Stockholms universitet

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Solar image Denoising
with Convolutional Neural Networks

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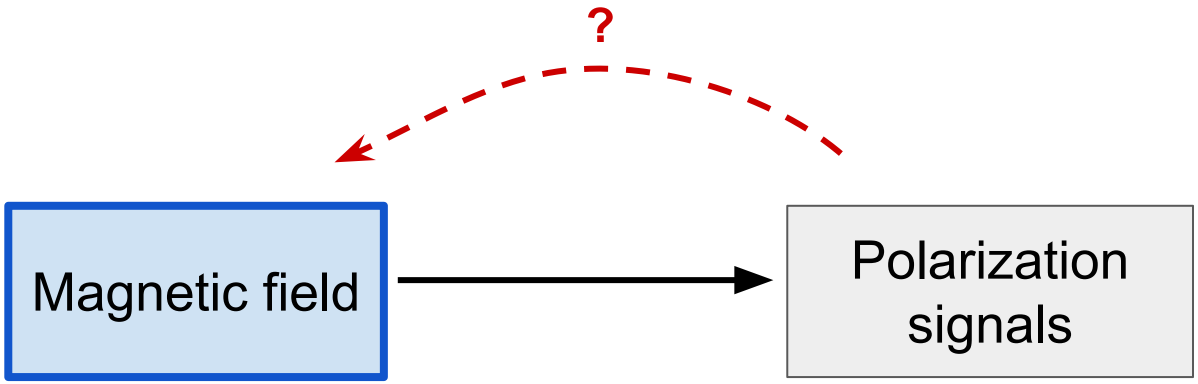
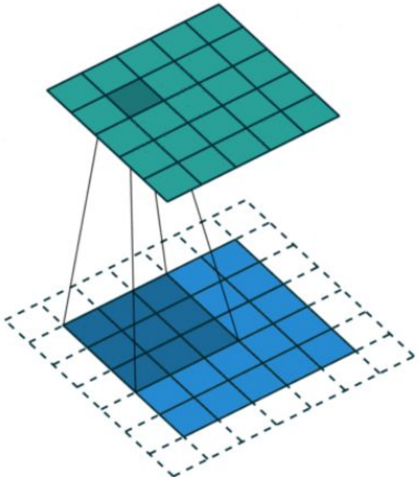
Magnetic field inference

The magnetic field plays a key role in the generation and evolution of many of the phenomena that take place in the Sun.



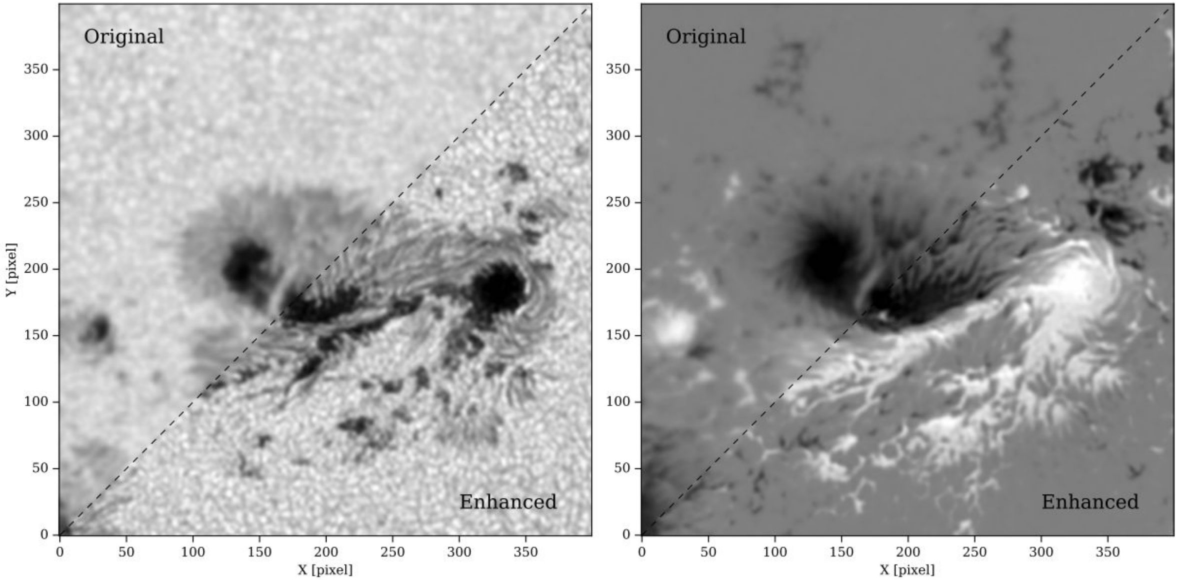
- **Time** average (or increasing the exposure time).
- **Spatial** average also removes spatial information.
- PCA: **spectral** shape of the polarization profiles.

