Deep learning denoising by dimension reduction

Application to the ORION-B line cubes

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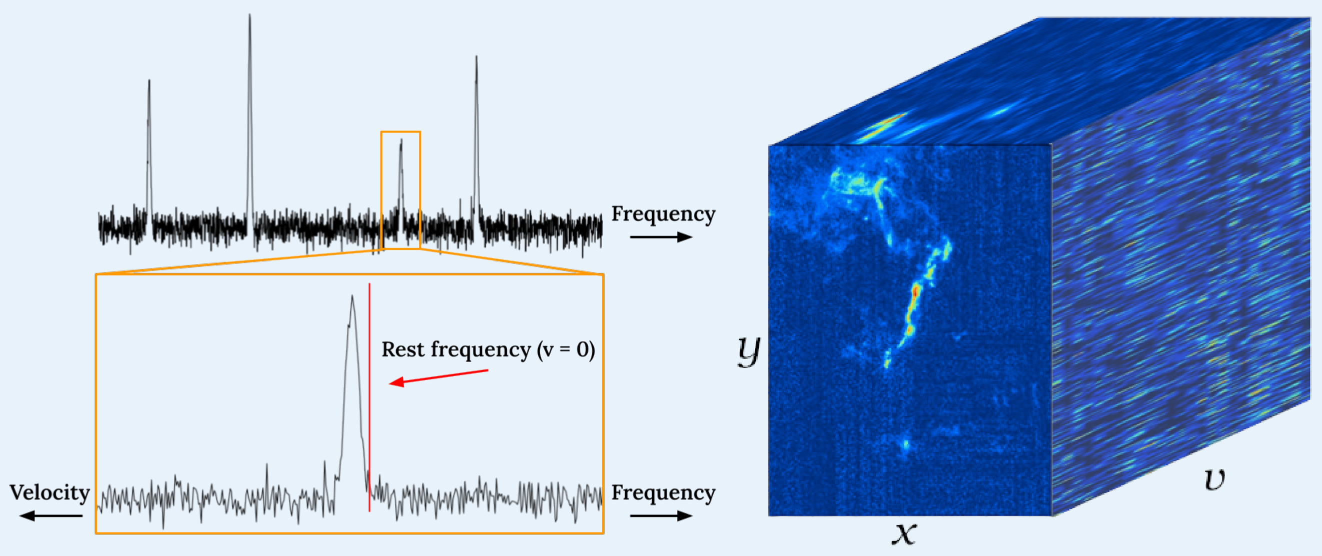
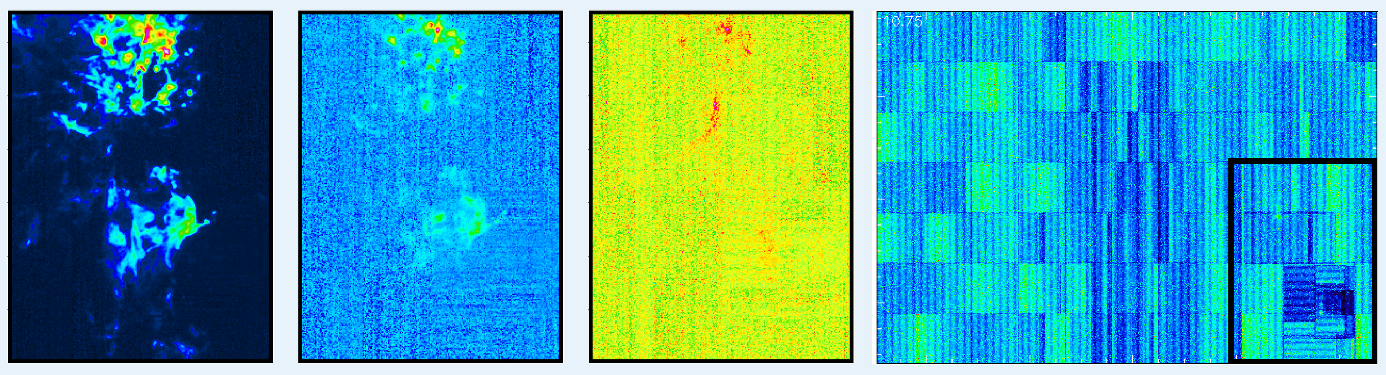
1/ Hyperspectral line cubes

- Large bandwidth receivers for millimeter radio-telescopes allows the acquisition of position-position-velocity (x, y, v) data cubes of the interstellar medium over a wide field of view and a broad frequency coverage. [**1**]
- Due to the Doppler effect of the moving gas, these lines do not have a dirac-shaped emission spectrum, but rather an envelope with a Gaussian appearance.
- Knowing the emission frequency of a molecule, we can interpret the spectral bands as an image of the emission a given molecule moving at a certain radial velocity.



