Bayesian Stokes inversion with Normalizing flows

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1. INTRODUCTION

In spectropolarimetry, the process of finding the solar parameters that give rise to the observed spectrum is known as inversion. This method is very slow when applied on many pixels or involves spectral lines with complex formation. Recently, standard artificial neural networks (**ANNs**) have been shown to be much faster in learning the average mapping between spectra and physical quantities, but they do not perform properly if there are degeneracies or several solutions, and they do not provide uncertainty estimates. On the other hand, Bayesian inference allows us to obtain the full probability distribution including uncertainties, correlations and whether our distribution is (or not) multimodal, but sampling methods are very computationally expensive. In the following, we introduce a new technique that allows us to perform fast Bayesian inference.

2. NORMALIZING FLOWS

The novel technique that allows us to perform fast Bayesian inference combines Bayesian inference and neural networks, and is known as normalizing flows (**NFlows**). They are a set of invertible and parameterized transformations that approximate the probability distribution of our target by a transformation from a simple probability distribution (usually a Gaussian). If these transformations are conditioned on observations (see lower panel of Fig. 1), we can train normalizing flows to return Bayesian posterior probabilities for any observation. For comparison, there is a sketch of a standard artificial neural network in upper panel of Fig. 1 which outputs the average mapping.

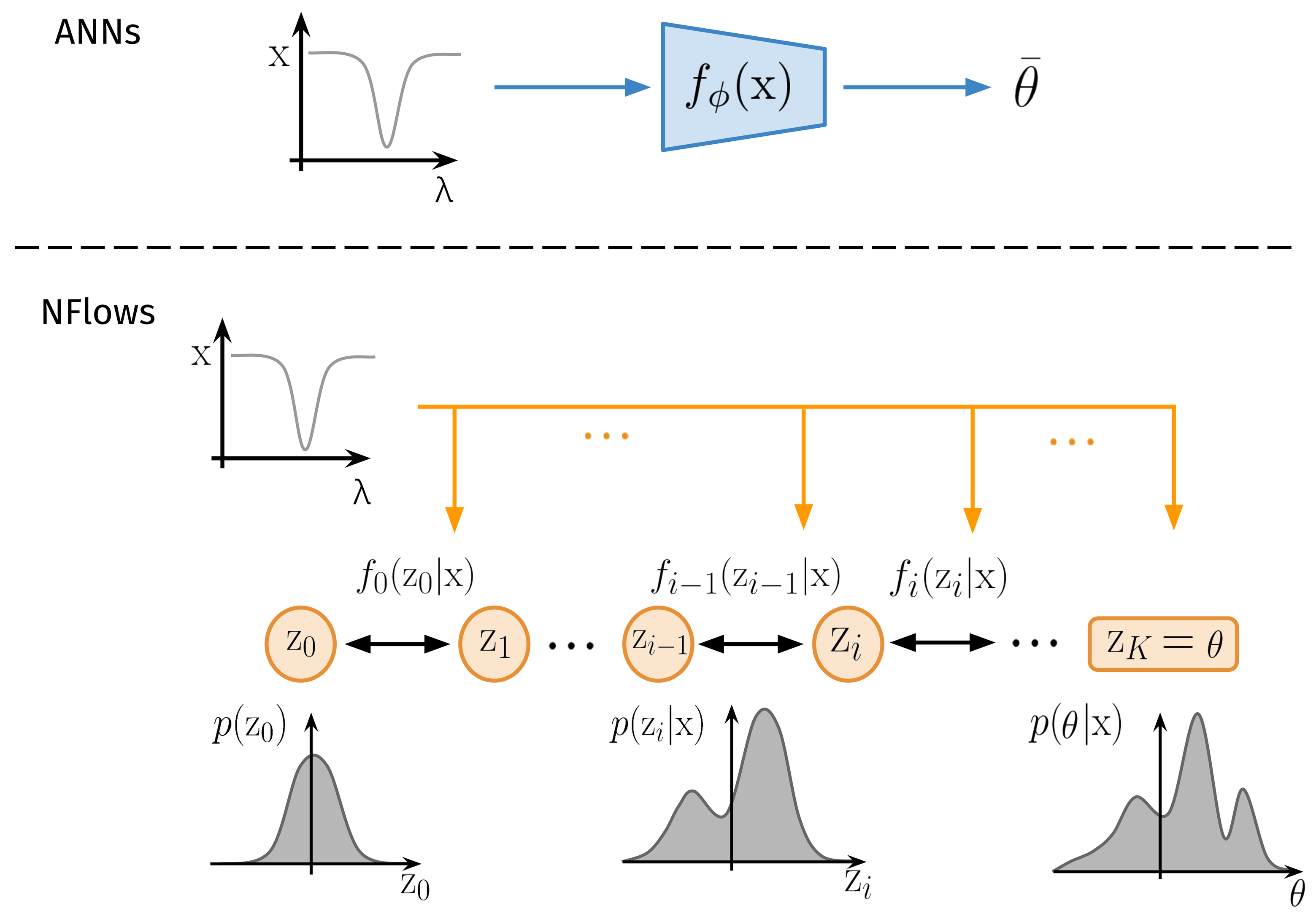

Fig. 1: Comparison between an artificial neural network and a conditional normalizing flow.

3. MILNE-EDDINGTON

As a first example, we illustrate here the capabilities of the method in a simple Milne-Eddington model where the forward model is analytic and fast enough to allow a comparison with the exact solution obtained with a Markov Chain Monte Carlo (MCMC) method. This model uses five parameters for controlling the intensity profile of the spectral line.

We created a database of 10^6 pairs of examples (parameters vs spectra) and we optimized the transformations of the normalizing flow, as in classical neural networks, but in this case to reproduce the distribution of the data. Once trained, the NFlow can produce the distributions for any given observation as accurate as the **MCMC** sampling method, with the corresponding uncertainties and degeneracies like the ones between the absorption of the line, the source function and the Doppler width with a banana shape.

