Unboxing the Black Box:
Learning to identify acoustic wave sources on the Sun from Deep Learning

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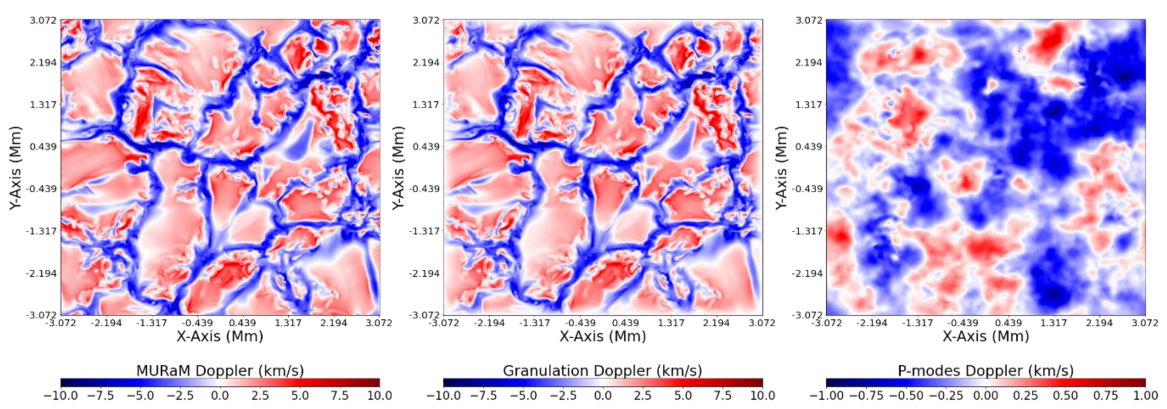
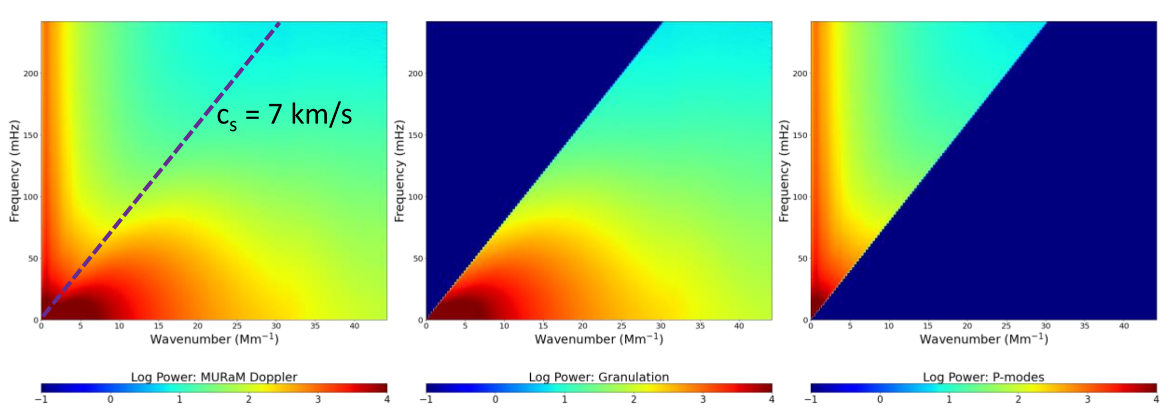
Problem Statement

In the photosphere of the Sun,
Dominant dynamics:
1. Magneto-convective Overshoot
2. Modes of oscillation caused by sound waves

Question: What are the sources of the sound waves?

Problem: the amplitudes of the emitted waves are several orders of magnitudes weaker than the background convective flows and global resonant p-modes (unambiguous separation remains problematic even in numerical simulations)

