More accurate ALMA chromospheric temperatures with machine learning

Eva Sola-Viladesau (Universidad de La Laguna, European Space Agency)
Dr. Henrik Eklund (European Space Agency)

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Context

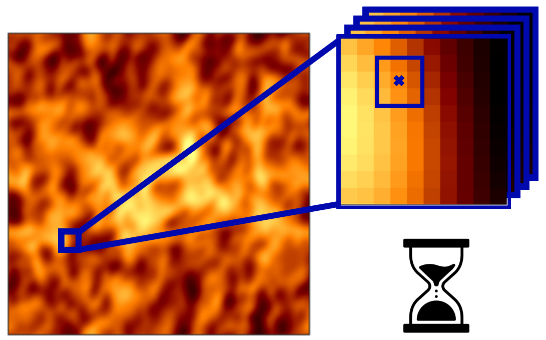
The **chromosphere** is the intermediate layer of the Sun's atmosphere. It is a **highly dynamic region** dominated by processes in **non-equilibrium**, and it presents **rapidly-changing small-scale events**. These complexities make it **challenging to obtain** reliable and accurate **temperature diagnostics**. Understanding the chromosphere is **essential for addressing fundamental questions**, such as the mechanisms responsible for **heating the upper layers** of the solar atmosphere.

Summary

We develop a **deep neural network** model to, given **only ALMA observations**, identify **locations where the millimeter wavelength emission** originates from a **single layer** in the atmosphere, where a **linear link between observed intensity and local temperature** is a good approximation[1], to obtain the **locations with most accurate temperature in a given field-of-view** of a solar observation.

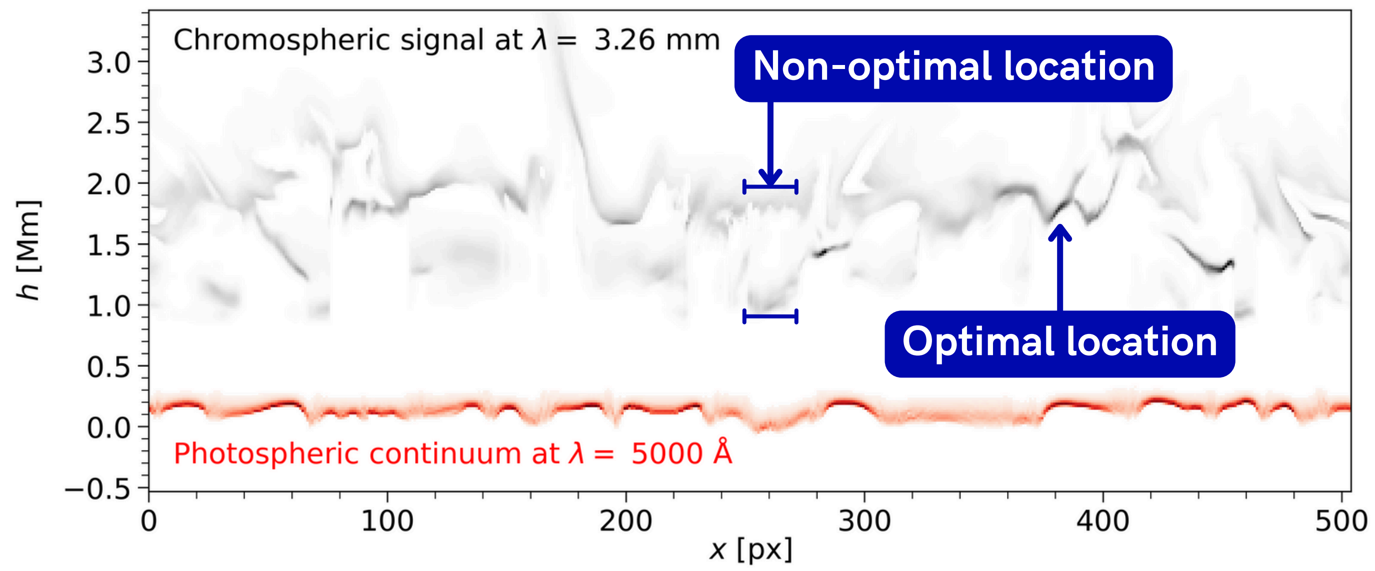
Neural networks

We use an architecture[2] that is both **convolutional**, used to find **spatial patterns**, and **long short-term memory**, used to find **patterns in time-series of data**.