Using spatial information: CNN



github.com/vdumoulin/

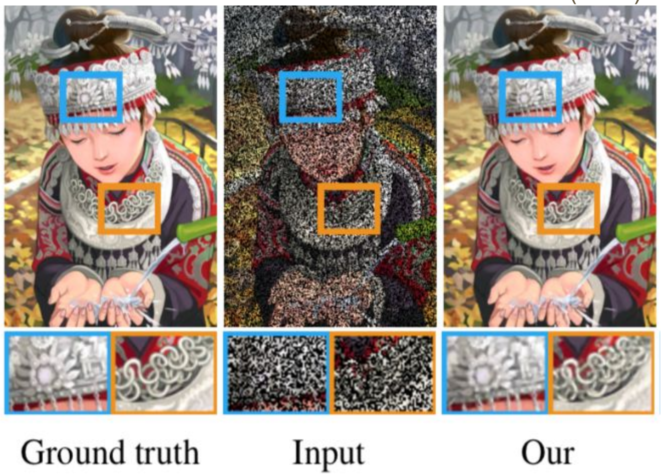
Díaz Baso et al. (2018)

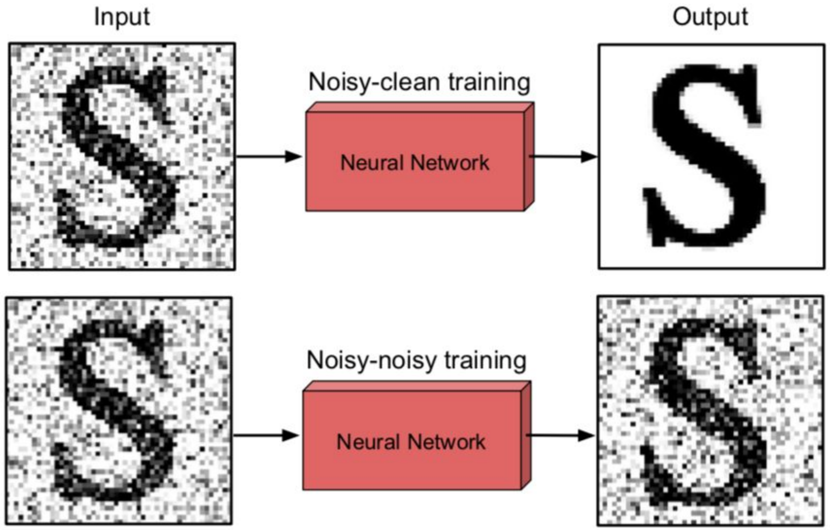


In CNNs each neuron perform convolutions, relating each pixel with the surroundings.

Training process - Noise2Noise

Lehtinen et al. (2018)



