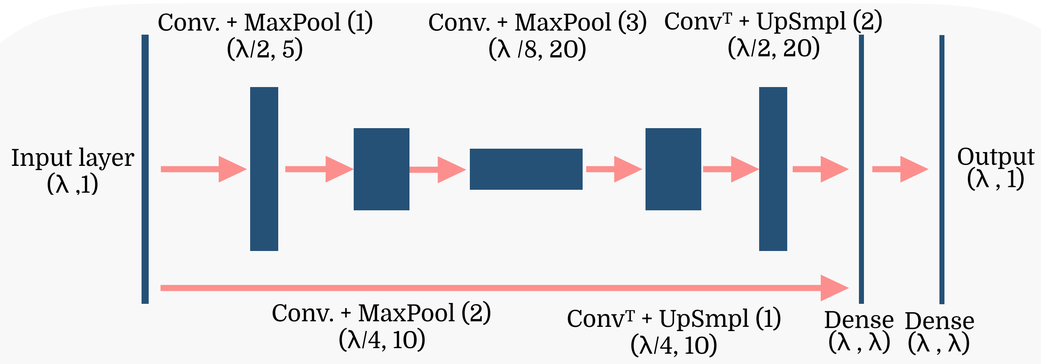



**Fig. 4** The encoder-decoder architecture of the Convolutional network used in our work. Its design is inspired by the successful application of this network design in [2].

We utilized deep Convolutional Neural Network (CNN) for the deconvolution process. We used an encoder-decoder architecture because it can extract the relevant features from noisy data (**encoder**) and then recreate the signal of interest from the latent space (**decoder**). Adding the input vector to the second to last dense layer of our network improved its performance, due to the reduced corrections the network had to introduce. However, this caused the core of the spectral lines to be poorly fit since the most significant corrections were needed there. To alleviate this issue we introduced a custom loss function which was a weighted mean square error. The weights were chosen such as to emphasize the core of the line predominantly (Fig. 5). We used Rectified Linear unit (ReLU) as an activation function in all layers beside the last one, where we used a linear activation function. We trained our network with the Adam optimizer[2] for about two thousand epochs before satisfactory convergence was achieved. The network was implemented and trained with Keras under Tensorflow. [3]

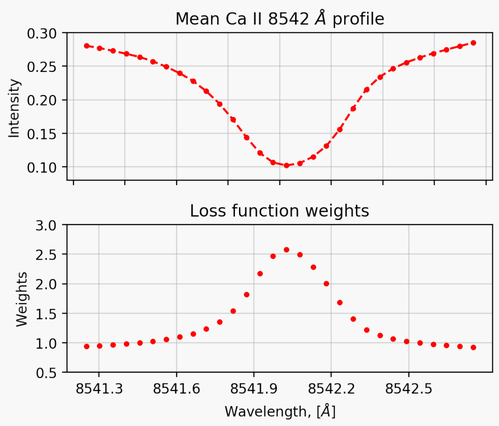



**Fig. 5** The custom loss function we used is a weighted least squares. In order to force the line core to be fit properly the the weights are proportional to the inverse of the mean line profile.

## Results (1): Deconvolving the Spectral PSF with DNNs

To test the CNN approach to SPSF deconvolution, we utilized Ca II 8542 Å data from the FISS/BBSO instrument (R~ 150,000) from June 22 2016. We created a training set by convolving each spectrum with the IBIS FP 2 (from Fig. 1) transmission profile with an effective R~30,000. Fig. 6 illustrates a sample profile from the FISS [4] instrument in blue and its convolution with the FP 2 profile in green.

The CNN was trained with this dataset which has dimensions of 100 x 250 spatial pixels. Satisfactory convergence was accomplished in about two thousand epochs — the relative RMS error at the last epoch of the training was about $1.5 \times 10^{-4}$. A sample input and inverted spectrum are shown in Fig. 6. The CNN's performance was tested on a different spectral scan and had similar RMS compared to the validation check. The CNN was able to recover the spectral line profiles for the validation set robustly. The recovered core intensity and flux absorbed are shown in figures 8 and 9.

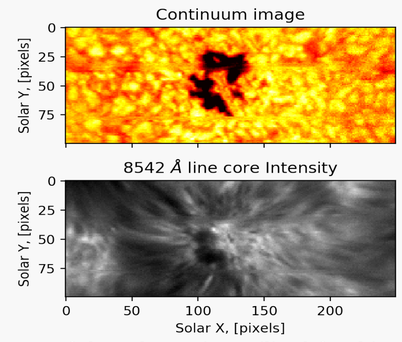



**Fig. 6** FOV of the solar region utilized for this work. The top panel shows a continuum image in the continuum, while the bottom panel shows line core intensity in Ca II 8542 Å.