- These cubes contain much information on the physical and chemical properties of the emitting gas but their large size coupled with inhomogenous signal-to-noise ratio are major challenges for consistent analysis and interpretation.



CO isotopologues emission (9 km/s) **Ex. of noise map**

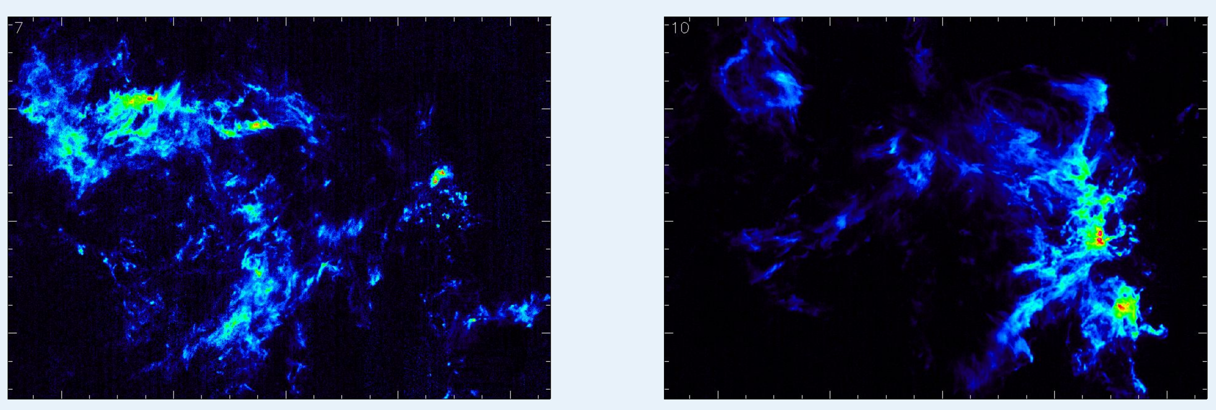
- **Goals**

★ Increase the signal-to-noise ratio, in particular in the region where it is low.
★ Reduce the dimension of the cube over the spectral axis.

➙ An autoencoder neural network could do both. [**2**]

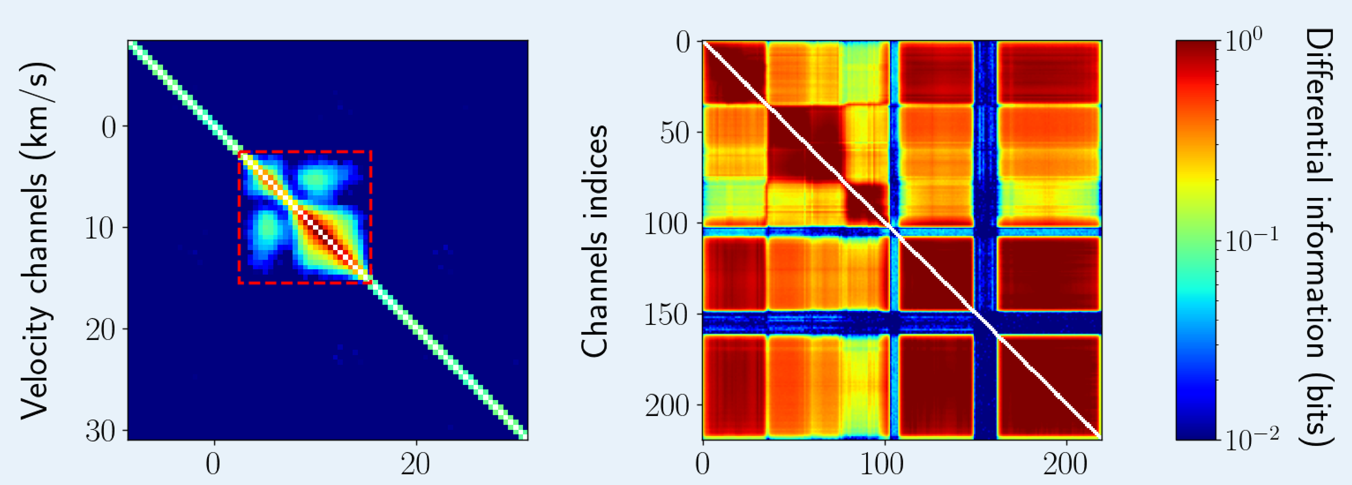
2/ Challenges

- As distant channels are statistically independant, the redundancy that can be exploited is only local.



^{13}CO (1-0) emission, 7 and 10 km/s channels

➙ The information shared with a given channel decreases with the distance. As a consequence, the amount of exploitable mutual information (MI) is very limited.