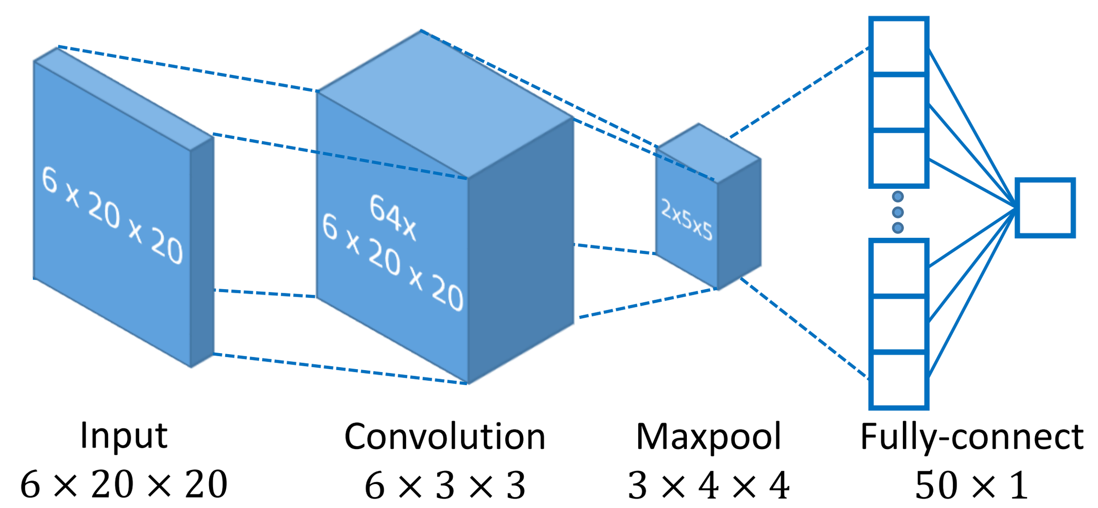




Since the spectral content of the low amplitude acoustic source signal overlaps that of the acoustic modes, and in part also that of the granular motion, linear filtering and frequency domain noise reduction techniques most often fail in source detection.

Signal = Sources of Individual Waves
Noise = Granular Motion + p–modes

Convolutional Neural Network



Input Image Time-series → *Output* P(Wave/No-wave)

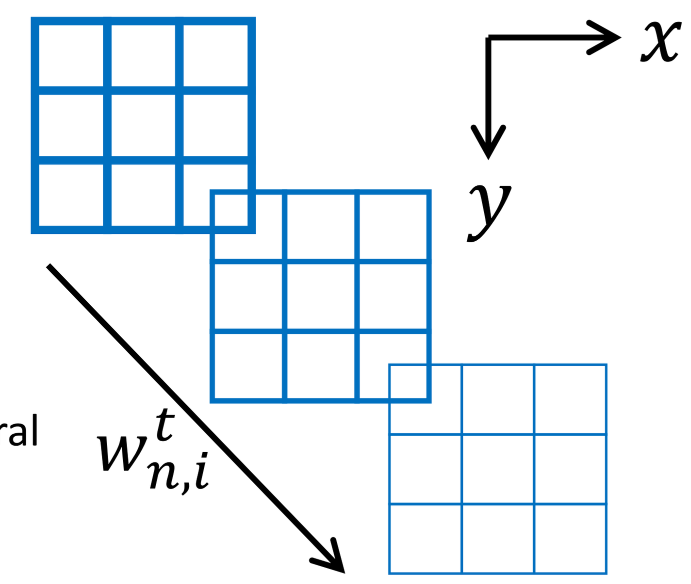
A simple CNN with 64 kernels trained on MURaM photo-sphere with 2 sec cadence and 16 km spatial resolution.

Although a simple CNN, it <u>**remains difficult to decipher**</u> what is happening at the kernel-level that filters out the noise and facilitate extracting the signal.

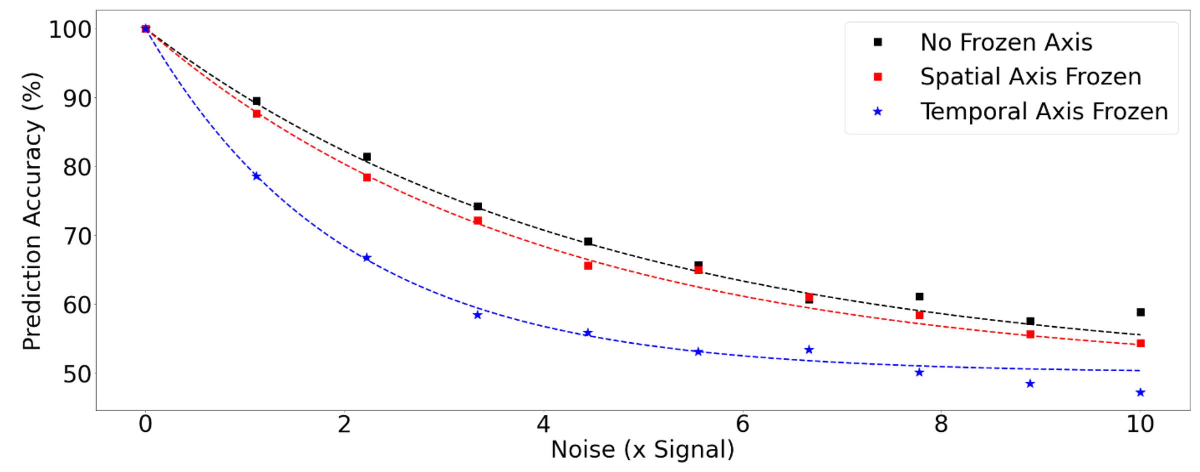
Possible Solution:

Once the neural network learns to identify wave-patterns in a noise-free sample,

Freeze Spatial Axis of the weights and let the Temporal Axis of the weights evolve and vice versa.

