Deep Learning Processing and Analysis of Mock Astrophysical Observations

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Abstract Deep Learning represents a promising, general purpose solution to process and analyse large, complex datasets in an automated and efficient fashion. We present the experience accomplished on radioastronomy and X-ray simulated astrophysical data, adopting two different approaches, Autoencoders and Fully Convolutional Networks. The former aims at denoising the data, the latter at detecting and identifying faint sources in noisy images. We give an overview of the main outcomes.

1 Introduction

In the upcoming decade, astronomers will have to face novel scientific and technological challenges. An avalanche of complex data will be delivered by current and upcoming telescopes. This will be difficult to manage with traditional approaches. Data will have to be stored in dedicated facilities, providing the necessary capacity at the highest performance. Corresponding data processing will have to be performed local to the data, exploiting available high performance computing resources. Data reduction and imaging software tools will have to be adapted, if not completely re-designed, in order to efficiently run at scale. Fully automated pipelines will be a

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compelling requirement for effective software stacks as the richness and complexity of incoming data will inhibit human interaction and supervision.

In order to develop such data processing methodologies, we have explored the potential of Machine Learning, a branch of Artificial Intelligence already successfully used in astronomy. Among the various Machine Learning approaches, we have focused on Deep Learning, which provides outstanding performance for tasks relating to computer vision, text analysis, fragmentation, speech recognition (see [1, 2] and reference therein) among others. Deep Learning has become increasingly popular in the last decade thanks to two concurrent factors: the availability of enough computing power to cope with complex, multi-layered neural networks, and the availability of enough data to perform the training. We have adopted Deep Learning solutions with two different objectives: the denoising of radio astronomy images, that will be described in Sect. 2, and the detection of X-ray sources in noisy data, that will be discussed in Sect. 3.

2 Denoising Radio Interferometric Data

In the case of radio interferometry, the aperture synthesis approach is exploited to generate observations in the radio band. Aperture synthesis consists in the adoption of sophisticated data processing techniques in order to obtain sky images from the collected signals, estimating the energy flux density coming from a given region of the sky, at a specific frequency. Besides random noise (of, e.g., thermal or electronic origin), these observations are affected by the resolution of the instrument, by the geometric pattern characterising the observation process (sparse antennas rotating with the Earth) and by a number of other effects related to the propagation of radio signals through the Earth's atmosphere (e.g. ionospheric disturbances or Radio-Frequency Interference) which may contaminate the final product. For a more extensive discussion of these aspects, we refer to [2] and reference therein.

We have adopted a Deep Learning based methodology to remove such noise and artefacts from images resulting from the imaging and deconvolution processes on data mimicking LOFAR HBA observations. More specifically, we have adopted an *autoencoder* based approach. An autoencoder is a type of neural network which aims at learning an identity map for the input data through encoding and decoding data pairs:

$$\tilde{I} = D(E(I)), \tag{1}$$

where I and $\tilde{I}$ are the input and reconstructed images respectively, and E and D are the encoder and decoder transforms, which minimise the difference of the reconstructed and the input data:

$$D, E = \mathrm{argmin}_{(\mathrm{D,E})}(\mathrm{MSE}(I - D(E(I))), \tag{2}$$

where MSE is the mean squared error. The architecture of the network consists in two convolutional plus two pooling layers for encoding, two convolutional with two unpooling layers for decoding and one dense layer made of 200/400 neurons. The 200 elements dense layer is to prefer for noisy data to avoid overfitting.

Realistic mock observations (Sky models), necessary for the training of the autoencoder, have been generated starting from light cones built from the results of cosmological simulations as described in [1] and [3]. A set of 1000 independent sky model images was generated by applying random rotations to each of the different redshift slices used to produce the lightcones. The nominal angular resolution of the images (pixel size) is 2 arcsec. The described procedure was used to generate 2000×2000 pixel images, both sky models and corresponding noisy images, sampling a field of view of $1.1° \times 1.1°$ and represent the dataset against which the autoencoder is trained.

Figure 1 shows an example of the denoising of an image where faint radio sources are present. In general, the autoencoder has proved to efficiently remove noise and artefacts preserving the properties of the regions of the sources with signal to noise ratio (S/N) of the order or lower than 1. However, the convolutional, multi-layer architecture of the encoder introduces numerical blurring which impacts in particular the highest peaks of the flux density distribution which result to be dimmed. Therefore the optimal adoption of the autoencoder seems to be for faint (i.e. at S/N $\sim$ 1 or below) sources and/or for performing data segmentation.