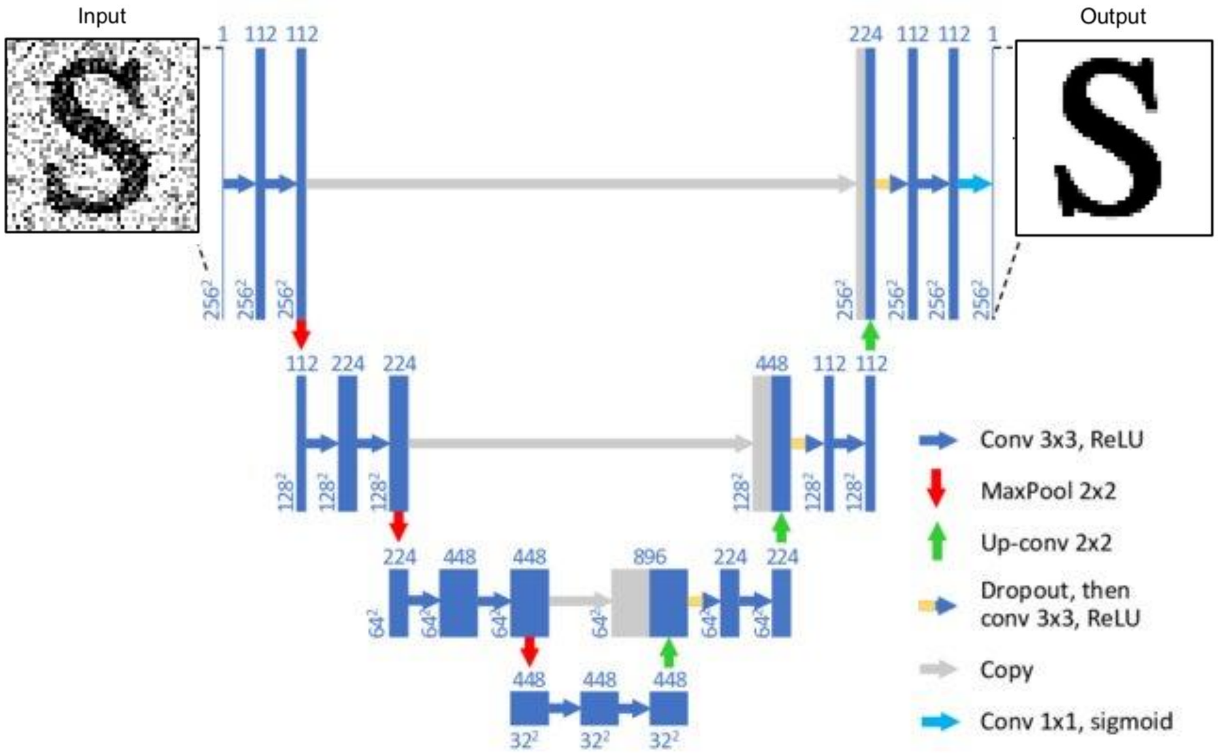


The characterization of the noise is not trivial when the data has been processed multiple times.

The method does not need prior information of the noise corruption or a clean image.

In our case: two images taken very close in time will differ only in the noise realization.

Neural network architecture - Unet



Ronneberger et al. (2015)

Simulated dataset & comparison

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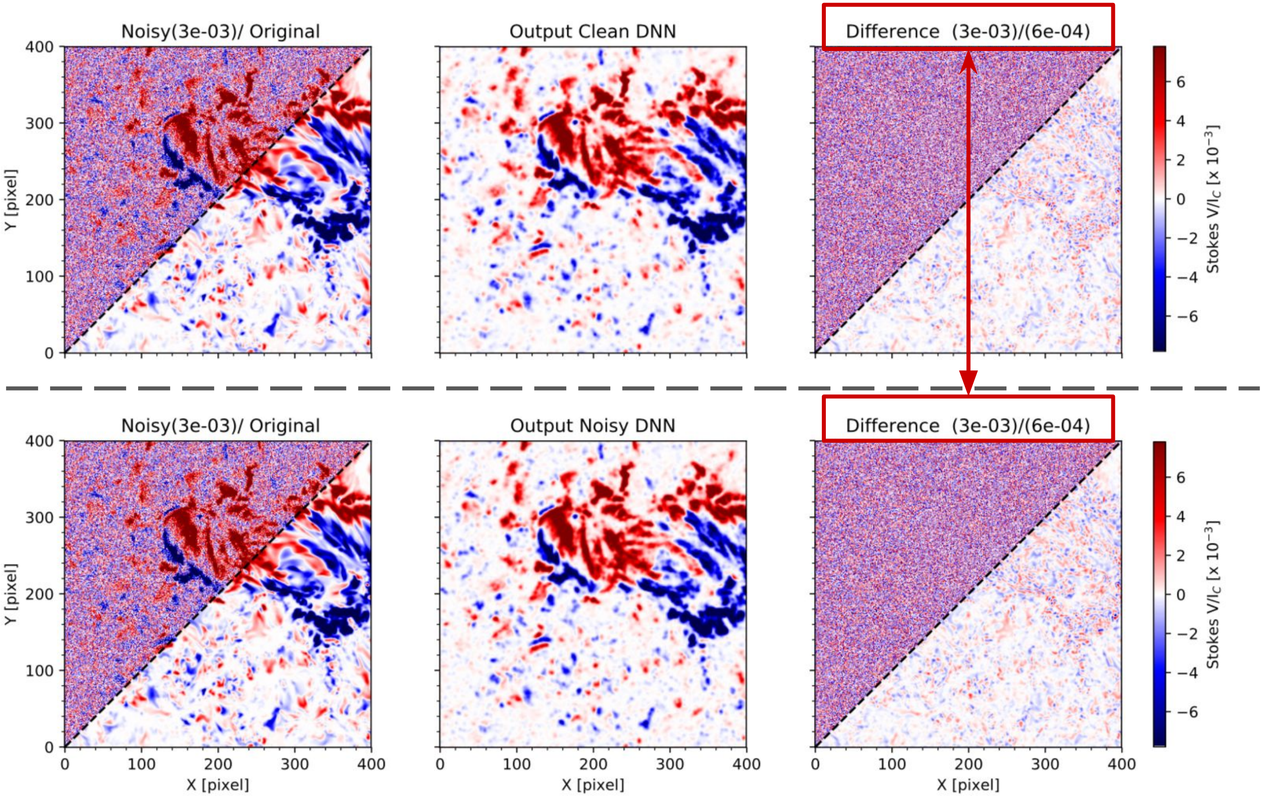
-MHD simulation of a flux emergence produced with MURaM code.