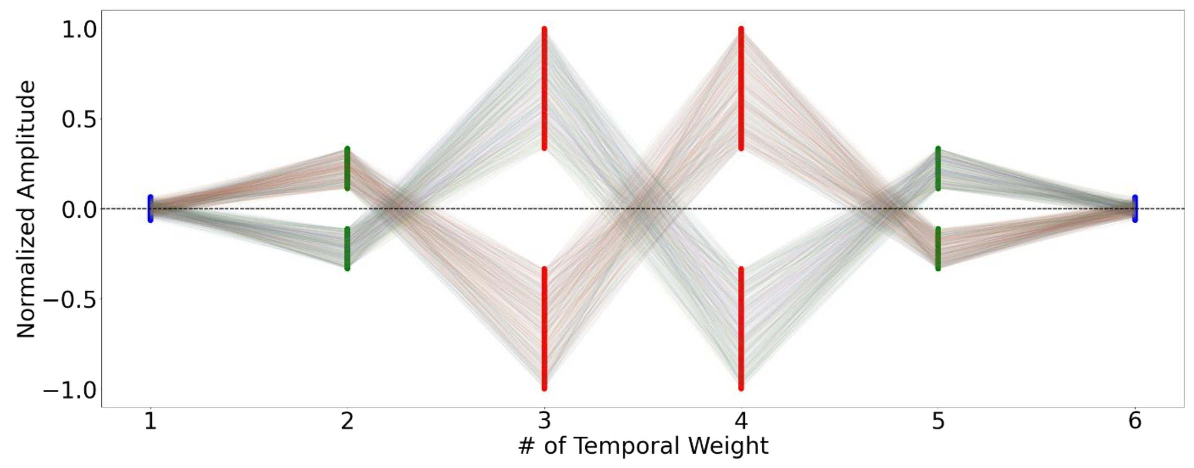


Opening the Black Box

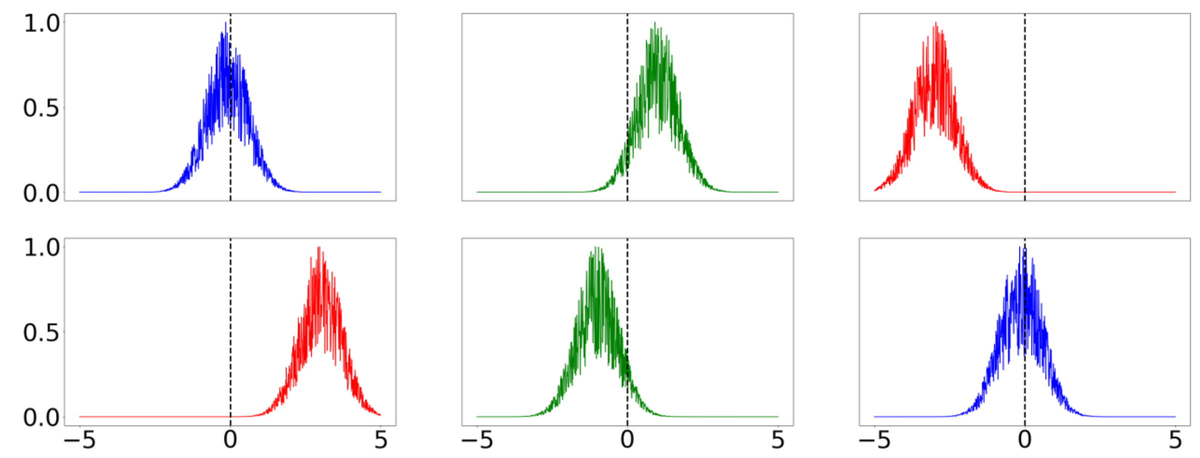


Prediction capability of the Neural Network falls as noise amplitude is increased. Freezing the spatial axis minimally affect the prediction accuracy, while freezing the temporal axis drastically reduce the accuracy.