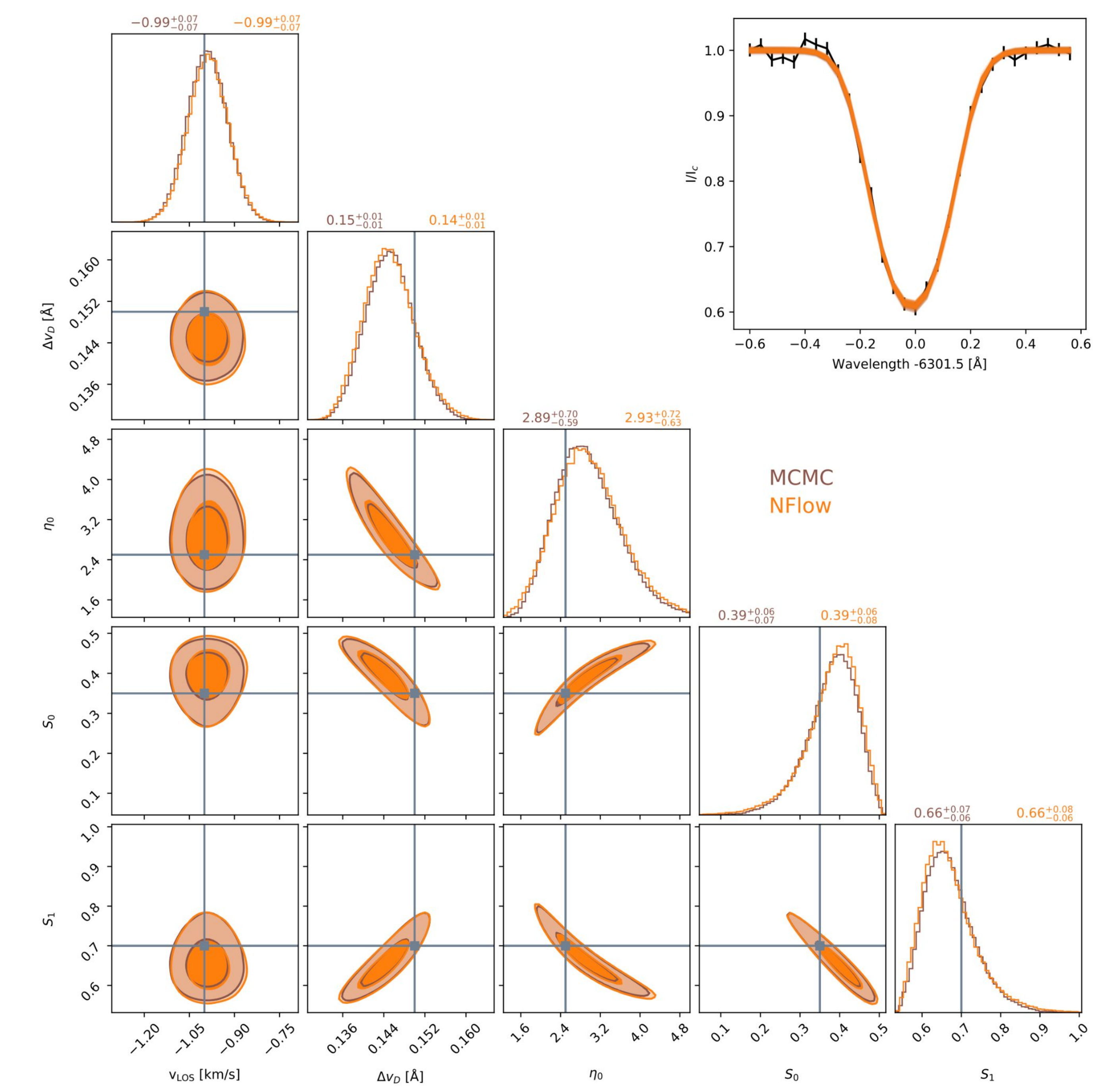

Fig. 2: Joint and marginal posterior distributions for the physical parameters involved in the Milne-Eddington model.

4. N-LTE INVERSION

The real improvement occurs when the new method is applied to non-LTE inversions, which are more computationally demanding. Following the same procedure, we created a large dataset with synthetic profiles of a photospheric FeI line at 6301Å and the chromospheric CaII line at 8542Å. To illustrate the performance of this technique with different spectral lines, we have trained two normalizing flows: one only using the photospheric FeI line which gives the orange solution and another which also uses the chromospheric CaII line and produces the brown solution.

Figure 3 shows an example of the inference of temperature, velocity and microturbulent velocity for a given observation. From the width of the solutions (here the bands representing 1 sigma of the distribution), we see that just by looking at the database, the normalizing flow learns the sensitivity range of each spectral line. This inference takes around 1 second (producing 10^4 samples) while an MCMC would take many hours or even days.