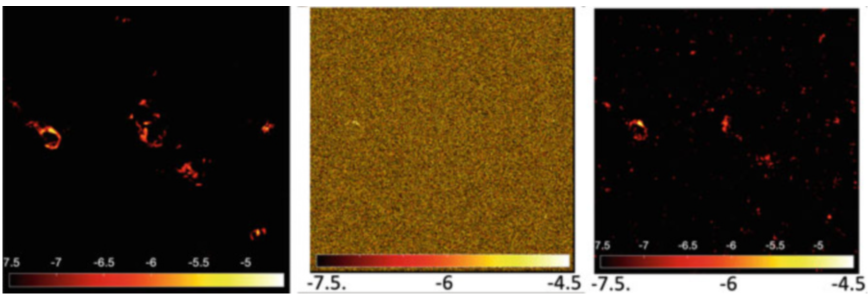

Fig. 1 Flux density maps of a sample sky model comparing the sky reference image (left), the noisy input image (center) and the autoencoder denoised image (right). Flux densities are in log(Jy/arcsec^2) scale

3 X-Ray Source Finder

In the case of X-ray observations, we have followed a similar procedure as that described in Sect. 2 to generate the mock images. In this case, however, we started from the Magneticum simulation [4] and we emulated Athena X-ray observatory data.[1]

The objective was to identify sources in a noisy background. We have adopted a *fully convolutional network* approach, that proved to be highly effective for the tasks related to image segmentation (e.g. [5]). It is interesting to notice that our Deep Learning model has been developed to perform the segmentation of data from a completely different scientific application, i.e. photoelastic images from experiments of granular materials [6] (see Fig. 2). However, it proved to be effective also for our astronomical data, highlighting the flexibility and the strength of Machine Learning.

The fully convolutional network consists of a contracting path and an expansive path. The contracting path is composed of an input layer, loading the input images, a downsampling convolutional network (composed by convolutional and pooling layers) which ends with a final level composed by convolutional layers. The expansive path starts from this deepest level, followed by an upsampling

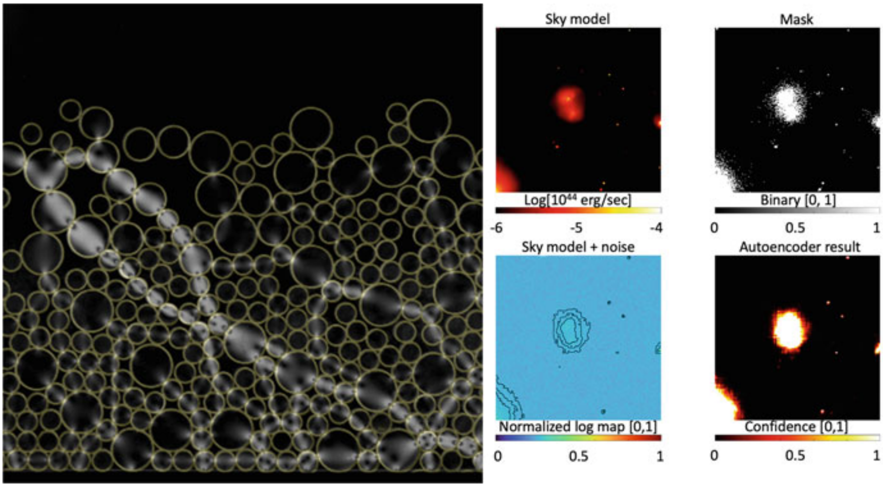

Fig. 2 Results of the application of the fully convolutional network for the segmentation of experimental granular flow data (left) and X-ray data (right). For X-ray data, the top left panel is the simulated X-ray Flux, the top right panel is the mask used for the training, the bottom left panel is the noisy image with probability contours superimposed and the bottom right panel is the probability distribution resulting from the network

[1] https://www.the-athena-x-ray-observatory.eu/.

convolutional network, specular to the downsampling one. At each upsampling level, the feature maps are summed to the corresponding feature maps from the contracting path, in order to supply the spatial information to precisely localise the identified features. The final output layer returns the results. In our case, the results are represented by the confidence maps, of the same size of the input ones, expressing the probability that a given pixel represents (or is part of) a source, as shown in Fig. 2.

4 Conclusions

Incoming astronomical observational facilities are going to deliver huge amounts of complex data. This data represents an ideal test case for novel Deep Learning approaches, that will effectively exploit increasingly capable computing resources. We have studied the usage of autoencoders to remove noise and artefacts from radio interferometric data, and the usage of fully convolutional networks for image segmentation. In both cases, the Deep Learning networks proved to be flexible and effective in their tasks, although further investigation is required to extend their adoption to observational data.

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