Result: **Filtering takes place in Temporal Axis.**



Distribution of weight amplitude along temporal axis. The weights changes sign alternatively and with an increasing and followed by a decreasing trend.



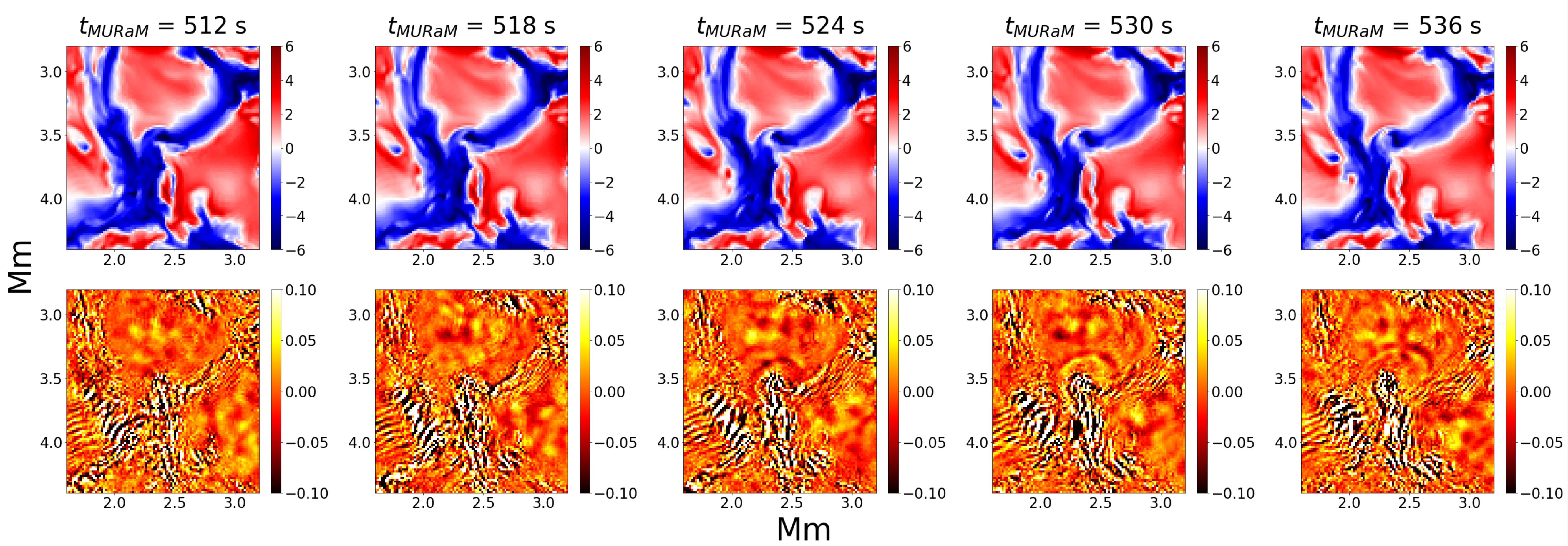
For 100s of successful training instances, the weights takes a Gaussian-like distribution, maintaining their conditional relationship.

By taking the mean of the distribution, we can explore what mathematical operation is performed by the neural network in order to filter the noise. In this case, the operation is closely equivalent to:

$$\approx \epsilon f(t_{-3}) \mp f(t_{-2}) \pm 3f(t_{-1}) \mp 3f(t_0) \pm f(t_1) + \epsilon f(t_2)$$

with, $\epsilon \to 0$

Thus a 3-difference filter would be able to filter out the noise from the signal. Indeed, it is a smooth high-pass frequency filter, removing the power of lower frequency perturbations, such as convective motions, and retaining higher frequency perturbations, such as acoustic wavefronts propagation, granule edge advection, and high frequency p-modes.



LOS velocity field (Top) and corresponding 3-differenced-filter-in-time images (Bottom) of a strong, isolated source at five different time stamps (t = 512 s, 518 s, 524 s, 530 s and 536 s) to illustrate the temporal evolution of the propagation of wave-front originated by acoustic source. – the experiment is run on MURaM simulated photosphere with 2 second cadence and 16 km spatial resolution.

For 2 second cadence, the 3-difference results the granulation to be nearly stationary. For faster cadence, same differencing would result being too short of a time scale that would remove both the granular evolution and the wave-front propagation.

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