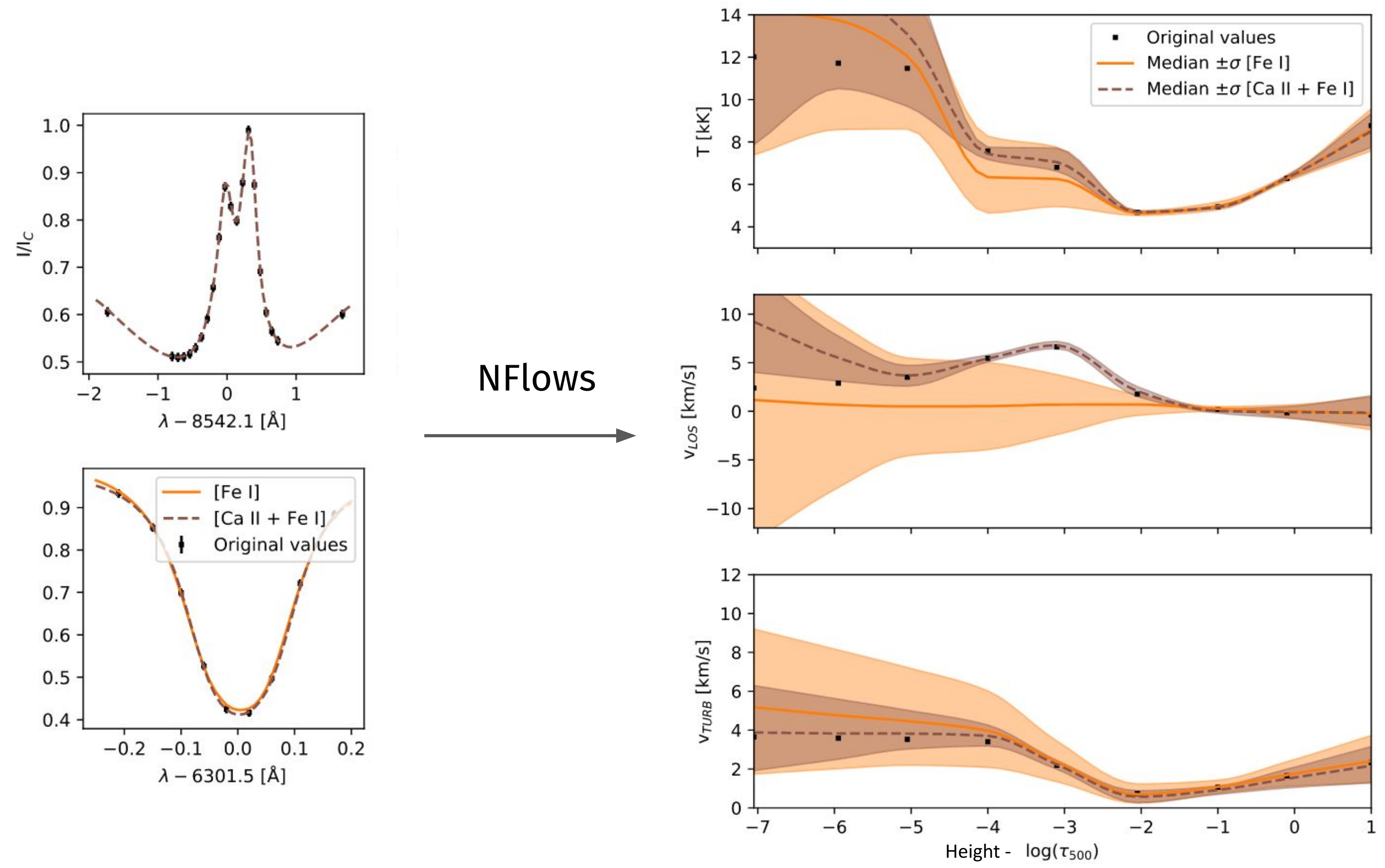

Fig. 3: Atmospheric stratification from observed intensity profiles. The colored bands indicate the standard deviation of each distribution.

Figure 4 shows in the left and right panels the mean stratification and standard deviation. The lower half of each panel shows the temperature at the photosphere, and the upper half provides a view of the chromosphere. The uncertainties tend to increase from the photosphere to the chromosphere. The magnitude and uncertainty are correlated since our spectral lines are less sensitive to higher chromospheric temperatures.