-Training set: Fe I line at 6302 Å (1Å /50 mÅ).

-Validation set: Fe I line at 6301 Å (1Å /50 mÅ).

-They reach same accuracy after training.



Spectral profiles & uncertainty

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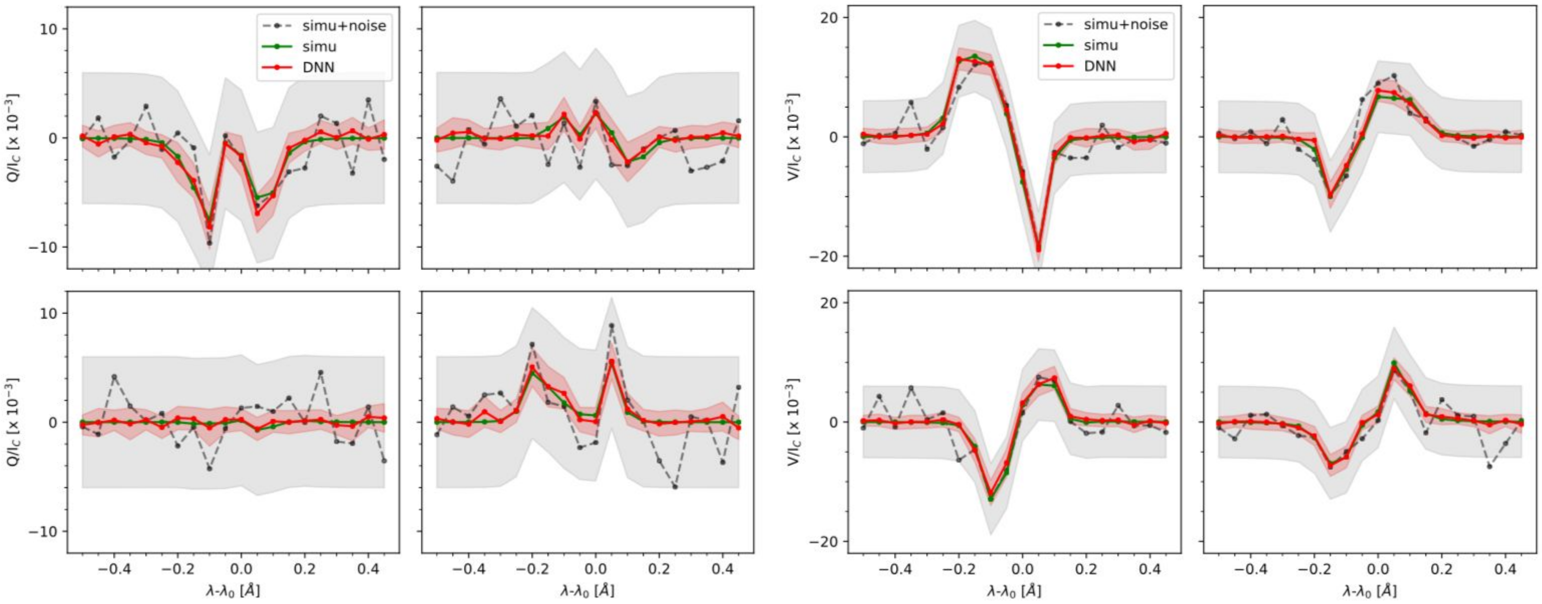