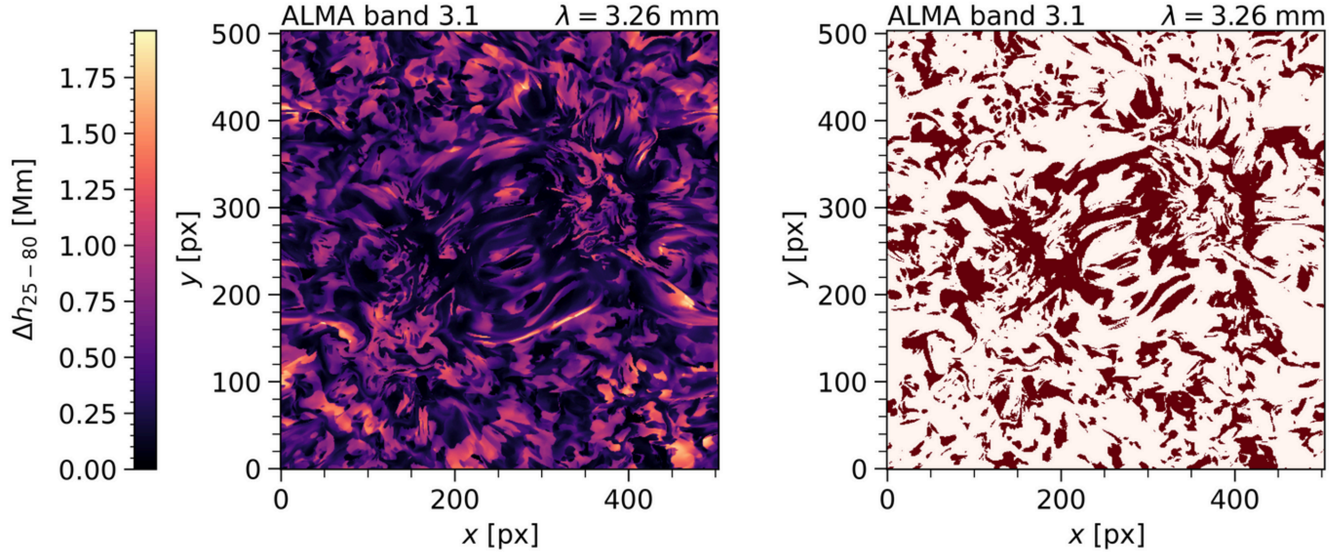
The objective

Our goal is to **reliably and automatically find locations** of **single-layer emission** in the millimeter continuum covered by ALMA. **Spatio-temporal small-scale dynamic patterns** from **r-MHD simulations**[3] can help us find these locations.



Strategy

We estimate the heights at which **25% and 80%** of the **cumulative integrated intensity** (obtained with the ART code[4]) are reached. **If they are close, the emission is single-layer.** Δh(25-80) is the distance between the thresholds.



Results & future work

We find the **formation height of the cumulative 80%** intensities with **high accuracy**, while the **25% estimations are more challenging**, likely due to a **higher variability in the parameter space.**

Our first performance tests reveal around a **60% precision in simulation samples** not seen by the network during training. We aim to **improve the true positive detection whilst maintaining false positive detection low** and to **ensure the model generalizes appropriately.**

References:
[1] Wedemeyer, S. et al. (2016). Solar Science with the Atacama Large Millimeter/Submillimeter Array - A New View of Our Sun., *Space Science Reviews*, 200(1-4):1-73.
[2] Eklund, H. (2023). Deep solar ALMA neural network estimator for image refinement and estimates of small-scale dynamics. *A&A*, 669:A106.
[3] Carlsson et al. (2016). A publicly available simulation of an enhanced network region of the Sun. *A&A*, 585:A4.
[4] De La Cruz Rodríguez et al. (2021). ART: Advanced (and fast!) Radiative Transfer code for Solar Physics. https://doi. org/10.5281/zenodo.4604825