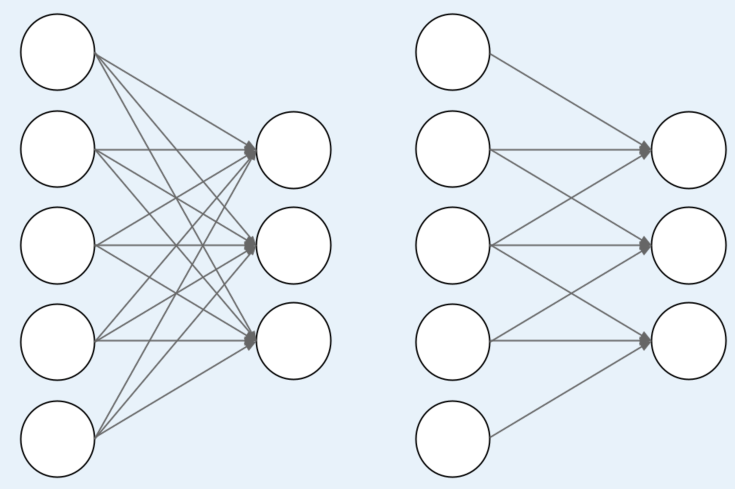


Band pairs MI for ^{13}CO (1-0) and the Indian Pines dataset

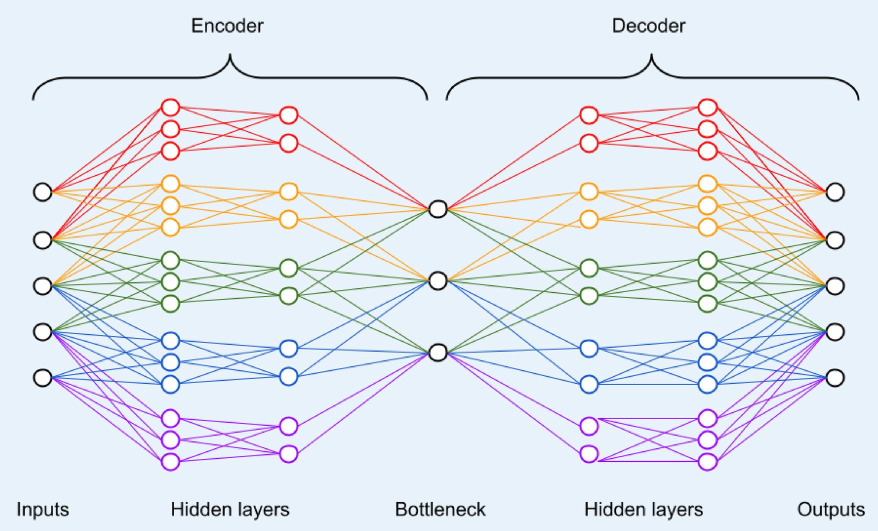
3/ Informed local autoencoder

➙ In order to encompass those challenges, we propose significant improvements of typical autoencoder neural network.

1. As distant channels are independant, they should not be encoded together. We propose an alternative autoencoder architecture.



Dense and locally dense layers



Example of locally dense autoencoder

The maximum distance between two channels encoded together is defined from the data analysis as the characteristic distance between two channels at which the remaining mutual information is of 5%.

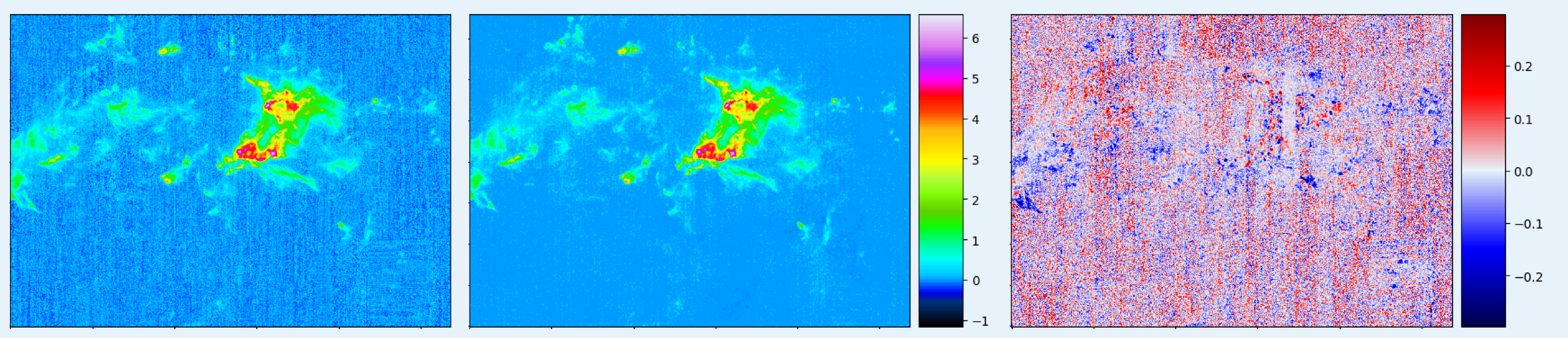
2. Moreover, as the major part of the voxels (samples (x, y, v)) are signal free, we want the autoencoder to encourage the sparcity of the denoised cube.