- We implemented the uncertainty calculation using astroNN (Leung & Bovy 2019).
  - Stokes Q and V profiles extracted from 4 different points of the map.

Real observations - monochromatic maps

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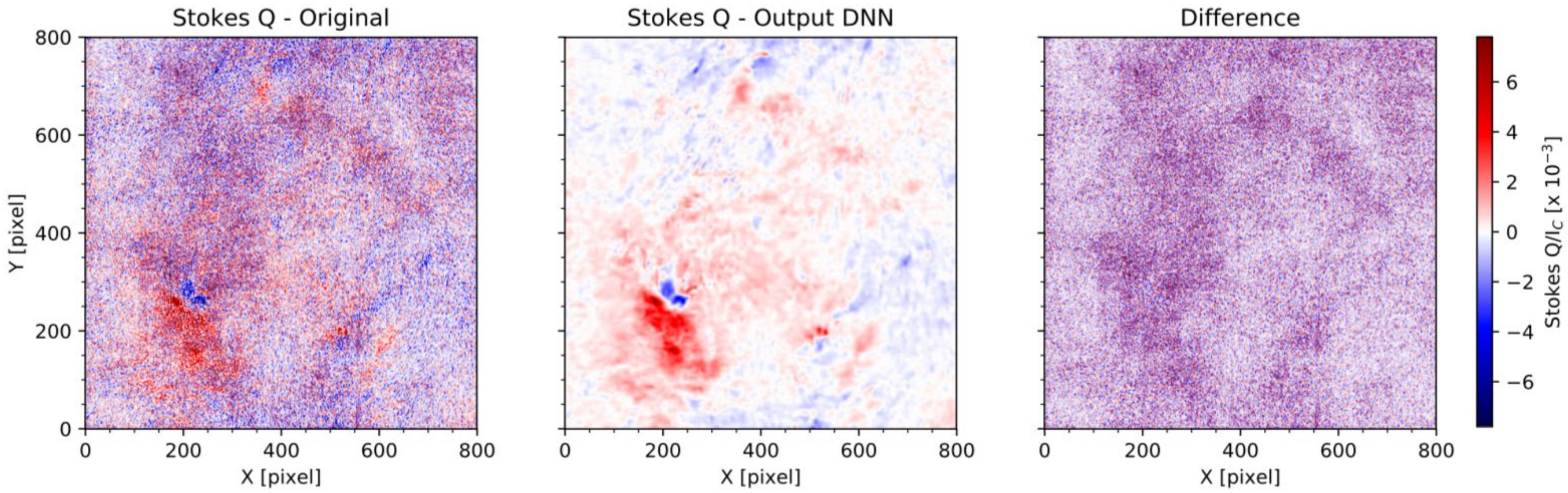

- Training set: two observations recorded with CRISP (Fabry-Perot) at the Swedish 1-m Solar Telescope.
- Two time series in the Ca II line at 8542 Å. Data augmentation: rotations, sign changes, and reverse order.

