Applying neural networks for the chemical analysis of star forming regions

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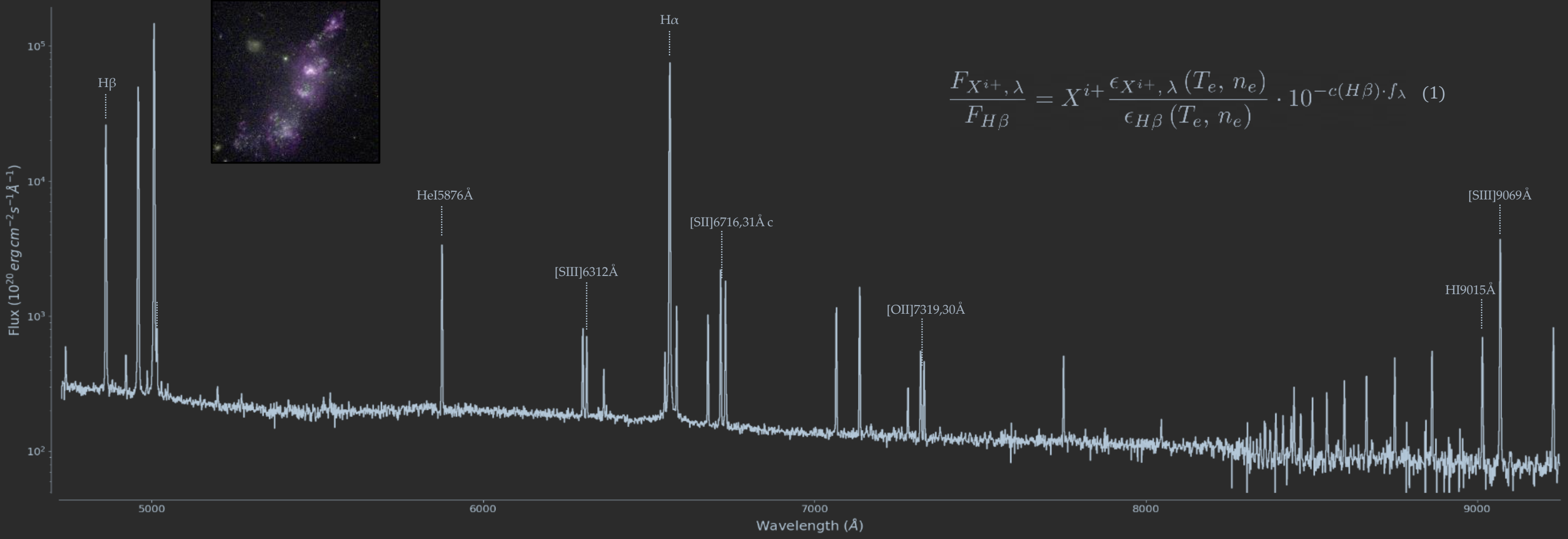
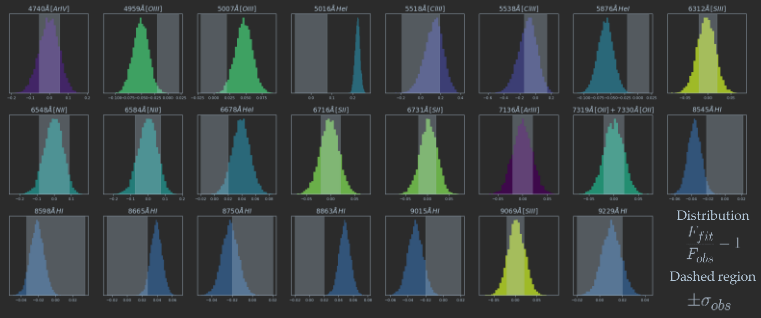


$$\frac{F_{X^{i+},\lambda}}{F_{H\beta}} = X^{i+}\frac{\epsilon_{X^{i+},\lambda}(T_e,\,n_e)}{\epsilon_{H\beta}(T_e,\,n_e)}\cdot 10^{-c(H\beta)\cdot f_\lambda} \quad (1)$$

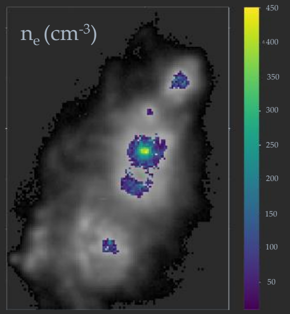
At ~10000K, the gas in star forming regions generates an intense emission spectrum. These lines provide the means to quantify the gas physical conditions and chemical composition.

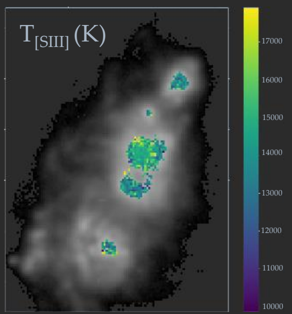
The spectrum on the left corresponds to the central core of the CGCG007-025 galaxy. This observation was obtained using the MUSE instrument. In this work, for the first time, we simultaneously fit the complete emission spectrum using the classical model (eq. 1). The parameter space, for this spectrum, consists in 15 dimensions: one electron density, two electron temperatures, the extinction coefficient and eleven ionic species.



This fitting was possible thanks to the application of neural networks. The algorithm was written with the PyMC3 library.

The grid on the left shows the fitted fluxes normalized by the observed ones (colour-coded by the source ion). The dashed region corresponds to the measurement uncertainty. In most cases, the fitted fluxes only diverge by a few percentage points.





An important advantage of the neural networks sampler is its speed and stability in the simulation convergence.

The maps on the left hand side show the density and temperature fittings for the density and temperature of the nearly 500 spaxels with the most intense radiation. These results took close to 15 hours with less than 2 minutes sampling simulation per input spectrum.