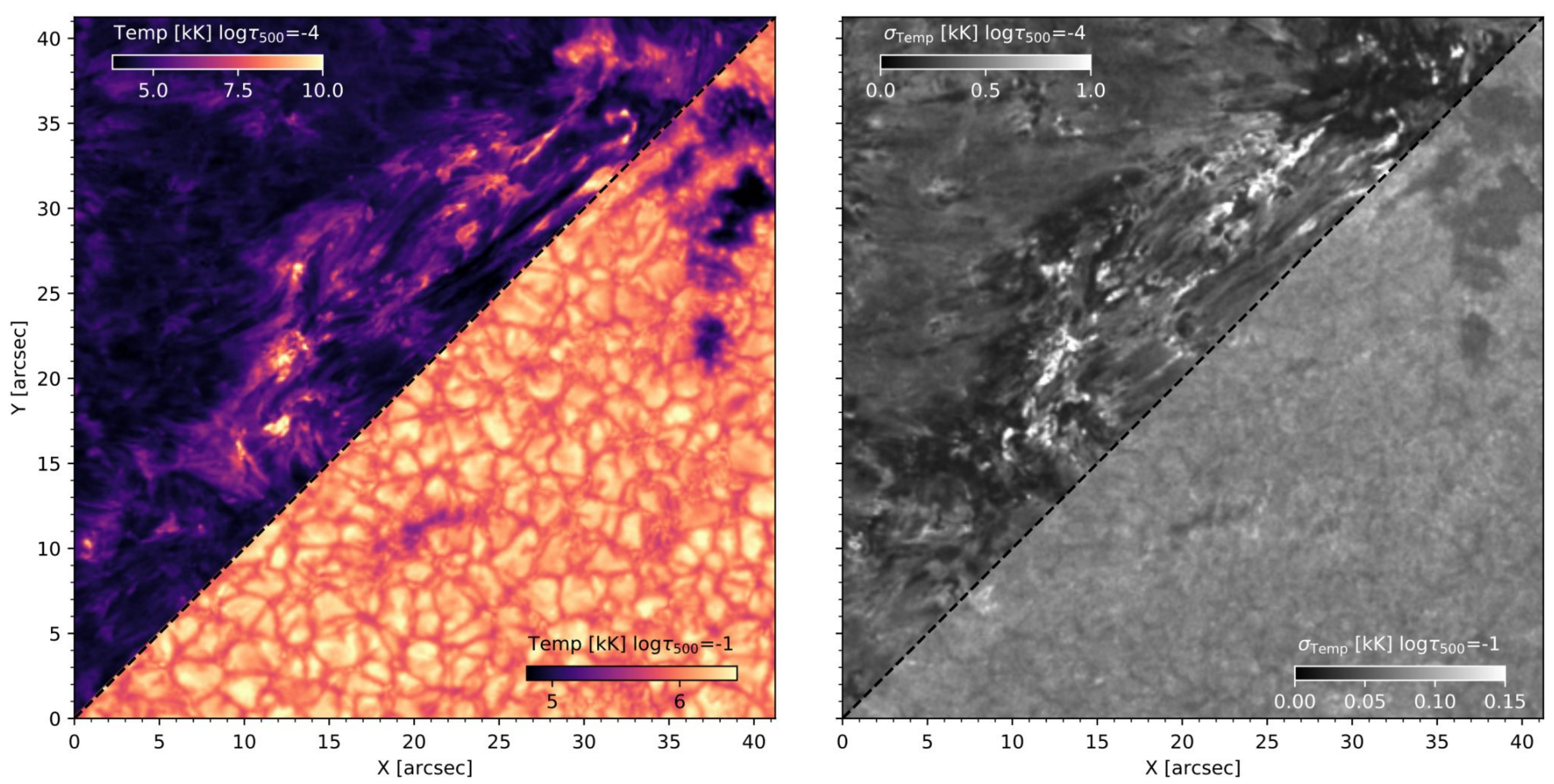

Fig. 4: Temperature and uncertainties of the FOV as inferred with the normalizing flow.

Finally, we have also tested the normalizing flows on a large field of view on some real observations carried out at the Swedish 1-m Solar Telescope on 2016-09-19 at 09:30UT. We have applied the neural network to a field of view of approximately 42×42 arcseconds (around $5\cdot10^5$ pixels). Spectra from individual pixels are analyzed independently. The normalizing flow was able to produce the posterior distribution in a few tens of minutes, whereas a standard inversion technique would have required several days only for a single point estimate.

5. SUMMARY

We have explored the performance of normalizing flows to accurately infer the posterior distribution of the solar model atmosphere (parameters, correlations, and uncertainties) from the interpretation of observed spectra. Given the generality of the technique, it can be applied to any inference process or physical quantity.

A natural extension of this work would be to include the four Stokes parameters to infer the magnetic properties of our target of interest, while also setting more constraints in the rest of the physical parameters. From a practical point of view, this method requires nothing more than the same pairs of examples that are used for training any other network.

More info here: Díaz Baso et al., 2022 (A&A) (https://arxiv.org/abs/2108.07089)

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