Real observations - monochromatic maps

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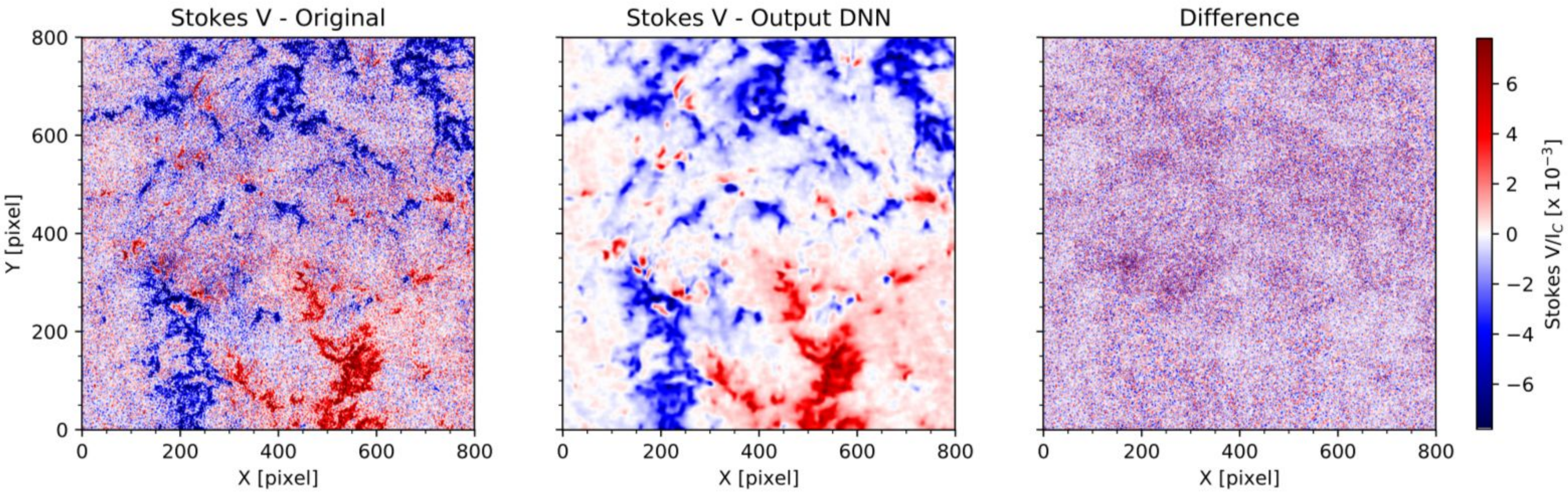

- Training set: two observations recorded with CRISP (Fabry-Perot) at the Swedish 1-m Solar Telescope.
- Two time series in the Ca II line at 8542 Å. Data augmentation: rotations, sign changes, and reverse order.

Real observations - general behavior

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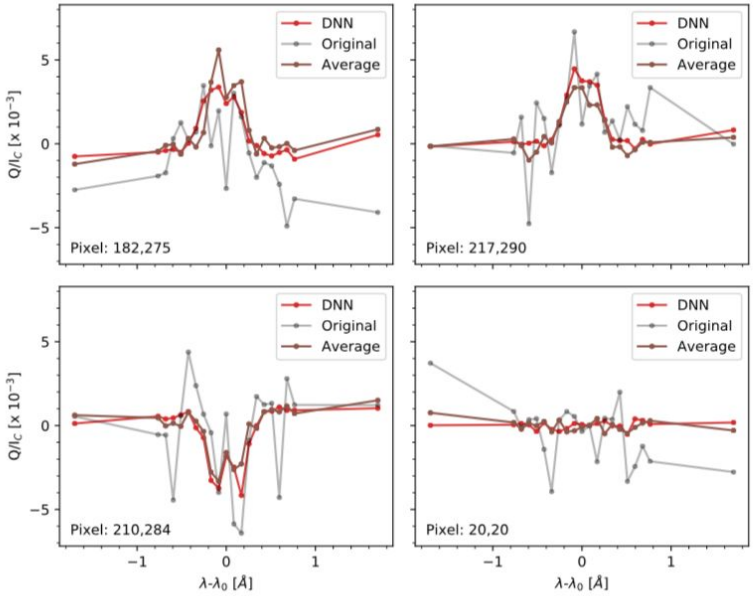