$$\mathcal{L}(\widehat{y}, y) = \frac{1}{K}\sum_{k=1}^{K}\left[\underbrace{\frac{1}{\sum_{j=1}^{J} w_{jk}}\sum_{j=1}^{J} w_{jk}\left(\frac{\widehat{y}_{jk}-y_jk}{\sigma_k}\right)^2}_{\text{Controls the reconstruction of the voxels that are likely to contain signal}} + \underbrace{\frac{1}{\sum_{j=1}^{J} \overline{w}_{jk}}\sum_{j=1}^{J} \overline{w}_{jk}\left|\frac{\widehat{y}_{jk}}{\sigma_k}\right|^q}_{\text{Controls the sparcity of the voxels that are likely to be signal-free}}\right]$$

where σ_k is the noise RMS for the k-th pixel and w_{jk} an a priori from another segmentation method indicating whether a pixel is likely to contain signal or not.

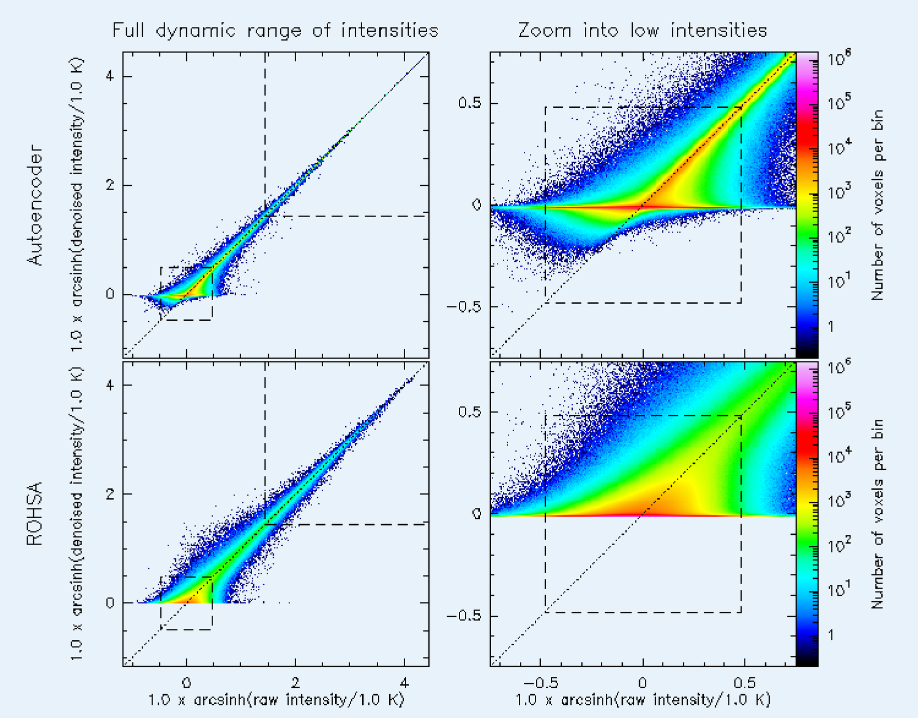
4/ Results

- We apply this method on some cubes. For each one, a new network has to be trained.



Example of noisy and denoised channel and the residues for ^{13}CO (1-0).

- We compare the denoising with that of the Gaussian fit method ROHSA. [**3**]
- We observe different behaviors, in particular the Gaussian fit denoise whatever the signal level and tends to distort the signal of high intensity. The autoencoder tends to preserve these regimes.
- The distortions of the signal (regions where the residuals are correlated) are quite low for the autoencoder.



5/ Conclusion

✓ Statistical denoising with low redundancy
✓ Data analysis based architecture and loss function
✓ Denoising of the low level signal
✗ No significant dimension reduction

6/ References

[1] Pety *et al.*, *The anatomy of the Orion B giant molecular cloud [...]*, 2017
[2] Licciardi *et al.*, *Nonlinear PCA for visible and thermal hyperspectral images [...]*, 2015
[3] Marchal *et al.*, *ROHSA: Regularized Optimization for Hyper-Spectral Analysis-Application [...]*, 2019