Deep learning denoising of molecular line cubes by dimension reduction

Giant molecular clouds are the birthplaces of stars. They are the regions of the interstellar medium with the highest density and lowest temperature. Consequently, observation of the gas in these structures is only possible in the millimeter-wave range, i.e., at frequencies of the order of 200 GHz. We then observe the emission lines of the chemical species present in the cloud, that corresponds to the photon emission at a precise frequency during the transition from a quantum energy level to a less excited level. The Doppler effect due to the cloud's kinematics induces a frequency shift for each line, which can be converted into a radial velocity. The availability of large bandwidth receivers for millimeter radio-telescopes allows the acquisition of position-position-velocity data cubes over a wide field of view and a broad frequency coverage. These cubes contain much information on the properties of the emitting gas, but their large size coupled with inhomogeneous signal-to-noise ratio (SNR) are major challenges for a consistent analysis and interpretation.

In this talk, I will present a new denoising method of the low SNR regions of molecular line data cubes. The nature of spectral line data cubes is distinct from that of the one usually studied in the remote sensing literature. In particular, there is a lack of redundancy in data which led us to adapt the method, notably by taking into account the sparsity of the signal. This method therefore implements significant adaptations of typical autoencoder neural networks, often used to denoise hyperspectral Earth remote sensing data. When applied to a 13CO (1-0) cube of about ten million voxels, the proposed method allows to recover the low SNR emission without distorting the signals with high SNR. We have compared the resulting denoised data with those derived with the multiple Gaussian fitting algorithm ROHSA, considered as the state-of-the-art procedure for line data cubes and show that the new method performs better. This algorithm opens interesting perspectives for wide-field studies of star formation.

Topic: `Learning unsupervised in 3D`