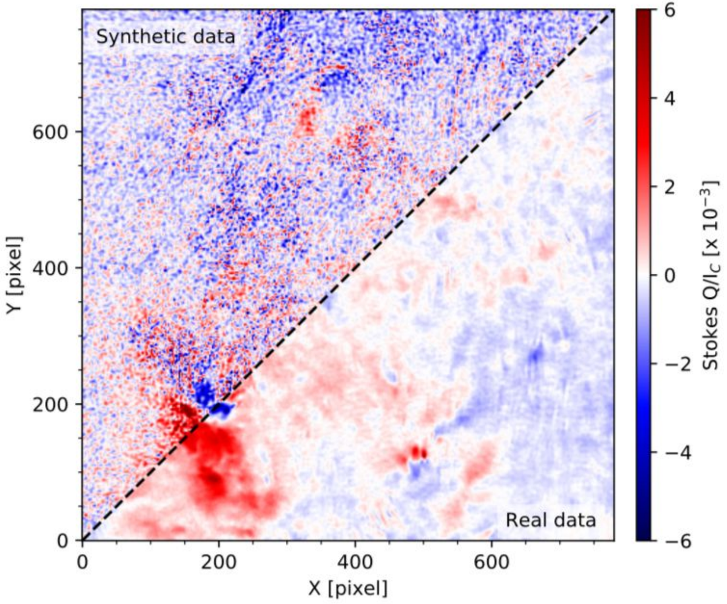

- Reconstructed profiles: keeping general behavior without losing the temporal evolution.

- Performance when the network is trained on images with a different spatial scale of noise.

Real observations - Stokes profiles

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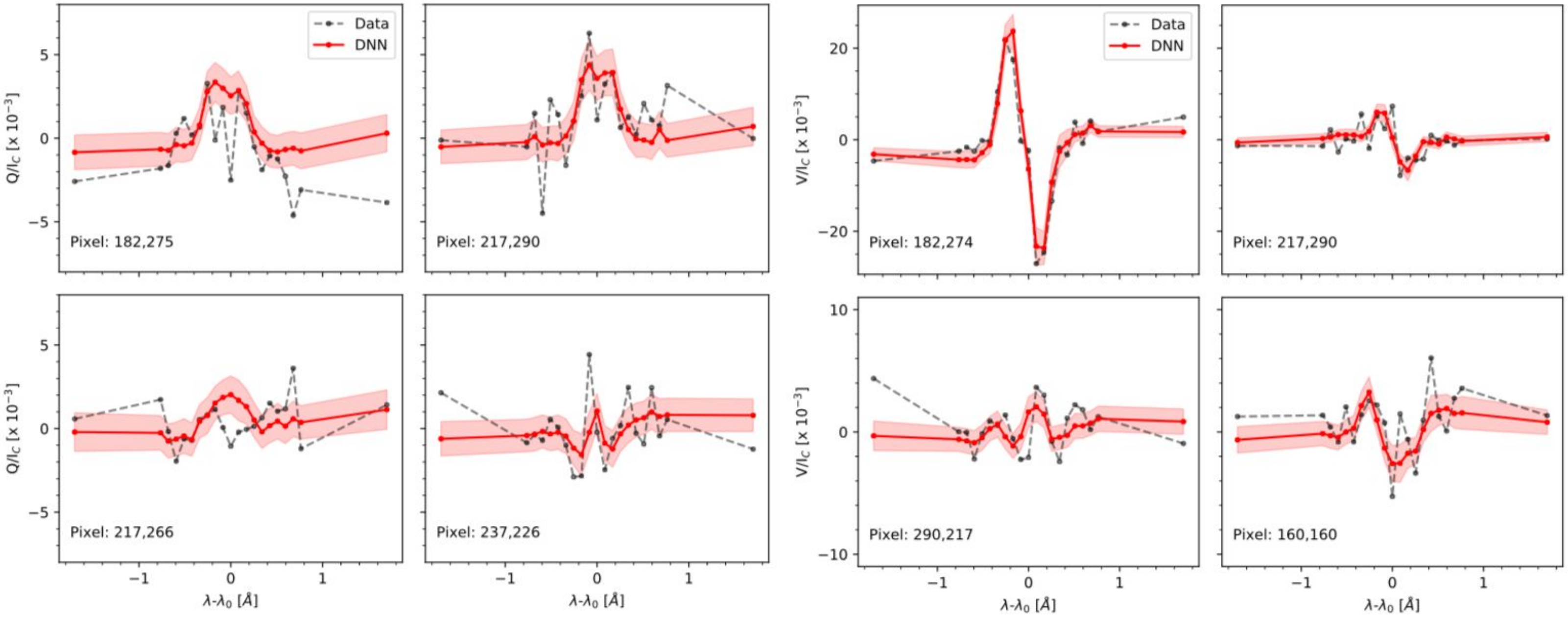

- Surprising aspect: high spectral coherence (not included during the training).
  - This estimation is restricted to Gaussian uncertainties.