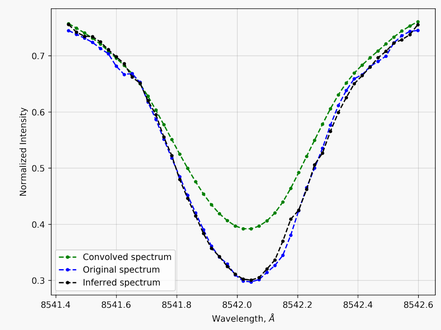



**Fig. 7** Sample spectrum from the FISS instrument at high spectral resolution (blue), degraded with a wide SPSF (green) and recovered by the CNN (in black).

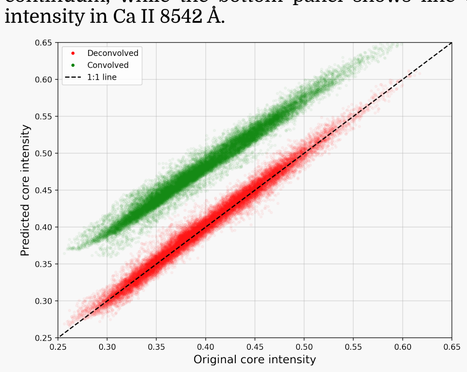



**Fig. 8** Line core intensity for the recovered FISS observations. The hi-res intensity is along the abscissa, the green dots are the line intensity of profiles convolved with wide PSF spectra; the recovered with the CNN intensities are in red. The black line represents the 1:1 relation.

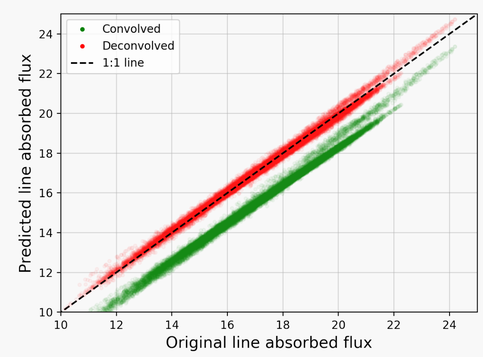



**Fig. 9** Same as Figure 8, but for the absorbed flux by the line — a proxy for the equivalent width of the line but just for its central (scanned) part. Again, the CNN is able to recover the original spectra property robustly.

## Results (2): Recovering spectral line profiles from undersampled observations convolved with IBIS FP 1 only

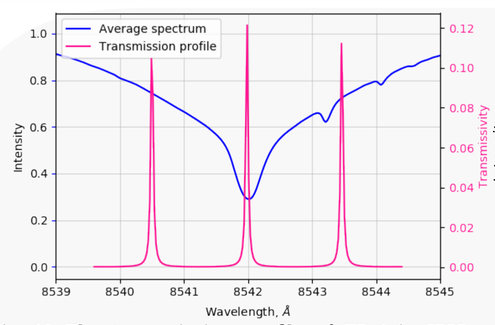



**Fig. 10** The transmission profile of FP 1 in IBIS illustrated in pink; the average Ca II 8542 Å profile shown in blue. The driver behind this part of the project is to show if we can recover the full profile of the spectral line with less measurements than with a narrowband transmission profile.

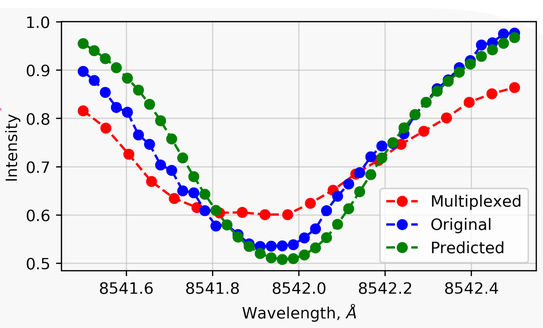



**Fig. 11** The result from utilizing the CNNs for recovering full spectral profiles multiplexed with multi-peaked transmission profiles is illustrated above. The CNNs were unable to reproduce the spectral profiles robustly as in Results (1). WHY?!

## Conclusions and future work

We have presented a novel way to perform spectral deconvolution of spectrograph data with deep learning. Our method is robust and reliable if we the PSF of the instrument is known a priori and we have a reliable training set. Furthermore, our method can deconvolve a single, 45-point spectrum in $1 \times 10^{-5}$ seconds on a CPU. Its speed makes this very effective for processing large numbers of spectra. Its performance can be further improved if the deconvolution is performed on batches of data on a GPU. With the next generation of solar instruments (such as the VTF[5] on the DKIST[6]) which will produce terabytes of spectral data per day the speed of the deconvolutional techniques will become increasingly important.

We tested an idea to recover the full spectral line profile if we observe it with a spectral transmission profile with multiple peaks, such as the FP1 transmission profile on the IBIS instruments. Our numerical experiments showed that there is not enough information if we multiplex the line like this to recover its full profile robustly with a CNN.

The code for this project is publicly available at the repository of the author: https://github.com/momomolnar/SPSF_remove or scan the QR code below.

## References

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