Spatial vs Spectral reconstruction

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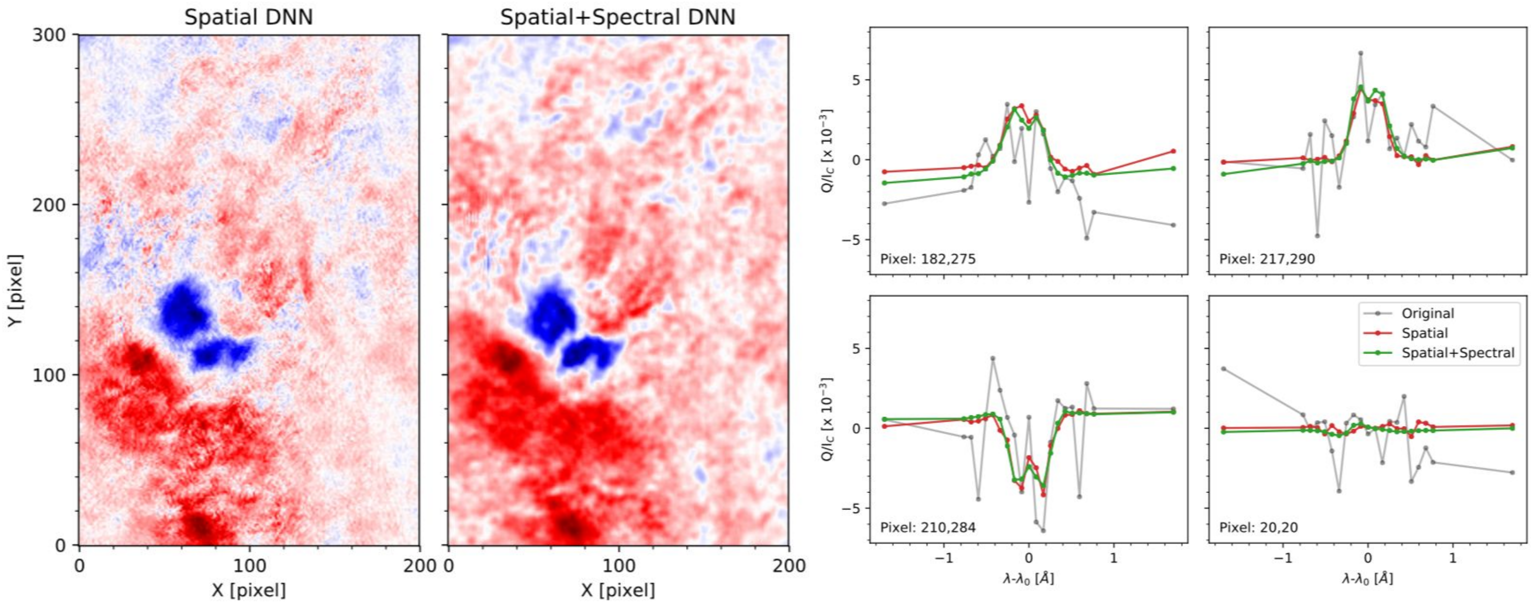

- The whole spectral shape is taken into account to do the reconstruction.
- The neural network is now specific (spectral line and sampling). Problems with strange profiles.

Summary and perspectives

1. We have proposed a new approach for recovering polarization signals under a complex noise corruption using neural networks. The training is done just with the raw images (main motivation).

2. We have shown some examples of typical signals that were strongly affected by the noise (data from the Swedish 1-m Solar Telescope). They are particularly relevant for studying the magnetization in the chromosphere and corona.

3. Although we have used this telescope as an example, given the generality of the technique, it can be applied to any telescope, instrument, solar region or physical quantity.

More details in the published article: https://arxiv.org/abs/1908.02815
The source code is at https://github.com/cdiazbas/denoiser

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